It’s not what Size, but what Type: Alliance Portfolios & Innovativeness in Biotechnology
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Abstract
Drawing on an integration of capabilities, learning, and embeddedness perspectives, this study unpacks alliance portfolio size along relational dimensions to explore how the numbers of high, mixed, and low intensity alliances influence the innovativeness of biotechnology firms. This study finds value in unpacking alliance portfolio size along relational dimensions. Specifically, mixed alliances marked by both high and low relational intensity have a positive impact on firm innovativeness. Furthermore, younger firms benefit more from mixed alliances than older firms, and firms with less technical diversity also benefit more from mixed alliances.

Key words: alliance portfolios, innovativeness, firm age, alliance portfolio size

INTRODUCTION
The pace of technological advances and the pressures of global competition create a challenging environment (Bettis & Hitt, 1995) in which firms find it increasingly difficult to develop sufficient expertise and resources internally (Prahalad & Hamel, 1994). Given the challenges of the contemporary environment the use of strategic alliances has become a pervasive feature in the landscape (Contractor & Lornage, 2002; Gulati, 1998); furthermore, in dynamic environments such as software and biotechnology firms often find themselves engaged in multiple alliances simultaneously (Ozcan & Eisenhardt, 2009; Lavie, 2007; George et al, 2001). Hence, the alliance portfolio perspective emerged as a fruitful and informative line of research that moved beyond an investigation of dyadic relationships to consider the set of alliances in which a firm is involved (Wassmer, 2010; Hoffman, 2007).

Work in the alliance portfolio perspective includes three key research areas addressing the emergence, configuration, and management of alliances portfolios (Wassmer, 2010). The current study falls within the stream of work addressing the performance implications of alliance portfolio configuration, but distinguishes itself by exploring portfolio size along relational dimensions. By unpacking alliance portfolio size along relational dimensions, this study is able to explore how the configuration of alliance portfolios along size and relational aspects impacts firm innovativeness.

This work explores the influence of relational dimensions of portfolio size within the context of biotechnology firms focused on protein identification and analysis for therapeutic purposes (i.e. proteomics) because this represents an emerging capability in the biopharmaceutical industry. The motivation for exploring questions about the relational dimensions of portfolio size within biotechnology is twofold. First, the incidence of alliance activity is high within biotechnology. Second, the players in the proteomic space face the challenge of continuing to develop their scientific resources and capabilities in addition to developing and accessing the requisite set of organizational capabilities in their value chains. The latter point lends itself to a discussion of the relative importance of various relational characteristics in the alliance portfolio since the dual challenge of accessing scientific and organizational capabilities through alliances necessitates a degree of efficiency within the alliance portfolio. Hence, can a certain configuration of relational dimensions be more advantageous for the innovative potential of a biotechnology firm?

THEORETICAL FRAMEWORK
The resource base view (Penrose, 1959; Wernerfelt, 1982; Barney, 1991) focuses on the importance of idiosyncratic firm resources as the source of competitive advantage. This perspective provides insight on

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the motivations for dyadic alliances which can also be extended to include alliance portfolios. Firms often use alliances to access resources held by partners (Das and Teng, 2000; Eisenhardt and Schoonhoven, 1996; Lavie, 2006) and to combine and exploit these resources (Parkhe, 1993; Spender et al., 1996) in an effort to create an advantage. Furthermore, given the challenges of the contemporary business environment, firms work together based on the idea that the combination of resources and capabilities across firms creates more lucrative opportunities than going it alone (Chakrabarti, 1991; Kanter, 1989), especially if the resources are complementary (Teece, 1987). Consequently, the resource based motivations for alliances also extend to alliance portfolios where firms use multiple alliances simultaneously to access various resources from different partners in an effort improve resource endowments and relational rents (Gulati, 2007; Hoffman, 2007; Lavie, 2006).

The resource based view also represents a theoretical foundation for further exploration of alliance portfolios since an alliance portfolio represents a firm resource that possesses potential to create value and to yield competitive advantage. Drawing from the seminal work by Penrose (1959), the key to capturing the benefit of a resource is the skillful use of the resource, as opposed to the mere possession. Hence, at the portfolio level the resource based perspective suggests that proper use of an alliance portfolio is a key factor in tapping into the potential of this resource to create value and to yield a competitive advantage.

Specifically, the capabilities perspective from within resource based thinking provides an avenue to shed light on key characteristics of alliance portfolios relevant for firms developing and employing new capabilities within their industry such as the biotechnology firms engaged in proteomics. The seeds of the capabilities perspective go back to the work of Penrose (1959) and its emphasis on resource manipulation. However, the importance of firm processes and activities remains salient within contemporary resource based thinking as exemplified by the discussions and research within the dynamic capabilities perspective (Teece, Pisano, & Shuen, 1997; Helfat et al., 2007). The dynamic capabilities perspective highlights the salience of repetition and experimentation in learning and capability development (Teece et al., 1997) which is relevant for firms developing and employing new capabilities.

The emphasis on firm activities or processes and capability development within the capabilities perspective also fosters an intersection with the organizational learning perspective. Organizational learning represents the process in which firms develop, improve, and organize routines and knowledge related to their activities and culture (Dodgson, 1993); or the process by which an organization expands its range of behaviors as the result of processing information (Huber, 1991). Hence, organizational learning represents a means to develop valuable capabilities that are difficult to imitate and therefore create competitive advantage (Crossan & Berdrow, 2003). This line of thought informs the investigation of alliance portfolios by supporting the relevance of portfolio characteristics that foster and facilitate the organizational learning needed for capability development.

Focusing on the sum of relationships held by a focal firm, the relational view highlights that a network of inter-firm relationships, such as an alliance portfolio, represents a source of competitive advantage resulting from the ability of the focal firm to create relational rents (Dyer and Singh, 1998; Gulati et al., 2000). A key factor in the ability of a firm to create these relational rents is the position of the focal firm in the network of its relationships (Dyer and Singh, 1998). The position of the focal firm in this network centers on the size and structure of the network, in addition to the relational characteristic of linkage intensity of the individual alliances, which taken together speaks to the configuration of the alliance portfolio (Hoffmann, 2007).

Hence, an integration of the capabilities, learning, and relational perspectives suggests that the configuration of an alliance portfolio represents an important cluster of factors in the ability of firms to create and gain benefit from engaging in an alliance portfolio. In particular, the configuration of an alliance portfolio impacts the amount and quality of resources that a focal firm can access which in turn influences firm performance and development (Hoffmann, 2007). Exploring how elements of portfolio configuration impact firm performance represents an effort that has the ability to provide insight for the
leadership of those firms employing alliance portfolios in an effort to improve performance and gain a competitive advantage. This effort also possesses the ability to contribute to the stream of research related to alliance portfolios by refining our knowledge about the influence of portfolio configuration by investigating the influence of portfolio size along relational dimensions. In contexts closest to the current study, prior research finds that portfolio size has either a positive linear (Shan, Walker, and Kogut, 1994) or a curvilinear relationship (Deeds and Hill, 1996) on the technological performance of entrepreneurial biotechnology firms. However, other studies suggest that other factors such as portfolio breadth (Ahuja, 2000; Gulati, 1999), efficiency (Baum et al., 2000) or partner quality (Stuart, 2000; Stuart, Hoang, and Hybels, 1999) outweigh the impact of portfolio size. Consequently, by drawing on an intersection of capabilities, learning, and relational perspectives this work aims to refine our understanding portfolio size by investigating a compound measure that embodies a combination of portfolio size and linkage intensity, a relational dimension, which has the potential to influence learning and capability development. This effort addresses a key weakness in prior work on portfolio size by employing a two-dimensional measure of portfolio size to gain more insight into the complexity of portfolio configuration (Wassmer, 2008). Specifically, the foundation of this study is the hypothesis that unpacking alliance portfolio size along relational dimensions provides more predictive value than the aggregate number of alliances in the portfolio.

**Hypothesis 0:** Separating the numbers of alliances into categories of varying relational intensity are better predictors of firm innovativeness than the total number of alliances in the alliance portfolio.

**HYPOTHESIS DEVELOPMENT**

The size of the alliance portfolio impacts the amount of information and resources that a firm can access from its alliances (Koka and Prescott, 2002). Hence, the capabilities and learning perspectives support the importance of larger alliance portfolios for learning and capability development which in turn fosters enhanced firm performance and outcomes. However, an alliance portfolio is also a set of inter-organizational relationships whose relational aspects influence the ability of firms to gain access to desired resources and capabilities resident within their partners. Specifically, relational aspects such as the linkage intensity of the individual alliances in the portfolio determine the quality and depth of information and resources that a firm can access through its alliance portfolio (Koka and Prescott, 2002; Kraatz, 1998).

The social embeddedness framework (Granovetter, 1985; Uzzi 1996, 1997) addresses how social ties and their structure influence commercial business transactions and outcomes. As a variable, social embeddedness describes the degree to which a commercial interaction also involves social ties and attachments which can vary from arm’s length to embedded (Dacin, Ventresca, and Beal, 1999; Powell, 1990; Uzzi, 1999). Arm’s length relationships involve low levels of social interaction or attachment and are generally governed by market mechanisms (Hirschman, 1982; Macneil, 1980). However, embedded relationships involve higher levels of social involvement where trust and reciprocity act as important governance mechanisms (Uzzi, 1999) that promote the sharing of private information and resources (Uzzi, 1997; Portes and Sensenbrenner, 1993).

However, research suggests that alliances characterized by the strong ties with a high degree of social embeddedness and interaction possess positive and negative implications. A portfolio of strong ties can yield a positive impact on a firm’s innovative capabilities as a result of trust, social interaction, and deepening mutual knowledge; however, these portfolios can also create a negative impact on innovative capabilities by restricting the number of contacts and reinforcing a decreasing responsiveness to new market trends (Capaldo, 2007). Furthermore, like portfolio size, the influence of linkage intensity or tie strength is only completely understood in the presence of other factors (Wassmer, 2008).

In the study of alliance portfolio configuration, both portfolio size and the relational aspect of tie strength or linkage intensity represent salient areas of focus. However, beyond the relevance of these two factors, the only area of agreement born of the inconclusive findings to date is a need to incorporate other factors.
to truly understand the impact of portfolio size and the role of linkage intensity (Wassmer, 2008). This study advances an exploration of portfolio size that incorporates relational dimensions related to tie strength to address questions of portfolio configuration in a manner that builds on existing research and advances our understanding of this complex relationship between portfolio configuration and firm outcomes.

The learning and capabilities perspectives suggest that a firm needs extended and in-depth interaction and exposure to the organizational processes or capabilities of its alliance partners for meaningful learning and capability development given the importance of access (Khanna, Gulati, and Norhia, 1998) and repetition (Teece et al., 1997) in learning and capability development. The social embeddedness framework (Granovetter, 1985; Uzzi, 1996, 1997) highlights that alliances marked by stronger ties of high linkage intensity foster the trust and access required for learning and the resulting capability development. Hence, drawing on an intersection of the capabilities, learning, and social embeddedness perspectives, we propose that an alliance portfolio containing a larger numbers of alliances marked by high linkage intensity will increase firm innovativeness as a result of the combined benefits of increased portfolio size coupled with increased linkage intensity of the alliances.

**Hypothesis 1:** Increased numbers of high linkage intensity alliances within an alliance portfolio increases firm innovativeness.

An emphasis on the aspects of alliance portfolio configuration that influence learning and capability development also engages a consideration of absorptive capacity which influences the ability of firms to learn. Specifically, absorptive capacity purports that organizational learning depends to some degree on previous experience in a firm’s ability to recognize and assimilate the knowledge needed to foster the development of innovative capabilities (Cohen and Levinthal, 1990). In particular, lower levels of absorptive capacity hinder the use of new and diverse knowledge (Levinthal and March, 1993; Levitt and March, 1988). Prior work demonstrates the relevance of unpacking absorptive capacity into two categories: 1) Latitudinal absorptive capacity that corresponds to diverse knowledge, and 2) longitudinal absorptive capacity that relates to distant knowledge (Vasudeva and Anand, 2011). Since the current study explores biotechnology firms engaged in the emerging area of proteomics, latitudinal absorptive capacity is more relevant because proteomics still resides in close proximity to the core of biotechnology. Furthermore, research finds that firm level knowledge impacts the ability of firms to utilize the breadth of knowledge that increased portfolio size brings (Vasudeva and Anand, 2011). Hence, the importance of latitudinal absorptive capacity to the immediate context suggests that firms with greater technological diversity have an advantage over firms with less technological diversity in their ability to capture the benefit of alliances with greater linkage intensity.

**Hypothesis 2:** Firms with higher levels of technological diversity receive more benefit from an increased number of embedded alliances relative to firms with lower levels of absorptive capacity.

In developing a discussion that supports the salience of a capabilities and learning rationale for the relevance of size and relational aspects of alliance portfolios, I do acknowledge firm age as an important intervening factors that emanates from an institutional argument. In the research intensive context of biotechnology, research finds that linkages to key external players greatly enhance a firm’s research efforts and that the stronger ties and histories of older firms represent an advantage, especially in the commercialization stage (Lynn, Reddy and Aram, 1996). Over time firms develop and maintain these relationships and the accumulation of positive connections fosters positive performance effects (Hannan, 1998). Therefore, consistent with a liability of newness argument (Stinchcombe, 1965), this argument acknowledges that younger firms face disadvantages as a function of their age. While the liability of newness argument has institutional and ecological roots, I highlight that the institutional impact of firm age is not necessarily in opposition to the learning and capabilities perspective.

The conceptualization of learning within the dynamic capabilities perspective (Teece et al., 1997), and the importance of repetition, experimentation, and history in capability development support the importance of the passage of time, or firm aging. Insight from evolutionary economics also supports the notion that the passage of time is important in the generation and storage of firm knowledge within firm routines.
(Nelson & Winter, 1982). Similar to the rationale of the dynamic capabilities perspective (Teece et al., 1997), the passage of time is important to the “learning by doing” process within evolutionary economics in which benefits accrue to older firms in the form of more firm knowledge. So far the rationale supports the idea that gives older firms an advantage over younger firms in their ability to gain innovativeness from alliances with higher linkage intensity. However, research suggests that the impact of firm age is particularly relevant for firms bringing new capabilities to their industry, such as proteomics-related biotechnology firms, given the tendency of newer technology-based firms to be deficient in technology development resources (Aspelund, Berg-Utby, and Skjevdal, 2005). Given an inherent deficiency of technology development resources, younger firms may have more to benefit from embedded alliances relative to older firms; hence, we propose firm age as a key intervening factor that enables younger firms to receive more benefit from increased numbers of high linkage intensity alliances within their portfolios.

**Hypothesis 3**: Younger firms receive more benefit from an increased number of embedded alliances relative to older firms.

**METHODS**

**Research Setting and Data**

The empirical context for this study is the biotechnology industry, specifically biotechnology firms involved in proteomics. Proteomics centers on the identification and analysis of proteins from a systems perspective, which represents a relatively new approach in protein science (Patterson & Aebersold, 2003). The biopharmaceutical space, created by an overlap of traditional pharmaceutical firms, biotechnology firms, and not-for-profit research institutions or centers, has an extremely high incidence of alliance activity that makes this industry a popular context for alliance research (Hagedoorn, 1993). The need to form alliances in an effort to fill in resource gaps is further heightened with proteomics firms because these firms face the dual challenge of building proteomic capabilities and obtaining the requisite organizational capabilities to survive in the dynamic biotechnology industry. Hence, this dual challenge makes this a good context to explore the influence of alliance portfolio configuration on firm innovativeness.

Following previous research (e.g. Lane & Lubatkin, 1998, Rothaermel, 2001; Rothaermel & Deeds, 2004), I used the Bioscan database to draw an international sample of 104 biotechnology firms involved in proteomics. The presence of detailed information on alliance activity, including descriptions of the alliances, represented a strong advantage of using the Bioscan database. I supplemented the firm and alliance information collected from Bioscan with descriptive firm data collected from the CorpTech and Lexis-Nexis Academic Universe databases. I also collected patent information for the firms in the sample from the European Patent Office (EPO) worldwide database through espacenet.com, which covers a total of 81 countries including the United States, China, and Japan (European Patent Office, 2008).

**Measures**

**Dependent variable**

The dependent variable in this study is firm innovativeness. Firm innovativeness represents a more relevant performance measure for this study given that the context is a fast cycle speed industry where response to change is critical to competitiveness (Nadkarni and Narayanan, 2007) and innovativeness is a salient strategic focus (Teece and Pisan, 1994). The measure of innovativeness is the number of patents held by the firm as of March 2008. Prior research establishes that patent data is a valid measure of innovation activity (Acs and Audretsch, 1989) that relates directly to innovation performance (Paks and Griliches, 1984) and technological novelty (Griliches, 1990).

**Independent variables**

The numbers of alliances across varying levels of linkage intensity represent the focal independent variables in this study. The Bioscan database provided the detailed descriptive data on the portfolio of alliances held by a firm including the number of alliances in the portfolio, the age of each alliance, and the nature or type of each alliance. I collected the Bioscan data during spring of 2007 which provided a one
year lag relative to the dependent variable. Alliance types included development, collaboration, R&D, contract, distribution, commercialization, marketing, and licensing.

Since alliances with higher linkage intensity involve higher levels of social involvement and interaction (Uzzi, 1999) that promote the sharing of private information and resources (Uzzi, 1997; Portes and Sensenbenner, 1993; Arrow, 1998), alliances described as development, collaboration, or R&D contributed to the number of high intensity alliances in the portfolio. Alternatively, alliance arrangements that involved low levels of social involvement and interaction (contract, distribution, commercialization, marketing, or licensing alliances) counted toward the number of low intensity alliances in the portfolio. However, Bioscan described some alliances using more than one alliance type. To capture those situations in which the alliance descriptions reflected both high and low linkage intensity relationship, these alliances counted toward the number of mixed intensity alliances in the alliance portfolio.

Additional independent variables of interest in this study include firm age and technical diversity of the firm. Firm age is the number of years since the firm was founded. Firm age is of empirical interest in this study since the passage of time embodied in greater firm age provides the opportunity for capability development (Teece et al., 1997) and knowledge storage (Nelson and Winter, 1982) that may enable a firm to receive more benefit from increased numbers of high linkage intensity alliances in the portfolio. If Bioscan did not provide the year of founding, then either CorpTech or Lexis-Nexis Academic Universe was used as a source of this data.

Like firm age, technical diversity of the firm is of empirical interest in this study since broader technical diversity may enable a firm to receive more benefit from increased numbers of high linkage intensity alliances in the portfolio. Specifically, technical diversity relates to the absorptive capacity of the firm where previous experience fosters the ability to recognize and assimilate the knowledge needed to foster the development of innovative capabilities (Cohen and Levinthal, 1990).

Control variables

Multiple control variables addressed other potential influences on firm innovativeness. The number of patents held by the firm as of 2003 is the control variable for the prior innovativeness of the firms. Since the average age of the firm alliances in the sample was 2.69 years, patents from 2003 are a fair representation of prior innovativeness. The average age of the alliances in the portfolio was the control variable that captured effects related to the life cycle of the portfolio and maturity of the alliances. The number of employees was the control variable for firm size to control for the effect of firm size on innovativeness. Since all of the firms in the sample were biotechnology firms involved in proteomics a control for industry effects was not required; however, a dummy variable for public (public=1) versus private (private = 0) firm ownership was a control variable to capture any potential advantages that may be attributed to ownership status.

Statistical Analysis

The dependent variable in this study was a count variable that only assumed non-negative integer values. The unconditional mean of the dependent variable was much lower than its variance, and the conditional means were also much lower than their variances. Since both of these conditions point to over dispersion in the data, I estimated a negative binomial regression model (Winkelmann and Zimmermann, 1995; Barron, 1992; Hausman, Hall, and Griliches, 1984) to test the models using the GENLIN, or generalized linear model, procedure in SPSS.

RESULTS

Table 1 reports the descriptive statistics and correlations. As expected, notable correlations exist between the number of patents in 2008 and the number of patents in 2003 (0.76), and between the total number of alliances and the numbers of alliances within each category of relational intensity as expected (0.84, 0.68, and 0.74). While these correlations are notable, all but one falls below the 0.80 benchmark (Kennedy, 1979). Otherwise, some moderate levels of correlation are present between some other independent variables, but these correlations fall well below the benchmark values of 0.75 (Tsui et al., 1995) or 0.80 (Kennedy, 1979).
Based on the negative binomial regression results shown in Table 2, I find support for Hypothesis 0. Model 1 represents the baseline model with just the control variables. Model 2 includes the control variables and total alliances. As expected, Model 2 shows significant improvement from Model 1 (χ2 Δ= 21.74, p<0.001), which supports the finding of prior work that alliance portfolio size is relevant and that increased size has a positive influence on firm innovativeness (β=0.094, p<0.001). Model 3 replaces total alliances with the numbers of alliances in each of the three levels of linkage intensity (high, mixed, and low) to investigate the benefit of unpacking alliance portfolio size along relational dimensions. The χ2 change statistic indicates that unpacking alliance portfolio size along relational dimensions has value (χ2 Δ=5.72, p<0.05) which supports Hypothesis 0.

However, the results of Model 3 provide mixed support for Hypothesis 1. The marginal significance of the coefficient for high linkage intensity alliances (β=0.060, p=0.08) provides some support for Hypothesis 1. However, the coefficient for low linkage intensity alliances is also marginally significant (β=0.082, p=0.08). Furthermore, the coefficient for the number of mixed intensity alliances is positive and significant (β=0.332, p=0.01). Taken together, these results provide mixed support for Hypothesis 1 since the mixed category captures alliances that have both high linkage intensity characteristics and low linkage intensity characteristics.

Table 3 presents the negative binomial regression models estimated to explore the interaction of technical diversity and the number of high linkage intensity alliances. The results in Table 3 do not support Hypotheses 2. The interaction term for high intensity alliances and technical diversity is not significant in Model 4; hence, firms with more technical diversity do not gain more innovative benefit from high intensity alliances. The interaction term for mixed intensity alliances and technical diversity is marginally significant, yet negative (β=-0.014, p=0.08) in Model 5, which suggests that firms with more technical diversity actually decreases the innovative benefit of mixed intensity alliances. Lastly, the interaction term for low intensity alliances and technical diversity is also not significant as anticipated; however, in sum the results do not support Hypothesis 2.

Table 4 presents the negative binomial regression models estimates to explore the interaction of firm age and high linkage intensity alliances. The results in Table 4 provide mixed support for Hypothesis 3. The interaction term for high intensity alliances and firm age is not significant in Model 7; hence, younger firms do not gain more innovative benefit from high intensity alliances. However, the interaction term for firm age and mixed intensity alliances is significant and negative (β=0.681, p<0.001) in Model 8, which suggests that younger firms receive more of an innovative benefit from mixed intensity alliances relative to older firms. The interaction term for low intensity alliances and firm age is also not significant as anticipated, so in sum the support for Hypothesis 3 is mixed.

**DISCUSSION**

This study aimed to demonstrate the relevance of unpacking alliance portfolio size along relational dimensions to achieve a more fine grained understanding of how this aspect of alliance portfolio configuration influences firm innovativeness. Motivated by an intersection of the capabilities and organizational learning perspectives, this study focused on the relational or linkage intensity of the alliances in a firm’s portfolio as a key influence on firm innovativeness given the ability of high intensity alliance relationships to facilitate capability development. The biotechnology industry represents an
advantageous context to explore these questions given the importance of scientific or technical capabilities, and the high incidence of alliances in the biopharmaceutical landscape (Hagedoorn, 1993). The findings of this study demonstrate the value in unpacking alliance portfolio size along relational dimensions. Alliances of high, mixed, and low linkage intensity do have different impact on the innovativeness of biotechnology firms. Specifically, alliances reflecting a mix of high linkage intensity characteristics and low linkage intensity characteristics have a significant positive influence on the innovativeness of proteomics firms. The high linkage intensity characteristics do provide the higher levels of social involvement that facilitate the sharing of information and resources (Uzzi, 1997; Portes and Sensenbenner, 1993; Arrow, 1998) needed for capability development. However, the addition of low linkage intensity characteristics within an alliance provides an efficiency advantage since the costs of developing new relationships is decreased (Burt, 1992; McEvily and Zaheer, 1999) as firms expand the alliance relationships with existing partners (Goerzen, 2007; Gulati and Gargiulo, 1999; Gulati, 1995). Hence, the presence of alliances of mixed relational intensity within a portfolio represents an efficient configuration since these alliances provide, “…access to more diverse information and capabilities per alliance, and thus produce desired benefits with minimum costs of redundancy, conflict and complexity.” (Baum, 2000: 270).

Furthermore, firm age and latitudinal absorptive capacity are relevant moderators on the relationship between alliances of mixed relational intensity and innovativeness. Specifically, mixed intensity alliances yield more innovativeness in younger firms relative to older firms. Mixed linkage intensity alliances enable younger firms to experience the higher levels of social involvement needed to facilitate the sharing of information and resources (Uzzi, 1997; Portes and Sensenbenner, 1993; Arrow, 1998) which is important since younger firms are often technologically deficient (Aspelund et al., 2005). However, the incorporation of low linkage intensity characteristics also has an important efficiency advantage for younger firms that may need to be more mindful of costs. Hence, the liability of newness (Stinchcombe, 1965) makes the advantages of mixed linkage intensity alliances even more important for younger firms. Mixed intensity alliances also yield more innovativeness for firms with less latitudinal absorptive capacity. Again the efficiency of mixed alliances provides more benefit for firms with less latitudinal absorptive capacity that lack diversity in their knowledge (Vasudeva and Anand, 2011). These firms benefit from the opportunity to develop capabilities afforded through high linkage intensity, while also benefiting from the opportunity to focus efforts on capability development instead of seeking and building new relationships.

These findings also have important implications for managers and decision-makers within biotechnology firms. Recent research shows that business strategy drives alliance portfolio configuration (Hoffmann, 2007); hence, these findings provide evidence to support the consideration of mixed intensity alliances within a firm’s portfolio of alliances given their dual benefits of depth and efficiency. Furthermore, even in situations where a firm’s set of alliances may not be intentionally conceptualized as a coherent portfolio (Bamford and Ernst, 2002; George et al., 2001; Doz and Hamel, 1998), managers and decision-makers can use the findings of this study to make more informed alliance decisions on an alliance-by-alliance basis as well, especially in light of the importance of mixed intensity alliances for younger firms and those with less technical breadth.

Like much previous work, this study is not without its limitations. The current study explores a two-dimensional view of alliance portfolio size which incorporates relational aspects within a compound measure; however, future research could continue to explore additional dimensions related to the number of partners and various partner level attributes (Wassmer, 2007) to continue to refine our understanding of the complex and multifaceted impact of portfolio configuration. Research along these lines could also refine our understanding by exploring the impact of a multi-dimensional view of alliance portfolio size on both financial and innovative performance. Furthermore, additional research could explore similar and new relationships in contexts outside of biotechnology in an effort to enhance to the generalizability of the research findings.
REFERENCES


### TABLE 1: Descriptive Statistics and Correlations \(^{ab}\)

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<th>Variable</th>
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<td>110</td>
<td>9.46</td>
<td>17.49</td>
<td>1160</td>
<td>1.69</td>
<td>4.66</td>
<td>2.02</td>
<td>.53</td>
<td>2.12</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>1094</td>
<td>402</td>
<td>8.90</td>
<td>23.21</td>
<td>5587</td>
<td>2.48</td>
<td>6.57</td>
<td>3.97</td>
<td>1.39</td>
<td>3.10</td>
</tr>
</tbody>
</table>

\(^a\) N = 104

\(^b\) Correlation coefficients larger than 0.20 in absolute value are significant at the 0.05 level.

### TABLE 2: Main effects: Negative binomial regression on firm patents \(^{ab}\)

<table>
<thead>
<tr>
<th>Patents (2008)</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patents (2003)</td>
<td>0.004*** (.0008)</td>
<td>0.004*** (.0007)</td>
<td>0.004*** (.0007)</td>
</tr>
<tr>
<td>Technical areas</td>
<td>0.000 (0.016)</td>
<td>-0.016 (0.016)</td>
<td>-0.021 (0.016)</td>
</tr>
<tr>
<td>Firm age</td>
<td>-0.001 (0.006)</td>
<td>0.002 (0.006)</td>
<td>0.003 (0.006)</td>
</tr>
<tr>
<td>Employees</td>
<td>0.0005* (.00002)</td>
<td>0.0002 (.00002)</td>
<td>0.0002 (.00002)</td>
</tr>
<tr>
<td>Ownership (public=1)</td>
<td>-1.19*** (0.242)</td>
<td>-1.031*** (0.256)</td>
<td>-0.912*** (0.268)</td>
</tr>
<tr>
<td>Average alliance age</td>
<td>0.169** (0.068)</td>
<td>0.053 (0.049)</td>
<td>0.038 (0.047)</td>
</tr>
<tr>
<td>Total # alliances</td>
<td>0.094*** (0.022)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High intensity alliances</td>
<td></td>
<td></td>
<td>0.060 (0.035)</td>
</tr>
<tr>
<td>Mix intensity alliances</td>
<td></td>
<td></td>
<td>0.332** (0.124)</td>
</tr>
<tr>
<td>Low intensity alliances</td>
<td></td>
<td></td>
<td>0.082 (0.047)</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-514.09</td>
<td>-503.22</td>
<td>-500.36</td>
</tr>
<tr>
<td>(\chi^2)</td>
<td>351.57***</td>
<td>373.30***</td>
<td>379.03***</td>
</tr>
<tr>
<td>(\chi^2) (\Delta)</td>
<td>(Models 1-2) 21.74***</td>
<td>(Models 2-3) 5.72***</td>
<td></td>
</tr>
</tbody>
</table>

\(^a\) N=104

\(^b\) Cells pertain to coefficients with standard errors in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001
### TABLE 3: Interaction effects of technical areas & alliance linkage intensity

<table>
<thead>
<tr>
<th></th>
<th>Patents (2008)</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patents (2003)</td>
<td>0.004*** (0.001)</td>
<td>0.004*** (0.001)</td>
<td>0.004*** (0.001)</td>
<td></td>
</tr>
<tr>
<td>Technical areas</td>
<td>0.001 (0.018)</td>
<td>0.005 (0.012)</td>
<td>-0.010 (0.024)</td>
<td></td>
</tr>
<tr>
<td>Firm age</td>
<td>0.001 (0.006)</td>
<td>0.003 (0.006)</td>
<td>0.000 (0.006)</td>
<td></td>
</tr>
<tr>
<td>Employees</td>
<td>0.00003 (.00002)</td>
<td>.00004 (.00002)</td>
<td>.00003 (.00002)</td>
<td></td>
</tr>
<tr>
<td>Ownership (public=1)</td>
<td>-1.137*** (0.247)</td>
<td>-0.915** (0.264)</td>
<td>-1.147*** (0.249)</td>
<td></td>
</tr>
<tr>
<td>Average alliance age</td>
<td>0.113 (0.061)</td>
<td>0.080 (0.060)</td>
<td>0.085 (0.057)</td>
<td></td>
</tr>
<tr>
<td>Total # alliances</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High intensity alliances</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mix intensity alliances</td>
<td></td>
<td>0.647*** (0.184)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low intensity alliances</td>
<td></td>
<td></td>
<td>0.177** (0.063)</td>
<td></td>
</tr>
<tr>
<td>High intensity x areas</td>
<td></td>
<td>-0.001 (0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mix intensity x areas</td>
<td></td>
<td>-0.014 (0.008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low intensity x areas</td>
<td></td>
<td></td>
<td>-0.002 (0.004)</td>
<td></td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-509.72</td>
<td>-504.29</td>
<td>-506.51</td>
<td></td>
</tr>
<tr>
<td>χ²</td>
<td>360.30***</td>
<td>371.16***</td>
<td>366.73***</td>
<td></td>
</tr>
</tbody>
</table>

N=104
Cells pertain to coefficients with standard errors in parentheses
* p< 0.05, ** p < 0.01, *** p < 0.001

### TABLE 4: Interaction effects of firm age & alliance linkage intensity

<table>
<thead>
<tr>
<th></th>
<th>Patents (2008)</th>
<th>Model 7</th>
<th>Model 8</th>
<th>Model 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patents (2003)</td>
<td>0.004*** (0.001)</td>
<td>0.004*** (0.001)</td>
<td>0.004*** (0.001)</td>
<td></td>
</tr>
<tr>
<td>Technical areas</td>
<td>0.000 (0.016)</td>
<td>-0.005 (0.017)</td>
<td>-0.011 (0.018)</td>
<td></td>
</tr>
<tr>
<td>Firm age</td>
<td>0.003 (0.007)</td>
<td>0.005 (0.006)</td>
<td>0.002 (0.006)</td>
<td></td>
</tr>
<tr>
<td>Employees</td>
<td>.00004 (.00003)</td>
<td>.00005 (.00003)</td>
<td>.00004 (.00002)</td>
<td></td>
</tr>
<tr>
<td>Ownership (public=1)</td>
<td>-1.097*** (0.248)</td>
<td>-0.815** (0.264)</td>
<td>-1.099*** (0.250)</td>
<td></td>
</tr>
<tr>
<td>Average alliance age</td>
<td>0.121 (0.062)</td>
<td>0.087 (0.059)</td>
<td>0.095 (0.059)</td>
<td></td>
</tr>
<tr>
<td>Total # alliances</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High intensity alliances</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mix intensity alliances</td>
<td></td>
<td>0.681*** (0.164)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low intensity alliances</td>
<td></td>
<td></td>
<td>0.181*** (0.050)</td>
<td></td>
</tr>
<tr>
<td>High intensity x age</td>
<td>-0.001 (0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mix intensity x age</td>
<td></td>
<td>-0.006** (0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low intensity x age</td>
<td></td>
<td></td>
<td>-0.001 (0.001)</td>
<td></td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-509.35</td>
<td>-502.14</td>
<td>-505.98</td>
<td></td>
</tr>
<tr>
<td>χ²</td>
<td>361.04***</td>
<td>375.46***</td>
<td>367.78***</td>
<td></td>
</tr>
</tbody>
</table>

N=104
Cells pertain to coefficients with standard errors in parentheses
* p< 0.05, ** p < 0.01, *** p < 0.001