Speed, coordination and individualistic behaviors: a pilot NK modeling study to investigate the moderating effects of organizational structure on performance in individual firms

Pablo E. Pinto Cornejo*, Jorge G. Montecinos A., Damian Hine, Peter Knights and Felipe Valdebenito Pedrero

*Corresponding author. Email: p.pinto@business.uq.edu.au
**A member of CLADEA (Latin American Council of Management Schools).

Abstract

A central concern within the field of organizational design is the study of the relationship between structure, innovation and performance. The basic understanding is that decentralized structures appear best suited to promoting innovation and change. Yet this comes at the cost of efficiency. Conversely, organizations that centralize power in the hands of a few appear well-suited functionally to achieving high levels of efficiency, but at the cost of generating inertia. Taking both forms as polar types at the opposite ends of a continuum, the managerial question of how much of each form is necessary to create a good configuration to perform satisfactorily in the long term remains unknown. In this pilot study, we attempt to answer this question by using an NK model. Our results show that exploration is facilitated by higher levels of decentralization, where a structure that combines centralization and decentralization features delivers the highest long-term performance. We also find that complex organizational forms achieve low performance. This suggests that problems with coordination are costly to manage. Assumptions of game-theory are introduced to quantify the risks of decentralization.

Keywords: Organizational structure, NK Model, exploration and exploitation, firm performance.

JEL codes: M21, C6, D21.
1. Introduction

A central concern within the field of organizational design and configuration is the study of the relationship between structure, innovation and organizational performance (Cyert & March, 1963; Lawrence & Lorsch, 1967; Mintzberg, 1979). This concern goes back at least to the work of Burns and Stalker (1961) on mechanistic and organic forms and prior to that with Weber’s (1947) consideration of corporate bureaucracy. A major driver has been the discovery of the most appropriate organizational structure to foster innovation and survival in the long run (Greenwood & Hannings, 1988; Lam, 2005). This has resulted in a number of organizational typologies (Galán et al., 2012) from the multidivisional structure (Chandler, 1962), to the adhocracy (Mintzberg, 1979), to the radical, and very unstable spaghetti organization (Foss, 2003). However, and despite the recently renewed interest in organizational design (Greenwood & Miller, 2010; Schreyögg & Sydow, 2010), the literature is, with few exceptions (see, for example, Siggelkow & Levinthal, 2003), still inconsistent in answering the question of what dimensions of the structure have the most significant impact on both innovation and performance in the long run (Badir et al., 2009).

In this pilot study we seek to expand the categories of analysis to organizational types that have been overlooked in recent simulation studies of organizational design. To address this problem, we employ an experimental design - an NK modeling technique to simulate the behavior of organizations composed of many interacting elements. This technique proposed by Kauffman (1969; 1993) for understanding mutational processes in biological systems has proven more than adequate in other contexts, including in organizational design (Levinthal, 1997; Rivkin & Siggelkow, 2007). We aim to understand how search activity in organizations is best structured to achieve performance improvements, and discuss some benefits and costs linked to mixed forms of organization not considered in previous simulation models. The model is built around two dimensions of organizational structure: the degree of centralization of decision-making and the interdependency among decisions. The degree of centralization reflects the locus of decision-making power and refers to the extent to which authority is distributed among different units in an organization (Miller & Dröge, 1986). The interdependency among decisions reflects the level of complexity of the system (Kauffman, 1993; Simon, 1962) and describes the many parts and processes that a system must coordinate to achieve some measure of overall success (Kauffman & Levin, 1987).

In line with previous studies (cf. Rivkin & Siggelkow, 2007), we simulate two organizational types which have been previously studied: a “Block-Diagonal” structure (Siggelkow & Levinthal, 2003), in which decisions are made independently in two divisions; and a “fully interdependent” structure (Kauffman, 1993), which is modeled using a matrix where all decisions interact with each other in a single firm with no divisions.

We also establish a different set of relationships within a firm structure with two divisions, so as to study two new designs. One termed “semi-decentralized” struc-
ture, in which each division makes proposals to their headquarters which selects the combination of decisions with the highest overall payoff for the firm (Wall, 2010). The second we refer to as an “individualistic” structure (Press, 2007), in which divisions seek to maximize their own partial fitness (utility), where the winning division forces the other to follow its lead, resulting in a potential win-lose situation, which cannibalizes the competencies of the other division. Game theory assumptions are employed to simulate the individualistic structure. This simulation design, and its concomitant results, provide an extension of previous research on organizational design.

2. Theoretical Foundations

The creation of the new ideas and innovations that support competitiveness and growth (Tripsas, 2009) rely on the ability of an organization to explore and find new opportunities, or high peaks in existing or new landscapes (March, 1991). In accordance with its ecological derivation, a landscape is an “area that is spatially heterogeneous in at least one factor of interest” (Turner et al., 2001, p. 3). The purpose of exploration; “is to find and occupy a high spot on this landscape, i.e., to select a combination of choices [i.e., decisions, activities] that, together, are highly successful.” (Siggelkow & Rivkin, 2005, p. 104).

The achievement of successful exploration however poses an organizational dilemma as managers seek to unleash the power of exploration at the lower levels of an organization in order to promote innovation, while maintaining strategic focus requires managers to preserve organizational unity in decision-making to bring to fruition future developments (Siggelkow & Rivkin, 2006). Failure to strike a balance between these two agendas can lead to incompatible and internally competitive actions (Nickerson & Zenger, 2002) hampering performance (O’Reilly & Tushman, 2007). Part of this challenge is that organizational choices made to bring efficiency gains can also hinder a firm’s ability to develop new knowledge (Tripsas & Gavetti, 2000).

Prior research on organizational design has shown that several elements found in more mechanistic forms of organization, including hierarchical structures, centralized decision-making and formal controls and communication channels, are likely to enhance operational efficiency but also produce risk aversion as firms avoid uncertain possibilities in favor of actions that have produced positive results in the past (Lam, 2005; Miller et al., 2006). Conversely, more organic structures include several elements that appear to foster creativity, complexity and adaptability, such as decentralized decision making, a lack of formally defined tasks and loose coupling systems, but at the cost of efficiency (Sheremata, 2000). The latter suggests that the coherence of an organizational design “is not accidental” (Greenwood & Hinings, 1988, p. 295); but that “there are several models of organization with differential efficiencies depending on the nature of the work and the types of tasks to be performed” (Litwak, 1961, p. 181).
While formal structure has been measured in a variety of dimensions (Price & Mueller, 1986), there appears to be a consensus that centralization (the distribution of authority within an organization), formalization (the degree of work standardization) and complexity (the degree of specialization, and number of hierarchical levels within an organization) are the basic dimensions of structure (Tsai, 2002; Van de Ven, 1976). Thus, we draw on the work of Van de Ven et al., making centralization and complexity the focal aspects of this paper.

Centralization

Centralization refers to the concentration of authority or decision-making power (Miller & Dröge, 1986), and points to whether the locus of authority and decision-making lies in the higher or lower levels of the organizational hierarchy (Jansen et al., 2006). In research on multidivisional organizations, centralization has focused on the dichotomous relationship between the relative degree of influence or control exercised by the corporate headquarters and the individual organizational units in relevant decision-making processes (Tsai, 2002).

The notion of centralization has long been a consideration in organizational design theorizing, from Weber’s notion of bureaucracy, to the work of the Aston group (Pugh et al., 1969), and to contingency theory (Lawrence & Lorsch, 1967). Most of the work within this tradition argues that organizations must centralize to attain superior efficiency (Adler & Borys, 1996). Centralized power in the hands of a few reduces diversity in decision-making (Siggelkow & Rivkin, 2005), thereby increasing speed, and control (Sheremata, 2000).

Centralization may however constrain a firm’s ability to experiment as there is less latitude for new strategic choices (Jansen et al., 2006). Centralization may also induce conformity with rules and established routines, making people “less receptive and supportive of ideas that might deviate from the status quo” (Lubatkin et al., 2006, p. 652), whereas the associated vertical decision process may reduce the felt need for interactions to solve problems collaboratively (Miller, 1987). The result may generate structural inertia (Hannan & Freeman, 1984), constraining an organization’s ability to respond to new opportunities, and thereby to change, grow, and compete (Oldham & Cummings, 1996).

Decentralization, on the other hand, appears best suited to igniting creativity (Nonaka & Konno, 1998; Zammuto & O’Connor, 1992), since it eliminates organizational constraints to freedom in the conduct of work (Amabile et al., 1996). Decentralization is beneficial to promote innovation and thus adaptability to unstable and more turbulent environments (Benner & Tushman, 2003). Yet this comes at the cost of efficiency.

Accordingly, several studies have observed that extreme degrees of decentralization may have negative effects on innovation (Van Looy et al., 2005). Extreme decentralization may lead to chaotic resource allocation (Demsetz, 1988) and the creation
of knowledge in areas so dissonant that top management cannot coordinate these efforts and effectively integrate them with the core business of the firm (Siggelkow & Rivkin, 2006). This can also lead independent divisions to develop products that are both incompatible and internally competitive, and firm performance can suffer as a result (Nickerson & Zenger, 2002).

The dichotomy between centralization and decentralization, however, is an oversimplification of the reality. The challenge remains not that a firm centralize or decentralize per se, but to strike a balance “that permits speedier improvement without completely sacrificing diversity of search” (Siggelkow & Rivkin, 2005, p. 117).

Based largely on this idea, numerous studies have turned to the notion of structural separation of activities or ambidexterity (Jansen et al., 2006). Unfortunately, there remains much confusion and contradiction in the literature, and it is still not clear how organizations can cope with countervailing functions, pattern maintenance, and adaptation (Schreyögg & Sydow, 2010) to successfully achieve ambidexterity (Raisch & Birkinshaw, 2008).

**Incorporating complexity into modeling**

Complexity refers to the characteristics of a system “of being intricate and compounded” (Olausson & Berggren, 2010, p. 384). A complex system is, according to Simon (1962, p. 468), “made up of a large number of parts that interact in a non-simple way”. Complex systems are structured in levels or hierarchies, with each level resting on the one below it (Simon, 1995). This property shared by hierarchically organized systems is called nearly complete decomposability NCD (Simon, 2002). Systems that display NCD properties tend to evolve faster than non-hierarchic systems of comparable size (Simon, 1962).

In this paper, we model designs that are built around the dimensions of centralization and complexity. The organizational structural modeling reflects, but also complements, that of Siggelkow and Levinthal (2003), Rivkin and Siggelkow (2007) and Wall (2010), with each organizational structural form varying according to the degree to which authority is distributed among different divisional units in the decision-making process (degree of centralization) and the level of complexity (interactions among decisions).

**3. Research Objectives and Methodology**

In this study, we aim to understand how search activity in organizations is best structured to achieve performance improvements, and discuss some benefits and costs linked to mixed forms of organization not considered in previous simulation models. In addressing this problem, we use an NK agent-based single firm level computational model.
Computer simulation modeling in organization science has a long history (Cohen & Cyert, 1965; Cyert & March, 1963; Simon & Newell, 1962). Unfortunately, the value of simulation techniques has been lost possibly due to their length of abstraction (Harrison et al., 2007) and the consequent difficulty in comparing simulation results with reality, which raises questions of validity and realism (Burton & Obel, 1995). On the upside, simulation has advantages over other techniques in studying the dynamic complexities of business behaviors (Moizer et al., 2007), and enabling control for multiple factors that otherwise would prove difficult in empirical research (Wall, 2010).

In this paper, we use an NK agent-based computer simulation model (Kauffman, 1969; 1993). An NK model is a stochastic combinatorial optimization model used to simulate systems composed of interacting elements. Five main parameters govern the mathematical complexity of the model: N (the number of elements of a system), k (the degree of interactions among the N elements), the influence matrix (the distribution of k among the N), the number of states of each of the N elements and the underlying distribution from which fitness values are assigned to each combination of elements (Kauffman, 1993).

An NK model assumes that an entity, given a certain interaction structure, is able to identify alternative configurations whose fitness values are superior to the current level of fitness (Levinthal, 1997). In this model, the process of searching involves the random evaluation of multiple alternatives in a limited space of possibilities (Rivkin & Siggelkow, 2007). A system (a firm for our purposes) is able to search for new configurations only in their immediate neighborhood, and then move towards that new position only if the fitness levels are superior in relation to the status quo situation (Levinthal, 1997). In an NK model, the system chooses the first superior set of choices it discovers, and then restates the search for a superior fitness in the next period. However, the likelihood to alter the current position depends on the starting point. If a firm is situated in a high peak, chances to move are comparatively lower than if the firm’s performance is faltering (Levinthal, 1997).

Conceptually, our model is very simple. Initially, two general cases are modeled: a single firm with no divisions or departments, and a firm consisting of a headquarters and two divisions. The latter is divided into three designs, namely Block-Diagonal, semi-decentralized, and individualistic. The former is modeled using a “fully interdependent” matrix (Siggelkow & Levinthal, 2003).

In our model, a firm “A” has control over N activities, \( A = [a_1, a_2, \ldots, a_N] \), 12 in our simulation. For simplicity we assume that each activity \( a_i \) takes on two states \([0, 1]\) (Weinberger, 1990). A firm can rearrange these activities in any given sequence \( Y \in A^N \), the space of possible sequences of length N, with \( Y \) the \( i \)th bit on one sequence and \( i = (1, \ldots, N) \) (Rosenberg, 2005). Thus, in our model the potential number of combinations is \( 2^{12} = 4,096 \).

The parameter \( K \) represents the degree of interactions among activities of a firm. Such interdependencies, called *epistatic interactions* (Kauffman, 1993, p. 41), describe the inner structure or architecture of the system (Marengo et al., 2000). We use \( k = 11 \) for a single firm with no divisions (fully interdependent), and \( k = 5 \) for
the Block-Diagonal, semi-decentralized and individualistic structures. In the case of a firm with divisions, Division I controls decisions regarding activities $a_1, a_2, \ldots, a_6$; where Division II makes decisions encompassing activities $a_7, a_8, \ldots, a_{12}$. In each period, each division searches for improvements within its own set of activities.

4. Data Analysis

In terms of the simulation model, we calculate the performance of different organizational structures over a given period of time. The simulation involved running a model for 100 periods, which is significant to provide good stability to the outcomes (Burton & Obel, 1995). Results are averaged over 100 and 1,000 different performance landscapes. To compute the performance of a firm, we use the ratio of the payoff reached by a specific organizational structure divided by the highest possible payoff in any given landscape (Siggelkow & Levinthal, 2003). The maximum expected performance is 1. The influence matrix of activities is pre-specified as a function of $N^*N$ (see Figure 1). All programming and numerical computation simulations were run using MATLAB software Version 7.13 (R2011b) (http://www.mathworks.com.au).

Figure 1. Interaction structures

To assess the reliability of our results, we reviewed and validated the logic behind all the operations and calculations, and also tested a random group of the numeric results “manually”. To ensure the robustness of the results, we also ran multiple simulations with different fitness landscapes (Press, 2007). We found no significant variation across the results. Further support of the external validity of our simulation results was conducted by comparing our estimates to previous studies (see Figure 2).
5. Results

In business we always need to consider time horizons when judging performance. In our model, comparing performance for the different structures yields a set of interesting results (see Table 1). The differences in performance data between structures that are reported here are statistically significant with \( \rho < 0.001 \), which is in line with prior work on the topic (Siggelkow & Rivkin, 2005).

Table 1. Simulated scenarios (averaged over 1,000 landscapes and 100 periods)

<table>
<thead>
<tr>
<th>A firm consisting of a headquarters and two divisions</th>
<th>A firm with no divisions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semi-Decentralized (n=12, k=5, i=1000)</td>
<td>Individualistic (n=12, k=5, i=1000)</td>
</tr>
<tr>
<td>Results (over 1,000 landscapes and 100 periods)</td>
<td></td>
</tr>
<tr>
<td>Maximum performance (*)</td>
<td></td>
</tr>
<tr>
<td>(Fitness / maximum performance attainable)</td>
<td>0.920</td>
</tr>
<tr>
<td>Difference in performance over best design</td>
<td>0.0%</td>
</tr>
<tr>
<td>Velocity 1 ((V_{t+1} - V_{t=0}))</td>
<td>0.0570</td>
</tr>
<tr>
<td>Velocity 2 ((V_{t+2} - V_{t+1}))</td>
<td>0.0303</td>
</tr>
<tr>
<td>Average lengths of the walk towards optima</td>
<td>3.8</td>
</tr>
<tr>
<td>Average period of number of local peaks</td>
<td>83.0</td>
</tr>
</tbody>
</table>

(*) Differences in performance are statistically significant with \( \rho < 0.001 \); two-tailed tests.
First, the simulations show that a semi-decentralized structure, in which each division makes proposals to the headquarters which chooses the combination with the highest overall payoff for the firm, is the most effective structure in the long run. In the short and medium term, however, a Block-Diagonal structure, in which decisions are made independently in two divisions, proves more effective. We suspect that this could represent coordination costs. The difference in velocity of adaption between both structures suggests that this intuition is right. The indicator of velocity in Table 1 measures the average difference in performance between a time t and t-1, with Velocity 1 \( V_{t=1} - V_{t=0} \) (Wall, 2010).

The underlying reason for this is that in order to implement changes in each division, there is no need to coordinate or seek for approval in a decentralized structure (Siggelekow & Rivkin, 2005), where in a semi-decentralized structure the headquarters assume the role of decision center. This gives a significant edge to more decentralized firms against more centralized firms in terms of adaptability and the ability to explore new opportunities faster. This finding is consistent with the literature on organizational innovation (cf. Lam, 2005). We signal this advantage with the nomenclature \( \Delta \) (delta) in speed (see Figure 3).

Figure 3. Organizational structure and performance (over 1,000 landscapes and 100 periods)

Second, recent studies have also shown that high-performing organizations combine features of a mechanistic structure, characterized by centralization of authority, hierarchical coordination and formal control mechanisms with those of an organic structure, characterized by an emphasis on informal systems, decentralization and horizontal coordination (Sheremata, 2000). We suspect that this is the reason why
semi-decentralized structures reach the highest long-term performance across all forms of organization. This is also consistent with Siggelkow and Levinthal (2003) and Puranam et al. (2006), who found advantages to organizational firms whose searching processes are initially decentralized but then became centralized to facilitate coordination across their divisions. We signal this advantage in Figure 3 with the nomenclature $\Delta$ (delta) in coordination.

Third, our major contribution in this paper comes, however, from introducing assumptions of game theory in the model. Although the relationship between game-theory and landscape theory was originally proposed by Kauffman (1993, Chapter 6), and Axelrod and Bennett (1993), it has passed relatively unexplored within management research.

In simple terms, game theory examines the possible outcomes of a game given the existence of n-players playing the game (Abbott et al., 2005). Players can play one or more times. To determine what it is worth to each player, the basis of the theory of n-person games in the theory of games is restricted to a special case of a two-person bargaining problem (Nash, 1950). This reduces the complexity of the problem of finding optimal behavior strategies (Koller & Megiddo, 1992).

This is analogous to the case of landscape theory in which each division (Division I and Division II) makes decisions independently and the final division’s payoff depends on its own action and upon that of the other division (Kauffman, 1993). In our model, we use this assumption to deform the second division’s payoff structure to some extent. This pattern can be observed, for example, in decisions regarding new firm location, research agenda, etc., in which the success in one division may potentially come at the cost of success in the other (e.g. Division II is forced out into a new location far distant from its customer base).

Thus, to account for this “interdependency” in players’ movement, we allow for a firm with two divisions to proceed via less fitter neighbors. This “walk” is only possible as long as at least one of the two divisions proceeds from the less fit to the more fit. This is compatible with the general postulates of the NK model.

For the purpose of the model, we assume the extreme case in which both Divisions’ (I and II) decisions are linked to each other. Like in previous cases, the model assigns a fitness contribution at random values between zero and one from a uniform distribution, $f_i \in [0, 1]$. In principle, each division’s objective is to maximize its own partial fitness. However, by moving to a higher ground, Division I (Division II) deforms the payoff structure of Division II (Division I), and forces it to move to a neighboring point regardless of the Division II’s (Division I’s) new fitness value or the overall firm fitness. A division’s subsequent state is thus determined both by its own action and by the action of the other division. In this game, Division II’s (Division I’s) new fitness value is uncertain. Division II (Division I) could be better off, worse off, or about the same, initially with the same probability. However, over time, this walk becomes more difficult, as Division I (or II) reaches higher fitness values.

The simulated organization shows that these new cross-divisional “interdependencies” among decisions affect the overall firm’s performance significantly. The
simulations show that a firm with two divisions, in which each division searches for its own local peaks giving no consideration to the overall firm’s performance, may find itself walking toward lower (as opposed to higher) peaks. This is because each division implements changes that may satisfy its own interests and be more profitable for the division’s sake, but not necessarily for the other division or the firm as a whole. This result evidences that divisions often operate from a narrower and more individualistic perspective, and unless optimum coordination mechanisms are put in place at the firm level, this individualistic type of organization is indeed likely to generate significant negative externalities and deliver the worst results. This is consistent with findings indicating that extreme decentralization is detrimental when the decision makers do not have an overall perspective of the firm (Mendelson, 2000; Siggelkow & Rivkin, 2006). This idea is also in line with the findings of Press (2007) in industrial districts. We signal this effect with the nomenclature (delta) in negative externalities (see Figure 4).

Figure 4. Negative externalities of an individualistic structure (over 100 landscapes and 100 periods)

Fourth, a single firm with no divisions, where the fitness contribution of each decision depends on all the others, shows less than average performance. A possible explanation is that more complex structures tend to increase the probability of firms being locked into local (rather than global) optima. This is a consequence of increasing conflicting constraints between decisions. There is indeed growing evidence that
firm size and complexity may also be related to greater coordination costs, significant diseconomies of scale and negative externalities (cf. Foss, 2003). This is due to the fact that by definition a fully interdependent structure requires to modify many choices simultaneously, a task that is inherently very difficult (Siggelkow, 2001).

Our findings are consistent with the literature on modularity, which suggests that the decomposition of a complex system into simpler components improves performance and speed (Schilling, 2000). In our model, modularity increases rapid adaptation, with large, complex firms benefiting from dividing the complex search process into manageable specialized tasks (MiHm et al., 2010). As presented previously, Figure 3 signalled this effect with $\Delta$ (delta) in complexity.

6. Conclusions

In this pilot study we analyzed the performance of different structures over time. Our analytical results confirmed existing findings in the organizational innovation literature. We found, for example, that exploration is facilitated by higher levels of decentralization, where a structure that combines both centralization and decentralization features delivers the highest long-term performance. Additionally, we found that coordination among units is critical to success, but also time consuming. We also found that complex structures yield less than average performance. This suggests that problems with coordination and information processing could be too complex and costly to manage in practice (Foss, 2003). This has managerial implications for the design of complex organizations, raising questions about, for example, the intentional introduction of chaos in the structure of a firm as currently being discussed in the management literature (see, for example, Smith & Paquette, 2010). We suspect in that sense that not all organizations can perform like Google or Pixar.

However, our major contribution in this paper comes from introducing assumptions of game theory. Our simulation quantified the negative effects of extreme individualistic behaviors of departments on the overall firm’s performance. We suggest that this is a result of a lack of coordination and incorrect incentives.

In light of our results, we suspect that firms and managers can learn significantly from modeling their decisions to find the delicate balance between exploration and exploitation.

References


Wall, F., 2010. “The (Beneficial) Role of Informational Imperfections in Enhancing Organisational Performance”. In M. L. Calzi, L. Milone and P. Pellizzari (Eds.),
Acknowledgements

The authors would like to thank Professors Martie-Louise Verreyrne, University of Queensland, Paul Jensen, University of Melbourne, and David Souder, University of Connecticut, and conference participants at the XLVII CLADEA Assembly 2012, Lima, Peru; 2012 Universitas 21 Inaugural Doctoral Research Conference in Business, University of Connecticut School of Business, Hartford, Connecticut and 2011 PhD Conference in Economics and Business, University of Queensland School of Economics, Brisbane, Australia, for helpful comments. The authors are grateful to the University of Queensland Business School in Australia, the Universidad Católica del Norte Business School in Chile, CRC Mining Australia, and CONICYT Chile for generous funding. Errors remain the authors’.

Notes on Contributors

Name: Pablo E. Pinto Cornejo
Position: PhD Candidate
School / Faculty: UQ Business School
University: The University of Queensland
Address: St. Lucia, Brisbane, QLD, Australia 4072
Telephone: +61 7 3346 5620
Email: p.pinto@business.uq.edu.au

Name: Jorge G. Montecinos Alvarado
Position: PhD Candidate
School / Faculty: School of Economics
University: The University of Queensland
Address: St. Lucia, Brisbane, QLD, Australia 4072
Telephone: +61 4 0281 7828
Email: j.montecinos@uq.edu.au
Name: Damian Hine  
Position: Associate Professor  
School / Faculty: UQ Business School  
University: The University of Queensland  
Address: St. Lucia, Brisbane, QLD, Australia 4072  
Telephone: +61 7 3346 8162  
Email: d.hine@uq.edu.au

Name: Peter Knights  
Position: BMA Chair and Professor  
School / Faculty: School of Mechanical and Mining Engineering  
University: The University of Queensland  
Address: St. Lucia, Brisbane, QLD, Australia 4072  
Telephone: +61 7 3365 3915  
Email: p.knights@uq.edu.au

Name: Felipe Valdebenito Pedrero  
Position: Freelance Consultant - Engineering  
Address: 2/43 Lambert Road Indooroopilly, Brisbane, Australia 4068  
Telephone: +61 4 1453 1154  
Email: felipe.valde@gmail.com