The Bright Side of Diversification: The Case of R&D Productivity*

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ABSTRACT

This paper examines the effects of corporate structure on innovation productivity. We find that conglomerates achieve greater innovation productivity relative to single-segment firms even though they spend less on R&D. We further show that conglomerates with segments more closely related in technology or with senior executives coordinating their innovation endeavors have greater R&D productivity. Using a quasi-experiment in the M&A setting, we find similar evidence as Seru (2014) that acquired target firms become less innovative following mergers relative to withdrawn target firms. However, we find that post-merger R&D productivity increases significantly for both acquiring and combined firms. This highlights that while disruption from post-merger integration may impede innovation for targets, it tends to be outweighed by the knowledge spillover gain for acquirers. Our results collectively suggest that a conglomerate corporate structure facilitates intra-firm knowledge spillover and thereby improves innovation productivity.

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I. INTRODUCTION

How corporate structure affects investment efficiency is an important yet unsettled question. A large body of early research documents that conglomerate firms allocate their capital investment inefficiently across divisions, causing them to be traded at a discount relative to the matched portfolios of single-segment firms (e.g., Lang and Stulz, 1994; Berger and Ofek, 1995; Shin and Stulz, 1998; Rajan, Servaes, and Zingales, 2000; Scharfstein and Stein, 2000). However, recent studies find that after carefully addressing measurement and other econometric issues, the diversification discount disappears, and sometimes even turns into a premium (e.g., Whited, 2001; Campa and Kedia, 2002; Villalonga, 2004; Custodio, 2013).

In this study, we focus on the effect of corporate structure on the productivity of research and development (R&D) investment. R&D investment has two unique features. First, successful innovation with a high impact often requires incorporating knowledge from different areas. Miller, Fern, and Cardinal (2007) show that the use of extra-organizational and inter-divisional knowledge has a significantly positive impact on the influence of an invention. Second, R&D often has a strong positive externality (i.e., R&D spillover effects); that is, the R&D of a particular firm not only increases its own productivity, but can also be useful for other firms operating in related technology areas, such as its industry peers and firms in its customer or supplier industries. Recent studies show that the social rate of return to R&D is approximately two to three times as large as the private return (e.g., Bloom, Schankerman, and Van Reenen, 2013; Colino, 2016), suggesting an economically significant R&D externality.

We posit that conglomerates can better take advantage of the above two features of R&D investment, and thus their corporate structure can be more efficient in promoting R&D productivity. First, while communication with researchers from different but related areas helps produce successful innovation with a high impact, the exchange of proprietary knowledge between different companies would be scarce because such communication might lead to the leakage of information to product market rivals, which could damage firms' competitive advantage and future performance (e.g., Bloom et al., 2013). In contrast, different divisions of a conglomerate should be much less concerned about such communication, as the proprietary knowledge would remain limited within the boundary of the firm. Consistent with this notion, prior studies show that smoother within-firm information sharing gives conglomerates a significant information advantage relative to single-segment firms (e.g., Massa and Rehman, 2008).

Second, even if a firm's R&D output is useful to other firms, it is very difficult for the firm to appropriate economic benefits through selling the knowledge via the market mechanism. The reason is straightforward: the value of knowledge can only be determined with reasonable precision after it is disclosed to a buyer, at which point the buyer has obtained the information at zero cost (e.g., Arrow, 1962; Teece, 1986; Miller et al., 2007). According to the neo-classical transaction cost theory (e.g., Coase, 1937; Williamson, 1979), such activities with high transaction costs are more efficiently handled within the boundary of the firm. By operating in different segments in related technology areas, conglomerates should be able to internalize, at least partially, the externality of R&D activities by individual segments.[1] In contrast, it is much more difficult for single-segment firms to capture such an externality due to the aforementioned market failure.

[1] For example, Amazon has done excellent job internalizing the externality of the R&D efforts of different segments. In a letter to shareholders in 2019, Amazon CEO Jeff Bezos said, "Development of the Fire phone and Echo was started around the same time…we were able to take our learnings as well as the developers (from the Fire phone) and accelerate our efforts building Echo and Alexa." Furthermore, he added, "The vision for Echo and Alexa…had origins in two other arenas: machine learning and the cloud. After many years of development, Echo debuted in 2014, powered by Alexa, who lives in the AWS cloud."

While the above arguments predict higher R&D productivity for conglomerates, agency problems associated with conglomerates may cause executives to allocate R&D investment in a suboptimal manner, similar to other capital investment (e.g., Amihud and Lev, 1981; Houston, James, and Ryngaert, 2001; Aggarwal and Samwick, 2003; Laeven and Levine, 2007; Andreou, Doukas, Louca, and Malmendier, 2010). However, such misallocation, especially overinvestment, should be much more contained for R&D investment than for other physical capital expenditures. Unlike other capital expenditures, which are capitalized as assets, R&D expenditures are mostly treated as expenses that reduce net income. Therefore, the expensing of R&D costs increases the perceived cost of R&D investment to managers and mitigates their incentive for inefficient R&D investment. To the extent that the benefits of inter-segment knowledge spillover and smoother collaboration across divisional-level R&D efforts can dominate the inefficient resource allocation driven by agency problems, we expect conglomerates to have higher R&D productivity.

We test the above prediction by first examining the differences in R&D investment and innovation output between multi-segment conglomerates and single-segment firms. Consistent with our prediction, we find that relative to single-segment firms, R&D investment (both R&D expenditures and R&D capital) by conglomerates is associated with not only a significantly greater number of future granted patents but also significantly higher patent quality as measured by patent citations and (inferred) patent market value. For example, the inter-quartile increase in R&D expenditures from the 25^{th} to the 75^{th} percentile is associated with a 143 percent increase in the number of patents for multi-segment conglomerates, compared to a 71 percent increase for single-segment firms. These results suggest that the benefits of inter-segment knowledge sharing and technology collaboration dominate the negative impact of the inefficient internal capital market on innovation productivity for conglomerates.[2]

We further develop two cross-sectional analyses with respect to where the benefits of inter-segment knowledge spillover and internal collaboration are likely to be more pronounced. The extent to which firms can benefit from intra-firm knowledge spillover is contingent on their ability to identify, assimilate, and exploit knowledge across and within their business units (Cohen and Levinthal, 1990). Two organizational mechanisms could potentially affect such ability: 1) the technology distance across the segments of a firm; and 2) the communication structure among the segments of a firm. Regarding the former, prior research shows that the technology distance and complementary knowledge across business units affect firms' knowledge sharing and innovation productivity (e.g., Adams and Jaffe, 1996; Helfat, 1997). As such, we expect that multi-segment firms with business units that are more technologically closely related are better able to capture the benefits of intra-firm knowledge spillover relative to their counterparts with technologically distant business units, leading to greater innovation productivity.

The second organizational mechanism relates to the communication structure within a firm. Recent research has shown that the coordination of knowledge workers within a firm not only enhances but also accelerates knowledge assimilation (e.g., Paruchuri and Awate, 2017; Moreira, Markus, and Laursen, 2018). To the extent that firms establish internal routines that facilitate better coordination of their knowledge workers, they are more likely to reap the

[2] In a recent study, Li, Qiu, and Wang (2019) find that technology conglomerates that form strategic alliances have greater tolerance for failure, and thus are more likely to explore new and risky technology areas and generate more impactful innovation. In an additional analysis, we test whether the higher innovation productivity of conglomerates relative to single-segment firms is attributable to their greater tolerance for failure. We find that conglomerates do not appear to file more patents in new technology areas.

benefits of intra-firm knowledge spillover. Having senior executives coordinating the firm's R&D endeavors can be one such routine. This is consistent with anecdotal evidence that all of the ten most innovative firms, including Apple and Google, have senior executives managing their R&D efforts.[3] Accordingly, we posit that conglomerate firms with such senior positions are likely to have greater innovation productivity.

Our empirical evidence is in line with both of our cross-sectional predictions. Using a measure of segment technology closeness developed in the same spirit as Lee, Sun, Wang, and Zhang (2018), we find that among conglomerate firms, the R&D investment of firms with greater technology closeness leads not only to more patent grants but also to higher quality patents with more citations and higher market value. With respect to R&D coordination across segments, we document that having senior executives, such as chief technology officers or chief R&D officers, to coordinate a conglomerate's R&D efforts also results in significantly higher R&D productivity as measured by the above three proxies.

These results suggest that conglomerates are associated with higher R&D productivity than single-segment firms. However, the corporate structure is an endogenous choice, which may be influenced by innovation productivity in the first place. To mitigate this endogeneity problem, we exploit a quasi-experiment on acquiring firms in the merger and acquisition (M&A) setting (Seru, 2014). Specifically, we compare the R&D productivity of a treatment sample of acquiring firms that complete the acquisition and become more diversified to that of a control sample where acquirers withdraw from the deal for reasons unrelated to innovation. Our results show that successful diversifying acquisitions help acquiring firms improve their R&D productivity compared to the control sample of withdrawn firms. The results hold even after we exclude the

[3] The ten most innovative firms are Apple, Google, Microsoft, Amazon, Samsung, Tesla, Facebook, IBM, Uber, and Alibaba, based on the Boston Consulting Group's 2018 Most Innovative Companies list.

patents filed by the newly acquired divisions. Specifically, using a difference-in-differences design, we find that, prior to mergers, acquiring firms in successful acquisitions are no different from their counterparts in withdrawn deals in terms of the number of patents, the associated citations, and the market value. Compared to acquiring firms in withdrawn mergers, those in successful deals, however, show an annual increase of approximately 15 more patents and 37 more citations in the three-year period following the merger relative to the three-year period prior to the merger.

In a related paper, Seru (2014) finds that compared to failed targets, firms acquired in diversifying mergers produce both fewer and less novel patents, concluding that "the diversified organization form impedes the pursuits of novelty in innovation inside its boundaries" (p. 402). Following major M&A deals, firms often carry out various restructurings, such as layoffs and relocation, to better integrate the business. The post-merger integration process can thus be quite distracting, especially for the employees of the target companies who are often concerned about their job security and stability (PricewaterhouseCoopers, 2017). Such distractions can adversely affect the productivity of target firms' R&D personnel, even if the conglomerate form of corporate structure is more conducive to innovation. Consistent with this notion, we find that while the innovation output of target firms appears to decrease for successful M&As relative to withdrawn cases, the innovation output of successful acquiring companies is associated with a significantly larger increase than that of withdrawn acquirers. For example, *target* firms in withdrawn mergers experience an annual increase of approximately four more patents in the three-year period following the merger relative to the three-year period prior to the merger than *target* firms in successful mergers (consistent with Seru, 2014). In contrast, *acquiring* firms in successful deals experience an annual increase of nearly 18 more patents following the merger relative to the pre-merger period than *acquiring* firms in withdrawn deals. Our results highlight the differential innovation productivity between acquiring and target firms, and thus the importance of considering the innovation activities of both parties to gain a more complete picture of the impact of the conglomerate form on R&D productivity.

We contribute to the literature in two significant ways. First, our study contributes to the important literature on the effect of diversification and the internal capital market on investment efficiency. The "bright side" view of the internal capital market posits that conglomerate headquarters are effective and efficient mechanisms in resource allocations to create firm value (e.g., Stein, 1997). However, the "dark side" view of the internal capital market posits that the diversity of resources or corporate "socialism" among conglomerates can lead to inefficient capital allocation (e.g., Rajan et al., 2000; Scharfstein and Stein, 2000). Our study sheds light on this debate by providing compelling new evidence for the "bright side" of diversification, that is, diversification facilitates access to *inter-divisional* knowledge in the R&D process and internal knowledge spillover, which helps improve the productivity of R&D investment.

Second, we contribute to the literature on the effect of M&A activity on innovation productivity. Using the M&A setting, Seru (2014) finds that internal capital market intensity negatively influences the R&D productivity of conglomerates. In particular, he finds a significant post-merger decline in the innovation productivity of *acquired targets* and conclude that conglomerate organizational form hinders R&D innovation. Our results suggest that such a conclusion is premature once we consider changes in acquirers' R&D productivity. Specifically, while post-merger R&D productivity declines for target firms due to factors such as disruption from post-merger integration, the acquiring firms experience a significant increase in post-merger R&D productivity which is more than sufficient to offset the decrease of the target firms.[4]

The rest of the paper proceeds as follows. Section 2 describes the sample construction and the measurement and descriptive statistics of the main variables. Section 3 provides the empirical results, and section 4 concludes the paper.

II. SAMPLE, VARIABLE MEASUREMENT, AND DESCRIPTIVE STATISTICS

Data and sample selection

To construct the sample, we begin with all firms reporting business segments in the Compustat Historical Segments file from 1980 to 2007. The sample selection starts in 1980 following Seru (2014), and ends in 2007 as this is the last year we can measure innovation output (i.e., patent and citation) while minimizing the truncation problem using the patent data developed by Kogan, Papanikolaou, Seru, and Stoffman (2017). We exclude firms with incomplete information on segment assets or sales, firms in the financial services (SIC codes 6000-6999) and utilities (SIC codes 4900-4949) industries, firms with total assets or sales less than $10 million, and firms with missing or zero R&D expenditures.[5] We further require that the cumulative investment in M&As over the past five years is no greater than 25 percent of the current total assets to mitigate the concern that the innovation output could be purchased through

[4] In another related study, Bena and Li (2014) use a similar setting to examine the role of technological overlap between firm pairs on corporate mergers and acquisitions. They document that the technological linkage between merging firms leads to greater incidence of M&A transaction and post-merger innovation improvement than cases with no technological overlap between merging firms. However, since Bena and Li (2014) primarily focus on the effect of technological linkage on the incidence and outcome of M&A activities, their evidence does not speak to the question how corporate structure affects innovation efficiency in general. We contribute by providing evidence on the first order effects that corporate structure does in fact facilitate innovation efficiency.

[5] As suggested in Koh and Reeb (2015), we include firms with missing R&D data in our robustness tests by setting missing values to either zero or the industry mean, and we find that our main inferences do not change.

acquiring innovative target firms (Sevilir and Tian, 2012) rather than through internal development.

To better compare multi-segment with single-segment firms, we require that each segment of a conglomerate has at least two single-segment firms as peers in the same year and industry (identified by the three digit SIC code). From the Compustat/CRSP Merged Annual Fundamental file, we obtain financial data to construct the control variables, and we use the firm identifier *permno* to merge with the patent data. Our final sample includes 2,946 multi-segment (conglomerate) firm-year observations and 11,895 single-segment firm-year observations from 1984 to 2007. For our final sample of conglomerates, on average, the aggregated segment sales account for more than 99 percent of the firm's total sales; the aggregated segment assets account for more than 87 percent of the firm's total assets.

Variable measurement

Measuring R&D investment

We use two measures of R&D investment: R&D expenditures ($R\&D\ Expenditure_{it}$) and R&D capital ($R\&D\ Capital_{it}$). $R\&D\ Expenditure_{it}$ is a firm's current R&D investment, and $R\&D\ Capital_{it}$ reflects the firm's stock of R&D investment over the past five years, assuming an annual depreciation rate of 20 percent, calculated as $R\&D\ Expenditure_{it} + 0.8 * R\&D\ Expenditure_{it-1} +\ 0.6 * R\&D\ Expenditure_{it-2} + 0.4 * R\&D\ Expenditure_{it-3} + 0.2 * R\&D\ Expenditure_{it-4}$ (e.g., Chan, Lakonishok, and Sougiannis, 2001). Note that we only require the current year's R&D expenditures to have a positive value from Compustat, and we set missing values for R&D to zero for the period from $t - 1$ to $t - 4$. Due to the right-skewed distribution of R&D investment, we use the natural logarithm of R&D expenditures and R&D capital in our main analysis.

Measuring innovation output

Patents capture the productivity of R&D investment, and are recognized as the most important measure of innovation output (e.g., Griliches, 1990). We obtain data on firms' patenting activity from the patent dataset constructed by Kogan et al. (2017), which covers all patents filed with and granted by the U.S. Patent and Trademark Office (USPTO) from 1926 to 2010. We create a measure of subsequent innovation output ($Patent_{it+1}$) at the firm-year level by counting the number of each firm's patent applications during year $t + 1$. Note that all of the patent applications covered in the dataset are ultimately granted by the USPTO, and we use the patent application year instead of the grant year because it better captures the actual time of innovation (Griliches, Pakes, and Hall, 1988).

Nevertheless, $Patent_{it+1}$ is a simple count of patents, and it does not necessarily capture the quality of a firm's innovation output. Indeed, patents vary widely in their technological influence and economic value, which are reflected in citations and the market response to patent grant news. Therefore, we use two measures of patent quality, weighted citations ($Citation_{it+1}$) and size-adjusted market value ($Market_{it+1}$), both of which are created by Kogan et al. (2017). $Market_{it+1}$ is inferred from the stock market response to patent grant news and is scaled by book assets. For firms with no patent filings, both measures equal zero.[6] We use the natural logarithm of one plus the patent count and patent quality measures in our main analysis due to the right-skewness in the distribution of these measures.

As discussed before, due to the truncation problem of the patent data, our sample period ends in 2007. Specifically, a patent obtains its official record and enters the dataset of Kogan et

[6] We run our analysis within firms with patenting activity for robustness check, and find that the main inferences do not change after the exclusion of non-patenting firms.

al. (2017) only when its application is granted by the USPTO. It takes two years on average for a patent application to go through the USPTO review process and eventually be granted. This average two-year lag between application and grant would result in a sharp decrease in the number of patent applications that are ultimately granted as the data approach 2009 and 2010. Hence, as suggested by prior research (e.g., Hall, Jaffe, and Trajtenberg, 2001), we end our sample period in 2007 to minimize this known truncation problem in the patent data.

Measuring control variables

Following the literature (e.g., Hall and Ziedonis, 2001), we include a vector of firm characteristics that may affect a firm's innovation output, which includes firm size measured as the natural logarithm of total assets ($Size_{it}$), sales growth ($Sales\ Growth_{it}$), leverage ($Leverage_{it}$), return-on-assets (ROA_{it}), profit margin ($Profit\ Margin_{it}$), Tobin's Q ($Tobin_{it}$), cash holdings ($Cash_{it}$), capital intensity ($Capital\ Intensity_{it}$), capital expenditures ($Capital\ Expenditure_{it}$), human capital measured as the natural logarithm of employee numbers ($Employee_{it}$), and firm age (Age_{it}), along with year and industry fixed effects. All control variables are measured for the year immediately before we measure the innovation output and are winsorized at the top and bottom one-percent levels of their distributions. Appendix 1 details the variable definitions.

Descriptive statistics

Table 1 summarizes the empirical distributions of the key variables for conglomerates and single-segment firms in Panel A and Panel B, respectively. An average conglomerate invests 6 percent of total assets in R&D, and the five-year cumulative R&D investment accounts for 16 percent of total assets. An average conglomerate generates approximately 41 patents in the subsequent year, and these patents receive total weighted citations of 87 and have an inferred market value of 432. An average single-segment firm has 10 percent of total assets in R&D expenditures and 27 percent of total assets in R&D capital. The R&D investment is associated with 13 patents which generate 28 total weighted citations and an inferred market value of 138. It appears that conglomerates do not invest more in R&D but generate more innovation output. Moreover, we find that relative to single-segment firms, conglomerates have a larger firm size, lower sales growth, higher profitability in terms of return-on-assets and profit margin, lower Tobin's Q and capital expenditures, lower leverage and cash holdings, higher capital intensity and capital expenditure, more employees, and longer operating histories.

III. EMPIRICAL RESULTS

A closer comparison of conglomerates and single-segment firms

To investigate whether the R&D investment is more productive for conglomerates than for single-segment firms, we first provide a univariate comparison of R&D productivity between conglomerates and their pseudo benchmark firms in Table 2. This comparison is different from the descriptive statistics reported separately for conglomerates and single-segment firms in Table 1, as in Table 2 we essentially "combine" several single-segment firms to create a pseudo benchmark firm mimicking a conglomerate with multiple segments. Specifically, for each segment of a conglomerate, we identify at least two single-segment peer firms operating in the same year and industry. We then use the median value across single-segment peers as the pseudo benchmark value for that segment. Finally, we use the mean value of the pseudo benchmark values across the segments weighted by the conglomerate's segment sales as the value of the pseudo benchmark firm.[7]

Table 2 shows that conglomerates invest significantly less in R&D, both currently and historically, relative to their pseudo benchmark firms. For example, for each dollar of sales, on average, conglomerates invest seven cents in R&D, while their pseudo benchmark firms invest nine cents. Conglomerates, however, are more innovative in terms of patent filings and patent quality as reflected in patent citations and market value. We find that each $10 million of R&D expenditures is associated with four patents for conglomerates and two patents for their pseudo benchmark firms in the following year, and that each $100 million of R&D capital cumulated over the past five years generates sixteen patents for conglomerates and nine patents for their pseudo benchmark firms. The differences in patent citations and market value are also statistically and economically significant for each unit of investment in R&D.

While this univariate comparison generates indicative and interesting results, we next turn our attention to regression analysis to further investigate whether and how corporate structure affects innovation productivity, after controlling for other firm characteristics. Table 3 reports the results of the OLS regressions of innovation output on R&D investment separately for conglomerates and single-segment firms, using the following model,

$$Innovation\ Output_{it+1} = \alpha + \beta \cdot R\&D\ Investment_{it} + \gamma' \cdot Controls_{it} + \varepsilon_{it}. \tag{1}$$

[7] We use a hypothetical conglomerate to illustrate the measurement of the R&D ratio (R&D expenditures scaled by total assets) for the pseudo benchmark firm. For example, the conglomerate has segments *S*1 and *S*2, and *S*1 and *S*2 account for 40 percent and 60 percent of its total sales, respectively. *S*1 has three single-segment peer firms, *A*1, *A*2, and *A*3, operating in the same year and industry, and *S*2 has three single-segment peer firms, *B*1, *B*2, and *B*3, operating in the same year and industry. The R&D ratio for the pseudo benchmark firm would be calculated as 40 percent of the median R&D ratio across *A*1, *A*2, and *A*3, plus 60 percent of the median R&D ratio across *B*1, *B*2, and *B*3.

where i indicates the firm and t indicates time. The dependent variable, innovation output in year t+1, is the natural logarithm of one plus the number of patents filed and eventually granted ($Patent$), the natural logarithm of one plus the weighted citations received by the filed patents ($Citation$), or the natural logarithm of one plus the market value of these patents ($Market$). The variable of interest, R&D investment, is R&D expenditures in year t ($R\&D\ Expenditure_{it}$) or R&D capital accumulated over the past five years ($R\&D\ Capital_{it}$). The vector of the control variables ($Controls_{it}$) includes firm characteristics that could affect a firm's innovation output, along with year and industry fixed effects based on Fama and French's (1997) 12-industry classification.[8] Throughout the paper, we base our statistical inferences on the standard errors clustered by firm and year to mitigate time-series and cross-sectional residual dependence (Petersen, 2009).

In Table 3, Panel A, we examine the productivity of R&D investment in terms of the number of patents filed in year $t + 1$. The coefficient estimates on R&D investment are significantly positive for both conglomerates and single-segment firms (*t-statistics* ≥ 7.37), suggesting that firms investing more in R&D file more patents. This positive relation, however, is significantly more pronounced for conglomerates than for single-segment firms (χ^2-*statistics* ≥ 7.21). Specifically, for single-segment firms, a one hundred percent increase in R&D expenditures is associated with a 22 percent increase in the number of patents. For conglomerates, however, the same increase in R&D expenditures can generate a 28 percent increase in the number of patents. Similarly a one hundred percent increase in R&D capital relates to a 23 percent versus 32 percent increase in the number of patents for single-segment firms and conglomerates, respectively. In Panels B and C, we examine the productivity of R&D

[8] Our results are not sensitive to the alternative industry classification based on the two digit SIC code.

investment in terms of patent citations and market value, respectively. The coefficient estimates on R&D investment remain significantly positive for both conglomerates and single-segment firms (*t-statistics* ≥ 7.10), and again this positive relation is significantly more pronounced for conglomerates (χ^2-*statistics* ≥ 9.25). For example, a one hundred percent increase in R&D expenditures is associated with 29 percent and 40 percent increases in patent citations for single-segment and conglomerate firms, respectively.[9]

A recent study by Li, Qiu, and Wang (2019) finds that technology conglomerates that form strategic alliances have a greater tolerance for failure, and thus are more likely to explore new and risky technology areas and generate more impactful innovation. In an untabulated analysis, we test whether our finding of higher innovation productivity for conglomerates relative to single-segment firms is attributable to their greater tolerance for failure. We count the number of patents that are filed in a new technology class where the firm has not filed over the past five years, and we find that conglomerates do not appear to file more patents in new technology areas compared to single-segment firms.

Taken together, our closer examination of innovation productivity across multi-segment conglomerates and single-segment firms provides evidence different from Seru (2014) that highlights the "dark side" of the multi-segment corporate structure with respect to an inefficient internal capital market. We argue that the higher innovation efficiency of conglomerates could be attributable to intra-firm knowledge spillover. Therefore, in the next section, we examine the role

[9] The results in Table 3 are robust when we compare conglomerates to a sample of single-segment firms matched on year, industry, and sales. The results in Table 3 are also robust to an alternative model specification where we pool together conglomerates and single-segment firms in one regression and introduce an indicator variable for conglomerates and an interaction term between the indicator and R&D investment. We find consistent evidence that conglomerates appear to be more productive in innovation than single-segment firms.

of intra-firm knowledge spillover in the innovation process within conglomerates after controlling for internal capital market intensity.

Intra-firm knowledge spillover within conglomerates

We identify two organizational mechanisms that could facilitate a conglomerate's knowledge sharing and technology collaboration, i.e., the technology distance across business segments and the communication structure among segments. Next, we examine how conglomerates may benefit from these two mechanisms.

Technology distance across segments

We predict that conglomerates with business segments that are closely related in technology space are better able to leverage inter-segment knowledge spillover than their counterparts with technologically unrelated units. To test this prediction, we introduce a measure of technology closeness across segments within a conglomerate ($Tech\ Close_{it}$), and estimate the following model.

$$Innovation\ Output_{it+1} = \alpha + \beta_1 \cdot R\&D\ Investment_{it} + \beta_2 \cdot Rank(Tech\ Close_{it}) + \beta_3 \cdot R\&D\ Investment_{it} \times Rank(Tech\ Close_{it}) + \gamma' \cdot Controls_{it} + \varepsilon_{it}. \quad (2)$$

Equation (2) extends equation (1) by including the standardized quintile rank of technology closeness across segments and its interaction term with R&D investment, along with a new control variable, internal capital market intensity. Our segment technology closeness measure ($Tech\ Close_{it}$) is developed in the spirit of Lee's (2018) inter-firm measure of technology closeness. First, by identifying the patent assignee's industry membership based on the three digit SIC code and the patent's application year, we assign each patent to an industry-year. The universe of patents in our data includes 427 different technology classes defined by the

USPTO. For each industry-year, we construct a vector T that represents the industry's patent distribution out of 427 different technology classes over the past five years. We then calculate the technology linkage between industry pairs ($Tech\ Link_{ijt}$, which is an uncentered correlation coefficient, as shown in equation (3),

$$Tech\ Link_{ijt} = \frac{(T_{it}T'_{jt})}{(T_{it}T'_{it})^{1/2}(T_{jt}T'_{jt})^{1/2}} \qquad (3)$$

where $T_{it} = (s_t^1, s_t^2, \ldots, s_t^\tau, \ldots, s_t^{427})$ is a vector of industry i's patent distribution in a space of 427 classes in year t, with s_t^τ being the average share of the number of patents in the USPTO technology class τ out of industry i's total number of patents over the past five years. $Tech\ Link_{ijt}$ ranges from zero to one, and increases with the degree of the linkage between two industries in the technology space.

Next, we turn to the segment technology closeness measure using the technology linkage between industry pairs. Within a conglomerate, we form unique pairs of segments, and then identify each segment's industry membership. The technology closeness of a segment pair is determined by the technology linkage of the corresponding industry pair for the two segments. For example, if a conglomerate has four business segments, it would have six unique segment pairs. $Tech\ Close_{it}$ is calculated as the average technology linkage correlation among these six unique segment pairs. In our analysis, we use the standardized quintile rank of $Tech\ Close_{it}$, which ranges from zero to one with one being the highest degree of technology closeness across business segments.

In equation (2), we also include a new control variable, internal capital market intensity ($ICM\ Intensity_{it}$), to account for the effect of inefficient capital allocation within conglomerates on corporate innovation (e.g., Seru, 2014). With limited financial data available at the segment level, we measure internal capital market intensity as the inverse of the Herfindahl index of segment sales, i.e., $1/\sum_{j=1}^{n}(Segment\ Sales_j/Total\ Sales)^2$.

Table 4 presents the results of the OLS regressions specified in equation (2). In Panel A, we examine the variation in the number of patents in year $t+1$ with the degree of technology closeness across business segments. The coefficient estimates on both R&D investment and its interaction term with the technology closeness of segments, $R\&D\ Investment_{it} \times Rank(Tech\ Close_{it})$, are significantly positive at the one percent level after controlling for internal capital market intensity (*t-statistics* ≥ 2.92). This indicates that conglomerates with more R&D expenditures and R&D capital tend to file more patents in the subsequent year. Furthermore, conglomerates with technologically closely related segments tend to file more patents than their counterparts with the same level of R&D investment but technologically less related segments.

To interpret the coefficients, for a conglomerate with segments that are hardly connected in technology space (the quintile rank of $Tech\ Close_{it}$ being zero), a one hundred percent increase in R&D expenditures is associated with a 19 percent increase in the number of patents. A conglomerate with highly connected units in technology space (the quintile rank of $Tech\ Close_{it}$ being one), however, could achieve a 37 percent increase in patents for the same increase in R&D expenditures. We find similar results using R&D capital as the R&D investment measure.

In Panels B and C of Table 4, we respectively examine the variation in patent citations and market value with the degree of technology closeness across business segments. The coefficient estimates on the interaction term between R&D investment and technology closeness ($R\&D\ Investment_{it} \times Rank(Tech\ Close_{it})$) remain statistically and economically significant, suggesting that conglomerates with segments closely related in technology not only file more patents but also tend to have more novel patents.

Overall, we find evidence that the technology closeness of conglomerates' innovation efforts is positively associated with the number of subsequent patent filings, patent citations, and market value. This finding supports our prediction that conglomerate forms where individual segments operate with close technology proximity facilitate intra-firm knowledge spillover and thus lead to higher innovation productivity.

Technology coordination among segments

The second organizational mechanism that could potentially lead to higher innovation productivity relates to the communication structure that facilitates technology coordination among segments within a conglomerate. We argue that conglomerates with routines to better manage and coordinate their R&D activities among knowledge workers across various segments are more likely to reap the benefits of intra-firm knowledge spillover, and are thus have higher innovation productivity. One such routine is to have senior executives, such as chief technology officers or chief R&D officers, coordinating the conglomerate's innovation activities.

To test our prediction, we introduce a measure of technology coordination among segments within a conglomerate ($Tech\ Coordinate_{it}$), and we estimate the following model:

$$Innovation\ Output_{it+1} = \alpha + \beta_1 \cdot R\&D\ Investment_{it} + \beta_2 \cdot Tech\ Coordinate_{it} + \beta_3 \cdot R\&D\ Investment_{it} \times Tech\ Coordinate_{it} + \gamma' \cdot Controls_{it} + \varepsilon_{it}. \quad (4)$$

Equation (4) is similar to equation (2) except that we replace technology closeness with technology coordination among segments ($Tech\ Coordinate_{it}$) and its interaction term with R&D investment. $Tech\ Coordinate_{it}$ is an indicator variable that equals one if the conglomerate has senior executives managing and coordinating its innovation efforts, and zero otherwise. Using executive information from BoardEx, we search for senior positions whose title includes any of these words or phrases: tech, innovate, innovation, engineer, engineering, product development, research, scientific, science, and patent. We find that approximately 13 percent of the conglomerates in our final sample have at least one such senior position to facilitate corporate innovation.

Table 5 presents the results of the OLS regressions specified in equation (4). In Panel A, we examine the variation in the number of patents filed in year $t + 1$ across conglomerates, with and without senior executives, to better coordinate innovation activities. The coefficient estimates on both R&D investment and its interaction term with technology coordination ($R\&D\ Investment_{it} \times Tech\ Coordinate_{it}$) are significantly positive at the five percent level after controlling for internal capital market intensity (*t-statistics* $\geq$ 2.27). These results reveal that conglomerates with senior executives in charge of innovation efforts tend to have more patents than their counterparts without such senior executives.

Turning to coefficient interpretation, for a conglomerate having no senior management to coordinate innovation activities across business segments ($Tech\ Coordinate_{it}$ being zero), a one hundred percent increase in R&D expenditures is associated with a 27 percent increase in patents. Its counterparts with such senior executives ($Tech\ Coordinate_{it}$ being one), however, could achieve a 37 percent increase in the number of patents for the same increase in R&D expenditures. We find similar results using R&D capital as the measure of R&D investment.

In Panels B and C of Table 5, we examine the effect of having such senior executives to coordinate R&D efforts on a conglomerate's innovation quality, i.e., patent citations and market value, respectively. The coefficient estimates on the interaction term between R&D investment and technology coordination, $R\&D\ Investment_{it} \times Tech\ Coordinate_{it}$, remain statistically and economically significant (*t-statistics* ≥ 2.04). The results suggest that having a senior executive coordinating R&D efforts improves the innovation quality of a conglomerate.

Overall, these findings are in line with our prediction that conglomerates with senior executives to coordinate their R&D efforts across divisions file more patents and also have higher quality patents in terms of citations and market value.

The quasi-experiment

In the previous section, we show that conglomerates are associated with higher innovation productivity relative to single-segment firms. However, it is difficult to draw a causal inference about the effect of corporate structure on innovation, as it is plausible that firms with higher innovation productivity select themselves into a group of conglomerates. Therefore, in this section, we improve the identification by exploiting a quasi-experiment involving acquiring firms in the M&A setting. Specifically, the treatment sample is a group of acquirers that successfully merge with the target firms and become more diversified after the merger, whereas the control sample includes acquirers that withdraw from the merger for reasons unrelated to the innovation activities of either party of the deal. This design helps generate exogenous variation in corporate structure, pre- and post-merger, which facilitates our investigation of its impact on innovation output across successful and withdrawn deals.

Sample construction

The control sample consists of acquiring firms that withdraw from friendly mergers that are announced between 1984 and 2004 and are covered by the SDC's Mergers and Acquisitions database. The sample period begins in 1984 because the M&A information in the SDC is less reliable before 1984, and the sample period ends in 2004 so that we can measure the subsequent innovation output that minimizes the data truncation problem for the three years after the withdrawal (i.e., from 2005 to 2007). We search news articles from Lexis-Nexis and Factiva for the reasons of the withdrawal, and we filter out the deals where the withdrawal could be related to the innovation activities of either party and the deals where the reason for failure could not be determined. The final control sample includes 143 unique failed mergers between 1984 and 2004 with reasons exogenous to innovation, specifically competing bids (61%), objections by regulatory agencies (27%), and unexpected market conditions (12%).

To construct the treatment sample, we begin with all completed friendly mergers announced between 1984 and 2004 and covered by the SDC's Mergers and Acquisitions database. We require that the acquirer owns less than 50 percent of the target firm prior to the merger, seeks more than 50 percent ownership of the target firm, and fully owns the target firm after the deal completion. To facilitate comparison with the control sample, we keep only those completed deals that meet the following two conditions: (1) the acquirer-target industry pairs (identified by the two digit SIC code) match the industry pairs of the deals in the control sample, and (2) the announcement date is within the three-year window centered on the announcement year of the deals in the control sample. The final treatment sample includes 3,112 unique successful mergers between 1984 and 2004.[10]

For the treatment (control) sample, we use the three years prior to the bidding announcement and the three years following the completion (withdrawal) in our analysis, and we require that we have complete financial data for each unique deal at least one year before and

[10] We find that 85 percent of the mergers in the treatment sample involve acquiring firms and target firms operating in different industries by the four digit SIC code, which is consistent with our assumption that acquiring firms in the treatment sample tend to be more diversified following successful mergers. To avoid further downsizing the control sample, we do not require that acquiring firms and target firms operate in different industries. Nevertheless, we find that our main results are robust if we exclude mergers with acquiring firms and target firms operating in the same industry.

one year after the deal completion (withdrawal), and can measure subsequent patent filings with minimal data truncation risk. In addition, we exclude firms in the financial services (SIC codes 6000-6999) and utilities (SIC codes 4900-4949) industries, firms with total assets or sales below $10 million, and firms with missing or zero R&D expenditures. The final treatment (control) sample consists of 13,277 (522) firm-year observations between 1981 and 2007.

Difference-in-differences analysis of acquiring firms

In this section, we examine the difference-in-differences for the innovation productivity of acquirers in successful versus withdrawn mergers. We argue that acquirers that become more multi-divisional after successful mergers are more likely to reap the benefits of intra-firm knowledge spillover and thereafter have higher innovation productivity relative to acquirers that withdraw from the mergers for exogenous reasons. We test this prediction in both univariate and multivariate settings.

Table 6 provides the univariate results of the difference-in-differences analysis of the acquiring firms' innovation productivity, before and after mergers, in successful versus withdrawn deals. Specifically, for each deal, we calculate the average number of patents filed in each year and their associated citations and inferred market value (1) over the three years prior to the bidding announcement, and (2) over the three years following the deal completion/withdrawal. We then take the average of these values across deals in the treatment and control samples and compare the two. Prior to the bidding announcement, we find no difference between acquiring firms in successful acquisitions versus withdrawn acquisitions in terms of the number of patents and their associated citations and market value (|*t-statistics*| $\leq$ 1.42). However, following a successful diversifying acquisition, acquiring firms tend to have significantly more patents and significantly higher quality innovation output in terms of citations and market value relative to their counterparts (*t-statistics* ≥ 1.76). For example, during the three years after the merger relative to the prior three years, acquiring firms in successful deals have an annual increase of approximately 15 more patents and 37 more citations than acquiring firms in withdrawn mergers. The univariate difference-in-differences results further indicate that the post-merger increase in the innovation productivity of successful acquiring firms is significantly greater across all three measures (*t-statistics* ≥ 2.08) compared with their counterparts in withdrawn deals.

Next, we estimate the following difference-in-differences regression model using the three years prior to the bidding announcement and the three years following the deal completion or withdrawal for each deal in the treatment and control sample.

$$Innovation\ Output_{it+1} = \alpha + \beta_1 \cdot R\&D\ Investment_{it} + \beta_2 \cdot R\&D\ Investment_{it} \times Post_{it} + \beta_3 \cdot R\&D\ Investment_{it} \times Treat_{it} + \beta_4 \cdot R\&D\ Investment_{it} \times Post_{it} \times Treat_{it} + \gamma_1 \cdot Post_{it} + \gamma_2 \cdot Treat_{it} + \gamma_3 \cdot Post_{it} \times Treat_{it} + \delta' \cdot Controls_{it} + \varepsilon_{it}. \tag{5}$$

In equation (5), $Post_{it}$ is an indicator variable that equals one if the firm-year observation is from the three-year period following the merger completion or withdrawal, and zero otherwise. $Treat_{it}$ is an indicator variable that equals one for treatment firms (i.e., successful cases) and zero for control firms (i.e., withdrawn cases). All other variables are defined as in equation (1). The change in innovation productivity before and after the merger is estimated by $\beta_2 + \beta_4$ for the treatment firms and by β_2 for the control firms. Hence, β_4 represents the difference-in-differences for innovation productivity between the treatment and control groups, which is predicted to be positive. We include year and industry fixed effects based on Fama and

French's (1997) 12-industry classification, and we base our statistical inferences on standard errors clustered by firm and year.

Table 7 presents the results of the OLS regressions specified in equation (5) using the number of patents, patent citations, and market value as the dependent variable, respectively, with and without the vector of the control variables. The following findings emerge. First, the coefficient estimates on the interaction term between R&D investment and the treatment indicator (β_3) are not significantly different from zero (*t-statistics* ≤ 1.51), suggesting that prior to the bidding announcement, the treatment and control firms have similar innovation productivity. This satisfies the parallel trend assumption of the difference-in-differences approach. Second, over the three years following deal completion/withdrawal, innovation productivity tends to increase for treatment firms relative to the three years preceding the bidding announcement, yet remain the same for control firms, as indicated by the insignificant coefficient estimate for β_2. Lastly, the coefficient estimates for β_4 ($R\&D\ Investment_{it} \times Post_{it} \times Treat_{it}$) are significantly positive at conventional levels, with or without controlling for acquirer firm characteristics, suggesting that successful acquirers exhibit much higher innovation productivity than withdrawn acquirers in the post-merger period relative to the pre-merger period. This supports our prediction that successful mergers allow acquirers to benefit from intra-firm knowledge spillover facilitated by a more diversified corporate environment following the business combination.[11]

[11] In an untabulated analysis, we run regressions based on equation (5) using the three years prior to the bidding announcement and each of the three years following the merger completion/withdrawal, and our main inferences do not change. In addition, we find robust results after we exclude the patents generated by the acquired target firms using a subsample of publicly listed target firms.

Difference-in-differences analysis of both acquiring and target firms

So far, our evidence indicates that a multi-segment corporate structure can facilitate intra-firm knowledge spillover and thus lead to higher innovation productivity for the acquiring firms. In contrast, Seru (2014) conclude that the inefficiency of the internal capital market embedded in multi-divisional firms tends to hinder corporate innovation for target firms following mergers. In this section, we seek to consider the innovation activities of both acquiring and target firms to gain a more complete picture of the impact of the conglomerate form on R&D productivity. We analyze M&A deals involving publicly listed target firms (118 deals completed and 20 withdrawn) where we can better track the patenting activity of acquirers and targets before and after the mergers.

Our goal is to compare the innovation output in the pre- and post-merger periods for both acquirers and targets in successful and withdrawn deals. To simplify the task, we focus only on the number of patents and associated citations. With both acquirers and targets being public firms, we can observe the patents filed by acquirers and targets in the pre-merger period for both completed and withdrawn deals. We can also observe patents filed in the post-withdrawn period where there is no business combination. However, for the post-merger period of completed deals, we can only observe patents generated by the combined business, not the individual acquirers and targets. The following exhibit illustrates the patent data availability.

		Acquiring firms	Target firms
Successful M&A deals ($Treatment$)	Pre	Available	Available
	$Post$	Not available	Not available
Withdrawn M&A deals ($Control$)	Pre	Available	Available
	$Post$	Available	Available

Using detailed data on the city where patents are filed, we address the issue of patent data availability as follows. For a completed deal, if a post-merger patent is filed in a city where the target firm has filed at least once and the acquirer has never filed any patent before the business combination, we identify this patent as the innovation output generated by the target firm. After excluding all such patents, we classify the remaining patents as the innovation output of the acquirer's existing divisions.

Table 8, Panel A, reports the results of the difference-in-differences analysis of *target* firms' patent filings before and after mergers. Specifically, for each deal, we calculate the average number of patents filed in each year (1) over the three years prior to the bidding announcement, and (2) over the three years following the deal completion/withdrawal.[12] We then take the average of these values across deals within the treatment and the control sample, respectively, and compare these two samples. We find that, in terms of patent filings before the bidding announcement, target firms in the treatment sample are similar to their counterparts in the control sample. Once combined with the acquirers, target firms become significantly less productive in corporate innovation compared to their counterparts that withdraw from mergers. Specifically, the increase in the patents of target firms in successful mergers from the pre-merger period is smaller than that experienced by target firms in withdrawn mergers by approximately four patents. This finding is largely consistent with Seru's (2014) finding that relative to the control sample, target firms experience a decline in innovation productivity after mergers.

In Table 8, Panel B, we investigate the patent filings of *acquiring* firms before and after mergers using the same research design as in Panel A. Note that we only count the patents filed by the acquirers' existing divisions in the post-merger period. Unlike target firms, successful acquirers tend to be more productive than withdrawn acquirers before the bidding

[12] In an untabulated analysis, we examine the number of annual patent filings in each of the three years following deal completion/withdrawal, and we find robust evidence of lowered (improved) innovation efficiency for target firms (acquirers' existing divisions) following mergers.

announcement. Moreover, after the merger, the advantage in innovation productivity of successful acquirers becomes even more pronounced. Specifically, the increase in the patents of acquiring firms in successful deals from the pre-merger period is greater than that experienced by acquiring firms in withdrawn deals by approximately 18 patents. This finding is consistent with our previous evidence that a multi-segment corporate structure could facilitate intra-firm knowledge spillover and thus lead to higher innovation productivity.

In Table 9, we further examine the novelty of the innovation output in terms of citations per patent in the pre- and post-merger period across both successful and withdrawn deals following Seru (2014). Again, we find consistent evidence that the acquired target firms in diversifying mergers produce less novel patents relative to their counterparts in withdrawn deals. Specifically, relative to the pre-merger period, *target* firms in successful deals show a decline of about four citations per patent more than target firms in withdrawn deals. In contrast, *acquiring* firms in successful mergers show a relative increase of around six more citations per patent than those in withdrawn mergers.

Taken together, our results suggest that acquired target firms tend to experience a decline in innovation productivity due to distractions during the post-merger integration process, whereas acquiring firms tend to experience a significant increase in R&D productivity which is more than sufficient to offset the decrease of the target firms. Therefore, it is important to consider the innovation activities of both acquiring and target companies when drawing inferences about the impact of the conglomerate form on R&D productivity.

IV. CONCLUSION

In this study, we examine whether the conglomerate form of corporate structure facilitates or hinders corporate innovation efforts. We posit that a conglomerate corporate structure not only facilitates internal knowledge sharing in the R&D process but also allows firms to better capture the "externality" of R&D outputs, and it can therefore improve R&D productivity. Our empirical evidence is uniformly consistent with these predictions. Furthermore, we identify two organizational mechanisms that facilitate internal knowledge spillover in conglomerate firms by showing that conglomerates with segments closely related in technology and with senior executives coordinating their R&D endeavors tend to experience higher innovation productivity.

Our study contributes to the recent literature on the effect of merger activities on innovation productivity. While we document evidence consistent with Seru (2014) that post-merger innovation productivity declines in *acquired target firms* relative to their counterparts in withdrawn deals, our evidence also suggests that *acquiring firms* experience significant improvements in post-merger innovation productivity, which amply offset the decline in target firms. The results provide further supporting evidence that the conglomerate corporate structure facilitates internal information sharing and knowledge spillover despite the temporary reduction in innovation productivity of the acquired target due to the distractive M&A integration process.

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APPENDIX 1
Key Variable Definitions

Variable	Definition
$Total\ Assets_{it}$	Total assets in millions of U.S. dollars.
$Sales_{it}$	Total sales in millions of U.S. dollars
$R\&D\ Expenditure_{it}$	R&D expenditures in millions of U.S. dollars. We require non-missing and positive R&D expenditures.
$R\&D\ Capital_{it}$	R&D capital in millions of U.S. dollars calculated as $R\&D\ Expenditure_{it} + 0.8 * R\&D\ Expenditure_{it-1} + 0.6 * R\&D\ Expenditure_{it-2} + 0.4 * R\&D\ Expenditure_{it-3} + 0.2 * R\&D\ Expenditure_{it-4}$. We require non-missing and positive R&D expenditures for period t, and set missing values for R&D to zero for the period from $t-1$ to $t-4$.
$Patent_{it+1}$	Number of patents filed during year $t+1$.
$Citation_{it+1}$	Weighted citations of patents filed during year $t+1$, i.e., the measure *tcw* from Kogan et al. (2017).
$Market_{it+1}$	Market value of patents filed during year $t+1$ inferred from the stock market response to patent grant news and scaled by book assets, i.e., the measure *tsm* from Kogan et al. (2017).
$Size_{it}$	The natural logarithm of total assets.
$Sales\ Growth_{it}$	Annual percentage growth in sales.
$Leverage_{it}$	Leverage ratio calculated as the sum of current and long-term debt divided by total assets.
ROA_{it}	Return-on-assets calculated as the ratio of operating income after depreciation to beginning total assets.
$Profit\ Margin_{it}$	Profit margin calculated as the ratio of income before extraordinary items to total sales.
$Tobin_{it}$	Ratio of market-to-book value of assets, where the market value of total debt is measured as the sum of the book value of current and long-term debt.
$Cash_{it}$	Cash holdings calculated as the ratio of cash and short-term investments to total assets.
$Capital\ Intensity_{it}$	Capital intensity calculated as the ratio of net property, plant and equipment to total assets.
$Capital\ Expenditure_{it}$	Capital expenditures divided by total sales.
$\log(Employee_{it})$	The natural logarithm of the number of employees in thousands.
Age_{it}	Number of years since the first year of Compustat coverage.
$ICM\ Intensity_{it}$	Internal capital market intensity calculated as the inverse of the Herfindahl index of segments sales within a conglomerate.
$Rank(Tech\ Close_{it})$	Annual standardized quintile rank ranging from zero to one, increasing with the degree of technology closeness across segments within a conglomerate.
$Tech\ Coordinate_{it}$	Indicator variable $=1$ if the conglomerate has senior executives to manage and coordinate its research and development efforts; $=0$ otherwise.
$Post_{it}$	Indicator variable $=1$ if the firm-year observation is from the three-year period following the merger completion or withdrawal; $=0$ otherwise.
$Treat_{it}$	Indicator variable $=1$ if the firm has a successful merger; $=0$ otherwise.

TABLE 1
Descriptive Statistics of Key Variables

Panel A: Sample of conglomerates.

$Variable$	N	$Mean$	$Std.dev.$	$Percentiles$		
				$25th$	$50th$	$75th$
$R\&D\ Expenditure_{it}\ (million)$	2,946	187.13	717.06	2.13	9.18	48.87
$R\&D\ Capital_{it}\ (million)$	2,946	499.15	1849.78	6.00	25.39	129.33
$R\&D\ Expenditure_{it}/Total\ Assets_{it}$	2,946	0.06	0.06	0.02	0.04	0.08
$R\&D\ Capital_{it}/Total\ Assets_{it}$	2,946	0.16	0.16	0.05	0.11	0.21
$Patent_{it+1}$	2,946	40.77	193.86	0.00	1.00	10.00
$Citation_{it+1}$	2,946	86.70	394.44	0.00	1.00	22.35
$Market_{it+1}$	2,946	432.13	2594.10	0.00	0.05	25.21
$Size_{it}$	2,946	5.74	2.05	4.07	5.43	7.20
$Sales\ Growth_{it}$	2,946	0.10	0.26	-0.01	0.07	0.16
$Leverage_{it}$	2,946	0.19	0.15	0.05	0.17	0.28
ROA_{it}	2,946	0.08	0.13	0.03	0.09	0.15
$Profit\ Margin_{it}$	2,946	0.01	0.25	0.01	0.04	0.08
$Tobin_{it}$	2,946	1.51	1.21	0.82	1.14	1.74
$Cash_{it}$	2,946	0.14	0.15	0.03	0.09	0.21
$Capital\ Intensity_{it}$	2,946	0.25	0.13	0.15	0.23	0.32
$Capital\ Expenditure_{it}$	2,946	0.05	0.06	0.02	0.04	0.06
$\log(Employee_{it})$	2,946	0.84	1.89	-0.68	0.64	2.30
Age_{it}	2,946	25.92	13.08	14.00	25.00	36.00
$Tech\ Close_{it}$	2,946	0.13	0.17	0.00	0.06	0.19
$Tech\ Coordinate_{it}$	2,946	0.13	0.34	0.00	0.00	0.00
$ICM\ Intensity_{it}$	2,946	2.08	0.87	1.48	1.91	2.56

Panel B: Sample of single-segment firms.

$Variable$	N	$Mean$	$Std.dev.$	$Percentiles$		
				$25th$	$50th$	$75th$
$R\&D\ Expenditure_{it}$ $(million)$	11,895	50.12	233.40	2.18	7.15	24.69
$R\&D\ Capital_{it}$ $(million)$	11,895	129.12	609.76	5.96	19.22	65.40
$R\&D\ Expenditure_{it}/Total\ Assets_{it}$	11,895	0.10	0.09	0.03	0.07	0.13
$R\&D\ Capital_{it}/Total\ Assets_{it}$	11,895	0.27	0.26	0.09	0.20	0.35
$Patent_{it+1}$	11,895	13.22	86.09	0.00	1.00	4.00
$Citation_{it+1}$	11,895	28.42	170.71	0.00	0.00	9.01
$Market_{it+1}$	11,895	138.13	1676.38	0.00	0.00	4.37
$Size_{it}$	11,895	4.79	1.57	3.56	4.57	5.78
$Sales\ Growth_{it}$	11,895	0.16	0.35	-0.01	0.11	0.26
$Leverage_{it}$	11,895	0.14	0.15	0.00	0.09	0.23
ROA_{it}	11,895	0.07	0.18	-0.01	0.08	0.17
$Profit\ Margin_{it}$	11,895	-0.05	0.41	-0.03	0.04	0.09
$Tobin_{it}$	11,895	1.98	1.74	0.91	1.41	2.41
$Cash_{it}$	11,895	0.24	0.21	0.06	0.19	0.37
$Capital\ Intensity_{it}$	11,895	0.21	0.14	0.10	0.18	0.29
$Capital\ Expenditure_{it}$	11,895	0.06	0.08	0.02	0.04	0.07
$\log(Employee_{it})$	11,895	-0.34	1.48	-1.50	-0.52	0.63
Age_{it}	11,895	15.93	9.65	9.00	13.00	20.00

This table presents the descriptive statistics of the main variables used in our analysis. Panel A is based on our sample of 2,946 conglomerate firm-year observations from 1984 to 2007, and Panel B is based on the sample of 11,895 single-segment firm-year observations from 1984 to 2007. We provide detailed variable definitions in Appendix 1.

TABLE 2
Comparison between Conglomerates and Their Pseudo Benchmark Firms Matched by Industry and Year

$Variable$	(1) $Conglomerates$	(2) $Pseudo$ $benchmark\ firms$	(1) – (2)	
			Diff.	*t-stat.*
$R\&D\ Expenditure_{it}/Sales_{it}$	0.07	0.09	-0.02***	*-5.46*
$R\&D\ Capital_{it}/Sales_{it}$	0.19	0.23	-0.04***	*-5.07*
$R\&D\ Expenditure_{it}/Total\ Assets_{it}$	0.06	0.07	-0.01***	*-10.32*
$R\&D\ Capital_{it}/Total\ Assets_{it}$	0.16	0.18	-0.02***	*-8.48*
$Patent_{it+1}/R\&D\ Expenditure_{it}$	0.44	0.23	0.21***	*11.65*
$Patent_{it+1}/R\&D\ Capital_{it}$	0.16	0.09	0.07***	*11.43*
$Citation_{it+1}/R\&D\ Expenditure_{it}$	0.76	0.29	0.47***	14.66
$Citation_{it+1}/R\&D\ Capital_{it}$	0.27	0.10	0.17***	15.00
$Market_{it+1}/R\&D\ Expenditure_{it}$	0.93	0.19	0.75***	17.59
$Market_{it+1}/R\&D\ Capital_{it}$	0.35	0.07	0.28***	16.57

This table presents the comparison of the mean values of R&D investment and innovation output between conglomerates and their pseudo benchmark firms. We create the pseudo benchmark firm by combining several single-segment firms to mimic a conglomerate with multiple segments. First, for each segment of a conglomerate, we identify at least two peer firms in the same year and industry based on the three digit SIC code. We then use the median value across single-segment peers as the pseudo benchmark value for that segment. Finally, we use the mean value of the pseudo benchmark values across the segments, weighted by the conglomerate's segment sales, as the value of the pseudo benchmark firm. *** indicates statistical significance at the 1% level based on two-tailed tests. Our sample includes 2,946 conglomerate firm-year observations and 11,895 single-segment firm-year observations from 1984 to 2007. Appendix 1 provides detailed variable definitions.

TABLE 3
Comparison of Innovation Efficiency between Conglomerates and Single-Segment Firms

Panel A: Count of patents.

	$Dependent\ variable\ = \log(1 + Patent_{it+1})$			
	$Conglomerates$	$Single\ segment\ firms$	$Conglomerates$	$Single\ segment\ firms$
$Intercept$	-1.903***	-1.307**	-2.089***	-1.501***
	-3.74	*-2.26*	*-4.10*	*-2.57*
$\mathbf{\log(R\&D\ Expenditure_{it})}$	**0.284*****	**0.221*****	.	.
	7.37	*9.57*		
$\mathbf{\log(R\&D\ Capital_{it})}$	.	.	**0.319*****	**0.234*****
			7.63	*9.61*
$Size_{it}$	0.342***	0.296***	0.304***	0.287***
	4.20	*7.08*	*3.70*	*6.77*
$Sales\ Growth_{it}$	-0.110	0.022	-0.058	0.048
	-1.36	*0.65*	*-0.76*	*1.40*
$Leverage_{it}$	-0.322	-0.081	-0.290	-0.098
	-1.21	*-0.61*	*-1.08*	*-0.74*
ROA_{it}	0.123	-0.071	0.231	0.002
	0.41	*-0.60*	*0.77*	*0.02*
$Profit\ Margin_{it}$	-0.193	0.045	-0.174	0.041
	-1.32	*1.00*	*-1.22*	*0.93*
$Tobin_{it}$	0.149***	0.056***	0.148***	0.057***
	4.21	*4.22*	*4.29*	*4.41*
$Cash_{it}$	0.221	0.267***	0.215	0.249**
	0.89	*2.63*	*0.86*	*2.42*
$Capital\ Intensity_{it}$	1.023***	0.594***	0.970***	0.569***
	2.69	*2.86*	*2.54*	*2.76*
$Capital\ Expenditure_{it}$	0.512	0.681***	0.774	0.814***
	0.67	*2.62*	*1.01*	*3.11*
$\log(Employee_{it})$	-0.063	0.000	-0.059	0.003
	-0.83	*0.01*	*-0.77*	*0.09*
Age_{it}	0.009**	0.005*	0.009*	0.004
	1.96	*1.72*	*1.90*	*1.53*
$Year\ fixed\ effects$	Yes	Yes	Yes	Yes
$Industry\ fixed\ effects$	Yes	Yes	Yes	Yes
Number of observations	2,946	11,895	2,946	11,895
Adjusted R^2	59.2%	47.0%	59.5%	47.1%
Coefficients comparison	$\log(R\&D\ Expenditure_{it})$		$\log(R\&D\ Capital_{it})$	
Chi-square statistics	7.21***		12.34***	

Panel B: Quality of patents based on weighted citations.

	$Dependent\ variable\ = \log(1 + Citation_{it+1})$			
	$Conglomerates$	$Single\ segment\ firms$	$Conglomerates$	$Single\ segment\ firms$
$Intercept$	-1.764***	-2.206***	-2.016***	-2.421***
	-2.65	*-4.73*	*-3.10*	*-5.19*
$\log(\boldsymbol{R\&D\ Expenditure_{it}})$	**0.396*****	**0.289*****	.	.
	8.46	*10.36*		
$\log(\boldsymbol{R\&D\ Capital_{it}})$	.	.	**0.448*****	**0.320*****
			8.78	*11.15*
$Size_{it}$	0.314***	0.375***	0.258***	0.349***
	3.33	*7.30*	*2.68*	*6.72*
$Sales\ Growth_{it}$	-0.197*	-0.001	-0.125	0.033
	-1.87	*-0.03*	*-1.26*	*0.82*
$Leverage_{it}$	-0.273	-0.066	-0.227	-0.077
	-0.86	*-0.43*	*-0.71*	*-0.50*
ROA_{it}	-0.013	-0.289*	0.141	-0.169
	-0.04	*-1.84*	*0.41*	*-1.13*
$Profit\ Margin_{it}$	-0.198	0.006	-0.170	0.005
	-1.21	*0.11*	*-1.09*	*0.09*
$Tobin_{it}$	0.171***	0.066***	0.170***	0.067***
	3.67	*3.71*	*3.78*	*3.86*
$Cash_{it}$	0.220	0.364***	0.212	0.330**
	0.70	*2.60*	*0.68*	*2.31*
$Capital\ Intensity_{it}$	1.121***	0.754***	1.048**	0.724***
	2.44	*2.92*	*2.27*	*2.82*
$Capital\ Expenditure_{it}$	0.335	0.832***	0.702	1.014***
	0.37	*2.49*	*0.79*	*3.02*
$\log(Employee_{it})$	-0.035	-0.013	-0.029	-0.010
	-0.39	*-0.25*	*-0.32*	*-0.20*
Age_{it}	0.011**	0.006	0.011**	0.006
	2.06	*1.60*	*2.00*	*1.46*
$Year\ fixed\ effects$	Yes	Yes	Yes	Yes
$Industry\ fixed\ effects$	Yes	Yes	Yes	Yes
Number of observations	2,946	11,895	2,946	11,895
Adjusted R^2	58.0%	44.8%	58.5%	45.1%
Coefficients comparison	$\log(R\&D\ Expenditure_{it})$		$\log(R\&D\ Capital_{it})$	
Chi-square statistics	14.28***		18.71***	

Panel C: Quality of patents based on market value.

	Dependent variable $= \log(1 + Market_{it+1})$			
	$Conglomerates$	$Single\ segment\ firms$	$Conglomerates$	$Single\ segment\ firms$
$Intercept$	-3.147***	-2.986***	-3.377***	-3.192***
	-4.46	*-4.52*	*-4.92*	*-4.83*
$\log(R\&D\ Expenditure_{it})$	**0.385*****	**0.290*****	.	.
	7.10	*9.16*		
$\log(R\&D\ Capital_{it})$	.	.	**0.440*****	**0.325*****
			7.53	*9.98*
$Size_{it}$	0.475***	0.556***	0.416***	0.527***
	4.31	*9.23*	*3.70*	*8.61*
$Sales\ Growth_{it}$	-0.258**	-0.070	-0.187	-0.035
	-2.06	*-1.31*	*-1.58*	*-0.66*
$Leverage_{it}$	-0.060	-0.011	-0.010	-0.019
	-0.18	*-0.07*	*-0.03*	*-0.12*
ROA_{it}	0.661*	0.104	0.817**	0.232
	1.71	*0.61*	*2.17*	*1.40*
$Profit\ Margin_{it}$	-0.241*	-0.022	-0.212*	-0.023
	-1.83	*-0.36*	*-1.68*	*-0.36*
$Tobin_{it}$	0.386***	0.191***	0.384***	0.192***
	5.88	*7.25*	*5.97*	*7.41*
$Cash_{it}$	-0.236	0.140	-0.245	0.103
	-0.62	*0.84*	*-0.65*	*0.60*
$Capital\ Intensity_{it}$	0.433	0.099	0.361	0.070
	0.82	*0.38*	*0.69*	*0.27*
$Capital\ Expenditure_{it}$	0.667	0.901**	1.028	1.086***
	0.63	*2.31*	*0.96*	*2.78*
$\log(Employee_{it})$	-0.066	-0.058	-0.059	-0.055
	-0.63	*-1.05*	*-0.58*	*-1.01*
Age_{it}	0.027***	0.009**	0.027***	0.009**
	4.51	*2.14*	*4.45*	*2.02*
$Year\ fixed\ effects$	Yes	Yes	Yes	Yes
$Industry\ fixed\ effects$	Yes	Yes	Yes	Yes
Number of observations	2,946	11,895	2,946	11,895
Adjusted R^2	67.0%	54.3%	67.3%	54.6%
Coefficients comparison	$\log(R\&D\ Expenditure_{it})$		$\log(R\&D\ Capital_{it})$	
Chi-square statistics	9.25***		12.51***	

This table reports the results of the OLS regressions of innovation output on R&D investment separately for conglomerates and single-segment firms. We compare the coefficients on R&D investment, i.e., $log(R\&D\ Expenditure)$ and $log(R\&D\ Capital)$, between conglomerates and single-segment firms. Industry fixed effects are based on Fama and French's (1997) 12-industry classification. The t-statistics are based on standard errors clustered by firm and year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, based on two-tailed tests. Our sample includes 2,946 conglomerate firm-year observations and 11,895 single-segment firm-year observations from 1984 to 2007. Appendix 1 provides detailed variable definitions.

TABLE 4
Intra-Firm Knowledge Spillover within Conglomerates: An Examination of Technology Closeness across Segments

Panel A: Count of patents.

	$Dependent\ variable\ = \log(1 + Patent_{it+1})$	
	$Z_{it} = \log(R\&D\ Expenditure_{it})$	$Z_{it} = \log(R\&D\ Capital_{it})$
$Intercept$	-1.312***	-1.373***
	-3.68	*-3.79*
$\boldsymbol{Z_{it}}$	**0.194*****	**0.227*****
	4.11	*4.61*
$Rank(Tech\ Close_{it})$	-0.095	-0.303*
	-0.83	*-1.81*
$\boldsymbol{Z_{it} * Rank(Tech\ Close_{it})}$	**0.178*****	**0.184*****
	2.92	*2.94*
$Size_{it}$	0.325***	0.285***
	4.22	*3.68*
$Sales\ Growth_{it}$	-0.086	-0.039
	-1.17	*-0.55*
$Leverage_{it}$	-0.214	-0.176
	-0.79	*-0.65*
ROA_{it}	0.282	0.391
	0.96	*1.33*
$Profit\ Margin_{it}$	-0.242	-0.221
	-1.53	*-1.43*
$Tobin_{it}$	0.146***	0.145***
	3.90	*3.98*
$Cash_{it}$	0.226	0.233
	0.99	*1.02*
$Capital\ Intensity_{it}$	1.079***	1.027***
	3.13	*2.99*
$Capital\ Expenditure_{it}$	0.559	0.829
	0.70	*1.05*
$\log(Employee_{it})$	-0.064	-0.059
	-0.87	*-0.80*
Age_{it}	0.010***	0.010***
	2.50	*2.44*
$ICM\ Intensity_{it}$	0.030	0.030
	0.49	*0.51*
$Year\ fixed\ effects$	Yes	Yes
$Industry\ fixed\ effects$	Yes	Yes
Number of observations	2,946	2,946
Adjusted R^2	58.7%	59.0%

Panel B: Quality of patents based on weighted citations.

	$Dependent\ variable = \log(1 + Citation_{it+1})$	
	$Z_{it} = \log(R\&D\ Expenditure_{it})$	$Z_{it} = \log(R\&D\ Capital_{it})$
$Intercept$	-1.137***	-1.252***
	-2.69	*-2.90*
$\boldsymbol{Z_{it}}$	**0.307*** **	**0.355*** **
	5.33	*5.93*
$Rank(Tech\ Close_{it})$	-0.120	-0.357*
	-0.87	*-1.84*
$\boldsymbol{Z_{it} * Rank(Tech\ Close_{it})}$	**0.198*** **	**0.206*** **
	2.90	*2.93*
$Size_{it}$	0.280***	0.221**
	3.03	*2.36*
$Sales\ Growth_{it}$	-0.171*	-0.102
	-1.72	*-1.08*
$Leverage_{it}$	-0.131	-0.077
	-0.41	*-0.24*
ROA_{it}	0.153	0.314
	0.46	*0.93*
$Profit\ Margin_{it}$	-0.228	-0.198
	-1.28	*-1.15*
$Tobin_{it}$	0.166***	0.165***
	3.42	*3.52*
$Cash_{it}$	0.210	0.217
	0.71	*0.73*
$Capital\ Intensity_{it}$	1.086***	1.011***
	2.70	*2.51*
$Capital\ Expenditure_{it}$	0.528	0.915
	0.57	*1.00*
$\log(Employee_{it})$	-0.031	-0.023
	-0.35	*-0.26*
Age_{it}	0.013***	0.013***
	2.57	*2.50*
$ICM\ Intensity_{it}$	0.030	0.031
	0.43	*0.45*
$Year\ fixed\ effects$	Yes	Yes
$Industry\ fixed\ effects$	Yes	Yes
Number of observations	2,946	2,946
Adjusted R^2	57.4%	57.8%

Panel C: Quality of patents based on market value.

	$Dependent\ variable\ = \log(1 + Market_{it+1})$	
	$Z_{it} = \log(R\&D\ Expenditure_{it})$	$Z_{it} = \log(R\&D\ Capital_{it})$
$Intercept$	-2.922***	-3.042***
	-6.02	*-6.26*
$\boldsymbol{Z_{it}}$	**0.316*** **	**0.370*** **
	4.89	*5.59*
$Rank(Tech\ Close_{it})$	-0.014	-0.159
	-0.10	*-0.81*
$\boldsymbol{Z_{it} * Rank(Tech\ Close_{it})}$	**0.122* **	**0.126* **
	1.72	*1.74*
$Size_{it}$	0.512***	0.449***
	4.92	*4.28*
$Sales\ Growth_{it}$	-0.255**	-0.189
	-2.04	*-1.59*
$Leverage_{it}$	0.105	0.162
	0.31	*0.47*
ROA_{it}	0.810**	0.971***
	2.14	*2.60*
$Profit\ Margin_{it}$	-0.304**	-0.274**
	-2.32	*-2.18*
$Tobin_{it}$	0.383***	0.381***
	5.76	*5.85*
$Cash_{it}$	-0.224	-0.221
	-0.63	*-0.62*
$Capital\ Intensity_{it}$	0.519	0.449
	1.12	*0.97*
$Capital\ Expenditure_{it}$	0.501	0.868
	0.46	*0.81*
$\log(Employee_{it})$	-0.094	-0.086
	-0.94	*-0.87*
Age_{it}	0.029***	0.029***
	4.99	*4.93*
$ICM\ Intensity_{it}$	0.025	0.026
	0.35	*0.36*
$Year\ fixed\ effects$	Yes	Yes
$Industry\ fixed\ effects$	Yes	Yes
Number of observations	2,946	2,946
Adjusted R^2	66.7%	67.0%

This table reports evidence of variation in innovation efficiency with the technology closeness across segments within conglomerates using OLS regressions. Industry fixed effects are based on Fama and French's (1997) 12-industry classification. The t-statistics are based on standard errors clustered by firm and year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, based on two-tailed tests. This analysis uses the sample of 2,946 conglomerate firm-year observations from 1984 to 2007. Appendix 1 provides detailed variable definitions.

TABLE 5
Intra-Firm Knowledge Spillover within Conglomerates: An Examination of Communication Structure for Technology Coordination

Panel A: Count of patents.

	$Dependent\ variable = \log(1 + Patent_{it+1})$	
	$Z_{it} = \log(R\&D\ Expenditure_{it})$	$Z_{it} = \log(R\&D\ Capital_{it})$
$Intercept$	-1.331***	-1.496***
	-3.70	*-4.18*
$\boldsymbol{Z_{it}}$	**0.271*** **	**0.303*** **
	7.20	*7.53*
$Tech\ Coordinate_{it}$	-0.059	-0.179
	-0.38	*-0.89*
$\boldsymbol{Z_{it} * Tech\ Coordinate_{it}}$	**0.099** **	**0.103** **
	2.27	*2.28*
$Size_{it}$	0.316***	0.281***
	3.95	*3.49*
$Sales\ Growth_{it}$	-0.073	-0.024
	-0.93	*-0.32*
$Leverage_{it}$	-0.270	-0.240
	-1.00	*-0.88*
ROA_{it}	0.123	0.233
	0.41	*0.77*
$Profit\ Margin_{it}$	-0.184	-0.165
	-1.11	*-1.03*
$Tobin_{it}$	0.120***	0.119***
	3.44	*3.49*
$Cash_{it}$	0.218	0.220
	0.96	*0.96*
$Capital\ Intensity_{it}$	1.048***	0.990***
	3.09	*2.93*
$Capital\ Expenditure_{it}$	0.611	0.890
	0.79	*1.17*
$\log(Employee_{it})$	-0.049	-0.045
	-0.65	*-0.60*
Age_{it}	0.010**	0.010**
	2.35	*2.29*
$ICM\ Intensity_{it}$	0.054	0.054
	0.90	*0.90*
$Year\ fixed\ effects$	Yes	Yes
$Industry\ fixed\ effects$	Yes	Yes
Number of observations	2,946	2,946
Adjusted R^2	58.2%	58.5%

Panel B: Quality of patents based on weighted citations.

	$Dependent\ variable\ = \log(1 + Citation_{it+1})$	
	$Z_{it} = \log(R\&D\ Expenditure_{it})$	$Z_{it} = \log(R\&D\ Capital_{it})$
$Intercept$	-1.167***	-1.398***
	-2.75	*-3.33*
$\boldsymbol{Z_{it}}$	**0.391******	**0.439******
	8.59	*9.05*
$Tech\ Coordinate_{it}$	-0.124	-0.270
	-0.57	*-0.95*
$\boldsymbol{Z_{it} * Tech\ Coordinate_{it}}$	**0.124****	**0.128****
	2.09	*2.04*
$Size_{it}$	0.271***	0.219**
	2.90	*2.30*
$Sales\ Growth_{it}$	-0.156	-0.086
	-1.47	*-0.85*
$Leverage_{it}$	-0.194	-0.148
	-0.61	*-0.46*
ROA_{it}	-0.030	0.132
	-0.08	*0.37*
$Profit\ Margin_{it}$	-0.163	-0.136
	-0.86	*-0.75*
$Tobin_{it}$	0.136***	0.134***
	2.93	*3.01*
$Cash_{it}$	0.205	0.207
	0.70	*0.70*
$Capital\ Intensity_{it}$	1.068***	0.986***
	2.73	*2.52*
$Capital\ Expenditure_{it}$	0.582	0.981
	0.65	*1.11*
$\log(Employee_{it})$	-0.015	-0.009
	-0.17	*-0.10*
Age_{it}	0.012**	0.012**
	2.39	*2.33*
$ICM\ Intensity_{it}$	0.057	0.057
	0.81	*0.82*
$Year\ fixed\ effects$	Yes	Yes
$Industry\ fixed\ effects$	Yes	Yes
Number of observations	2,946	2,946
Adjusted R^2	57.0%	57.4%

Panel C: Quality of patents based on market value.

	$Dependent\ variable\ = \log(1 + Market_{it+1})$	
	$Z_{it} = \log(R\&D\ Expenditure_{it})$	$Z_{it} = \log(R\&D\ Capital_{it})$
$Intercept$	-2.737***	-2.906***
	-5.59	*-6.01*
$\boldsymbol{Z_{it}}$	**0.335******	**0.385******
	6.60	*7.22*
$Tech\ Coordinate_{it}$	-0.392	-0.761**
	-1.38	*-2.07*
$\boldsymbol{Z_{it} * Tech\ Coordinate_{it}}$	**0.307******	**0.318******
	4.19	*4.20*
$Size_{it}$	0.483***	0.428***
	4.60	*4.01*
$Sales\ Growth_{it}$	-0.236*	-0.172
	-1.79	*-1.39*
$Leverage_{it}$	0.054	0.106
	0.16	*0.31*
ROA_{it}	0.582	0.740**
	1.57	*2.04*
$Profit\ Margin_{it}$	-0.231	-0.201
	-1.51	*-1.40*
$Tobin_{it}$	0.327***	0.324***
	5.44	*5.57*
$Cash_{it}$	-0.196	-0.189
	-0.58	*-0.56*
$Capital\ Intensity_{it}$	0.627	0.540
	1.44	*1.25*
$Capital\ Expenditure_{it}$	0.455	0.865
	0.45	*0.86*
$\log(Employee_{it})$	-0.065	-0.060
	-0.65	*-0.60*
Age_{it}	0.026***	0.026***
	4.55	*4.49*
$ICM\ Intensity_{it}$	0.042	0.042
	0.59	*0.60*
$Year\ fixed\ effects$	Yes	Yes
$Industry\ fixed\ effects$	Yes	Yes
Number of observations	2,946	2,946
Adjusted R^2	68.0%	68.3%

This table reports evidence of variation in innovation efficiency across conglomerates with and without senior executives to manage and coordinate research and development efforts using OLS regressions. Industry fixed effects are based on Fama and French's (1997) 12-industry classification. The t-statistics are based on standard errors clustered by firm and year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, based on two-tailed tests. This analysis uses the sample of 2,946 conglomerate firm-year observations from 1984 to 2007. Appendix 1 provides detailed variable definitions.

TABLE 6
Difference-in-Differences Analysis of Innovation Efficiency of Acquiring Firms in Successful versus Withdrawn Mergers and Acquisitions: Univariate Results

Panel A: Count of patents.

	$Patent_{it+1}$		$Treatment - Control$	
	Acquiring firms in successful M&A deals ($Treatment$)	Acquiring firms in withdrawn M&A deals ($Control$)	Diff.	*t-stat.*
Number of observations	13,277	522	.	.
Average over the three years prior to M&A (Pre)	49.42	50.98	-1.56	*-0.12*
Average over the three years following M& ($Post$)	58.97	45.13	13.85*	*1.76*
$Post - Pre$	9.55**	-5.85	15.41***	*2.94*

Panel B: Quality of patents based on weighted citations.

	$Citation_{it+1}$		$Treatment - Control$	
	Acquiring firms in successful M&A deals ($Treatment$)	Acquiring firms in withdrawn M&A deals ($Control$)	Diff.	*t-stat.*
Number of observations	13,277	522	.	.
Average over the three years prior to M&A (Pre)	123.62	108.95	14.67	*1.24*
Average over the three years following M&A ($Post$)	141.07	88.98	52.09***	*3.08*
$Post - Pre$	17.45*	-19.97*	37.42***	*4.70*

Panel C: Quality of patents based on market value.

	$Market_{it+1}$		$Treatment - Control$	
	Acquiring firms in successful M&A deals ($Treatment$)	Acquiring firms in withdrawn M&A deals ($Control$)	Diff.	*t-stat.*
Number of observations	13,277	522	.	.
Average over the three years prior to M&A (Pre)	844.84	783.56	61.28	*1.42*
Average over the three years following M&A ($Post$)	1128.88	575.12	553.76***	*4.01*
$Post - Pre$	284.04***	-208.45**	492.48**	*2.08*

This table reports evidence of improved innovation efficiency for acquiring firms following successful mergers. This analysis employs a difference-in-differences approach by comparing innovation output over the three years prior to the bidding announcement to that over the three years following the deal completion/withdrawal between treatment firms in successful deals and control firms in withdrawn deals. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, based on two-tailed tests. This analysis uses the treatment sample of 13,277 firm-year observations for 3,112 unique successful deals and the control sample of 522 firm-year observations for 143 unique withdrawn deals between 1984 and 2004. Appendix 1 provides detailed variable definitions.

TABLE 7
Difference-in-Differences Analysis of Innovation Efficiency of Acquiring Firms in Successful versus Withdrawn Mergers and Acquisitions: Regression Results

Panel A: Count of patents.

	$Dependent\ variable = \log(1 + Patent_{it+1})$			
	$Z_{it} = \log(R\&D\ Expenditure_{it})$		$Z_{it} = \log(R\&D\ Capital_{it})$	
$Intercept$	0.561	-1.578***	0.129	-1.622***
	1.50	*-2.84*	*0.27*	*-2.58*
$\boldsymbol{Z_{it}}$	**0.492*** **	**0.284** **	**0.499*** **	**0.329*** **
	3.98	*2.25*	*4.07*	*2.62*
$Z_{it} * Post_{it}$	-0.056	-0.061	-0.041	-0.050
	-1.25	*-1.45*	*-0.88*	*-1.10*
$Z_{it} * Treat_{it}$	0.140	0.149	0.150	0.153
	1.21	*1.33*	*1.29*	*1.38*
$\boldsymbol{Z_{it} * Post_{it} * Treat_{it}}$	**0.089** **	**0.097** **	**0.079* **	**0.091** **
	2.01	*2.34*	*1.76*	*2.04*
$Post_{it}$	-0.036	0.024	-0.069	0.025
	-0.21	*0.15*	*-0.34*	*0.12*
$Treat_{it}$	-0.435	-0.411	-0.607	-0.577
	-1.27	*-1.22*	*-1.36*	*-1.34*
$Post_{it} * Treat_{it}$	-0.090	-0.225	-0.120	-0.278
	-0.52	*-1.42*	*-0.60*	*-1.36*
$Size_{it}$	.	0.235***	.	0.188***
		3.34		*2.65*
$Sales\ Growth_{it}$	.	-0.001	.	0.006
		-0.19		*1.28*
$Leverage_{it}$	.	0.086	.	0.152
		0.35		*0.63*
ROA_{it}	.	-0.249*	.	-0.142
		-1.80		*-1.23*
$Profit\ Margin_{it}$	.	0.000	.	0.000
		0.10		*0.30*
$Tobin_{it}$	.	0.009	.	0.017
		0.56		*1.08*
$Cash_{it}$	.	0.299	.	0.221
		1.36		*1.03*
$Capital\ Intensity_{it}$	.	1.200***	.	1.178***
		2.96		*2.95*
$Capital\ Expenditure_{it}$	.	-0.023	.	-0.004
		-0.43		*-0.09*
$\log(Employee_{it})$	.	-0.113*	.	-0.107
		-1.67		*-1.57*
Age_{it}	.	0.027***	.	0.026***
		6.20		*5.83*
$Year\ fixed\ effects$	Yes	Yes	Yes	Yes
$Industry\ fixed\ effects$	Yes	Yes	Yes	Yes
Number of observations	13,799	13,799	13,799	13,799
Adjusted R^2	57.2%	61.3%	58.8%	62.1%

Panel B: Quality of patents based on weighted citations.

	$Dependent\ variable\ = \log(1 + Citation_{it+1})$			
	$Z_{it} = \log(R\&D\ Expenditure_{it})$		$Z_{it} = \log(R\&D\ Capital_{it})$	
$Intercept$	0.726*	-1.532***	0.222	-1.627**
	1.68	*-2.45*	*0.40*	*-2.29*
$\boldsymbol{Z_{it}}$	**0.576***	**0.354***	**0.584***	**0.403***
	4.09	*2.46*	*4.17*	*2.80*
$Z_{it} * Post_{it}$	-0.090	-0.094	-0.069	-0.078
	-1.42	*-1.54*	*-1.04*	*-1.19*
$Z_{it} * Treat_{it}$	0.182	0.187	0.191	0.191
	1.37	*1.47*	*1.44*	*1.51*
$\boldsymbol{Z_{it} * Post_{it} * Treat_{it}}$	**0.124**	**0.130**	**0.108***	**0.116***
	1.96	*2.09*	*1.64*	*1.75*
$Post_{it}$	-0.046	0.021	-0.075	0.029
	-0.21	*0.10*	*-0.26*	*0.10*
$Treat_{it}$	-0.502	-0.472	-0.715	-0.676
	-1.31	*-1.30*	*-1.43*	*-1.43*
$Post_{it} * Treat_{it}$	-0.203	-0.319	-0.235	-0.371
	-0.88	*-1.38*	*-0.81*	*-1.20*
$Size_{it}$	.	0.267***	.	0.218***
		3.17		*2.54*
$Sales\ Growth_{it}$	.	0.002	.	0.011*
		0.21		*1.76*
$Leverage_{it}$	.	0.044	.	0.114
		0.15		*0.40*
ROA_{it}	.	-0.092	.	0.033
		-0.70		*0.28*
$Profit\ Margin_{it}$	.	-0.000	.	0.000
		-0.08		*0.13*
$Tobin_{it}$	.	0.035*	.	0.045**
		1.71		*2.28*
$Cash_{it}$	.	0.279	.	0.193
		1.06		*0.75*
$Capital\ Intensity_{it}$	.	1.173***	.	1.150***
		2.63		*2.61*
$Capital\ Expenditure_{it}$	.	-0.016	.	0.007
		-0.30		*0.15*
$\log(Employee_{it})$	.	-0.122	.	-0.115
		-1.46		*-1.36*
Age_{it}	.	0.025***	.	0.023***
		4.69		*4.29*
$Year\ fixed\ effects$	Yes	Yes	Yes	Yes
$Industry\ fixed\ effects$	Yes	Yes	Yes	Yes
Number of observations	13,799	13,799	13,799	13,799
Adjusted R^2	54.6%	57.1%	55.8%	57.8%

Panel C: Quality of patents based on market value.

	$Dependent\ variable\ = \log(1 + Market_{it+1})$			
	$Z_{it} = \log(R\&D\ Expenditure_{it})$		$Z_{it} = \log(R\&D\ Capital_{it})$	
$Intercept$	0.417	-3.692***	-0.336	-3.819***
	0.71	*-4.84*	*-0.44*	*-4.26*
$\boldsymbol{Z_{it}}$	**0.878*****	**0.412****	**0.882*****	**0.463****
	4.41	*2.09*	*4.47*	*2.37*
$Z_{it} * Post_{it}$	-0.150*	-0.159**	-0.120	-0.143*
	-1.70	*-1.93*	*-1.39*	*-1.69*
$Z_{it} * Treat_{it}$	0.152	0.156	0.166	0.161
	0.83	*0.90*	*0.91*	*0.94*
$\boldsymbol{Z_{it} * Post_{it} * Treat_{it}}$	**0.223*****	**0.218*****	**0.201*****	**0.206*****
	2.65	*2.71*	*2.47*	*2.51*
$Post_{it}$	-0.029	0.119	-0.051	0.194
	-0.10	*0.43*	*-0.15*	*0.53*
$Treat_{it}$	-0.510	-0.458	-0.718	-0.639
	-0.95	*-0.88*	*-1.02*	*-0.95*
$Post_{it} * Treat_{it}$	-0.394	-0.499*	-0.488	-0.645*
	-1.40	*-1.76*	*-1.48*	*-1.76*
$Size_{it}$	.	0.589***	.	0.536***
		6.14		*5.55*
$Sales\ Growth_{it}$	.	0.005	.	0.015*
		0.50		*1.81*
$Leverage_{it}$	.	-0.203	.	-0.129
		-0.59		*-0.38*
ROA_{it}	.	0.301**	.	0.435***
		2.15		*3.20*
$Profit\ Margin_{it}$	.	0.000	.	0.000
		0.26		*0.47*
$Tobin_{it}$	.	0.186***	.	0.197***
		6.89		*7.53*
$Cash_{it}$	.	0.407	.	0.314
		1.22		*0.96*
$Capital\ Intensity_{it}$	.	1.168**	.	1.143**
		2.44		*2.42*
$Capital\ Expenditure_{it}$	.	0.020	.	0.045
		0.38		*0.84*
$\log(Employee_{it})$	.	-0.206**	.	-0.198**
		-2.13		*-2.04*
Age_{it}	.	0.033***	.	0.030***
		5.48		*5.10*
$Year\ fixed\ effects$	Yes	Yes	Yes	Yes
$Industry\ fixed\ effects$	Yes	Yes	Yes	Yes
Number of observations	13,799	13,799	13,799	13,799
Adjusted R^2	61.9%	66.6%	62.8%	67.2%

This table reports evidence of improved innovation efficiency for acquiring firms following successful mergers. This analysis employs a difference-in-differences approach by comparing innovation output over the three years prior to the bidding announcement to that over the three years following the deal completion/withdrawal between treatment firms in successful deals and control firms in withdrawn deals. Industry fixed effects are based on Fama and French's (1997) 12-industry classification. The t-statistics are based on standard errors clustered by firm and year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, based on two-tailed tests. This analysis uses the treatment sample of 13,277 firm-year observations for 3,112 unique successful deals and the control sample of 522 firm-year observations for 143 unique withdrawn deals between 1984 and 2004. Appendix 1 provides detailed variable definitions.

TABLE 8
Difference-in-Differences of Patent Filings of Publicly Listed Target Firms and Their Acquiring Firms in Successful versus Withdrawn Mergers and Acquisitions

Panel A: Patent filings of public *target* firms prior to and following mergers and acquisitions.

	$Patent_{it+1}$		$Treatment - Control$	
	Public target firms in successful M&A deals ($Treatment$)	Public target firms in withdrawn M&A deals ($Control$)	Diff.	*t-stat.*
Number of observations	1,352	180	.	.
Average over the three years prior to M&A (Pre)	4.84	6.83	-1.99	*-0.87*
Average over the three years following M&A ($Post$)	18.33	24.65	-6.32**	*-2.36*
$Post - Pre$	13.49**	17.82*	-4.33**	*-2.02*

Panel B: Patent filings of *acquiring* firms prior to and following mergers and acquisitions.

	$Patent_{it+1}$		$Treatment - Control$	
	Acquiring firms in successful M&A deals ($Treatment$)	Acquiring firms in withdrawn M&A deals ($Control$)	Diff.	*t-stat.*
Number of observations	1,352	180	.	.
Average over the three years prior to M&A (Pre)	109.75	27.01	82.74***	*5.41*
Average over the three years following M&A, excluding patents filed by the acquired target ($Post$)	122.10	21.21	100.89***	*5.56*
$Post - Pre$	12.35**	-5.80	18.15**	*2.23*

This table reports evidence of lowered innovation efficiency for public target firms (Panel A) and evidence of improved innovation efficiency for acquirers' existing divisions (Panel B) following mergers. This analysis employs a difference-in-differences approach by comparing the average of the number of patents filed in each year over the three years prior to the bidding announcement to that over the three years following the deal completion/withdrawal between treatment firms in successful deals and control firms in withdrawn deals. ***, and ** indicate statistical significance at the 1%, and 5% level, respectively, based on two-tailed tests. This analysis uses the treatment sample of 1,352 firm-year observations for 118 unique successful deals and the control sample of 180 firm-year observations for 20 unique withdrawn deals between 1984 and 2004. Appendix 1 provides detailed variable definitions.

TABLE 9
Difference-in-Differences of Citations per Patent of Publicly Listed Target Firms and Their Acquiring Firms in Successful versus Withdrawn Mergers and Acquisitions

Panel A: Citations per patent of public *target* firms prior to and following mergers and acquisitions.

	$Citation_{it+1}/Patent_{it+1}$		$Treatment - Control$	
	Public target firms in successful M&A deals ($Treatment$)	Public target firms in withdrawn M&A deals ($Control$)	Diff.	*t-stat.*
Number of observations	1,352	180	.	.
Average over the three years prior to M&A (Pre)	10.45	9.91	0.54	*0.52*
Average over the three years following M&A ($Post$)	2.61	6.51	-3.90**	*-1.96*
$Post - Pre$	-7.84***	-3.40*	-4.44**	*-2.49*

Panel B: Citations per patent of *acquiring* firms prior to and following mergers and acquisitions.

	$Citation_{it+1}/Patent_{it+1}$		$Treatment - Control$	
	Acquiring firms in successful M&A deals ($Treatment$)	Acquiring firms in withdrawn M&A deals ($Control$)	Diff.	*t-stat.*
Number of observations	1,352	180	.	.
Average over the three years prior to M&A (Pre)	10.43	4.36	6.07***	*2.69*
Average over the three years following M&A, excluding patents filed by the acquired target ($Post$)	16.72	5.07	11.65***	*4.86*
$Post - Pre$	6.29**	0.71*	5.58***	*2.65*

This table reports evidence of lowered innovation efficiency for public target firms (Panel A) and evidence of improved innovation efficiency for acquirers' existing divisions (Panel B) following mergers. This analysis employs a difference-in-differences approach by comparing the average of citations per patent over the three years prior to the bidding announcement to that over the three years following the deal completion/withdrawal between treatment firms in successful deals and control firms in withdrawn deals. ***, and ** indicate statistical significance at the 1%, and 5% level, respectively, based on two-tailed tests. This analysis uses the treatment sample of 1,352 firm-year observations for 118 unique successful deals and the control sample of 180 firm-year observations for 20 unique withdrawn deals between 1984 and 2004. Appendix 1 provides detailed variable definitions.