FINAL YEAR PROJECT DISSERTATION

Inter Firm Modularity and Digitalization in IT-Enabled Hypercompetitive Landscape

By

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ABSTRACT

In a world with increasing hypercompetition, the cause of the hypercompetition may be of concern to some decision or policy makers. Interfirm modularity could potentially be a factor that leads to the phenomenon, with firms borrowing, mixing and matching different technology components to build an integrated system. Other factors such as innovation power, cost, and complexity also influences the degree of hypercompetition. In this paper, we evaluated the hypercompetition by industry average performance and ranking changes, and studied propositions generated from the simulation experiment with NK model. In the model, the firms were simulated to be able to make five different types of decisions: experiential search, adding a resource, dropping a resource, borrowing from another firm or switching partners. The firms would automatically lend out a component if they found they own all resources in the component. The dependencies among firms increased instability of firm performances and rankings, which resembles the scenario of hypercompetition. The propositions explained the relationship between 4 independent variables (innovation, cost, modularity and dependency) with the dependent variable (fitness, ranking, and firm sizes) to deduce insights of how hypercompetition could be impacted by the variables.

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1. INTRODUCTION

1.1 Motivation

In the past few decades, increased globalization has improved the speed of resource circulation, which subsequently boosted the development of technology. Due to the fast-paced digital world, the quantity and quality of the buyer-supplier-competitor value chain were impacted. Integration and partnership between firms became more important for firm survival, and thus set the stage for an industrial-wide hypercompetition (Goeltz and Kessler, 2013). However, the process of how the digitalization and partnership would lead to the arousal of hypercompetition is still unclear.

Hypercompetition is defined as having high-paced changes, increased competitive pressure and uncertainty (Goeltz and Kessler, 2013). Competitive advantage is no longer sustainable under such an environment, and the status quo is constantly disrupted. The unsustainable equilibrium is the major attribute differentiating hypercompetition from the perfect competition in economics (Hanssen-Bauer and Snow, 1996). It is difficult to predict a firm's future, while it may fail due to a small misstep, or succeed and grow business quickly. The market would pick winners of the industry from the great pool of competing firms, but which will be chosen is highly uncertain; and winners may not be able to stand for long, since the market may find a better successor, break the status quo and give up on the previous instantly, as in the case of Nokia versus iPhone. All in all, researchers concluded that the level of hypercompetition can be measured by 'the frequent changes in performance rank orderings of firms in the industry (Lim 2019; McAfee and Brynjolfsson 2008; Nan and Tanriverdi 2017), which is a core theory supporting the NK model we used in this paper.

Cost and quality, timing and know-how, creation and destruction of strongholds, and deep pockets are the 4 arenas in sustainable advantages competition (D'Aveni, 1994). Hypercompetition accelerates the speed and intensifies the aggressiveness of competition in these arenas and shortens the sustainable advantage life cycle. For example, the phenomenon of hypercompetition includes growing customer demand, increasing firms' knowledge base, lower entry barriers, and partnerships between companies. Strongholds are affected by the declining entry barriers, while deep pockets were impacted by the alliance between companies across different industries and regions (Goeltz and Kessler, 2013). It is harder to maintain superior performance over time, and the difficulty level increases with the duration (Lim 2019).

Goeltz and Kessler (2013) mentioned that from a macro perspective, competition has a cyclical nature. The landscape of the hypercompetitive environment is dependent on the number of competitors, individual firm strategies, costs of the competitive cycle, the ability of the top management team (i.e. decision speed and aggressiveness), and whether there are complementary products and services.

However, despite there are rich theories about the characteristics and behaviors of hypercompetition and the industry landscape, researchers have rarely exploited the causes of hypercompetition (Lim, 2019; D'Aveni et al. 2010). Several who studied the cause deduced that the disequilibrium results from an innovation-based competition in the mainstream product market, which is also called the Schumpeter's speculation (Lim, 2019; D'Aveni and Gunther 1994; Schumpeter 1942; Wiggins and Ruefli 2005). Another possibility is that digitalization induces hypercompetition (Nan and Tanriverdi 2017).

Besides the aforementioned uncertainty and fierce competition, hypercompetition is also characterized by 'digitized, interdependent resources, and resource partnerships' (Lim, 2019; Subramaniam et al. 2019). McAfee and Brynjolfsson (2008) observe the phenomenon of higher hypercompetition in high IT-intensive industries, driven by a greater disruption in the firm's performance rank orderings. Whilst other scholars find that there exist companies as digital giants, controlling a great number of resources and able to penetrate markets not only in their industry but also others (e.g. 'Alphabet, Amazon, Apple, Facebook, IBM, Microsoft, Alibaba, Tencent, Samsung, etc.') (Lim, 2019). In the meanwhile, declining dynamism and competition have been reported in the U.S. economy, alongside with the occurrence of monopoly power.

The contradiction of statements and empirical evidence on the causes of hypercompetition leads us to explore the advantages that IT-enabled resources bring about to the industry as well as firms. Do digitalization, microservices, and partnership amplify or attenuate the hypercompetition phenomenon? Why are monopoly powers together with a high degree of competition? How should a firm and policymakers react to the occurrence of hypercompetition to maximize efficiency as well as social utility?

Besides the importance of discussing the contradiction in the phenomenon of hypercompetition, it is also crucial for firms to understand the actions to take to survive. Firms need to consider different factors to repetitively win the game given that most competitive advantages are transient, except the ability to generate new advantages (D'Aveni 1994). With the declining cost of technology and the difficulty of knowledge transfer across industries and regions, firms must strive to become better learners. The competitive fitness of the firm can then be evaluated by the ability to innovate and adopt knowledge, often in collaboration with other firms (Alter and Hage 1993). The capability to shape and influence the environment is also considered important for a firm to be more competitive (Hanssen-Bauer and Snow, 1996).

1.2 Objectives

The primary goal of this research paper is to understand the mechanism of how hypercompetition arises due to the inter firm modularity and digitalization of resources by observing firms' and landscape's performances. Based on Lim's (2019) theoretical and methodological background, this paper would address the interdependence and partnership (or interfirm modularity) between firms to create a more realistic hypercompetition simulation model. The conclusion derived from the model can be further utilized by future academic researchers, and hopefully firms and policymakers.

2. METHODS

2.1 NK model

The gist of our argument is that partnership and firm interdependency can intensify or attenuates the hypercompetition phenomenon, and firms can achieve better performance by wisely selecting bundled resources to borrow. Part of what prevented the progress of the previous papers on digitalization and hypercompetition is that there is no formal model to simulate and prove the conceptual theories. In this section, we propose a model in which firms can perform a local experiential search, long-jump innovation, as well as modular innovation, i.e. borrowing and switching resource bundles.

The NK model is applied to simulate the hypercompetition context. There are several reasons for this modeling choice. Firstly, the NK model is a common analytical platform to answer strategic questions regarding organizational decisions. Besides, the NK model manifests interrelationship between each N element as well as their performance which is represented by fitness value. It maps the possible firm configuration and evolution to respective payoffs, which are represented by the metaphorical expression of the landscape performance (Gavetti et al., 2017). In the software industry, products can be highly complementary and interdependent. The change in the activity level of one software can increase or decrease the sale of another, although their functionality may not be fully substitutable (Topkis, 1998). Third, the NK model can serve as a good representation to study the hypercompetition environment, given its feature of high interdependence between firms and resources.

In the NK model, N represents the number of resources in the landscape, and the configuration of each resource is either a 0 or 1. Most of the research conducted using the NK model defined N as the number of 'decisions' to understand how different decisions an organization made would impact the overall firm performance, and the same concept is named as 'resource' in this paper. It assumes each resource is affected by exactly K other resources, and thus there are N * (K + 1) interactions in total and can be displayed in the format of an influence matrix as below (Figure 1). Each row and column corresponds to a resource, and a symbol 'x' at (i, j) denotes that resource j affects the fitness value of resource i (Rivkin, 2007).

We extended this basic NK model to add in the point that the i^{th} firm owns M_i ($M_i < N$) resources, and can be represented by a bit array (e.g. 101101). Each firm has 2^{M_i} possible configurations, whilst the landscape has 2^N. When a firm decides to change any one of these N resources, its performance will increase or decrease, which is captured by the fitness value.

The contribution of a resource to the overall fitness value is influenced by K other resources, according to the influence matrix. Since the degree of resource contribution to overall fitness value depends on the value of other attributes, the landscape is highly interactive, and it tends to be quite rugged (Levinthal, 1997).

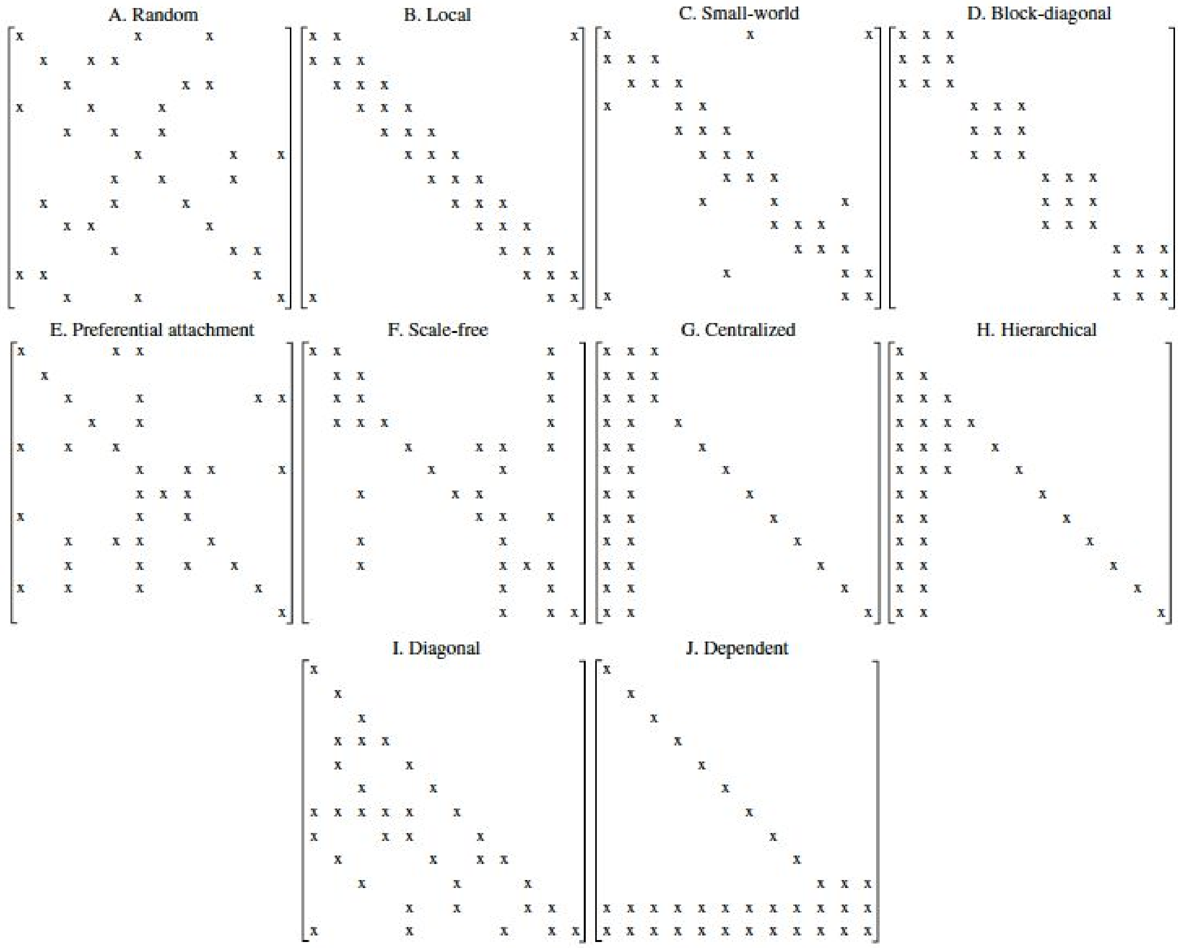

*Figure 1. Influence Matrix with N = 12, K = 2, N * (K + 1) = 36 (Rivkin, 2007)*

The model was firstly applied in biology to understand the inter forces between genes. Levinthal (1997) was the first to apply the model to study the interrelationship between firms, focusing on the adaptation process and selection pressures. Adaptation is described as climbing a local hill, whose height represents the level of fitness value of the firm. Since the landscape is fairly rugged, there could be many local hills to climb. A neighborhood is the set of configurations that are only one bit different from the current firm. A random number of attributes specified anew is a ‘long-jump’.

The same model has also been applied to study the shapers and searchers. This research is an extension of Levinthal (1997) local search, and cognitive search by Gavetti and Levinthal (2000). A shaper is a firm that changed the payoff structure for all firms in the landscape, for example, Apple's inventing iPhone; while search means those who follow the trend. The N in previous models is split into two parts: search and shaping dimension. Only a few firms can change the shaping dimension, while most are followers. The code of this paper has also embedded the option of creating different types of firm to study the interactions. However, the focus is still single-typed-firm industry to reduce the analysis complexity.

2.2 Experiment Design

The key innovation of the model in this research paper is that, in addition to experiential search, local and long-jump innovation, the impact of having resource bundles to share and borrow is included as one type of decision to innovate. Figure 2 illustrates the workflow of the decision-making process.

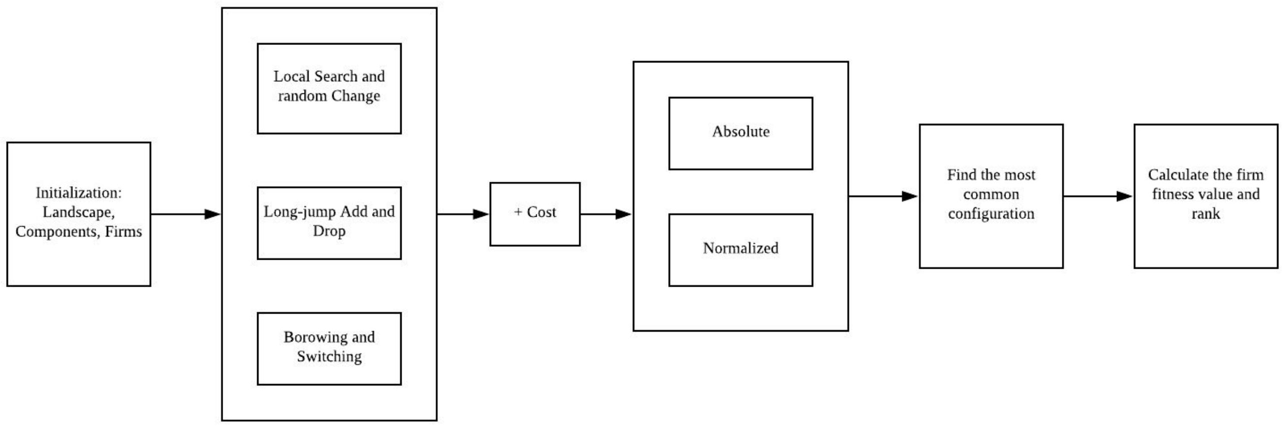

Figure 2. Logic flow of company decision makers

Each resource bundle is represented by resources from the landscape and is mutually exclusive. If a bundle has C resources, it will have 2^C possible configurations, depending on which would maximize the fitness value of the firm who is sharing. One resource can only exist in one component. The reason for this design is to reduce the complexity of multiple layers of dependencies.

When a firm does not have any resources in a component C_i, it can choose to use the entire component configuration from a shared resource pool, given that other firms are sharing the component configuration. Otherwise, if it has all the resources in a component, the firm would generously share the component to the market. It can also choose to switch to another partner and apply an entirely different set of configurations of that particular component.

The rationale of this feature is that firms may choose to develop a software component themselves or they can source it from other firms. Examples are Uber using Google Maps in their ride-hailing services and small firms paying fees to use cloud services. The competition in the IT industry differs from other industries by firms providing Application Program Interfaces (APIs) to make their service accessible to the public. API is defined as 'a set of definitions and protocols for building and integrating application software' (Red Hat, n.d.). It is usually in the form of functions, by calling which the user can utilize the function in another totally different application or context. The implementation of the function is usually encapsulated from the user. The usage of API can effectively boost digital innovation, given that other firms are able to build their application based on the existing shared services and resources and invest the excess cash to innovative projects that create more value. As an example of the 'switching', it can be mapped to the case where a firm is trying to switch cloud service from Google to Amazon. However, one drawback of sourcing the component from other firms is that the borrowing firm does not have complete control over the corresponding resources in that component. They are highly dependent on the performance or configuration of the 'parents' of the borrowed components.

Ethiraj and Levinthal (2003) have already examined the process of adaptation with and without selection at the component level, as well as the sensitivity to over- and under-modularization. The landscape is a complex system, while N represents decision variables. The system has M modules and K design structure, and every module is of the same size. The k^{th} module comprises N/K decision variables. Except for innovation in module level, they also introduced the term ‘recombination’ and defined it as a firm-level module innovation, which behaves similar to the concept of ‘switching’ in this report.

Although the concept of borrowing and switching has been attempted, the differentiating hypothesis in this report is that the model is applied in a hypercompetition context, and the cost of firm or module level decision is considered. Besides, the model also allows users to innovate at the single resource level. Firms have more choices and ways to innovate and improve their fitness value.

3. THEORY AND PROPOSITIONS

The NK model has been transformed in many ways to serve different purposes by the previous researchers. The most basic form is mentioned by Levinthal (1997), where a firm could own all resources in the industry (N), and the evolution of firms is not about competition, but mainly internal improvement. Each firm improves their overall performance by trial and error, exploring the optimal configuration of its resources. The subsequent researchers have made an effort to add in more flexibility in the original model as aforementioned, whereby the model is applied in many different information systems fields to study various topics.

The most innovative change we have contributed to the variations of the model is adding in the concept of ‘component’, or groupings of resources. For example, for a firm in an industry N = 6 with configuration 01..10, where ‘.’ represents the firm does not own the resource and thus have no configuration, it can still group the resource at position 2, 5, and 6 and lend it to other firms that do not have any of the three resources, such as firm with configuration 0.11... , or 1……. The resource can be interpreted as organization structure, leadership style, human resource, technology such as API etc. There is currently no measurement of profit earned during the lending process, given the consideration that the resources can be ‘learnt’ from other companies instead of purchasing.

To understand the rationale of how partnership and digitalization impact the evolution of hypercompetition is crucial to the survival of firms and policy makers. The definition of partnership in this paper is dissimilar to its legal term in business. It is defined as companies incorporating groups of resources from others in order to enhance their own performance, which can also be interpreted as inter firm components borrowing and lending. It can also be interpreted as inter firm modularity. A common example would be API as mentioned above. Many leading technology firms, such as Google, are sharing their API packages with a certain price to users, but the price of selling the service is set lower than developing a similar service by the users themselves. According to Enlyft (2020), there are around 1,186,926 companies incorporates the technology Google Map into their business[1]. It is not hard to imagine that with Google Map enjoying such a popularity, small businesses are unlikely to attract many customers if they decide to build a similar navigation and mapping product. Besides, Google Map is very user-friendly and reliable, and has been improved throughout the years. It has built trust and brand name among a large population and lots of businesses, and some would work together with Google to include more information as well as resources to the map application. It is not only difficult to surpass Google Map speaking of its rich information and resources, but it is also unlikely for a small business with limited human resources to build a more successful navigation tool than Google Map technically. Thus, small businesses would prefer to enjoy the information from Google Maps directly rather than build one on their own and unable to utilize the resources from Google. To use Google Map service, the businesses can simply call the APIs in their programming code, which has made the integration process fairly costless. Similar to API, there are many other concepts that can be interpreted as 'resource' and are borrow-able, while only the owning company is able to change the configuration of those resource groups, which may impose positive or negative influences on companies who are borrowing them.

The degree of hypercompetition is mainly measured by performance level and ranking changes. During the firms' decision making process, we have applied a value of 'penalty' to simulate the situation where managers would take firm's size into consideration. In reality, bigger firms have a smaller space to improve, and thus would suffer from a larger penalty. Landscape maximum fitness is given the dependency K, 2^N possible configurations were

[1] https://enlyft.com/tech/products/google-maps

tested and the combination that yields maximum fitness would be selected. We assume larger firms would still generally enjoy a higher performance level, thus among all the tested data, the combinations does not have any null resources. The reason to divide the maximum is to limit the firm fitness value to 0 - 1 to facilitate further analysis.

penalty = (scale / N)^2 scale = number of borrowed resources + number of owned resources $fitness_{decision}$ = (∑ each resource contribution to performance / scale * penalty) / landscape maximum fitness

At the end of each iteration, after all firms have made their decisions, their fitness value is calculated again, this time removing the consideration towards scales. The calculation of ranking is based on this fitness value.

$fitness_{ranking}$ = (∑ each resource contribution to performance / N) / landscape maximum fitness

3.1 Modularity and Overall Performance

Hypercompetition is defined with characteristics that each participants (firms) have to make fast moves to 'build advantage and erode advantage of their rivals' (D' Aveni, 1994). One way to improve the performance quickly and achieve this objective is by adopting the practices from other firms. In the technology aspect, it could be the usage of the APIs, internet services and established network developed by other companies etc. This borrowing and lending behavior is summarized as interfirm modularity, where firms borrowing the same component would have common architecture, which makes it easier for customers to mix and match, and compare across those firms (Staudenmayer, Tripsas, & Tucci, 2005). There is an increasing occurrence of interfirm modularity in recent years. While adopting components or modules from other firms help with fast development and potentially better quality apps, the borrowing firms are facing challenges.

Firstly, they may not have the entire control of the architecture they are adopting. Take APIs as an example, only the function names, inputs, outputs, and usage are specified in the documentation, many times the actual implementation is hidden from whoever is using the functions. When the lending firm decides to modify some of their features or implementations, it may affect the borrowing firm negatively. Besides, the borrowing firms do not have the ability to customize some of the functions or features, since those are dependent on the underlying architecture that they do not have access to (Staudenmayer, Tripsas, & Tucci, 2005). Second, interfirm modularity may incur much complexity to the decision making process of a firm's management team. In the NK model, intrafirm dependency represented by K has already made the calculation and forecast of fitness value fairly complexed. Interfirm modularity will further add interdependence between firms. In our model, there are cases where a lending firm suddenly decided to drop a sharing project or changed its configuration. In the case of dropping, the borrowing firms' projects depending on this will also need to be abandoned, which decreases their performance. Moreover, the borrowing firms may have made several decisions of resource configuration change based on the project they were borrowing. When the project is gone, those prior decisions or changes may not be appropriate. They have to reassess the current situation and start over. This will change the firm's performance and ranking drastically, and slow down its pace of improvement. In the case of a lending firm changing the configuration, the borrowing firms may not be satisfied with the changes. Similar to dropping, the borrowers need to review the process and decide to add or drop other resources to compensate for the loss. They can also make 'switching' decisions, whereas they found another similar project containing the exact same resources shared by a different company. They may evaluate the project and 'partner' with them. The firms may experience a decreasing performance when their first choice is not available any more and they have to move to the second alternatives.

The interdependencies can also be explained further by the theory of complex systems. Complex system is defined as having a lot of interacting elements. In our model, the interdependent resources across the industry or a firm can be interpreted as a complex system. A complex system usually has nonlinear interactions, which implies the butterfly effect (Cilliers 2007, as cited in Lim 2019): a configuration change in a single resource may cause the fitness value to fluctuate greatly. For example, to a firm borrowing from another, a minor change in the shared service may affect the borrower greatly.

The interactions usually do not have a long jump (Fleming and Sorenson 2003, as cited in Lim 2019). A firm would prefer to explore combinations of configurations closest to its current one, instead of making risky decisions to change the structure extensively. Thus, when making decisions, a firm is usually ignorant of the ecosystem, focusing the decision making based on the configurations of their own resources, which are the configurations that are most similar to their current one. The result of those interactions can be both negative or positive to the borrowers, as discussed in the previous paragraphs.

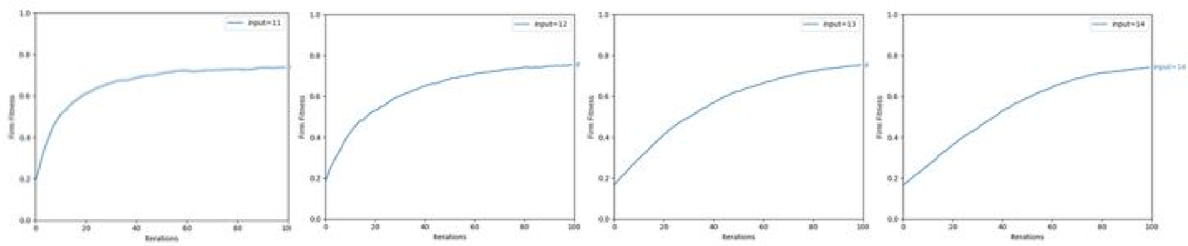

Figure 3. Overall firm average performance trend during time t = 0 to t = 99 with K = 9, cost = 0.01, and innovation power = 1. From left to right, the component size is set from 2 to 5. Dependent variable: performance, independent variable: time.

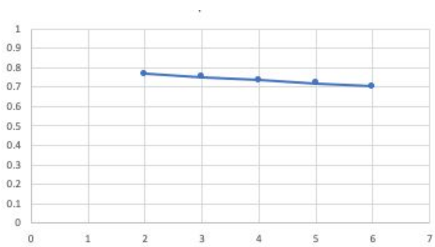

Figure 4. Performance at t = 99, component size at 2 to 5. Dependent variable: performance, independent variable: time.

From the experiment, we have observed a declining trend in the average firm performance level when the component size increases (Figure 3 & 4), and a smoother slope of the average performance improvement. The initial setting is all firms have only 5 resources. While they start to increase their size and make different decisions, the performance climbs up. When component size = 2, which means firms are sharing resources in a group of 2, we could observe very obvious interfirm modularity and firms are able to improve very fast. The reason could be when one firm developed a successful combination of resources, other firms can quickly adopt it. Since the module is rather small, borrowers would have less trouble to integrate with their own system. Many firms are able to afford sharing different configurations of groups, and in the meantime borrowers also have more options and they would always only choose the one that can increase their performance, although may be not the best. Thus, initially, the average performance would increase very fast and the firm dependencies could also be high.

On the other hand, although firms experience a promising growth at approximately $t < 25$, the growth rate slows down in later phase and eventually yields a lower average industry performance level than ecosystems having a larger component size and thus lower depencies. However, when we study the range and spread of the firm performance, it seems larger component size would also contribute to a larger gap between the top and the bottom firms (see Appendix). It seems that when interfirm modularity is small, firms tend to share the knowledge among each other, which yields a higher average industry performance as well as a lower spread. To policy makers, this insight could potentially mean that hypercompetition is a positive phenomenon to the economy and is to be encouraged. To firms, they may want to decrease the scale of components they are sharing. The grouping of the components in our model can be interpreted as resources having similar functionalities, and usually are tightly coupled. Reducing the scale could not only help with easier maintenance and fast improvement of the component by the sharing company, but also facilitate the borrowers, since smaller modules could take less time and costs to be integrated with the rest of their system.

PROPOSITION 1. Larger size of the lend-able components would result in a decreasing average performance and a larger gap between the top and the bottom firms.

3.2 Modularity and Ranking

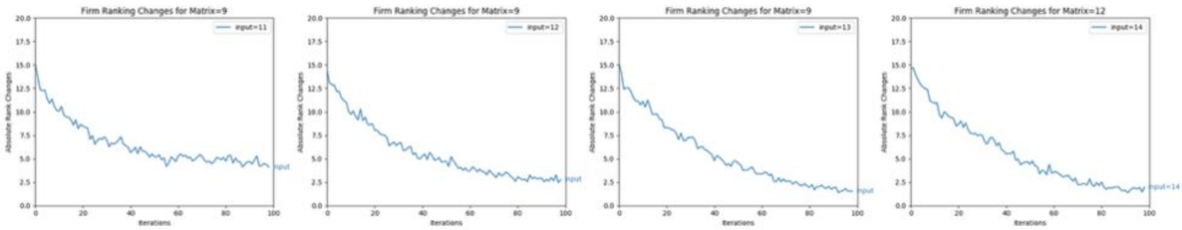

Figure 6. Overall firm total ranking changes during time t = 0 to t = 99 with K = 9, cost = 0.01, and innovation power = 1. From left to right, the component size is set from 2 to 5. Dependent variable: average ranking changes, independent variable: time.

Turbulence in firm ranking is a very direct measurement to the degree of hypercompetition (Lim, 2019). The number of sample firms is 50, and we run the simulation process for 100 iterations to simulate the time factor. In each iteration, a firm can make the decision of experiential search, adding a resource, dropping a resource, borrowing a component from other companies and switching to a different partner. Among those, firms would choose adding or dropping but not both. For each iteration, the value of total rank change is calculated by adding up the absolute ranking change of all 50 firms. Then this entire simulation would be run for another 50 times. The average value for one firm's ranking change in each iteration is then plotted to Figure 6.

From the graph, it is easy to observe that when component size becomes larger, the ranking changes become smaller, and so does the hypercompetition. The ranking changes tend to decrease with time, however it is still at a pretty high level when component size = 2. One explanation to this result could be in the very beginning where firm sizes are generally small (initially each firm only owns 5 resources), a small misstep or successful move could push them to the top or bottom ranking. However, when some of them grow larger, the change in few resources will not influence the ranking that much as before.

PROPOSITION 2. Smaller size of the lend-able components would result in a higher degree of hypercompetition, and the amount of total changes tend to be stabilized over time.

From the first two propositions, we can conclude that component size = 2 fits the definition and phenomenon of hypercompetition the best. The form of Interfirm modularity, or even formal partnership, are getting more and more popular. Those cooperations between firms seem to contribute to hypercompetition. During the experiments, we have tested component size from 2 to 5, K with the value of 3,6,9,12,15, cost with value of 0.01,0.25, 0.5, innovation power with value of 0.5,.75,1. The complete result is made into a dynamic webpage, and the link can be found in the Appendix for cross checking purposes. In the later sections, the default setting of component size = 2, K = 9, cost = 0.01, and innovation power = 1 will be used to study the cause of hypercompetition, except mentioned otherwise.

3.3 The Role of Innovation and Costs between Modularity and Hypercompetition

The innovation power in the experiment controls whether a firm has the ability to explore new possibilities and make decisions to improve the performance. A random number between 0 - 1 is generated in each iteration to be compared with the innovation power value. If the innovation value is larger than the random number, the firm would proceed with decisions. Cost is defined as a percentage term of threshold, and based on the improvements in the current fitness level, a firm would make the decision only when the improvement is large enough to cover the cost. For example, if a firm has a fitness value of 0.7 at the end of period 4, with an industry cost threshold of 0.05, then in period 5, the firm would first evaluate all possible opportunities to increase performance by experimental search. The decision has to increase the current value 0.05*0.7 = 0.035, which means the firm fitness value has to reach 0.735 by making the decision, the firm would consider to actually implement the action. The reason to use multiplication instead of addition is to take the scale of the firms into consideration. For a small firm with fitness value 0.3, a 0.035 change would be fairly high. They may accept the solution of even only a 0.05*0.3 = 0.015 improvement, since they are more desperately in need of growth than the high performance firms.

In Figure 7 & 8, we can observe that increase in industry cost would decrease the average performance level the most, compared to other factors such as innovation or component size. The cost can be interpreted as a knowledge transfer barrier, or any costs incurred by the decision makers. Firms would only choose projects with positive net present value, so when cost goes up, firms facing a decreasing or negative profit would prefer to stay put instead of making any changes in their current configuration.

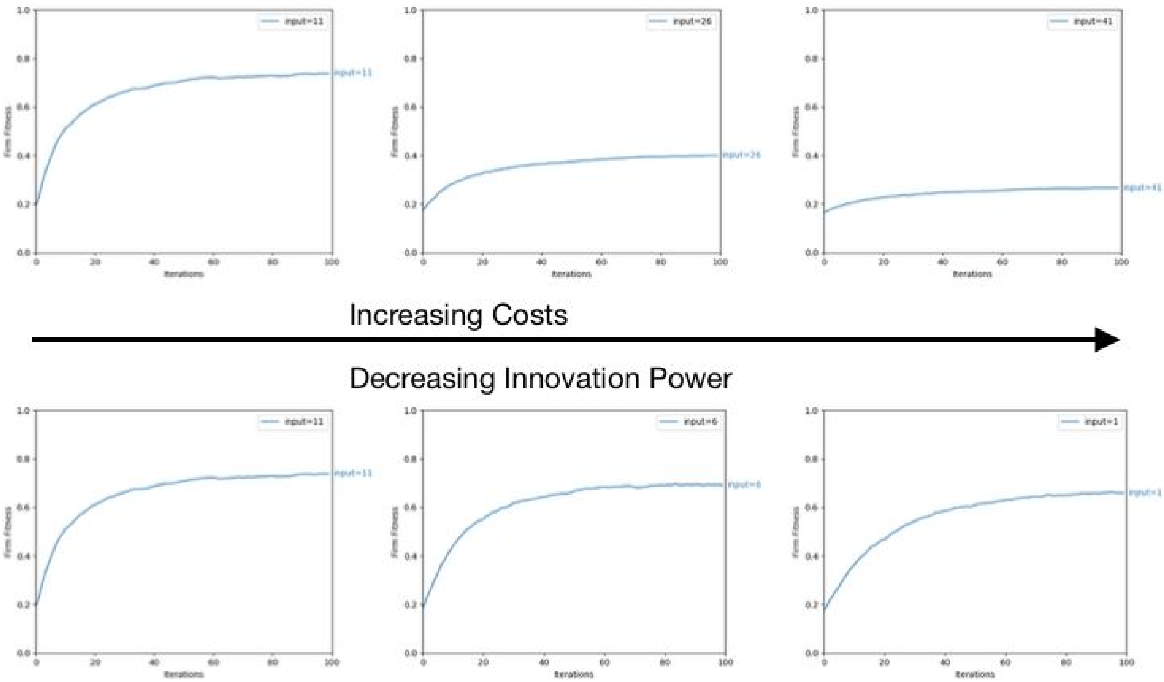

Figure 7. Influence of costs and innovation power to performance

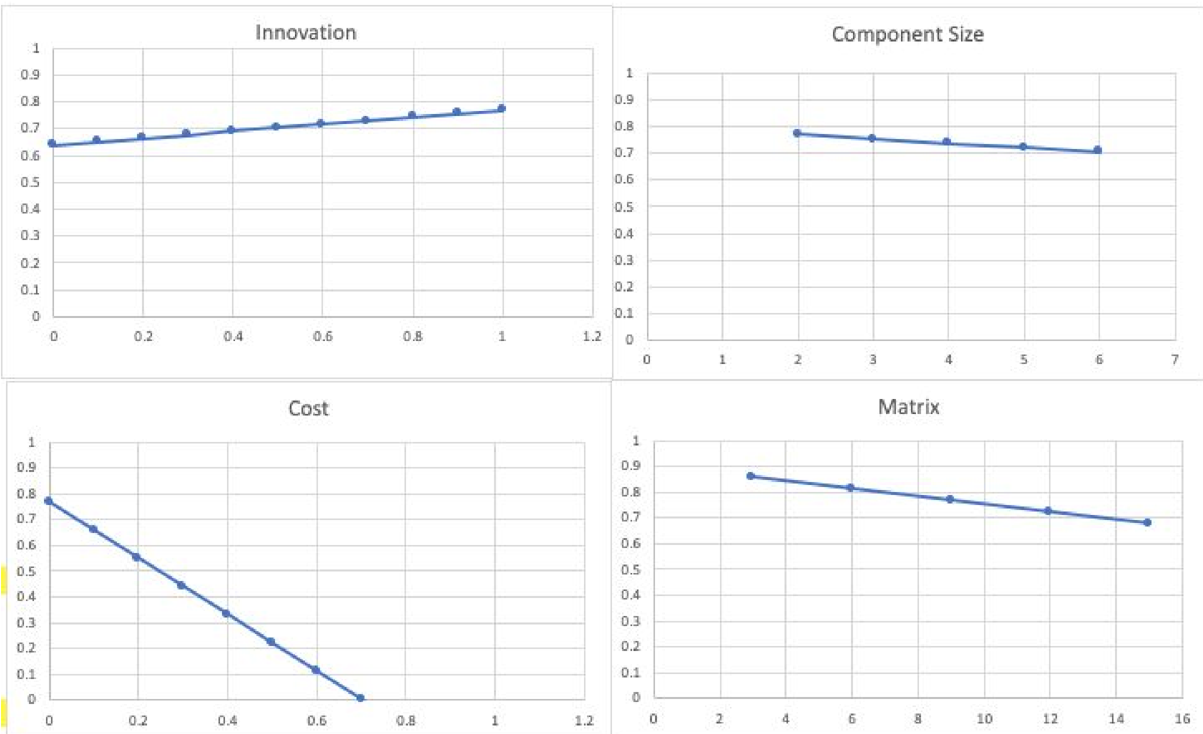

Figure 8. Average performance level at time t = 99 with different values in variables innovation, cost, component size, and matrix (dependency K).

PROPOSITION 3. Innovation power has a positive effect on overall performance while increasing decision costs has a negative effect. Both of the two factors lead to higher levels of hypercompetition.

3.4 How Firm Sizes Come into Scene

During the observation of factors influencing the level of performance and ranking changes, we are also curious about the distribution of firm sizes and the correlation between firm sizes and hypercompetition.

In Figure 9, the reason the firms are having gaps is because we are adopting component size = 2 to component size = 5. Since N = 20, the left-over resources will be grouped together. For example, if component size = 3, 20 % 3 = 2 will be the last component. The entire industry has the same set of resource groupings that can be borrowed or lent. The bar chart shows the distribution of firm sizes excluding borrowed resources. It seems that while component size decreases, firms tend to be able to generally grow larger; when component size is large, there would be a big gap among the firm sizes. In hypercompetition, usually there are firms that are very large or very small, and a great number of firms would only be of medium size. When component size increases, the number of big and small firms both increases. Besides, at component size = 2, which we analysed as the case closest to hypercompetition, the shape of firm sizes seem to follow a normal distribution.

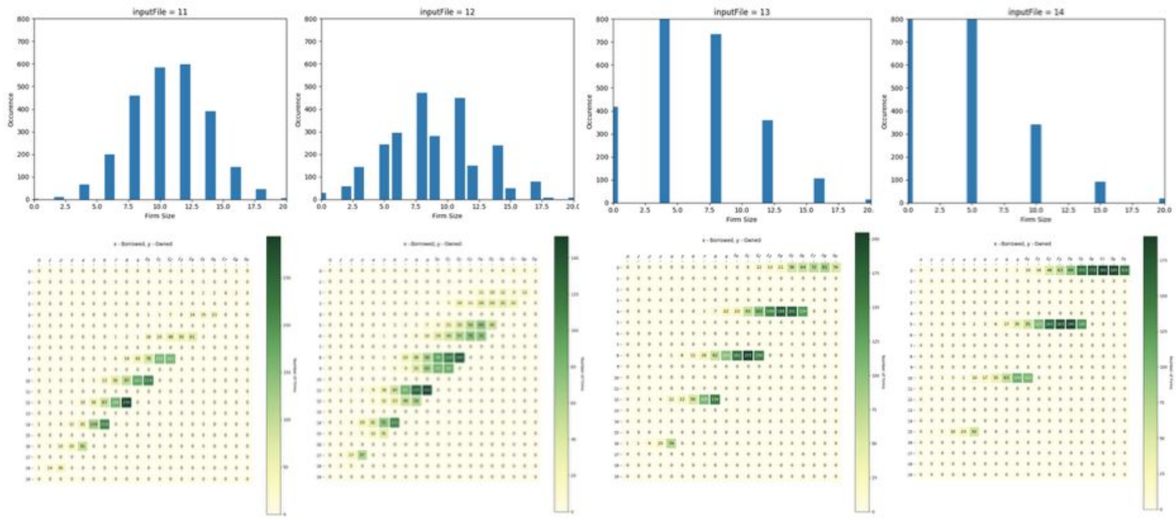

Figure 9. Distribution of firm sizes. Bar Chart: x is firm size, y is the number of firms of size x. Heat Map: x axis is the size of borrowed components while y axis is the size of owned resources.

Besides using fixed component sizes, we have also conducted the experiment under the condition that a component size can be randomly distributed between 2 - 5. The resulting graph is as below (Figure 10). The sizes follow a positively skewed distribution, and most firms tend to have almost half of resources borrowed while half owned.

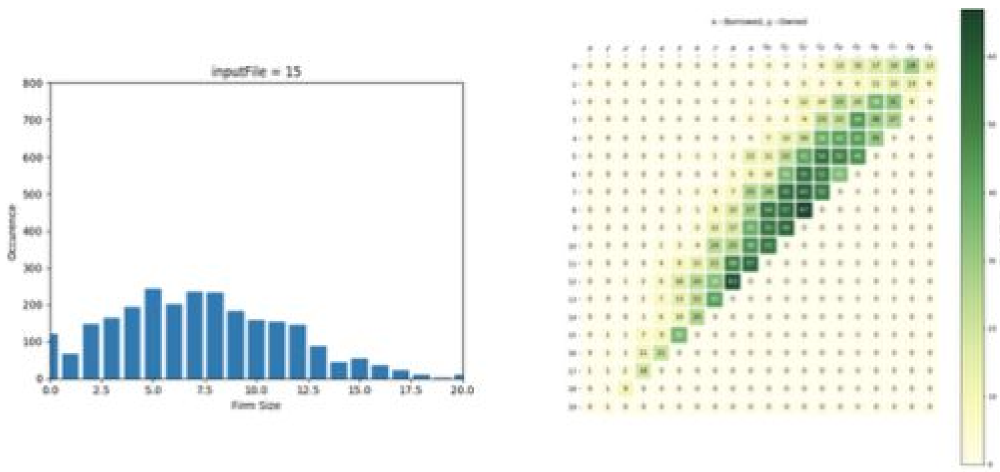

Figure 10. Distribution of firm sizes with random component size between 2 to 5

We have also conducted regression analysis regarding how component size would affect firm sizes and the relationship between firm sizes and hypercompetition. An increase in the component size, or interfirm modularity, would enlarge the gap between top and bottom firms, which is consistent with the conclusion from the chart. The slope is 0.244 with a confidence level of 95%. It does not significantly affect the firm size positively, given that in the same experiment, the slope of cost is -11.67 (see Appendix). The reason why cost has almost the biggest influence towards performance or firm sizes is because if implementation of a decision incurs too much expenses, the firm would not be able to make profit or increase performance, and they would rather abandon the chance of changing configurations.

To measure the hypercompetition, we generally use performance level and ranking changes. We conducted both linear and nonlinear regression analysis on the relationship between performance, ranking, and firm size, and there is no direct evidence that they correlates with each other, But from the scatter plot, a slight positive trend between performance and firm size is noticed, while a negative trend is observed between average ranking changes and average firm sizes.

PROPOSITION 4. Larger component size reduces the hypercompetition effect, increases firms' size and decreases the desire to borrow components from others.

3.5 How Decision Making Process is Impacted

The decision making process has several steps. Firstly, a firm would do an experiential search, hoping to increase the performance value by flipping a random resource configuration that it already owned. Then it would either add or drop a resource, based on which yields the largest fitness value. Next it considers borrowing a component from other firms. Finally, switching existing components to the offering of another firm is also an available option.

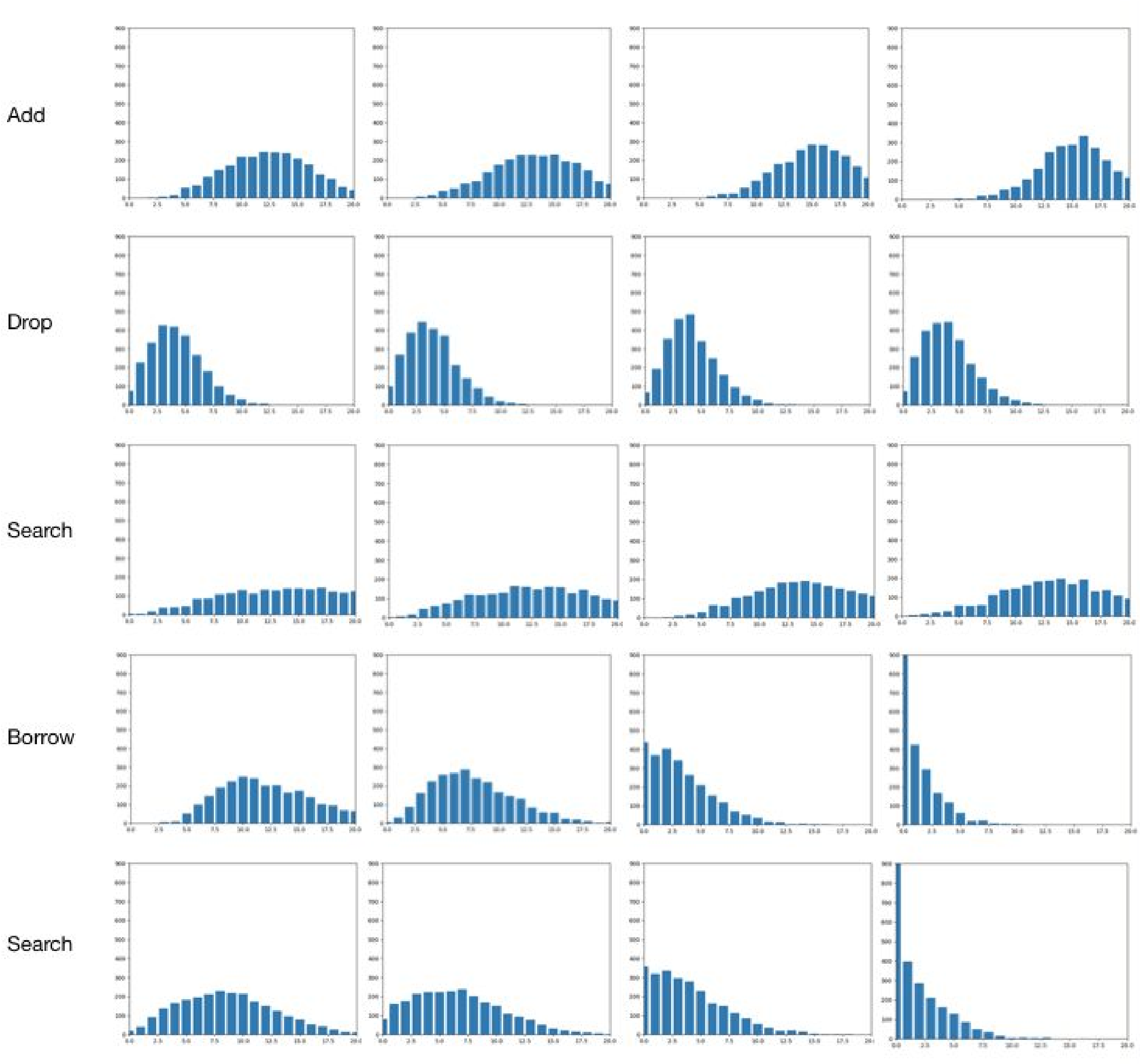

Figure 11. Decision making statistics. The graphs are presented with left the smallest component size (= 2) to right the largest (= 5). X axis: during 100 iterations, how many times the firm has acted on the decision. Y axis: number of firms that made the same number of decisions across 50 repetitive simulation runs.

From Figure 11, it appears component size does not have a very significant influence to search, add and drop decisions. However, larger grouping of resources would reduce the amount of borrowing and switching decisions. According to Staudenmayer, Tripsas, and Tucci (2005), smaller modularity is recommended since it is more flexible to be developed by sharer as well as integrated by the borrower.

PROPOSITION 5. Larger component size leads to an increasing number of adding and experimental search decisions. Searching decisions tend to be impacted the most by a change in the complexity of modularity as well as resource dependency.

4. LIMITATIONS AND FUTURE WORK

The NK model is built in an institutional context, which means the behaviors of the entities in the model follows a certain social and regulation rules (North, 1990). However, as proposed by (Hermelo and Vassolo, 2010), the hypercompetition of entities in the emerging markets is dissimilar from the currently applied model. Those entities are more vulnerable to exogenous shocks and the general risks are higher. Besides, the landscape, which is the macroeconomic environment is more volatile and unpredictable. Those uncertainties and volatility may lead to a shorter exploitation period, and some assumptions made before applying the NK model may not be valid anymore.

Another possible improvement is to consider the profits to lenders of the components. In reality, those firms could increase their brand name and good will if they enjoy a large user base to their platform, which may contribute to their current fitness.

Those will add too much complexity to the current model for now, and they are not a focus or important to this research. There is a trade-off between complexity, which makes the paper closer to reality, with the efficiency of finding applicable business and organizational patterns. Those points will not be discussed in this paper, but can potentially be a direction for future researchers to explore.

5. CONCLUSION

The research is based on the NK model previously implemented by Lim (2019) and Ethiraj & Levinthal (2003). It differs from Lim by including the borrowing and switching process, and differs from Ethiraj & Levinthal by applying the model in a hypercompetition context, and allows firms to make single-resource-level, module-level as well as firm-level decisions.

In this research, the hypercompetition context is simulated by the NK model with N representing resources. Each firm is represented by M resources, and each mutual exclusive component is represented by C resources. In each period, the firm would first conduct a local search, then decide whether to add or drop a resource. Subsequently it moves on to interfirm modularity decisions: borrowing and switching. In the meantime, if it finds that it owns all resources (excluding those it borrowed) in a group that can be shared, it will share the component with no cost or profit. Hypercompetition is measured by industry average performance and firms' ranking fluctuations. Factors that may influence the fitness value and the decision process such as innovation, costs, component size and dependencies K is taken into consideration.

From the charts and regression models, we conclude that a smaller interfirm modularity may increase the level of hypercompetition by increasing average performance and increasing the range of fitness values. Ranking changes are also enlarged by a decreasing modularity. Some side effects of small component size include decreasing firm sizes but increased borrowing. Other factors such as innovation power are positively related to overall performance, while cost negative. Hypercompetition phenomenon is most obvious when innovation = 1 and cost = 0. Speaking of influences to decision makers, a large component size would increase adding and searching decisions but reduce the number of borrowing and switching.

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7. APPENDIX

Charts are at https://alina-pang.github.io/FYPData/
Regression results are in the attached excel.

User guide of the web page:

1. Please select at least one variable with value 'X Axis' and another with 'Y Axis' before clicking the 'submit' button.
2. All five menu items cannot be empty.