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ABSTRACT

Acquisition and collaboration are actively used for external knowledge acquisition and organisational learning but little is known about how different patterns of sequencing and the intensity of these activities impact on the innovation performance of firms. This paper fills in this important gap in the literature by identifying a typology of sequencing strategies of collaborative and acquisition activities and examining their impact on innovation using a panel dataset of Chinese firms from 2007 to 2011. It identifies four different types of sequencing strategies and finds contrasting innovation outcomes are associated with these different patterns. Furthermore, the impact of sequencing patterns is moderated by the intensity with which collaborations and acquisitions are implemented. Undertaking both collaborations and acquisitions simultaneously and continuously can produce the best innovation performance; but if this is implemented at a high intensity, this may hamper innovation. Firms should not just pay attention to absorption but should also consider digestion when evaluating potential collaborations and acquisitions.

Key Words: Innovation, Sequencing Patterns, Collaboration, Acquisition, Intensity

INTRODUCTION

Strategic formations, such as collaborations and acquisitions (C&As) have been identified as important for firm innovation, but much of the research has ignored the sequencing of such strategic actions (Rimoldi, 2000). Sequencing patterns have significant resource allocation and performance implications (McNamara *et al.*, 2008) but most studies ignore how such processes affect a firm's innovation performance, organizational routines for inter-firm learning and strategic development.

One stream of literature has emphasized that acquisitions and collaborations can be considered as external technological inputs, and hence have tended to analyse how the characteristics of collaborations and acquisitions have influenced innovation performance. Ahuja *et al.* (2001) developed a theoretical model that predicts that the innovation performance of acquiring firms is affected by acquisition characteristics such as size of the acquired knowledge base, relative size of the acquired knowledge and the relatedness of acquired and acquiring knowledge bases. Colombo *et al.* (2014) also explored the relationship between technological similarity, post-acquisition R&D reorganization and innovation performance in horizontal acquisitions. Firms, however, frequently engage in multiple acquisitions or collaborations to execute their strategy (Schipper *et al.*, 1983), and the overall impact on performance may not be solely driven by the characteristics of individual acquisitions but may also depend on the process through which such strategies are implemented (Laamanen *et al.*, 2008). In the collaboration literature, most of the studies find R&D collaboration benefits innovation performance of firms, eg. Enkel and Heil (2014), Leeuw, et al. (2014), and Kafouros, et al. (2015). On the other hand, collaborative innovation also bears some costs (Katz and Martin, 1997). Some find network complexity and position of a firm affect innovation outcome (Hird and Pfotenhauer, 2017). As far as we are aware, the only paper that has attempted to identify the impact of collaboration and acquisition sequencing is financial is Shi and Prescott (2011) which focused on financial performance.

Other studies have highlighted that acquisitions and collaborations are ways of learning new technologies and accumulating new capabilities. Such studies have examined how a firm's experience of acquisition helps it to improve its acquisition selection (Hayward, 2002; Laamanen *et al.*, 2008), as well as to acquire resources and knowledge (Hardy *et al.*, 2003; Pangarkar, 2009). The organizational learning perspective has, however, largely ignored how sequencing of collaborations and acquisitions may be influenced by accumulated knowledge and capabilities.

Some classical studies have identified that the effective absorption of new knowledge requires time and consistency to develop the appropriate capabilities to develop innovative outputs (Abbott *et al.*, 1990; Ariño *et al.*, 2008; Daunfeldt *et al.*, 2015; Liebeskind, 1997). These studies suggest that learning mechanisms and the capability building process depend upon sequencing patterns (Shi & Prescott, 2011) or repetitive activities (e.g. Aktas *et al.*, 2013; Hayward, 2002; Laamanen *et al.*, 2008; Shi *et al.*, 2011). However, no research has so far examined how intensity influences the impact of sequencing patterns.

This paper attempts to fill these gaps by examining the impact of the sequencing patterns of collaborations and acquisitions on innovation outcomes and by examining the intensity of these activities and its role in moderating the impact of sequencing on innovation. It uses a longitudinal dataset of 560 'Innovative Firms' accredited by the Ministry of Science and Technology of China (MOST) from 2007 to 2011. Furthermore, it employs a novel technique in the social sciences - optimal matching - to identify the sequencing patterns of collaborations and acquisitions. The paper is organized as follows. Following this introductory section, section 2 reviews the literature and develops our hypotheses. Sections 3 and 4 describe the methodology for the empirical analysis and presents the results. Section 5 summarizes the findings and considers the implication for management and the directions for future research.

LITERATURE REVIEW AND HYPOTHESIS

Effective collaborations and acquisitions require synergy between partners. It has been emphasised that the creation of synergy depends on the characteristics of collaboration and acquisition strategies (Kusewitt, 1985). Inappropriate strategies can lead to 'corporate indigestion' with a failure to collaborate or integrate which can severely hamper firm performance (Wan and Yui, 2009). This study argues that organisational learning is required to ensure effective collaborations and acquisitions and the effective ‘digestion’ of knowledge. Furthermore, such organisational learning will be influenced by the sequencing of collaborations, and the intensity with which such sequencing is implemented. In the natural sciences, DNA sequencing is used to determine the physical order of bases in a molecule of DNA. In this paper we use an optimal matching technique to map the sequencing over time of collaborations and acquisitions in the corporate world.

Generic knowledge accumulation in collaborations or acquisitions

A collaboration is defined as any inter-firm collaborations to achieve the strategic objectives of both sides (Das *et al.*, 1998) and an acquisition is considered as a final irreversible transaction of transferring ownership (Wang *et al.*, 2007). These definitions exclude pure customer relationships (Patzelt *et al.*, 2008) and self-purchases, but does not limit the collaboration and acquisition to any particular type.

Collaborations and acquisitions involve at least two firms (or organisations) which may face some common issues such as financial investigation, strategic analysis, cultural fit, relationship configuration and contractual implementation (Bronder *et al.*, 1992; Finkelstein *et al.*, 2002; Hamel, 1991; Hayward, 2002; Laamanen *et al.*, 2008). Such issues, and how they are resolved, leads to the accumulation of generic inter-firm knowledge, which can facilitate the development of relational capability (Wang *et al.*, 2007).

Relational capability – the ability to interact across organizational boundaries - is critical to resource acquisition and allocation and is important to maximise the impact of collaboration and acquisitions as it enables interactions with other firms and organisations (Lorenzoni *et al.*, 1999). Relational capability can be developed by learning from collaborations and acquisitions through an iterative and dynamic process where the firm acquires experiences, draws inferences and learns for future activities (Levitt *et al.*, 1988). Thus, collaboration and acquisition routines and capabilities can be accumulated by over time as firms are able to digest new knowledge, improving their capacity to effectively collaborate or to acquire.

Specific knowledge differences in collaborations and acquisitions

Collaborations and acquisitions may also lead to the accumulation and exchange of knowledge that is specific to the individual transaction mechanism. Specific knowledge - which may include transaction details, technology and governance mechanisms - is acquired through the iterative process of interacting, and the success of such knowledge learning is closely related the effectiveness of interactions (Daft *et al.*, 1986; Marsden, 1990). Table I summarises the different types of knowledge acquired following different sequence patterns of collaboration and acquisitions as identified in the literature and discussed below.

INSERT TABLE I ABOUT HERE

Inter-firm specific knowledge can only be acquired from a specific collaboration or acquisition. Collaborations and acquisitions are distinct relational activities involving different routines. With an acquisition, the influence of the acquired organisation may be reduced and the acquiring firm may be the dominate partner in reorganising and positioning the newly integrated company. In contrast, collaborations do not involve full integration between firms which maintain their own corporate identities (de Man *et al.*, 2005; Vanhaverbeke *et al.*, 2002). With such contrasts, the routines that develop may be very different. For instance, collaborations may be considered as outcome-based contracts whereby firms develop specific collaborative routines, such as joint decision-making, managerial interest alignment, cultural conflict management and reward distribution (Reuer *et al.*, 1997). Acquisitions, however, may provide firms with opportunities to develop routines to identify strategic and organisational fits between acquirers and targets to ensure better synergy and problem-solving in post-acquisition integration.

Technological knowledge can be tacit and sticky, and its acquisition, use and impact may be different with collaborations compared to that of acquisitions. Learning by collaboration is achieved through observation ((Levitt *et al.*, 1988; March *et al.*, 1958). Partners in collaborations are often competitors and the fear of sharing technological knowledge may lead to ineffective collaborations (Hamel, 1991; Reich *et al.*, 1998). There may be an asymmetry in knowledge sharing with firms open to acquiring knowledge from other firms but reluctant to share their own knowledge with other firms. Thus, collaborations may not mutually facilitate innovation performance. With an acquisition, two firms only need to learn from each prior to the final irreversible transaction of transferring ownership. Consequently, acquisition may avoid the issues of insufficient trust with collaborations, leading to improved learning performance (Grandori, 1999; Grimpe *et al.*, 2010).

There are other factors which may favour the use of either collaborations or acquisitions to absorb specific technological knowledge and innovation competences of external partners (Van de Vrande, 2013). For instance, when a firm evaluates that its level of market and technological familiarity is low, collaborations may be preferred over acquisitions (Dyer *et al.*, 2003). Collaborations are also pursued in the early stage of technological development (Vanhaverbeke *et al.*, 2002) or following an environmental shock (Van de Vrande, 2013). Conversely, technological know-how is often tacit and therefore maynot be easily transmitted from one firm to another within a collaborative structure (Larsson *et al.*, 1998). Thus, firms may be inclined to engage in an acquisition in order to improve the transmission of tacit knowledge (Bresman *et al.*, 1999).

The specific knowledge involved in collaborations is normally different to that in acquisitions: collaboration-specific knowledge may not adequately provide specialized routines and inferences for acquisition-specific issues. Similarly, acquisition-specific knowledge may not provide specialized routines and inferences for collaboration-specific issues. Thus, the sequencing patterns of collaborations and acquisitions may influence the innovation performance of firms

Four strategies configurations and innovation performances

We can conceptualise the sequencing behaviour of firms across two dimensions. First, continuity - do firms engage in collaborations and acquisitions continuously or occasionally? Second, simultaneity - do firms engage in collaborations and acquisitions at the same time or at different times? As shown in Figure 1, this framework provides four strategic configurations.

First, firms may choose to collaborate *and* acquire (configurations 1 and 2 in Figure 1) at the same time, which can be associated with either high continuity (configuration 1 in Figure 1) or low continuity (configuration 2 in Figure 1). Second, firms may choose to collaborate *or* acquire (configurations 3 and 4 in Figure 1) at any one time, which can be associated with either high continuity (configuration 3 in figure 1) or low continuity (configuration 4 in Figure 1) (e.g. Aldrich, 1999).

INSERT FIGURE 1 ABOUT HERE

These four strategic configurations may lead to differences in innovative performance because the different sequencing may lead to differences in knowledge acquisition and learning.

The innovation performance with different sequencing patterns of collaborations and acquisitions

In Figure 1, the firm sequencing pattern in configuration 1 is undertaking both collaborations and acquisitions simultaneously and continuously. On one hand, a sequencing strategy undertaking simultaneous collaborations and acquisitions may result in superior innovative performance through learning because of the variety of knowledge and capabilities accumulated which may be critical when firms are facing contrasting situations a volatile and changing world (Pangarkar, 2009). For example, under conditions of low technological change, the absorption of external knowledge and control over new knowledge are facilitated by integration through acquisitions. Whereas, if there are also conditions of environmental uncertainty, loose governance structures such as collaborations, may be more effective than formal and institutionalised modes of organisation and control such as acquisitions (Pfeffer *et al.*, 2003).

Firms in configuration 3 are continuously engaging in *either* collaboration *or* in acquisitions and this may constrain their performance for in two ways ((Brown *et al.*, 1997). First, with rapid technological change, firms require flexible and appropriate governance structures (such as *both* collaborations and acquisitions) to acquire new knowledge quickly (Hagedoorn, 1993; Pangarkar, 2009). Although, collaborations may not be appropriate to acquire tacit knowledge, under conditions of slow technological change, the importance of absorbing external knowledge may not be a high priority. Second, under conditions of environmental uncertainty, the effectiveness and adaptiveness of loose governance structures (such as collaborations) may be lower compared to formal and well institutionalised modes of organisation and control (such as acquisition) (Pfeffer *et al.*, 2003).

A persistent sequence of either collaborations or acquisitions may also leave a firm vulnerable to technological shocks as it may be disrupted by new entrants with emerging technologies. Persistent sequencing also hampers learning because of the lack of interplay among reinforcing sources of knowledge (Lave *et al.*, 1991). Poor performing organisations are typically late in adopting new technologies (Brown *et al.*, 1997). Such firms often only use either collaborations or acquisitions as their limited experiences, capabilities and learning are not suitable for the use of multiple methods. Use of a single method limits the capability of firms to respond to change. Thus, persisting with a specific form of inter-organisational relationship may help develop capabilities to further engage in this form of relationship (Gulati, 1999), but it limits the flexibility to use multiple forms. We, therefore, propose the following hypothesis:

Hypothesis 1: Firms that only engage continuously in either collaborations or in acquisitions have weaker innovation performance compared to those firms that engage in both collaborations and acquisitions simultaneously and continuously.

An innovative collaboration or acquisition requires an effective flow of knowledge. Inter-organisational interactions can generate relational rents, it is also important to understand such interactions can result in competitive advantage through the learning of specific knowledge.

An acquisition or a collaboration with another firm can enhance an acquiring or partnering potential for innovative activities (Henderson *et al.*, 1996). For example, a firm undertaking an acquisition or a collaboration develops adaptive and relational capabilities that facilitates further inter-organisational relationships with other firms (Gulati, 1999; Nelson *et al.*, 2009). This type of knowledge is, to some extent, tacit and sticky, and is specific to its owner and is difficult to imitate and transfer (John *et al.*, 1999; Larsson *et al.*, 1998).

It is also important to comparing firm that engage in collaborations and acquisitions continuously (configuration 1) with those firms that engage in both collaborations and acquisitions occasionally (configuration 2). It may be expected that firms engage in continuous activity may have a superior innovation performance due to their cumulative experience and capabilities (Laamanen *et al.*, 2008). Their knowledge base will be larger and their organizational capacity will be more mature with a greater experience of the direct, intimate, and extensive interactions of collaborations and acquisition (Daft *et al.*, 1986; Marsden, 1990). This suggests that occasional use of collaborations and acquisitions will be less successful than the continuous use of such mechanisms leading to our second hypothesis.

Hypothesis 2: Firms that carry out collaborations or acquisitions sporadically will have inferior innovation performance compared with firms that engage in continuous collaborations or acquisitions.

Firms that are only engaging occasionally in either collaboration or in acquisitions, as in configuration 2, are likely to have the most inferior innovation performance of the four configurations. Compared to firms engaged in continuous activities (configurations 3 and 4) firm that are engaged in occasional activity are likely to have less knowledge and accumulated capabilities. Undertaking either a collaboration or an acquisition occasionally will require extra efforts particularly when firms face different technological conditions, environmental uncertainty, governance structures and learning inertia. Furthermore, firms in configuration 3 only engage in one strategy reducing their ability to acquire generic and specific inter-form knowledge. This leads to our third hypothesis below.

Hypothesis 3: firms that only engage occasionally in either a collaboration or in an acquisition will have weaker innovation performance compared to those firms that engage in both collaborations and acquisitions simultaneously or continuously.

The moderating effect of intensity on the four strategic configurations

In order to consider how the intensity of sequencing may influence their effectiveness, we consider the number of collaborations or acquisitions in a defined time period. A lower intensity indicates that the time between successive collaborations or acquisitions is longer and *visa versa*.

The intensity of collaborations and acquisitions are important for learning and for innovation performance (Al-Laham *et al.*, 2010; Rovit *et al.*, 2003). As intensity increases, complex strategic partnerships may improve the effectiveness and the efficiency of learning external knowledge (Van de Vrande, 2013). Technological diversity in the partner base may accelerate and improve the recombination of existing knowledge into new innovations (Fleming, 2001) as investing in a wide range of learning opportunities allows firms to avoid the risk of being trapped into a specific technological trajectory.

As intensity increases, however, the development of complex strategic partnerships may limit the effectiveness and the efficiency of learning external knowledge (Van de Vrande, 2013). Furthermore, technology diversity may threaten the absorption of external intangible resources as the higher degree of complexity increases the costs of monitoring. As Levitt *et al.* (1988) argued, ‘*the more complex an activity, the more significant the learning potential, but the more difficult to harness the learning*’ and, in a worst case scenario, a high level of technological diversity may lead a ‘complexity catastrophe’. In summary, building innovation capabilities requires sufficient time to make sense and learn from experiences (Zollo *et al.*, 2002).

The acquisition of new knowledge requires considerable time and consistency to develop corporate capabilities (Abbott *et al.*, 1990; Ariño *et al.*, 2008; Daunfeldt *et al.*, 2015; Liebeskind, 1997). For example, with a high acquisition rate, time compression diseconomies may develop and an acquirer may be unable to effectively accumulate capabilities (Dierickx *et al.*, 1989; Hayward, 2002; Vermeulen *et al.*, 2002). Conversely, a long time interval between acquisitions may reduce the effective absorption and use of knowledge from acquisitions as relevant knowledge may become inaccessible, forgotten or irrelevant (Chang, 1996; Huber, 1991). Of course, there may be countervailing processes, as a long time interval may enable acquiring firms to: learn and accumulate knowledge and develop routines for screening and purchasing targets (Amburgey *et al.*, 1992); manage the acquisition integration process (Pablo, 1994); enhance capabilities to transfer and integrate knowledge, thereby building up ‘‘architectural competence’’ (Henderson *et al.*, 1994). Thus, when a firm engages in multiple acquisitions and or collaborations over time, it may create a strategic momentum that persists for several years (Amburgey *et al.*, 1992); and building relating capabilities requires sufficient time to make sense and learn from experiences (Zollo *et al.*, 2002). This leads to our fourth hypothesis below.

Hypothesis 4: The lower the intensity of collaborations and acquisitions the more effective the sequencing pattern of innovation.

METHODS

Sample and data

Our analysis uses a sample of 'Innovation Enterprises' surveyed by the China's Ministry of Science and Technology (MOST), State-owned Assets Supervision and Administration Commission (SASAC) and All-China Federation of Trade Unions (ACFTU). This is a sample of 653 firms which were selected according to whether they: (1) own IPR on core technology; (2) possess continuous innovation capacity; (3) enjoy leadership in the industry and its own brand; (4) have strong profitability and management capabilities; and (5) have a strategy and culture oriented to innovation. The firms come from more than 40 industries which are categorized according to the 2011 revised China National Industrial Classification for National Economic Activities (GB/T 4754-2011), covering all strategic emerging industries in China.

We tracked the sample firms' strategic behaviours and innovation performance at the firm-level. The sample contains a wide range of information related to innovation activities, including innovation expenditures/output, innovation collaborations and acquisitions, sources of knowledge, patent applications, IPR protection and incentive schemes, and other firm characteristics. In terms of collaboration and acquisition activities, the data provides a clear picture of the number of acquisitions and collaborations conducted annually and transitions between the two forms of governance structure.

To construct a clean sample, we deleted any firms that had missing or inconsistent data. Due to reporting errors in the data file or incorrectly consolidated data, there were a few outliers in the sample. Since their inclusion may bias the estimation, we further trimmed the data by dropping the observations below the 1^{st} percentile and above the 99^{th} percentile. Moreover, our sample firms were classified as an 'Innovation Enterprise' based on five batches of selection conducted in different years. As the panel years progress, the number of firms increases. The total number of firms in the last year of sample time period represent the size of the unbalanced sample, including 560 firms with 2214 firm-year observations.

Firms in the sample cover most industries from agriculture to manufacturing and public services. More than 80 percent of the firms are in the manufacturing sector as the sample represents leading innovative firms in China. In 2012, the total profits of the sampled firms ranked in the top 25 percent of all Chinese firms and performed 38 percent of China's R&D expenditure and more than 50 percent of China's PCT applications. The firms made 442 technological takeovers between 2007 and 2011 whereas the total number of technological acquisitions made by all Chinese firms during the same period was 759 (according to Securities Data Company (SDC)). Appendix 1 summarises the industrial distribution (primary industrial category) and statistics of the surveyed firms during the sample period.

Measures

Dependent variable: number of successful patent applications. The dependent variable ($Patent_{it}$), measured at the firm level, represents the extent of 'innovativeness' of the partners or target firms. Patents are considered by application year, but only patents which were granted are counted. The application date is preferred to the grant date, because the completion timing for application-to-grant process may vary with different types of patents, and also application dates are closer to the timing of innovations (Griliches, 1998). Successful patent counts have been shown to correlate well with the introduction of new products and invention counts (Basberg, 1987). Patents are considered as valid and robust measures of knowledge creation (e.g. Schilling *et al.*, 2007; Trajtenberg, 1987) and they provide a measure of inventive novelty that is externally validated and examined by the patent office (Griliches, 1998). A challenge when employing a patent-based measurement is the significant differences in the number of patents generated by the firm which may vary with industry, firm size, or other factors, which may result in scaling biases (Levin *et al.*, 1987), known as the 'propensity to patent' (Scherer, 1983). We addressed this concern in two ways. First, we included a technological level measurement controlling for industrial differences in the propensity to patent. Second, we used dummy variables for each firm to control for unobserved variation affecting the firm-level propensity to patent.

Independent variables

Sequencing patterns of collaborations and acquisitions

To analyse the sequencing patterns, we employed an 'optimal matching process' which is commonly used in the deriving the sequencing patterns of DNA. The optimal matching (OM) algorithms do not measure the impact of sequencing patterns, but they distinguish the interval level measures of resemblance between sequences (Abbott *et al.*, 1990). To explore the sequencing patterns of firms' collaborations and acquisitions, we constructed a two-stage procedure: a sequential procedure for the definition of algebras that permit the creation of metric distances between sequences; and a clustering procedure to identify the sequence patterns. Based on the sequencing evidence, we use an estimated model to examine properties of those sequences in affecting innovation. For each stage, we follow the standard reference on optimal matching by Sankoff *et al.* (1983), and Abbott *et al.* (1990).

In the case of our sample, OM offers an effective way to measure sequence resemblance (Sankoff *et al.*, 1983). Unlike in DNA sequencing analysis which often compares sequence of a particular part of the gene chain, here we are interested in the similarities of an entire sequence. We use the year as the unit-time interval and transformed the raw data into a sequence data format. Each corporate event in a sequence is then represented using a string of algebras indicating collaboration, acquisition, their mixture or inactivity. For example, a sequence SEQ1 consisting of some acquisitions in year 1 and 3, collaborations in year 2, both governance structures in year 4, and none of events in year 5, would be represented by the string A, C, A, M, N. We then use the OM technique to calculate the similarity (known as distance) between any pair of sequences.

The fundamental rationale underlying this dynamic calculation is to minimise the use of algebras in the operations of substitutions, insertions and deletions in order to transform one sequence into another. Here, insertions and deletions are often known simply as *indel.* For example, the distance between SEQ1 and another example sequence SEQ2, consisting of events A, C, C, M, A, may be computed using the number of aforementioned steps required to transform one sequence into the other. One possible way that we can transform SEQ1 into SEQ2 is by substituting the third A (collaboration series) with another strategic series of formations (C representing collaboration series), inserting the A (acquisition series) at the end and finally deleting N. Assuming that each step of the combination of replacement and indels is equal to one 'cost', this procedure would incur a total cost of three, for one insertion, one deletion and one substitution. However, this may not be the only way to transform SEQ1 into SEQ2. An alternative way is to substitute the third A with C and N with A, respectively. This takes only two actions as the cost, the two substitutions.

In order to compute the closest inter-sequence distance, the algorithm calculates the costs of all possible transforming procedures and then obtains the one with the minimum cost. Having taken all possible distances, the algorithm results in a dissimilarity matrix between all pairs of sequences rather than a single sequence. This matrix is empirically analysed with a form of a dual-data reduction scheme. In this study, we used cluster analysis (Lorr, 1983) which produces a viable set of clusters that share similar trajectory patterns through a hierarchical procedure. According to Cohen (1960)'s *k* statistic, Blashfield (1976) suggested that Ward Jr (1963)'s method performed significantly better and was more efficient than other hierarchical methods. Following Blashfield (1976), the clusters are obtained using Ward's procedure through minimisation of the squared Euclidean distance to the centre mean.

To select the number of clusters, the fusion coefficients are calculated at each agglomerative stage for each of the clustering algorithms (Ulrich *et al.*, 1990). We present the hierarchical cluster tree for detecting clusters in a dendrogram where the number of clusters is judged based on significant jumps in fusion coefficients. To test for the differences among clusters, we perform an ANOVA comparison test among clusters based on the mean distance of within-group and across-group. To interpret the clusters, we visually inspected the various sequences with each cluster and prepared an 'ideal type' for each cluster. These types are hypothetical sequencing patterns that best represent the clusters.

We identify four distinct clusters based on the dendrogram generated by the cluster analysis based on the computation of distance of sequences between firms. The one-way ANOVA for dissimilarity across sequences is employed to test the significance of the differences (see Appendix 2). Bartlett's test of homogeneity of variances is rejected ($p<0.01$), suggesting that there is a good evidence of significant differences between the variances of the four sequential groups (Dunnill *et al.*, 1969). To ensure that the family-wise error rate (FWE) does not exceed ALPHA for unbalance one-way design, we used Dunnett (1980) procedure for pairwise comparisons. Figure 2 shows that the sequencing patterns derived from our cluster analysis and the visual inspection of each cluster forms four significantly distinctive types.

INSERT FIGURE 2 ABOUT HERE

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*Type 1 — Ambitious player*s. Firms in cluster 1 predominately adopt collaborations and acquisitions simultaneously and continuously (configuration 1). These firms have experiences in inter-organisational relationships and capabilities in relational management. Experience with diverse governance structure experiences may provide the capability to effectively manage collaborations and acquisitions at the same time (Villalonga *et al.*, 2005).

Type 2 — Random player. Firms in cluster 2 adopt a random approach with activity conducted sporadically (configuration 2). This suggests that the occasional use of unfamiliar mechanisms and the subsequent abandonment of such mechanisms. Random players have a very irregular pattern of collaborations and acquisitions which may be the result of unclear strategic actions.

Type 3 — Continuous collaborators. The third type of firm are continuous collaborators (configuration 3). Such firms may choose collaboration as a technological booster as it is relatively costless, time-saving and has low uncertainty (Dyer *et al.*, 2003). The result is consistent with the concept of governance specialisation and path dependence, where a firm that has persisted with one mechanism is likely to use the same form in the future (Wang *et al.*, 2007).

Type 4 — Choppy players. Firms in cluster 4 conducted only a few collaborations and few acquisitions during the sample period (configuration 4).

Number of collaborations and acquisitions

To examine the impact of collaborative and acquisition intensity in sequencing, we use the number of collaborations and acquisitions in the current year. We also use three-year and five-year counting measures for robustness checks for three reasons. First, the number of collaborations and acquisitions in a specific time period reflects a firm's managerial and corporate efforts to make the firms more resistant to potential challenges. Second, a firm's history of making collaborations and acquisitions captures its accumulated capacity to deal with current collaborations and acquisitions. Third, an acquisition might take longer to complete compared with a collaboration.

Control variables

We include a number of control variables as suggested by the literature.

R&D intensity – which may correlate with internal capacity and the effectiveness of innovation strategies (Aktas *et al.*, 2013; Cohen *et al.*, 1989). The variable 'R&D intensity', for each firm, was measured by the ratio of R&D expenditures to total sales at the firm level.

Protection of Intellectual rights (IPR) - help to curb opportunistic behaviour and thus prevent leakage of critical know-how (Kale *et al.*, 2000). There are, however, limits to the effectiveness of IPRs. Solving the problems of coordinating mechanisms does not obviate the need for appropriate measures to protect IP. A strong patent protection strategy provided by formal crafting of contracts to deliver a credible alignment of incentives and risk-mitigation measures influences a firm's collaboration with different types of partners. Thus, we include in the model whether the firm adopts a specific defensive mechanism or not in year *t* (yes = 1 and no = 0).

Firm size. It is conventional to control for firm-size effects in analyses of innovative productivity and performance (Cohen *et al.*, 1989), because large firms tend to have higher patenting propensities compared to small firms. We used the natural logarithm of a firm's total assets as a measure of firm size.

Technological level (TECH LEVEL). This variable, an industry classification dummies for firm *i*, controls for the industrial environment. We use the OECD industry classification system to group industries and divided firms into two broad categories: high-technology (the dummy takes the value 1) and low-technology (the dummy takes the value 0).

Incentives. In a transition economy (such as China), institutional participation may affect a firm's engagement in collaborations and acquisitions. For example, public research funding agencies increasingly require inter-organizational collaboration for research (Lee *et al.*, 2005). Importantly, the Chinese government has been creating a stable and supportive institutional environment so that strong Chinese firms can implement a long-term M&A strategy by focusing on the acquisition of intangible assets such as technology and managerial capabilities from global giants. We control for this institutional effect by using a dummy variable equal to 1 if innovation of a firm *i* is supported by government funds in year *t* and 0 if otherwise.

Inventor. Although we have controlled for *R&D intensity*, the total number of R&D personnel is also used as a measure of strategic effectiveness and absorptive capacity. We add this variable to control for different aspect of strategic effectiveness and human resource management. The variable also measures the potential cost of a heavy emphasis on secrecy which might inhibit learning (Liebeskind, 1997). To be consistent with the measure of *R&D intensity,* we use the natural logarithm. A brief description of measures used in our empirical analysis is provided in Table II.

INSERT TABLE II ABOUT HERE

Econometric modeling

Having identified the sequencing patterns, we employ a Poisson procedure for the estimation of positive count data. Our first specification (Eq. 1) includes all dummies denoting different sequencing patterns with controls to examine the impact of the different patterns. This model examines the impact of sequencing within the sample span. A second specification (Eq. 2) provides a closer look at the characteristics of elements in the sequences. The model examines whether the different use of collaborations and acquisitions can facilitate innovative productivity. Thus, the first baseline specification can be written as:

$$Patent_{i,t} = f\left(SE_i, R\&D\ Intensity_{i,t}, IPR_{i,t}, Firm\ Size_{i,t}, TECH\ \ LEVEL_i, Incentive_{i,t}, Inventor_{i,t}\right) \qquad (1)$$

The second baseline model can be written as:

$$Patent_{i,t} = f\left(Number\ \ of\ \ C\&A_{i,t}, R\&D\ Intensity_{i,t}, IPR_{i,t}, Firm\ Size_{i,t}, TECH\ \ LEVEL_i, Incentive_{i,t}, Inventor_{i,t}\right) \qquad (2)$$

The vector SE_i includes a number of sequencing pattern dummies depending on the results obtained from the cluster analysis. The *number of* $C\&A_{i,t}$ denotes the number of collaborations and acquisitions a firm *i* made in year *t*. Considering the unobserved heterogeneity stemming from unmeasured systematic time period effects, we use year dummies in our estimation.

RESULTS

The impacts of sequencing patterns

Our empirical analysis examines how the sequencing patter affects the innovativeness of firms. To enable this, a series of dummies were included to represent the sequencing patterns, with the firms that rarely engage in collaborations and acquisitions as the reference group. Correlation coefficients are reported in Appendix 3.

Table III presents the results of the multivariate analysis testing Hypotheses 1 to 3 regarding the impacts of different sequencing patterns. In model 1, we regress the count of patent applications on our set of control variables. In model 2, we include the terms for the sequencing patterns 1 to 3. From the full model, we observe that sequencing patterns 1, 2 and 3 are positively associated to patent applications ($p <.001$). The coefficient for the first sequence pattern of *ambitious player* ($\beta =0.259, p <.001$) is the highest; followed by *continuous collaborators* ($\beta =0.213, p <.001$); and *random player* ($\beta =0.204, p <.001$). The coefficients of the sequencing patterns are tested for significant differences using a coefficient difference test. We use a Wald test and find that the null hypothesis of equality of estimated parameters between *SE1* and *SE2* ($p <.001$), and *SE1* and *SE3* ($p <.001$) is rejected; but not rejected for *SE2* and *SE 3* ($p =.193$). Thus, we can conclude that the innovation impact of *ambitious player*, and the continuous collaborators and the random players sequences are significantly different. The results suggest that firms achieve the highest innovation impact when they are performing both collaboration and acquisition simultaneously and continuously (*ambitious player*), while the innovation impact is weakest for *continuous collaborators and random players*.

As predicted, those firms that are more capable of managing inter-organisational relationship and translating external knowledge into internal innovative capabilities, perform the best. This suggest that a sequence of collaborations and acquisitions helps to create the capacity and conditions to generate and exchange knowledge. This may foster the acquisition of both generic knowledge and deal-specific knowledge and lower the transaction costs of technological knowledge leading to superior innovation performance. Conversely, firms that do not have a similar sequencing history may be less capable in relational management.

In summary, at a strategic level, improving innovation performance through sequential strategies are effective when firms employ varied and effective mechanisms that allow the realisation of relational rents through organisational learning. The variety of targets and partners and their distinctive competencies provide firms with flexibility to improve their innovative process (Srivastava *et al.*, 2011). Given that the increasing complexity of technological development goes beyond the capabilities of individual firms, our results provide support for our Hypotheses 1, 2 and 3.

INSERT TABLE III ABOUT HERE

The impacts of intensity

We further analyse the sequencing behaviour of firms in terms of the intensity of collaborations and acquisitions. Table IV presents how intensity, measured by the number of collaborations and acquisitions, influences innovation performance. Our intensity variable is negatively related to patent applications ($\beta = -0.0004$, $p < .001$), which suggests that a high number of collaborations and acquisitions has a negative impact on innovation. This suggests that when firms ‘bite off more than they can chew’, their innovation performance is damaged due to relational over-commitment.

INSERT TABLE IV ABOUT HERE

Table V presents results for the moderating effect. In model 1, we include both *intensity* and *sequencing patterns* terms, and in model 2, we added the interaction terms. We find that the intensity of ambitious players ($SE1_i \times Number\ of\ C\&A_{i,t}$) is negatively associated to patent applications (β =-0.0043, p <.001). A similar negative results is also found for *continuous collaborators* ($SE3_i \times Number\ of\ C\&A_{i,t,}$, β =0.0031, p <.001) *and random players* ($SE2_i \times Number\ of\ C\&A_{i,t,}$, β =0.0038, p <.001), but the coefficients are lower than for ambitious firms. With one unit of intensity, the ambitious firms have 0.0038 (p < .000) fewer patent applications than those firms who are not performing the sequencing patterns; nonetheless, for firms adopting the other sequencing patterns (continuous collaborators and random players) then they file 0.0038 and 0.0031 fewer patent applications compared with those who are *choppy players*.

These results suggest that if firms engage in too much collaboration and acquisition activity in a short time period (i.e. one year), this may have an adverse impact on innovation as firms have too little time for problem-solving and knowledge acquisition.

It should be noted that control variables are statistically significant. *Firm size* is significantly related to *successfully patent applications*, and this is broadly consistent with Ahuja (2000) that larger firm have more granted patents. Both of the strategic effectiveness measures (*inventor* and *R&D intensity*) are significantly and positively associated with the number of successful patent applications; with the exception of R&D intensity in acquisition after collaboration. Intellectual rights protection (*IPR*) is positive and significant, indicating that firm-level patent-law characteristic significantly affects innovation. Improvements in firm-level IPR can encourage innovation by providing effective legal protection against theft of IP. The coefficients on incentive (the measure of the institutional effect on firm's innovativeness) are significant and negative, strengthening the argument that institutional participation and intervention issues are likely to be important to innovation in a transition economy (Hitt *et al.*, 2004). Technological level has a significantly positive impact on innovation performance, suggesting that high technology firms have higher innovation than low technology firms. This is consistent with the view that firms in high technology industries actively adopt collaborations and acquisitions to enhance their innovation capacity (Chaudhuri *et al.*, 1998; Vonortas, 1997). Our results show that the magnitudes of the control variables are not significantly different, suggesting that multicollinearity is not a problem.

INSERT TABLE V ABOUT HERE

Robustness checks

We implemented a range of robustness tests to ensure our results were not affected by: other potential factors; different operationalisation of variables; and our choice of estimator. First, we employed a negative binomial regression model to estimate the specifications in Tables III (Column 3 and 4), Table IV (Column 2) and Table V (Column 3 and 4). Second, we estimated the specifications in Table IV with two variables constructed to measure the intensity of collaborations and acquisitions in the past three and five years as the development of a patent takes time to be implemented and this time varies across sectors (Column 3 and 4 of Table IV). The results of these two tests are fully consistent with those presented in Column (1) of Table IV. Third, we examined additional factors that are potentially important to in the context of the Chinese economy. Earlier studies have suggested that in transition economies, such as China, government plays a key role in developing innovation capabilities through direct intervention and through active industrial and science and technology policies (e.g. Choi *et al.*, 2011; Zhou *et al.*, 2017). We included a firm's ownership structure in the regressions in Table III to further control for institutional intervention (Choi *et al.*, 2011). We included an ownership dummy equal to 1 if a firm is state-owned, and also interactions between the ownership dummy and the *intensity variable* and the sequencing dummies. The results of the interactions between the state ownership dummy and the sequencing dummies do not significantly influence the overall results (see Table VI). Moreover, we found that state-ownership only strengthens the impact of the sequencing pattern on innovation for simultaneous and continuous collaborations and acquisitions, whilst it weakens the impact of other sequencing patterns.

While we believe the patent count variable is appropriate to measure innovation performance, we examined whether our results were affected if we employed other measure of innovation performance. We therefore employed an alternative proxy for the innovation performance - *New Product Sales*. The definition of new products adopted is the same as used by the China National Bureau of Statistics (NBS) where a new product is defined as either a completed new product or an existing product which has been significantly improved through the adoption of a new structure, new materials or a new manufacturing technique as ‘novelty’ (Veugelers *et al.*, 1999). Using this measure has two advantages: first, new product sales are commonly acknowledged as a proxy that directly quantifies the innovation and its success in the market; second, it includes innovations which are not patented, which enables us to have an appropriate measure for innovation performance that would otherwise have been undervalued (Atuahene-Gima *et al.*, 2004; Autio *et al.*, 2000; Laursen *et al.*, 2006). We employed an OLS regression model in Table III (Column 5 and 6), and a fixed effect panel regression model in Table IV (Column 5) and Table V (Column 5 and 6) to re-estimate our specifications. Overall, the alternative results are consistent with our main results.

Finally, we accounted for the potential endogeneity of reciprocity in the relationship between collaboration and acquisition and a firm’s innovation performance (See Table VII). Specifically, more collaborations can lead to the better innovation, while at the same time better innovation performance can also facilitate collaborations with others. The method may be used in applications where other sources of identification, such as instrumental variables or repeated measurements, are not available. To mitigate concerns about endogeneity, we conducted additional analyses using a novel instrumental variables (IV) approach suggested by Lewbel (2012) which allows identification based on higher moments without the need for outside instruments. Lewbel (2012) shows that if no traditional instrumental variables are available, parameters of a triangular, or a fully recursive system, can still be identified if errors are heteroskedastic. Following Lewbel (2012), we exploited the heteroscedasticity of residuals. Due to the skewness of the residual's distribution, we use the natural logarithm of the patent application counts in the estimation. To avoid losing firm-year observations with zero patents or citations per patent, we added one to the actual values when calculating the natural logarithm. We then employed the IV estimation for a linear approximation of the innovation performance equation (See *Eq.1*). The results presented in Table III are not affected by endogeneity. Overall, our results are unaffected by measurement error, incorrect specification or endogeneity.

INSERT TABLES VI AND VII ABOUT HERE

CONCLUSIONS AND DISCUSSION

This paper identifies collaboration and acquisition sequencing patterns and examines their impacts on innovation outcomes. We developed a framework in which collaborations and acquisitions lead to knowledge learning and capability building. Our research shows the impact of sequential collaborations and acquisitions on innovation where 'ambitious players' - which use a combination of collaborations and acquisitions simultaneously and continuously - perform the best. In terms of innovation performance, this group are followed by 'continuous collaborators' who focus on collaborations, and 'random players' who mainly undertake collaborations while occasionally engaging with acquisitions.

The intensity of using collaborations and acquisitions is also found to play an important role in moderating the impact of different sequencing patterns on innovation. Our results, in general, show a negative moderating effect of the intensity of using collaborations and acquisitions. This suggests that innovation performance requires attention to the type of connection and the intensity (timing intervals) of collaborations and acquisitions. Sequential behaviour may provide a mechanism of 'learning-by-interacting' based on new knowledge and capabilities acquired in different inter-organisational relationships.

Theoretical implications

This study makes several contributions through combining innovation management, knowledge and capability accumulation, learning theories and the digestion theory of collaborations and acquisitions. First, this study offers the first systematic analysis and empirical explanation of the impact of sequencing of external resources acquisition strategies. Our results are consistent with the study of Shi *et al.* (2011) which considers the impact of the 'whole' sequencing pattern of firms' acquisitions and alliances on financial performance. Second, this study adds to organizational learning theory by showing that the impact of inter-firm collaborations on innovation are influenced by timing (Aktas *et al.*, 2013) and repetitive momentum (Hayward, 2002). Third, the result on intensity suggest that 'excessive' collaboration and acquisition activity can lead to 'corporate indigestion' of knowledge which can hamper innovation. Fourth, this study, adopts a novel approach by applying an optimal matching technique.

Managerial implications

Our research also has important implications for management. First, it confirms that a firm can acquire knowledge and capabilities through serial collaborations and acquisitions. Second, there are different preferences in the acquisition of technological, and deal-specific knowledge and capabilities between collaborations and acquisitions; for example, an acquisition can help acquire tacit technology while collaborations are more elastic organizational structures. Third, undertaking both collaborations and acquisitions simultaneously and continuously can produce the best innovation performance; but if this is implemented at a high intensity, this may hamper innovation. Fourth, a firm should not just pay attention to absorption, but should also consider digestion when evaluating potential collaborations and acquisitions.

Further research

This study sheds light on the importance of capability sequencing for innovation. There are, however, areas for further research. First, the characteristics of collaborations and acquisitions need to be controlled. Second, it is important to consider how knowledge characteristics - such as tacit or explicit, complex or simple - can influence the knowledge creation and innovation process (Zander *et al.*, 1995). Further research should distinguish what types of knowledge are effectively acquired in different sequencing patterns and how they contribute to innovation outcomes. Third, China is an emerging economy and future research could examine whether firms in industrialised countries follow similar patterns to the sequences identified in this paper.

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Figure 1. The strategic choices of firms.

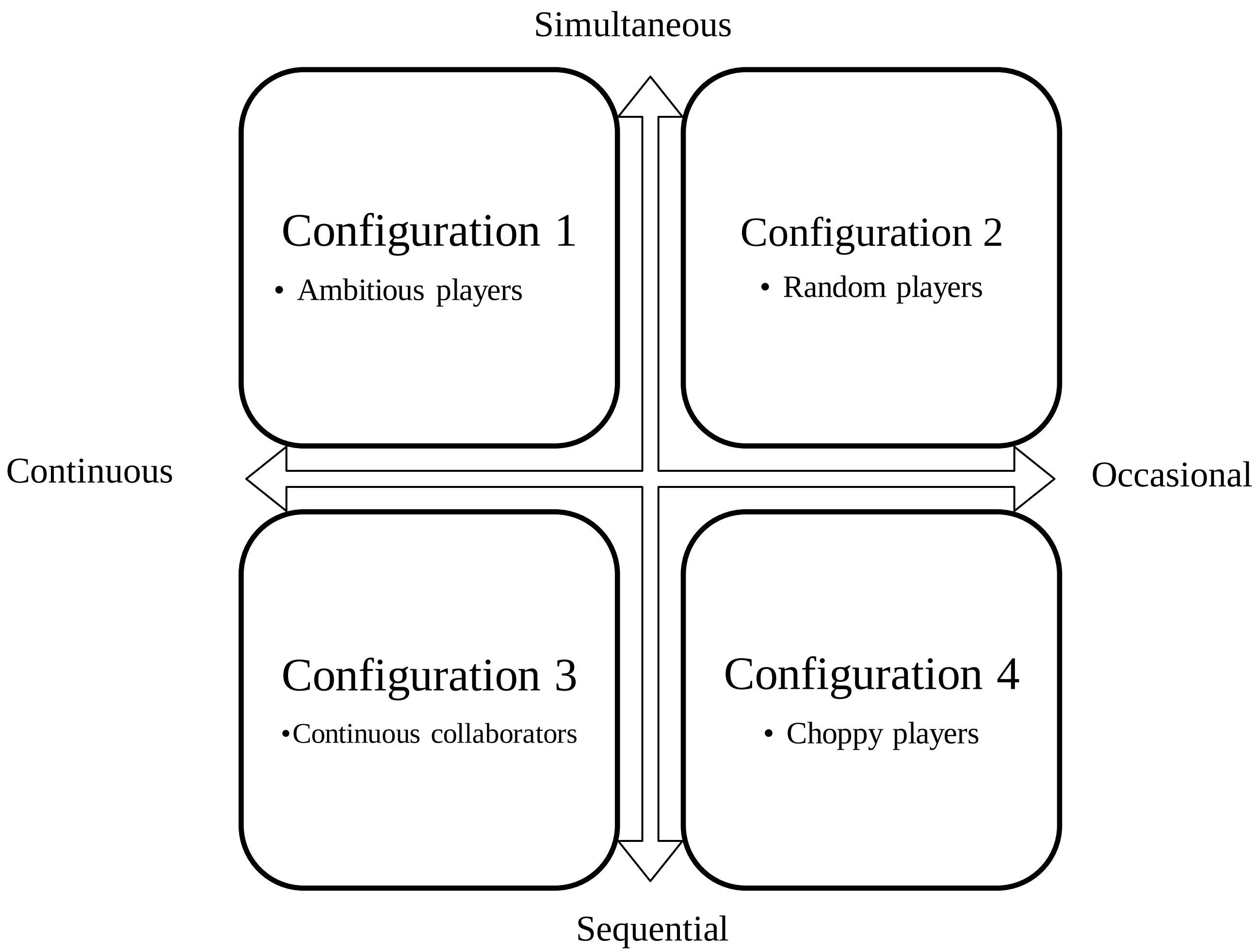

Figure 2. The taxonomy of sequences

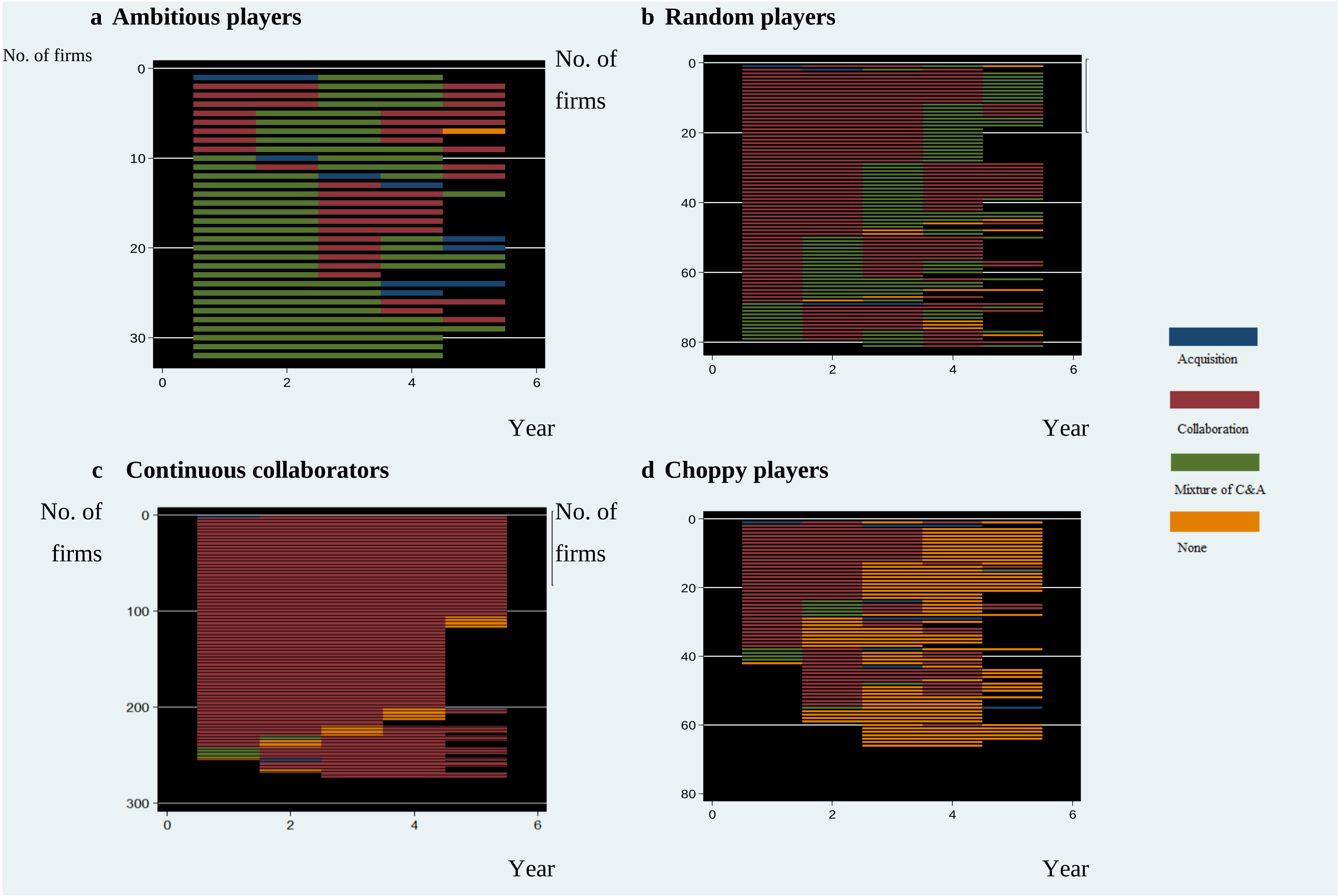

Table I. The relationship between knowledge acquisition and sequence patterns of C&As

Acquisition of knowledge	**Undertake collaboration and acquisition simultaneously and continuously**	**Persistent in one relationship**	**Occasional engagement in an unfamiliar inter-firm relationship**
Common knowledge	Same	Same	Same
Specific knowledge			
Technological knowledge	The transformation of different specific and technological knowledge into the sharing knowledge through multiple integration	Specific and technological knowledge of Cs or As	It has not been totally transformed into knowledge that can be shared because of the lack of relevant knowledge and capabilities
Mainly acquired knowledge	All	Focused knowledge	Focused knowledge with disturbance
Mainly accumulated Capabilities	Flexibly deal with any interfirm relationships	Good at a specific interfirm relationship	Good at a specific interfirm relationship with disturbance by inappropriate path dependence
The effects Integrative knowledge system to firm innovation	Very positive	Positive, less than firms undertaking C&As simultaneously	Positive, less than firms Persistent in one relationship

Table II. Summary of variables

Variable name	Measure
Dependent variables	
Number of successful patent applications	The number of patent applications that a firm *i* successfully have been granted in year *t*.
Independent variables and controls	
SE1	Dummy equals 1 if a firm predominately adopts collaborations and acquisitions simultaneously and continuously.
SE2	Dummy equals 1 if a firm in adopts a random approach with evidence of simultaneous activity conducted sporadically.
SE3	Dummy equals 1 if a firm is continuous collaborator.
Number of collaborations and acquisitions (Number of C&A)	The count of collaborations and acquisitions for firm *i* in year *t*.
R&D Intensity	The ratio of R&D expenditures to the total sales for firm *i* in year *t*.
Protection of Intellectual rights (IPR)	Dummy variable equals to 1 if a firm *i* carries out a certain legal protection for intellectual property embedded in technological innovations in year *t* and 0 otherwise.
Firm Size	The natural logarithm of firm's total assets.
Technological level (Tech Level)	Dummy equals to 1 if a firm *i* located in high-technology industry and 0 otherwise.
Incentive	Dummy variable equals to 1 if innovation of a firm *i* is supported by government funds in year *t* and 0 otherwise.
Inventor	The natural logarithm of the total R&D personnel count.

Table II. Estimated results for impact across sequence patterns

	Poisson (DV=No. of granted patents)		Negative binomial (DV=No. of granted patents)		OLS (DV=New product sales)	
	(1)	(2)	(3)	(4)	(5)	(6)
Firm size$_{i,t}$	0.218***	0.206***	0.249***	0.236***	0.382***	0.371***
	(0.017)	(0.018)	(0.026)	(0.026)	(0.030)	(0.030)
Inventor$_{i,t}$	0.296***	0.307***	0.368***	0.378***	0.397***	0.400***
	(0.021)	(0.021)	(0.033)	(0.032)	(0.037)	(0.037)
R&D intensity$_{i,t}$	2.054**	1.957**	5.235***	4.898***	-2.268***	-2.266***
	(0.830)	(0.840)	(1.049)	(1.078)	(0.364)	(0.358)
IPR$_{i,t}$	0.095	0.086	0.137	0.132	0.206	0.199
	(0.121)	(0.120)	(0.191)	(0.198)	(0.188)	(0.188)
Incentive$_{i,t}$	-0.186*	-0.187*	-0.130	-0.174	0.069	0.065
	(0.104)	(0.104)	(0.131)	(0.131)	(0.149)	(0.150)
Tech. level$_i$	0.208***	0.210***	0.092*	0.097*	0.084**	0.078**
	(0.033)	(0.035)	(0.050)	(0.050)	(0.039)	(0.039)
SE1$_i$		0.295***		0.497***		0.415***
		(0.099)		(0.118)		(0.103)
SE2$_i$		0.204***		0.195**		0.155*
		(0.082)		(0.094)		(0.085)
SE3$_i$		0.213***		0.229***		0.188***
		(0.076)		(0.086)		(0.062)
Constant	-1.309***	-1.405***	-2.206***	-2.324***	3.964***	3.935***
	(0.229)	(0.237)	(0.343)	(0.348)	(0.262)	(0.262)
Firm fixed	NO	NO	NO	NO	NO	NO
Year dummy	YES	YES	YES	YES	YES	YES
Observations	2027	2027	2027	2027	2023	2023
Number of firms	456	456	456	456	456	456
Adj. R^2					0.66	0.67
	SE1=SE2	0.000***	SE1=SE2	0.000***	SE1=SE2	0.000***
Wald test with Bonferroni-adjusted p-value	SE1=SE3	0.000***	SE1=SE3	0.000***	SE1=SE3	0.000***
	SE2=SE3	0.193	SE2=SE3	0.241	SE2=SE3	0.451

Note. Robust standard errors reported in parentheses. * Significance at the 10% level; ** Significance at the 5% level; *** Significance at the 1% level.

Table IIII. Estimated results for impact of intensity on successful patent applications

	Poisson (1)	Negative binomial (2)	Poisson (3)	Poisson (4)	Fixed effects (5)
	(DV=No. of granted patents)				(DV=New product sales)
Firm size$_{i,t}$	0.212***	0.249***	0.200***	0.200***	0.402***
	(0.009)	(0.025)	(0.010)	(0.010)	(0.019)
Inventor$_{i,t}$	0.061***	0.372***	0.061***	0.065***	0.397***
	(0.007)	(0.033)	(0.007)	(0.007)	(0.025)
R&D intensity$_{i,t}$	0.253***	0.396***	0.190**	0.204***	-2.160***
	(0.075)	(0.056)	(0.076)	(0.076)	(0.371)
IPR$_{i,t}$	0.165***	0.068	0.169***	0.159***	0.199
	(0.019)	(0.208)	(0.019)	(0.019)	(0.139)
Incentive$_{i,t}$	-0.105***	-0.013	-0.102***	-0.089***	0.078
	(0.014)	(0.139)	(0.014)	(0.014)	(0.131)
Tech. level$_{i}$	0.125***	0.131***	0.129***	0.132***	0.080**
	(0.014)	(0.047)	(0.014)	(0.014)	(0.036)
Number of C&A$_{i,t}$	-0.0004***	-0.0008**			-0.0008***
	(0.0001)	(0.0003)			(0.0003)
3-year Number of C&A$_{i,t}$			-0.0002***		
			(0.0000)		
5- year Number of C&A$_{i,t}$				-0.0001***	
				(0.0000)	
Firm fixed	YES	YES	YES	YES	YES
Year dummy	YES	YES	YES	YES	YES
Observations	1936	1936	1936	1936	2023
Number of firms	453	453	453	453	453
Adj. R^2					0.67

Note. Robust standard errors reported in parentheses. * Significance at the 10% level; ** Significance at the 5% level; *** Significance at the 1% level.

Table IV. Estimated results for the impact of intensity interacting with sequence patterns

	Poisson		Negative binomial		OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
	(DV=No. of granted patents)				(DV=New product sales)	
Firm size$_{i,t}$	0.207***	0.195***	0.090***	0.091***	0.345***	0.354***
	(0.002)	(0.002)	(0.015)	(0.013)	(0.032)	(0.022)
Inventor$_{i,t}$	0.327***	0.331***	0.198***	0.190***	0.415***	0.405***
	(0.003)	(0.003)	(0.019)	(0.018)	(0.038)	(0.027)
R&D intensity$_{i,t}$	0.801***	0.757***	0.993***	0.979***	-4.994***	-4.915***
	(0.052)	(0.052)	(0.278)	(0.288)	(0.704)	(0.779)
IPR$_{i,t}$	0.099***	0.108***	0.108	0.077	0.214	0.202
	(0.021)	(0.021)	(0.112)	(0.135)	(0.214)	(0.148)
Incentive$_{i,t}$	-0.158***	-0.174***	0.006	0.114	0.044	0.059
	(0.017)	(0.017)	(0.094)	(0.092)	(0.167)	(0.136)
Tech. level$_i$	0.214***	0.219***	0.077***	0.076***	0.098**	0.102***
	(0.005)	(0.005)	(0.026)	(0.024)	(0.039)	(0.036)
SE1$_i$	0.291***	0.326***	0.325***	0.329***	0.403***	0.558***
	(0.014)	(0.016)	(0.073)	(0.073)	(0.103)	(0.182)
SE2$_i$	0.230***	0.185***	0.262***	0.266***	0.156*	0.165**
	(0.012)	(0.013)	(0.058)	(0.062)	(0.086)	(0.084)
SE3$_i$	0.237***	0.260***	0.268***	0.286***	0.203***	0.195***
	(0.011)	(0.012)	(0.047)	(0.058)	(0.065)	(0.067)
Number of C&A$_{i,t}$	-0.002***	-0.003***	-0.002**	-0.007**	-0.0001*	-0.0003*
	(0.001)	(0.001)	(0.001)	(0.003)	(0.0018)	(0.0012)
SE1$_i$ × Number of C&A$_{i,t}$		-0.0043***		-0.007*		-0.018***
		(0.0007)		(0.004)		(0.061)
SE2$_i$ × Number of C&A$_{i,t}$		-0.0031***		-0.007**		-0.012***
		(0.0006)		(0.003)		(0.000)
SE2$_i$ × Number of C&A$_{i,t}$		-0.0038***		-0.008**		-0.014***
		(0.0006)		(0.003)		(0.001)
Constant	-1.523***	-1.436***	0.035	-0.053	-1.523***	-1.436***
	(0.034)	(0.033)	(0.182)	(0.194)	(0.034)	(0.033)
Firm fixed	NO	NO	NO	NO	NO	NO
Year dummy	YES	YES	YES	YES	YES	YES
Observations	1936	1936	1936	1936	1936	1936
No. of firms	452	452	452	452	452	452

Note. Robust standard errors reported in parentheses. * Significance at the 10% level; ** Significance at the 5% level; *** Significance at the 1% level.

Table VI. Estimated results for the impact across sequence patterns controlling for ownership structure

Variables	(1)	(2)
Firm size$_{i,t}$	0.208***	0.206***
	(0.011)	(0.011)
Inventor$_{i,t}$	0.313***	0.317***
	(0.004)	(0.003)
R&D intensity$_{i,t}$	0.734	0.719
	(0.063)	(0.064)
IPR$_{i,t}$	0.083	0.081
	(0.018)	(0.015)
Incentive$_{i,t}$	-0.183*	-0.190*
	(0.017)	(0.019)
Tech. level$_{i}$	0.224***	0.224***
	(0.024)	(0.027)
State ownership$_{i}$	0.064***	0.206***
	(0.004)	(0.003)
SE1$_{i}$	0.320***	0.290***
	(0.016)	(0.011)
SE2$_{i}$	0.242***	0.202***
	(0.013)	(0.012)
SE3$_{i}$	0.260***	0.210***
	(0.012)	(0.014)
SE1$_{i}$ × *State ownership*$_{i}$		0.097***
		(0.007)
SE2$_{i}$ × *State ownership*$_{i}$		0.070***
		(0.009)
SE3$_{i}$ × *State ownership*$_{i}$		0.074***
		(0.004)
Constant	-1.728***	-1.532***
	(0.043)	(0.033)
Firm fixed	NO	NO
Year dummy	YES	YES
Observations	2023	2023
Number of firms	456	456

Note. Dependent variable is number of patent applications that a firm successfully made in year *t*. Robust standard errors reported in parentheses. A Poisson model is used to estimate the values reported in the table.* Significance at the 10% level; ** Significance at the 5% level; *** Significance at the 1% level.

Table VII. Estimated results for the impact across sequence patterns using Lewbel's (2012) method of internal instruments for identification

Variables	(1)
Firm size$_{i,t}$	0.210***
	(0.023)
Inventor$_{i,t}$	0.335***
	(0.030)
R&D intensity$_{i,t}$	3.292***
	(0.911)
IPR$_{i,t}$	0.157
	(0.166)
Incentive$_{i,t}$	0.083
	(0.150)
Tech. level$_{i}$	0.167***
	(0.039)
SE1$_{i}$	0.548***
	(0.188)
SE2$_{i}$	0.333*
	(0.187)
SE3$_{i}$	0.460***
	(0.156)
Constant	-2.906***
	(0.274)
Firm dummy	NO
Year dummy	YES
Adj. R^2	0.67
Observations	2027
Number of firms	456
Breusch-Pagan test for heteroskedasticity	85.61***
Underidentification LM test	108.394***
Stock-Yogo weak instrument test(Critical Value at 5% level: 16.80):	20.27**
Hansen J statistic	22.632

Note. Dependent variable is the logarithm of number of patent applications that a firm successfully made in year *t*. Robust standard errors are reported in parentheses. A Lewbel's (2012) instrumental variables model based on heteroskedasticity is used to estimate the values reported in the table.

* Significance at the 10% level; ** Significance at the 5% level; *** Significance at the 1% level.

Appendix 1. Descriptive statistics

Panel A. Number of firms by industry and year

Industry	2007 *N*	2007 %	2008 *N*	2008 %	2009 *N*	2009 %	2010 *N*	2010 %	2011 *N*	2011 %
Administrative and support and waste management and remediation services	1	0.4	1	0.2	1	0.2	2	0.4	4	0.7
Agriculture, forestry, fishing	5	1.8	6	1.3	6	1.3	8	1.5	10	1.8
Construction	6	2.1	8	1.7	8	1.7	9	1.7	9	1.6
Information transmission, computer services and software industry	13	4.6	20	4.3	20	4.4	27	5.0	28	5.0
Manufacturing	233	82.3	389	83.7	383	83.4	452	83.2	456	81.4
Mining	6	2.1	13	2.8	13	2.8	14	2.6	16	2.9
Professional, scientific, and technical services	11	3.9	15	3.2	15	3.3	16	2.9	16	2.9
Transportation and warehousing	1	0.4	2	0.4	2	0.4	2	0.4	4	0.7
Utilities	6	2.1	8	1.7	8	1.7	9	1.7	11	2.0
Wholesale and retail	1	0.4	3	0.6	3	0.7	4	0.7	6	1.1
Total	**283**		**465**		**459**		**543**		**560**	

Panel B. Sample statistics by year

Variable	2007 Total	2007 Avg.	2008 Total	2008 Avg.	2009 Total	2009 Avg.	2010 Total	2010 Avg.	2011 Total	2011 Avg.
Total Sales (¥trillion)	8.14	0.029	12.00	0.026	13.22	0.029	17.86	0.033	22.35	0.041
Total assets (¥trillion)	11.13	0.039	16.09	0.035	19.84	0.043	24.26	0.045	29.17	0.053
R&D Expenses (¥billion)	129.65	0.460	209.86	0.451	245.90	0.536	266.67	0.491	406.49	0.742
Employees (#million)	8.11	0.029	10.73	0.023	12.08	0.026	13.85	0.025	15.75	0.029
No. of Patents (#thousand)	60.07	0.213	111.11	0.239	157.67	0.343	195.34	0.360	294.70	0.538
Inventors (#thousand)	423.17	1.501	656.99	1.413	804.75	1.753	842.10	1.551	1050.12	1.916

Note. Industry data are organized using China Industrial classification for national economic activities (GB/T 4754-2011). For each of the firm count, a particular firm is represented only once per year, but may be represented multiple times over the 5-year period.

Appendix 2. The ANOVA test for dissimilarity across sequences

Panel A. Distances

Clusters	No. of firms	Mean of sq. Euclidean distance	S.D. of sq. Euclidean distance	*P-value*
Sequence 1	33	1.67	2.76	<0.001
Sequence 2	82	0.61	0.79	<0.001
Sequence 3	274	0.32	0.33	<0.001
Sequence 4	67	0.94	2.14	<0.001
Overall	456	0.56	1.23	

Panel B. Pairwise comparisons of means (unequal variances) through Dunnett' s C procedure

	Sequence 1	Sequence 2	Sequence 3	Sequence 4
Sequence 2	1.06***			
Sequence 3	1.34***	0.29***		
Sequence 4	0.76***	-0.30***	-0.59***	

Note. * Difference is significant at the 10% level; ** difference is significant at the 5% level; ***difference is significant at the 1% level.

Appendix 3. Correlations of variables

	Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1	*Firm Size*$_{i,t}$	12.79	2.15	1.00									
2	*R&D Intensity*$_{i,t}$	0.05	0.07	-0.31***	1.00								
3	*Inventor*$_{i,t}$	6.02	1.54	0.22***	-0.14***	1.00							
4	*IPR*$_{i,t}$	0.98	0.19	0.00	0.04*	-0.01	1.00						
5	*Incentive*$_{i,t}$	0.99	0.21	-0.01	0.07***	0.00	0.27***	1.00					
6	*Tech Level*$_{i}$	0.99	0.63	-0.15***	0.22***	-0.09***	0.01	0.04	1.00				
7	*Number of C&A*$_{i,t}$	26.33	92.46	0.40***	-0.13***	0.34***	-0.00	0.01	-0.07***	1.00			
8	*SE1*$_{i}$	0.07	0.26	0.12***	-0.04*	0.06***	0.01	0.00	0.05**	0.35***	1.00		
9	*SE2*$_{i}$	0.18	0.38	0.21***	-0.06***	0.17***	0.00	-0.01	-0.03	0.23***	-0.13***	1.00	
10	*SE3*$_{i}$	0.60	0.49	-0.06***	0.02	-0.04	0.01	0.02	-0.03	-0.36***	-0.34***	-0.27***	1.00

Note. *Firm Size*$_{i,t}$ is the natural logarithm of firm's total assets. *R&D Intensity*$_{i,t}$ is the ratio of R&D expenditures to the total sales at the firm level. *Inventor*$_{i,t}$ is the natural logarithm of the total R&D personnel count. *IPR*$_{i,t}$ is a dummy variable equal to 1 if a firm i carries out a certain legal protection for intellectual rights in year t and 0 otherwise. *Incentive*$_{i,t}$ is a dummy variable equal to 1 if innovation of a firm i is supported by government funds in year t and 0 otherwise. *Tech Level*$_{i}$ is a dummy equal to 1 if a firm i located in high-technology industry and 0 otherwise. *SE1*$_{i,t}$, *SE2*$_{i,t}$ and *SE3*$_{i,t}$ are dummies if firms are ambitious players, random players and continuous players, respectively. *Number of C&A*$_{i,t}$ denotes number of collaborations and acquisitions a firm undertakes in year *t*.

* Significance at the 10% level; ** Significance at the 5% level; *** Significance at the 1% level.