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LEARNING TO COLLABORATE THROUGH COLLABORATION: HOW ALLYING WITH EXPERT FIRMS INFLUENCES COLLABORATIVE INNOVATION WITHIN NOVICE FIRMS

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Research summary: *Strategic alliances have been recognized as a means for firms to learn their partners' proprietary knowledge; such alliances are also valuable opportunities for partner firms to learn tacit organizational routines from their counterparts. We consider how relatively novice technology firms can learn intraorganizational collaborative routines from more experienced alliance partners and then deploy them independently for their own innovative pursuits. We examine the alliance relationships between Eli Lilly & Co. (Lilly), a recognized expert in collaborative innovation, and 55 small biotech partner firms. Using three levels of analysis (firm, patent, and inventor dyad), we find that greater social interaction between the partner firm and Lilly subsequently increases internal collaboration among the partner firm's inventors.*

Managerial summary: *Can collaborating externally advance internal collaboration? Yes. Our research found that collaboration among scientists at small, early-stage biotechnology firms significantly increased after these firms formed highly interactive R&D alliances with a large pharmaceutical company known for its expertise in such collaboration. It is well known that alliances help new firms learn specific new technologies and commercialize innovations. Our study broadens the scope of potential benefits of alliances. New firms can also learn collaboration techniques, deploying them internally to enhance their own abilities in collaborative innovation. Managers should take this additional benefit into consideration in developing their alliance strategies. Pursuing alliance partners with expertise in collaboration and keeping a high level of mutual interactions with partner firm personnel should be important considerations to extract this value.*

INTRODUCTION

Within technology-based industries, alliances are thought to provide opportunities for firms to learn specific content (e.g., commercialization know-how, technologies) from their partners (Powell, 1998). For example, tighter and more highly interactive relationships between alliance partners have been shown to enhance the learning of each other's technologies (Mowery, Oxley, and Silverman, 1996). One model of alliance engagement suggests that early-stage technology firms provide larger established firms a window into their novel technologies in exchange for access to their technologies and complemen-

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tary commercialization assets including product development infrastructure, manufacturing, sales, and distribution (Dushnitsky and Lenox, 2005; Rothaermel and Boeker, 2008). By allying with established firms, novice firms can learn not only the finer points of product commercialization, but the art of collaborating with others as well (Powell, 1998). Alliance participants can develop routines for managing external engagements and formalize them into an alliance management process that improves their ability to select and cooperate with external partners (Kale and Singh, 2007).

Although early-stage technology firms can clearly gain from acquiring specific technologies and commercialization skills from their more established counterparts, and developing routines for managing external partnerships more generally, this may be an incomplete litany of potential benefits derived from their alliances. These novice firms often lack organizational routines needed to sustain ongoing independent innovation beyond their embryonic technologies (Kelley and Rice, 2002; Yli-Renko, Autio, and Sapienza, 2001). Without these routines, such firms are unlikely to mature to the point where they are able to thrive through internal innovation. Little consideration has been given to the notion that novice firms can learn these essential routines from their more experienced alliance partners.

Specifically, we suggest that by observing the routines of an alliance partner that has particular expertise in intraorganizational collaborative innovation, and practicing these over the course of the alliance, a novice firm can subsequently deploy similar routines for its *independent and internal* innovative pursuits. Recognizing the potential to learn such routines from partner firms expands the realm of how smaller novice firms may benefit from alliance strategies, and the learning opportunities that should be weighed when selecting partners. Acquiring such routines may be more critical to the long-term viability of early-stage firms than acquiring specific assets or technologies that can quickly become obsolete. By comparison, routines can be directly applied to new situations and endure over time (Nelson and Winter, 1982) or be adapted to different applications (Feldman, 2000).

We examine the research and development (R&D) alliance relationships between Eli Lilly & Co. (Lilly) and their portfolio of small early-stage biotech partners. Lilly is recognized within the pharmaceutical industry for its expertise in collaborative innovation and alliance management. The company's approach includes a systematic structure for external engagement (Powell, Koput, and Smith-Doerr, 1996), a formal office of alliance management (Dhanaraj, Lyles, and Lai, 2007; Kale and Singh, 2007), and procedures to coordinate alliance activities across business and technology experts (Rothaermel and Deeds, 2006).

We propose that social interaction between organizations that have expertise in intraorganizational collaborative innovation and their less proficient partner firms allows these partners to learn through experience and acquire collaborative routines that can be used subsequently in their internal innovation. We explore inventor collaboration patterns within Lilly's partner firms both before and after their alliance with Lilly. Using three levels of analysis—inventor dyad, patent, firm—we observe both micro- and firm-level internal collaboration. We find that greater social interaction between the partner firm and Lilly subsequently led to greater increases in internal collaboration among the partner firm's inventors.

Experiential learning in alliances

Alliances are an effective vehicle for learning, allowing partner firms to exchange concepts not easily attained through market transactions, and validate them within the confines of the alliance (Liebeskind *et al.,* 1996; Muthusamy and White, 2005). Learning from an alliance partner may provide both common and private benefits (Khanna, Gulati, and Nohria, 1998). Common benefits accrue when what is learned is applied to objectives central to the alliance. Partner firms obtain private benefits when they apply the acquired knowledge to their own operations, apart from the alliance. For example, Firm A could enhance its understanding of the specific technologies of Firm B when they codevelop a product. The technologies could then be applied to Firm A's internal innovation efforts separate from those pursued with Firm B (Mody, 1993; Rosenkopf and Almeida, 2003). Similarly, alliance partners may develop skills in managing external collaboration that can be applied to future alliances with different partners (Dyer and Singh, 1998).

Other private benefits may be more subtle. An alliance offers not only the chance to gain experience in managing external engagements and observe the specific technologies of a partner; it also exposes the partner's valuable organizing

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routines—templates and processes for how things get done. These routines are dynamic, collective patterns of behavior, and the foundation for organizational capabilities (Dosi, Nelson, and Winter, 2000; Feldman and Pentland, 2003). They are built on a framework of micro-level processes and aggregated habits of individuals that generate routine action within an organization (Cohen, 2012). Micro-level processes incorporate multiple perspectives and interpretations of individuals within the organization, allowing them to solve the challenge of effectively replicating valuable routines while permitting innovation in applying them to new organizational goals (D'Adderio, 2014). As Feldman (2000: 613) observes, rather than immutable scripts, routines are "flows of connected ideas, actions, and outcomes." She notes that individuals within the organization can transpose routines from one context to another, adapting them as needed to suit the new application. Although organizational routines can be transmitted through a variety of sources including personnel movements, and mergers and acquisitions (Levitt and March, 1988), firms can also develop competitively distinctive routines through experiential learning and first-hand practice (Levitt and March, 1988; Sapienza *et al.,* 2006).

By allying with expert partners, individual participants from relatively novice firms can observe micro-level intraorganizational collaborative processes and routines, practice them within the alliance under expert guidance, and modify them in ways suitable for subsequent internal collaboration within their own firms. Doing so may yield significant benefits to novice technology firms. Because biotech firms (the setting for our investigation) specialize in discovery and provide university-like independence and incentives, they typically attract scientists seeking autonomy that large pharmaceutical firms, with their conventional emphasis on commercialization, are unable to provide (Argyres and Liebeskind, 2002). However, too much emphasis on autonomy may not be ideal; creative genius often requires a coordinated effort (Taylor and Greve, 2006). Bailyn (1985) observed that balancing autonomy and coordination can enhance R&D productivity. Being able to form temporary collaborative teams may provide such balance. Such collaboration can shape information flow (Chua, Morris, and Ingram, 2010; Nerkar and Paruchuri, 2005) and generally increases innovation within a firm (Paruchuri, 2010). The focal activities of an R&D alliance provide a context for relatively novice firms in terms of collaborative innovation to experience and practice collaborative routines guided by a relative expert, which can be applied to their own operations.

Social interaction and experiential learning

However, learning from an alliance partner is not a foregone conclusion; it requires those who have expertise to interact with those who do not (Larsson *et al.,* 1998; Lavie, Haunschild, and Khanna, 2012). Transferring routines is difficult even between groups within the same firm, let alone across firms (Winter and Szulanski, 2001). While routines are more easily obtained from expert sources (Oddou, Osland, and Blakeney, 2009), and the recipient organization is more likely to adopt them (Szulanski, 1996), learning across firm boundaries depends on the nature of the engagement.

Social interaction with a firm that is expert in managing internal collaborative innovation is essential for a relative novice to learn the expert's collaborative routines in two ways. First, more frequent and intense interaction between alliance participants builds trust (Kale, Singh, and Perlmutter, 2000) and increases the flow of tacit information between them (Dhanaraj *et al.,* 2004; Reagans and McEvily, 2003). Trusted partners will gain more insight into the expert's collaborative routines and the favorable outcomes from practicing such routines. Nonetheless, simple observation and an appreciation for the benefits of collaborative routines may not be sufficient for learning to occur. Novice firms are likely to lack the capacity to understand and implement the full range of favorable collaborative routines deployed by the expert firm without directly practicing them with the expert, and learning them through "doing" (Szulanski, 1996). Social interaction not only creates trust, but is also indicative of the novice firm's real time practice of collaboration within the alliance. Through their application within the framework of a socially interactive alliance, the novice firm gains competence and confidence with the expert's routines.

The level of social interaction varies substantially across alliance engagements; partner firms experiencing little social interaction with their expert counterpart may struggle to absorb and implement new routines, while firms experiencing greater interaction have a stronger opportunity to learn. Social interaction with expert partners can facilitate

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the maturation of relatively novice firms by promoting their development of durable routines, including those that support collaborative innovation. These learned routines can be diffused to others within the novice firm and integrated into its internal fabric (Holmqvist, 2004).

Hypothesis: The greater the social interaction between a relatively expert partner in intraorganizational collaborative innovation and a relative novice partner, the greater the subsequent increase in collaboration among the novice's internal scientists.

METHODS

Sample and survey

Our sample examines alliance relationships between Lilly and its biotechnology partner firms from 1991 to 2004. The biotech industry is a popular context for studying technology development. With strong support in the courts, patenting has become the preferred method in biotech for protecting intellectual property, offering an objective archival record of innovation within the industry. Thus, we rely on patent records to develop our measures of intraorganizational collaborative innovation.

Lilly has pursued a clear strategy of enhancing their R&D through alliances, emphasizing a systematic approach not only for internal collaboration, but also with outside firms (Powell *et al.,* 1996), particularly smaller startups (Powell, 1998). Through its alliances, Lilly encourages interaction between internal and external scientists to reap the benefits of knowledge sharing and joint problem solving. Lilly operates a formal Office of Alliance Management (OAM) to oversee external collaborative projects (Dhanaraj *et al.,* 2007; Kale and Singh, 2007). OAM managers work with internal and external team leaders to document and share best practices through alliance summits, shared-learning events, white papers, and other methods of communication (Rothaermel and Deeds, 2006). They engage in extensive benchmarking and participate in academic studies to understand and enhance learning opportunities from their alliances. Lilly's encouragement of collaboration among scientists provides an opportunity for their alliance partners to observe and emulate their internal collaborative routines. By relying on Lilly as a common collaborator across all observed alliances, we also control for much heterogeneity that would otherwise exist in a study design that varied the firms on both sides of the alliance engagement.

We collected a unique dataset on these engagements, using both archival and survey methods. With the cooperation of Lilly OAM, we identified key individuals on both sides of each sample alliance (i.e., Lilly and partner) to administer a survey in 2005. Through the survey, we collected data on 80 alliances from 179 respondents, with an individual response rate of 55 percent and an alliance response rate of 96 percent. We limited our analysis to the 55 alliances that involved partner firms having 90 or fewer R&D scientists listed on patent applications prior to their alliance with Lilly; the mean number of patent inventors within these partner firms was 11. The median start year for these alliances was 2000. These partner firms clearly had significantly less collective experience managing large complex R&D projects, and were in a position to learn collaborative techniques from a more experienced and expert partner such as Lilly. From the subset of 55 alliances, 159 individuals completed the survey; 85 from Lilly and 74 from Lilly partner firms. Of the 55 alliances, 51 had responses from both Lilly and partner firm representatives.

We relied on this survey to collect our primary independent variable, *social interaction*, using an eight-item likert scale (1–7, strongly disagree to strongly agree).[1] Sample items included "Managers from both firms have high face-to-face interaction with each other," "I feel reasonably close to my counterparts in the partner firm," "joint teams are used to manage the critical tasks in the alliance," "we frequently have team-building activities and social events that bring together members from both firms."[2] Cronbach's alpha for this scale was 0.82. To establish comprehensive measures for the survey variables, we took the average of within-firm scores (either Lilly or the partner), averaging scores across firms in cases where responses from both organizations were available. The ICC value for *social interaction* across the two firms was 0.49 ($p < 0.05$), providing additional evidence of reliability. We explored whether the *social interaction* scores of Lilly and partner firm respondents were

[1] Note that this measure represents an aggregate score across the eight items in the scale and can range from 7 to 56.

[2] All survey measures are available upon request.

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systematically biased. A t-test showed that the mean difference between the scores from Lilly and the partner firms was not significantly different from zero. Thus, neither partner nor Lilly personnel systematically rated *social interaction* higher than the other.

Dependent variables

To test our core hypothesis regarding increasing levels of internal collaboration among Lilly's partner firm inventors, we developed three separate data structures and associated dependent variables at the firm, patent, and inventor-dyad level of analysis. The inventor-dyad models capture micro-level processes of collaborative tie formation at the inventor relationship level, patent observation models reflect changes in collaboration at the project level, and the firm-level analysis reflects the broader implications for intraorganizational collaboration. As we elaborate below, this multiple-level approach provides different, complementary insights into the effects of engaging with Lilly.

Firm level

Examining the effects of the Lilly alliance at the firm level provides a broad perspective on changes to internal collaboration that most likely reflect underlying adoption of routines at the organizational level. For each partner firm (n = 55), we measured *innovation network density* by calculating the proportion of patent collaboration ties between inventors within the partner firm both before and after the Lilly alliance. We examined all U.S. patent applications filed by the partner firm for the five years from the start of its alliance with Lilly, recording individual scientists listed as inventors on each. For example, if the alliance began in 2003, we considered patent applications through 2008. We used this data to model the internal innovation network of the firm—the social network of internal scientists connected to each other through collaboration ties. A collaboration tie is the common listing of two scientists on the same patent application. We calculate network density as the ratio of observed collaboration ties to the total number of possible ties, given the number of actively patenting scientists. The innovation network would have a density value of 1 if all inventors collaborated with each other at some point during the five-year observation window, or 0 if all firm scientists worked in isolation with only a single inventor listed on any one patent application. In practice, innovation network density lies somewhere in between these two extremes.

Lacking a panel data design, a good alternative to controlling for firm fixed effects, as well as any omitted variables encompassed within such fixed effects, is controlling for prior-period values of dependent variables (Bettis *et al.,* 2014). To assess the change in *innovation network density*, we controlled for *prior innovation network density*. This was again measured as a proportion of the patent collaboration links observed between inventors within the focal firm relative to the total possible number of such links. In this case, the measure was calculated for the two years prior to the announcement of the alliance with Lilly.

Patent level

A patent-level analysis is used to assess intrafirm collaboration at the project level. We compiled all patents developed by partner firms with applications submitted to the U.S. Patent and Trademark Office (USPTO) in the five-year period following the start of their alliance with Lilly (n = 504). We observed the *number of new collaboration ties*; inventor pairs listed on the patent application that had not collaborated in the period prior to the Lilly alliance. We limited the observation of new collaboration ties to partner firm inventors employed prior to the alliance, based on their being listed on pre-alliance patents. This eliminated possible confounding effects from new-inventor hires after the alliance, and ensured that all sampled inventor pairs may have been influenced by the firm's alliance engagement with Lilly.

The patent-level data structure complemented our other analyses by allowing us to observe whether new collaboration ties at the patent level were associated with the citation of Lilly patents. We reasoned that inventors working on specific post-alliance patents that cited Lilly patents were more likely to be directly involved in the Lilly alliance, and would be particularly susceptible to any influence from the Lilly alliance. Our patent-level analysis included an additional independent variable, *backward citations of Lilly patents*, measuring the count of Lilly patents that are cited by the partner firm patent. This allowed us to test more directly whether engagement with Lilly enhances the level of post-alliance collaboration.

Inventor dyad level

The inventor dyad level analysis observes when a new tie is formed between a specific pair of inventors. This analysis allows us to link the effects of socially interactive collaboration with Lilly to the interactions between each potential inventor pair. Observing the formation of new collaboration ties between specific inventors offers the best observation of micro-level processes underlying the adaptation of collaboration routines. Distinct from the patent-level analysis, this captures the behavior of individual inventors in forming new collaboration ties with their colleagues in the post-alliance period. We constructed a risk set of all pairs of partner firm inventors (1) listed on patents prior to the alliance, and (2) who had not previously collaborated (i.e. had not been listed as coinventors on a previous patent). The sample size for this analysis is 14,015 inventor dyads. The dependent variable is the *number of new patent collaborations* for each dyad, measured as the count of successful partner firm patent applications listing both dyad members as inventors for the five years following the onset of the Lilly alliance.

Control variables

We used a series of survey-based controls for alternative factors that might account for our proposed relationships. First, alliance performance may influence the partner firm's subsequent decision to change innovation practices. To address this, we include a four-item measure of *alliance performance* ($\alpha = 0.83$; ICC = 0.68, $p < 0.01$), asking respondents to rate the success of the focal alliance. We gauged the level of *alliance management office support* using a five-item measure ($\alpha = 0.96$; ICC = 0.64, $p < 0.02$); greater involvement of Lilly's OAM could enhance the success of the relationship and impact partner firm learning. Similarity in practices between Lilly and their partners could shape organizational learning in alliances (Lane and Lubatkin, 1998). We control for *commonality of organizational practices* between Lilly and each alliance counterpart in our sample, using a three-item measure ($\alpha = 0.81$; ICC = 0.73, $p < 0.001$).[3]

We use patent-based measures to control for other factors that may influence alliance learning. *Prior rate of innovation* measures patent activity of the focal firm prior to the alliance. We totaled the successful patent applications pursued by the partner firm in the preceding 10 years. In the inventor dyad analysis, we adjusted this variable, counting the successful patent applications that listed one dyad member as an inventor. In the firm-level analysis, we control for *partner firm post-alliance patents* by measuring the total patents in the five-year period following the alliance.[4] We also retain *prior innovation network density* as a control variable in the patent-level analysis. For the dyad analysis, we controlled for *centrality* by counting the total number of collaboration partners who worked with dyad members in the two years prior to the Lilly alliance. A larger pool of inventors might influence the effects of *social interaction* on collaboration. *Innovation network size* was measured as the number of unique inventors on partner firm patents in the 10 years prior to the alliance. *Technological relatedness* between Lilly and each counterpart was measured as the knowledge base overlap between the two firms, based on direct and common patent citations (Ahuja and Katila, 2001). *Prior collaboration ties* counts the unique dyadic collaborative relationships between inventors listed on partner firm patents in the 10 years prior to the alliance.

Analysis and results

Firm level

The measure of *innovation network density* is a proportion, yielding continuously distributed data with values between 0 and 1. Using a proportional dependent variable in OLS regression creates challenges (Greene, 1997). We addressed this by following the standard econometric approach of using a log odds transformation for the dependent variable (Greene, 1997; Yang, Phelps, and Steensma, 2010).[5] Bivariate correlations and descriptive statistics for the firm-level analysis are provided in Table 1.

As shown in Table 1, post-alliance *innovation network density* is significantly correlated with *prior innovation network density* and *social interaction*. Models 1 and 2 in Table 4 provide the

[3] All survey items are available upon request.

[4] This control is not included in patent- or dyad-level analyses, given that these models are already focused at the patent level.

[5] The transformation is calculated as ln(*innovation network density*/(1 – *innovation network density*)). This variable is undefined for values of 0 or 1, thus we converted any values of 0 to 0.0001 and 1 to 0.9999 prior to conducting the transformation.

Table 1. Descriptive statistics and correlations—firm–level sample

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1. Innovation network density	−3.73	5.91										
2. Social interaction	37.20	7.70	0.37**									
3. Alliance performance	14.76	3.29	0.02	0.51**								
4. Alliance management office support	82.73	21.12	0.07	0.21	0.02							
5. Commonality of organizational practices	12.61	3.57	−0.04	0.41**	0.47**	0.20						
6. Technological relatedness	0.02	0.04	0.21	0.07	−0.28*	−0.08	−0.25					
7. Partner firm post-alliance patents	20.87	50.17	0.06	0.14	−0.12	−0.01	−0.11	−0.012				
8. Prior innovation network density	0.15	0.22	0.60**	0.32*	0.07	0.12	0.12	0.12	−0.09			
9. Prior collaboration ties	0.56	2.35	0.14	−0.02	−0.13	0.14	−0.01	0.15	−0.04	0.12		
10. Innovation network size	11.53	21.26	0.18	0.21	0.02	0.01	−0.19	0.13	0.70**	−0.04	−0.015	
11. Prior rate of innovation	24.44	67.74	0.04	0.18	0.18	0.03	−0.05	−0.01	0.69**	−0.04	0.00	0.54**

*p < 0.05; **p < 0.01

regression analysis of the firm-level data: Model 1 incorporates the control variables; Model 2 adds the direct effect of *social interaction*. The coefficient for this variable is positive and significant ($\beta = 0.220$, $p < 0.05$), providing support for our hypothesis. A 1 standard deviation increase in *social interaction* corresponds to a 45 percent increase in the dependent variable, with all other predictors held at their means.

Patent level

The measure of *number of new collaboration ties* following partner firm engagement with Lilly is a count and assumes only nonnegative integer values. These data are over-dispersed, with a standard deviation that exceeds the mean. Given these conditions, we employ the negative binomial regression model for analyses (Hausman, Hall, and Griliches, 1984). Descriptive statistics and bivariate correlations for the patent-level data are shown in Table 2.

Models 3 and 4 in Table 4 provide the patent-level results. Model 4 tests the direct effects of *social interaction* and *backward citations of Lilly technologies* on the *number of new collaboration ties*. The coefficients for both variables are positive and significant ($\beta = 0.105$, $p < 0.05$ for *social interaction*; $\beta = 1.161$, $p < 0.01$ for *backward citations of LiIly patents*). These results suggest that higher levels of social interaction between Lilly and partner firms, and possible inventor connections to the alliance as evidenced by a patent's building on Lilly technologies increase the *number of new collaboration ties* in our sample patents. Analysis of the effect sizes in the patent-level data reveals that the *number of new collaboration ties* increases by 107 percent with a 1 standard deviation increase in *social interaction* and by 60 percent with a 1 standard deviation increase in the *backward citations of Lilly patents*.

Inventor dyad level

As with the dependent variable for the patent-level data, *number of new patent collaborations* has an overdispersed, nonnegative count distribution, making the negative binomial model the proper model specification. Correlations and descriptive statistics for the dyad-level data are provided in Table 3. Models 5 and 6 of Table 4 provide the results for the inventor dyad data structure. In Model 6, the coefficient for *social interaction* is positive and significant ($\beta = 0.105$, $p < 0.05$). The *number of new collaboration ties* increases by 82 percent for a 1 standard deviation increase in *social interaction*.

Consistent, significant results across the three data structures provide support for our core hypothesis; i.e., greater *social interaction* between a relatively expert partner in collaborative innovation and a relative novice partner leads to greater subsequent collaboration among the novice's internal scientists.

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Table 2. Descriptive statistics and correlations—patent–level sample

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1. Number of new collaboration ties	0.18	1.00										
2. Social interaction	40.62	6.91	−0.01									
3. Backward citation of Lilly patents	0.10	0.40	0.20**	−0.02								
4. Alliance performance	15.18	3.00	−0.04	0.51**	−0.09*							
5. Alliance management office support	82.33	16.91	−0.02	−0.40**	0.05	−0.04						
6. Commonality of organizational practices	11.76	3.08	−0.05	0.62**	0.00	0.59**	0.06					
7. Technological relatedness	0.02	0.04	0.03	−0.25**	0.29**	−0.39**	0.06	−0.13**				
8. Prior innovation network density	0.12	0.17	0.03	−0.05	0.01	0.12**	0.28**	0.12**	0.39**			
9. Prior collaboration ties	0.32	1.45	−0.02	−0.04	0.03	−0.13**	0.24**	0.09*	0.21**	0.20**		
10. Innovation network size	48.27	34.86	0.03	0.42**	−0.12**	0.01	−0.52**	−0.17**	−0.60**	−0.55**	−0.24**	
11. Prior rate of innovation	172.59	148.71	−0.11*	0.48**	−0.20**	0.45**	−0.35**	0.08	−0.30**	−0.38**	−0.22**	0.53**

*p < 0.05; **p < 0.01

Table 3. Descriptive statistics and correlations—dyad–level sample

Variable	Mean	S.D.	1	2	3	4	5	6	7	8
1. New patent collaborations	0.01	0.12								
2. Social interaction	41.02	5.73	0.00							
3. Alliance performance	14.96	2.99	0.01	0.71**						
4. Alliance management office support	81.22	13.47	−0.01	−0.53**	−0.16**					
5. Common organizational practices	11.54	2.61	−0.01	0.62**	0.80**	0.06**				
6. Technological relatedness	0.02	0.02	0.02**	−0.25**	−0.26**	0.33**	−0.20**			
7. Prior innovation network density	13.69	14.01	0.04**	0.09**	0.18**	−0.13**	0.14**	0.00		
8. Innovation network size	66.99	19.99	−0.03**	0.54**	0.23**	−0.43**	0.38**	−0.64**	0.00	
9. Prior rate of innovation	3.42	2.17	0.04**	0.10**	0.19**	−0.18**	0.08**	0.00	0.71**	−0.04**

**p < 0.01

Robustness tests

Because decisions pursued by executives are not random but informed by the conditions and opportunities facing their firms, endogeneity is an important concern in strategy research (Shaver, 1998). We limit the likelihood that endogenous effects confound our results through our study design. Controlling for prior period values of the dependent variable as we do for *innovation network density* limits estimation bias from endogeneity due to omitted variables (Bettis *et al.,* 2014). We also identify and directly control for a number of plausible alternative explanations for the observed learning outcomes due to alliance performance, OAM support, and various patent-based measures. Finally, we conducted a direct analysis of endogeneity in our firm-level sample using the Hausman specification test to evaluate the consistency of our model relative to a regression model using instrumental variables for *social interaction* (Greene, 1997). From our survey, we identified measures associated with the technology focus of the alliance: *change in technology* and *uncertainty of technology*, which could be used as instruments for *social interaction*. The C statistic of the

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Table 4. Regression models

	Partner firm		Patent		Inventor dyad	
Level of analysis	Innovation network density		Number of new collaboration ties		Number of new patent collaborations	
Dependent variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	−7.273*	−8.633**	−4.048*	−2.570	−6.006***	−6.994***
Independent variables						
Social interaction		0.228*		0.105*		0.105*
Backward citation of Lilly patents				1.161**		
Control variables						
Alliance performance	0.126	−0.149	0.061	−0.073	0.153*	−0.035
Alliance management office support	0.004	−0.010	−0.004	−0.015	−0.010	−0.008
Commonality of organizational practices	−0.150	−0.251	−0.051	−0.198	−0.202*	−0.130
Technological relatedness	15.528	3.755	9.933†	−1.761	18.430**	9.020
Partner firm post-alliance patents	0.003	−0.007	n/a	n/a	n/a	n/a
Prior innovation network density	15.857***	13.982**	3.963*	2.288	n/a	n/a
Centrality	n/a	n/a	n/a	n/a	0.044**	0.047**
Prior collaboration ties	0.166†	0.183*	−0.056	−0.110	n/a	n/a
Innovation network size	0.057†	0.050	0.056***	0.036**	−0.003	−0.023***
Prior rate of innovation[a]	−0.007	−0.003	−0.010***	−0.011***	0.096	0.086
Number of observations	55	55	504	504	14,015	14,015
Wald chi^2			63.88***	68.87***	83.24***	174.51***
Log pseudolikelihood			−152.40	−148.95	−338.06	−336.98
F-value	7.53***	7.36***				
R^2	0.43	0.47				

[a] Firm-level patents in firm, patent models; dyad member patent totals in inventor dyad models.
†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; two-tailed tests shown for all coefficients.

Hausman specification test between the instrumented and noninstrumented models was 1.04 ($p < 0.31$), indicating that the estimator in our baseline model is consistent, and endogeneity is not a concern.[6]

We conducted a number of other tests to evaluate the robustness of our findings. We tested alternative formulations of the *prior innovation network density* control variable, measuring this value over 3-, 5-, and 10-year windows of time prior to the Lilly alliance. Our findings remained consistent in all cases, and the magnitude and significance of *social interaction* on post-alliance innovation network density actually increased with longer windows of observation for this control. We calculated the variance inflation factor for *social interaction*, yielding results across the three levels of analysis well below the rule-of-thumb value of 10 that would indicate multicollinearlity problems (Neter, Wasserman, and Kutner, 1990). We ran alternative regression models using only the responses from Lilly personnel. Because Lilly is the expert partner common to all of

[6] Analysis is available on request.

the alliance engagements in our sample, their personnel may provide a fairly consistent assessment of social interaction across alliances (as opposed to partner firm respondents). The results from these analyses matched our baseline findings. We tested for moderating effects of *commonality of organizational practices*, examining the alternative proposition that the partner firm may observe and adopt aspects of Lilly's organizational structure and practices, rather than its organizational routines. This interaction was not significant, providing some evidence that changes in partners' organizational structure and practices due to learning from Lilly do not fully account for the observed outcomes.

DISCUSSION

Strategy researchers have long considered knowledge transfer in strategic alliances. Firms learn specific technologies from their partners (e.g., Khanna *et al.,* 1998). Those that collaborate with others may also gain experience with routines that enhance their proficiency in subsequent interfirm collaboration (Zollo, Reuer, and Singh, 2002). However, little attention has been given to the prospect that novice firms also learn collaborative routines from expert partners, enhancing collaboration of their inventors internally.

The novice firms who experienced greater social interaction with Lilly during their R&D alliance subsequently enjoyed significantly more collaboration among their own inventors. We suggest that such interaction enabled the firms to learn through experience Lilly's well-developed and institutionalized collaborative routines and employ them in their own inventive pursuits. We also found that inventive pursuits within these novice firms post-Lilly alliance that built directly on Lilly technologies were more collaborative. To the extent that building on Lilly technologies in these inventions indicates that the inventors may have been directly involved in the Lilly alliance, this result provides additional evidence that engagement with Lilly enhanced their subsequent collaboration.

We contribute to important streams of work in organizational routines. Our study offers empirical evidence supporting the relationship between micro-level processes and organizational routines discussed in prior research (Cohen, 2012; D'Adderio, 2014). We observe specific changes in collaboration both at the level of individual scientists engaged in technology development projects and at the broader organizational level, revealing the multilevel effects that may be associated with the adoption of new routines. By linking downstream effects on intrafirm collaboration to socially interactive interfirm engagement with a partner having clear expertise in collaboration, we provide further support for the adaptation and transposition of routines to different contexts (Feldman, 2000). This continues the trend away from the original notions of routines as fixed, immutable scripts that must be closely replicated in order to gain their benefits.

We are mindful of the limitations of our study. Our theoretical framework examines intraorganizational collaborative routines learned through external engagement. We do not suggest that this is the only source or even the dominant source of such practices; we simply identify alliances as a potentially useful path to collaboration routines, especially for young, novice organizations. Furthermore, we infer the role of routines without the ability to measure their presence and transfer directly. In this regard, we follow in the path of prior work, which has treated routines as an unobserved, underlying mechanism of firm-level strategy and performance (e.g., Sampson, 2007; Zollo *et al.,* 2002). We welcome future research that may identify more direct means of studying organizational routines and their effects.

While the potential for learning proprietary technologies from alliance partners has been well documented, emphasizing only these learning opportunities may undersell the value of such alliances. The prospect of learning tacit organizational routines from expert alliance partners may be particularly valuable for relatively novice entrants. While we focus on collaborative routines, future work could consider other types of organizational routines and organizing principles. By the same token, alliance partners may also learn bad habits from their counterparts that hamper subsequent performance. A broader understanding of organizational routines learned through alliances and their implications would be valuable.

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