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熱手：績效是來自運氣還是能力?

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中 華 民 國 103 年 10 月 27 日

中 文 摘 要 ： 策略管理研究的中心議題是發掘廠商成功與失敗的因素，長期財務指標廣泛用來衡量廠商長期持續績效。然而，以往研究指出財務績效指標含有隨機漫步效果，因此，究竟廠商績效是來目宮理能力還是運氣變成混淆。本研究旨在發掘銀行體系之績效，區分此績效是來自管理能力或是運氣。本研究依據看得到的年度財務績效指標，將銀行分為兩群，潛在群組成長分析(LCGA)將母體分為兩個異質的群組，此兩群組之不同的績效軌跡係由看不到的因素所造成。長期平均報酬率較高的群組被定義為成功群組，有效高的管理水準；而長期平均報酬率較低的群組則被定義為錯誤群組，管理水準較低。當較高管理水準的廠商呈現的長期報酬率較較低管理水準之廠商的平均報酬率低，被定義為「壞運氣」；相對地，較低管理水準的廠商呈現的長期報酬率較較高管理水準之廠商的平均報酬率高，則被定義為「好運氣」。實證研究結果發現，有 10 家低管理水準之銀行，因運氣好而長期績效較高管理水準之銀行佳；而有 2 家高管理水準之銀行，因運氣差而長期績效較低管理水準之銀行差。此研究結果支持殊途同歸的假說，即我們雖不知道各廠商背後不同的策略因素，廠商可由其看得到的績效分群。此外，分析較優績效的研究宜先排除好運氣及壞運氣影響之廠商，以提高研究結果之有效性。

中文關鍵詞： 持續性較優績效、潛在群組成長分析法、運氣、銀行產業

英 文 摘 要 ： The central theme of the strategic management research is to identify why some firms succeed and others fail. Longitudinal financial indicators are widely used to investigate the persistence of performance of firms in the long run. However, the variation of annual financial indicator is found to follow random walk. It is ambiguous whether the persistence of performance is driven by latent managerial factors or simply because of luck. This research aims to identify performance driven by luck from those driven by latent managing factors such as capabilities or resource employment in the banking sector. Banks are classified into two groups using the observed annual return data. The latent class growth analysis (LCGA) identified two heterogeneous groups, which presents the unobserved factor that driving the observed trajectories of the annual performance. The group with high long-term average

return is defined as successful firms competing at the high-level axis and the other group is defined as competing at the low-level axis. Good luck is then defined as the situation that firms at the high-level axis performed worse than the average return of the firms competing at the low-level axis. Bad luck is defined as the situation that firms at the low-level axis performed better than the average return of the firms competing at the high-level axis. The results show that ten banks which successful performance trajectories of at the low-level axis were driven by good luck and those of two firms at the high-level axis were driven by bad luck. This implication supports the proposition of equifinality: even without knowing their underlying strategic differences, firms can be grouped simply by their observed performance. In addition, the performance driven by good luck or bad luck should be excluded when researchers investigate the sources of superior performance.

英文關鍵詞： persistent superior performance, latent class growth analysis, luck, banking industry

Hot hands: Is firm performance sourced from luck or capability?

Abstract

The central theme of the strategic management research is to identify why some firms succeed and others fail. Longitudinal financial indicators are widely used to investigate the persistence of performance of firms in the long run. However, the variation of annual financial indicator is found to follow random walk. It is ambiguous whether the persistence of performance is driven by latent managerial factors or simply because of luck. This research aims to identify performance driven by luck from those driven by latent managing factors such as capabilities or resource employment in the banking sector. Banks are classified into two groups using the observed annual return data. The LCGA identified two heterogeneous groups, which presents the unobserved factor that driving the observed trajectories of the annual performance. The group with high long-term average return is defined as successful firms competing at the high-level axis and the other group is defined as competing at the low-level axis. Good luck is then defined as the situation that firms at the high-level axis performed worse than the average return of the firms competing at the low-level axis. Bad luck is defined as the situation that firms at the low-level axis performed better than the average return of the firms competing at the high-level axis. The results show that ten banks which successful performance trajectories of at the low-level axis were driven by good luck and those of two firms at the high-level axis were driven by bad luck. This implication supports the proposition of equifinality: even without knowing their underlying strategic differences, firms can be grouped simply by their observed performance. In addition, the performance driven by good luck or bad luck should be excluded when researchers investigate the sources of superior performance.

Keywords: persistent performance, latent class growth analysis, luck, banking industry

1. Introduction

The central theme of the strategic management research is to identify why some firms succeed and others fail. If the annual performance (success or fail) of a firm follows a random binomial distribution like flipping a two-side coin, only one out of 1,024 ($=2^{10}$) firms can luckily survive in 10 year. Henderson et al (2012) find that the 10^{th} percentile competitive performers sustainably survive more than 40 years long and some of them show persistent performance. How have these firm succeeded? Because of luck or capability?

Many people believe that basketball players who make a home-run are more likely to hit the next shot than players who miss a shot (Camerer, 1989). This hot-hand fallacy indicates that people tend to have difficulty thinking properly about independent events because successful shot, or "home-run strike," boosts the observers' subjective probability of another hit (Gilovich, Vallone, and Tversky, 1985). Contrarily, people belief that, for random events, runs of a particular outcome (home-run

strike) will be balanced by a tendency for the opposite outcome, i.e., a streak of "lucky" events is likely to end. This gambler's fallacy presents that a streak of heads makes it more likely that the next flip will be a tail, that is, the random sequences should exhibit systematic reversals (Rabin and Yayanos, 2010). Hot hands are found exist in fund investment (Hendricks, Patel and Zeckhauser, 1993), especially among the superior hedge funds managed by skilled fund management (Jagannathan, Malakhov and Novikov, 2010).

The hot-hand and gambler's fallacies indicate that people usually adjust their believe over time by selecting an indicator, which is a function of past observations and has a observable performance (Brock and Hommes, 1997). This iterative procedure can be described by the conditional probability function:

$$\boldsymbol{Prob}(q|p) = \frac{\boldsymbol{Prob}(p|q) \times \boldsymbol{Prob}(q)}{\boldsymbol{Prob}(p|q) \times \boldsymbol{Prob}(q) + \boldsymbol{Prob}(p|\sim q) \times \boldsymbol{Prob}(\sim q)} \quad (1)$$

Consider, for example, a banker who knows, prior to the approval of an investment project, the successful rate of the new project is 10%, prob(q). In economic boom time, the chance for such project to yield above average profit is 50%, Prob(p|q) while the recession time is only 5%, prob(p|~q). According to Bayes's theorem, the posterior probability that such project can yield above-average profit Prob (q|p), that approved by the firm who perceived the economic might be booming is (0.50)(0.10)/[(0.50)(0.10) + (0.05)(0.90)] = 53%. This perceived probability is higher than a naïve guess (50%).

Several strategic management studies use Bayesian epistemology to interpret the causal relations between competitive advantage and firm performance (Denrell, 2004; Powell, 2001; 2002; 2003; Tang and Liou, 2010). They suggest a probabilistic inference: 'Sustainable competitive advantage is more probable in firms that have already achieved sustained superior performance" (Powell, 2001: 879). Furthermore, with resource configuration as an auxiliary hypotheses, Tang and Liou (2010) illustrate how financial indicators can be used to unfold the resource and capability bundles, which are indicated to be indistinguishable because they have complex linkages (Powell, Lovallo and Caringal, 2006), complementarities (Milgrom and Roberts, 1990; 1995) and tacit dimensions (Nelson and Winter, 1982).

Since the evidence of superior performance cannot conclusively indicate the existence of competitive advantage, it is a difficult task to identify firms with competitive advantage from those without. On one hand, firms generating superior performance may reflect their competitive advantage through operating in a favorable industry structure (monopoly rents), employing difficult to imitate resources (Ricardian rents), taking innovative projects (Schumpeterian rents), or just be lucky (Barney, 1986). On the other hand, these firms may fail to show distinguished performance simply because of unluckiness. Similarly, firms that lack of capabilities in developing and augmenting its resources may still show remarkable performance simply due to lucky randomness (Denrell, 2004; Levinthal, 1990; Henderson et al., 2012).

Most studies use a single financial return as a proxy of firm performance. These ratios include book return such as return on equity (ROE), return on assets (ROA), and return on investment

(ROI), as well as market measures such as Tobin's q, PE ratio, and stock prices. Many financial studies have shown that financial ratios usually follow a random-walk pattern (Tippett and Whittington, 1995; Whittington and Tippett, 1999; Jose and Lancaster, 1996). The finding that the success of a majority of firms in COMPUSTAT are subject to chances due to lucky random walks instead of systematic determinants (Henderson et al., 2012) is not surprising since the result is derived from a single randomly-moved financial ratio, ROA or Tonbin's q, as the proxy of firm performance.

The agency cost and the theory of the firm argues that the firms in the competitive market are forced "the evolution of devices for efficiently monitoring the performance of the entire team and of its individual members" (Fama, 1980). Firms maximize their value only if the interest of its stakeholders including shareholders, bondholders, employees, consumers, capital market, and the entire society, are satisfied (Porter and Kramer, 2011). If competitive advantage is the ability of a company to transfer strategic resources to create long-term value to its stakeholders, an indicator that measures a firm's long-term value may indicate the unobservable competitive advantage more appropriately than a historical short-term financial ratio.

1.1 The research questions

To examine the sources of firm performance with an empirical study, one has to determine, among others, two major issues: (1) the selection of an appropriate indicator, usually an evidenced outcome, as a proxy variable of firm performance to distinguish firms that have reached "success" from others; and (2) the identification of sources, commonly refer to the unobserved competitive advantage (Barney, 1991; Grant, 1991; Porter, 1980; 1985), organization or resource configuration (Miller, 1986; Siggelkow, 2002; Tang & Liou, 2010; Teece, et al. 1997), and capabilities (Grant, 1991), that lead to the underlying performance.

To precisely address the central theme in strategic management research, we need to answer two questions as follows:

1. The single financial ratios commonly used in the strategic management studies poorly indicate competitive advantage of the firm because most of them are short-term measures. Can a long-term value measurement that can better predict the performance of firms?
2. Why some firms are more sustained than others in huge environmental turmoil? Are they because of luck or capabilities? Based on the indicator developed in question 1 this research studies performance persistence in global banking industry across the global financial crisis.

1.2 Research framework

The report is structured as follows. The first section describes the research background, motivation and questions. The second section reviews the related literatures including the causal linkage between competitive advantage and firm performance and the drivers of randomness. The third section develops the research model by giving definitions about short-term and long-term performance, luck and unluck, and latent mechanism driving long-term performance. The latent class growth model for analyzing the long-term trajectories of performance is introduced. The

empirical study is given in section four,. Section five provides managerial implications, conclusions, and suggestions for future research.

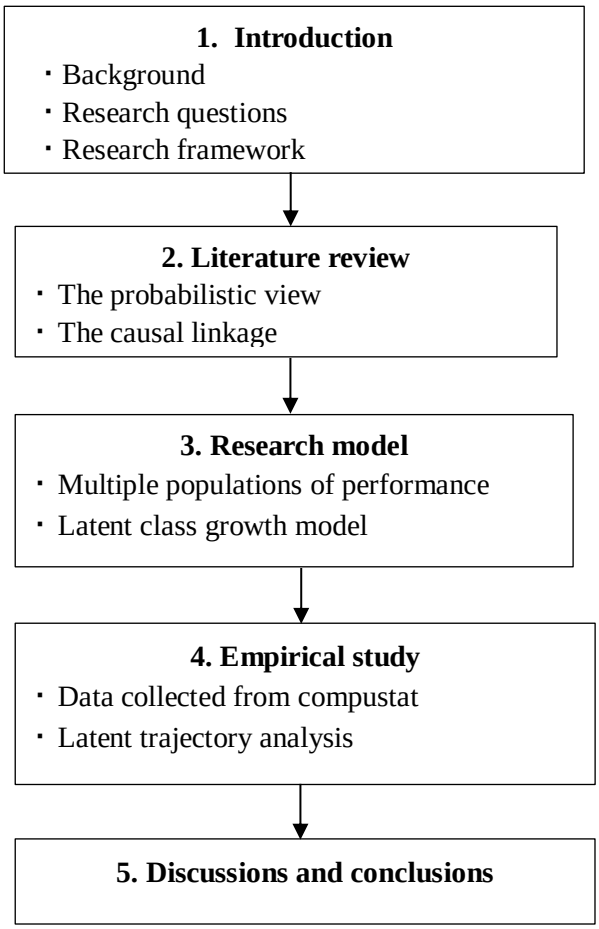

Figure 1. Research framework

2. Literature Review

2.1 The probabilistic view of competitive advantage and competitive disadvantage

Competitive advantage is not visible but can be revealed by the performance of the firm (Tang and Liou, 2010). However, since the superior performance a firm may also can be the result of or some manifestation of luck (Barney, 1986), the provision of performance does not guarantee the existence of competitive advantage. Therefore, the relationship between competitive advantage and performance is not deterministic but probabilistic (conditional). That is, the firms that have achieved superior performance may not definitely lead by competitive advantage however they are most probable to have competitive advantage (Powell, 2001; 2002; 2003). The probabilistic relationship is stated as equation (1), whereas, Prob$(q|p)$: the probability that a firm has sustainable competitive advantage given the provision of performance of that firm; prob(q): the probability that a firm has competitive advantage among a group of firms; prob(~q): the probability that a firm has no competitive advantage among a group of firms; Prob$(p|q)$: the

probability that a firm's performance is the result of sustainable competitive advantage; Prob$(p|\sim q)$: the probability that a firm's performance is not led by sustainable competitive advantages achieve sustained superior performance.

Tang and Liou (2010) generalize equation (1) to equation (2) illustrate the relationship between competitive advantage hypotheses or theories ($\boldsymbol{\theta}$) and superior performance ($\mathbf{Y}$). They then extend the competitive advantage- performance causal relation by introducing organizational configuration as the auxiliary hypotheses to mediate the two. Furthermore, Liou (2011) add strategy to the front of the causal relations to evaluate the effects of corporate strategy on firm value. The causal relation of strategy-competitive advantage-configuration-performance can be expressed as equation (3).

$$P(\boldsymbol{\theta}|\mathbf{Y}) = \frac{P(\mathbf{Y}|\boldsymbol{\theta})P(\boldsymbol{\theta})}{P(\mathbf{Y}|\boldsymbol{\theta})P(\boldsymbol{\theta})+P(\mathbf{Y}|\sim\boldsymbol{\theta})P(\sim\boldsymbol{\theta})} = \frac{P(\mathbf{Y}|\boldsymbol{\theta})P(\boldsymbol{\theta})}{P(\mathbf{Y})} \quad (2)$$

$$P(\boldsymbol{\theta},\psi|\mathbf{Y}) = P(\boldsymbol{\theta}|\psi,\mathbf{Y})\times P(\psi|\mathbf{Y}) \quad (3)$$

$$\psi = (x,\lambda)$$

Whereas ψ is an auxiliary proposition representing a mixture of heterogeneous resource bundles **x** and their associated weights **λ**.

This epistemological significance of the Bayesian process is a parameterizing process that to assert a relationship between 'rational constructions' and the unobserved properties of behavioral theories, and to derive an instance of the relationship based on empirical data that are easier to observe and measure (Tang and Liou, 2010: p. 45). Bayesian discriminant model (Sivia, 1996), which assumes that the population of firms is composed of two unaffiliated factions: those with competitive advantage and those without (i.e., having competitive disadvantage) is suggested to be used to extract the causal series with tangible data. The probability of the competitive advantage (or disadvantage) hypothesis $\boldsymbol{\theta}$ is derived from statistical inference based on the unobserved configurations of heterogeneous resource bundles ψ and the empirical evidence of performance $\mathbf{Y}$. They subsequently propose a resource configuration of competitive advantage to generate the possible rational construction of sustainable competitive advantage and competitive disadvantage.

2.2 The causal linkage between competitive advantage and performance

Causal ambiguity, which refers to the knowledge-based impediments to competitors' imitation, plays an important role in strategic management thinking. Strategic researchers suggest that company resources can generate causal ambiguity in sustainable competitive advantages, which exploit information asymmetry and raise barriers to imitation, and thus yield superior performance (Barney, 1991; Coff, 1999; Lippman and Rumelt, 1982; Peteraf, 1993; Porter, 1985; Reed and DeFillippi, 1990). The resource configuration framework based on tangible information attempt to uncover the causal ambiguity between competitive advantage and performance.

Information constitutes those significant regularities residing in the data that receivers attempt to extract from. The act of extracting involves an assignment of the data to existing categories

according to some set of pre-established schemas or constructs that shape expectations of the receivers (Boisot and Canals, 2004). These a priori expectations will be in turn modified subsequently by the arrival of information (Arrow, 1984).

Data is the originating in discernible differences between at least two physical states (Boisot and Canals, 2004) such as higher or lower stock price, new or old formula, and various levels of product sales. Data is the resource as well as the constraining affordance to transform it into information. Data can be the financial variables or survey results generated by the focal firm. However, not every data is meaningful unless the informees (the individual, the organization, the firm, etc.) obtain the data and comprehend it (Kuhn, 1974). Although a bountiful supply of data are available to the public, only those in possession of the "key position" can epistemically extract from it (Singh, 1999). This cryptographic nature of the data limits the ability of individuals or firms in transforming (receiving, storing, retrieving, transmitting) the data into information (Williamson, 1981).

Financial statements systematically record firm's daily activities and operations which notoriously leave a trail of derivative information for outsiders. Financial ratios are basic data revealing the corresponding firm's dynamic strategies in response to the external environment (Frecka and Lee, 1983; Lee and Wu, 1988; Lev, 1969). However, the undaunted great number of financial indicators and ratios are chaotic to use. Financial managers usually compare ratios with those of benchmarks to examine the strength and weakness of the firm.

2. The Research Model

3.1 *Luck in performance*

There is no universally accepted definition of "persistent superior performance". This ambiguity has encouraged scholars to develop many different methodologies for testing their theories and identifying long-term outperformers. Persistent superior performance includes two qualities: superiority and sustainability. Whatever methods are used to measure sustained superior performance must quantify and satisfy both elements (McGahan and Porter 2003). While superior performance is measured using yearly data, sustainability is usually examined by statistical methodologies with longitudinal data. This research defines short-term superior performance as above-industry average in a specific year. It further defines long-term superior performance as the tendency to perform higher than long-term industry average over the study period.

Assume that firms are competing at two axes: the axis of success and the axis of error (Powell and Arrengel, 2007). Firms competing at the axis of success are high-performing firms with inimitable resources and capabilities while those competing at the axis of e fail to attend to the activities, resources and opportunities that are equally available to all firms. We therefore expect that better capabilities in managing inimitable resources are positively associated with higher performance than those with worse managing skills. However, the performances of all firms are driven not only by capability or resources but also by luckiness (Barney, 1986). Figure 2 illustrates the probabilistic distribution of performance along the given level of capability at the two axes. There is bad luck for firms at higher level of capability perform worse than the average performance

of firms at the lower level of capability. Contrarily, it is good luck for forms at lower level of capability performance superior than the average performance of firms at the higher level of capability.

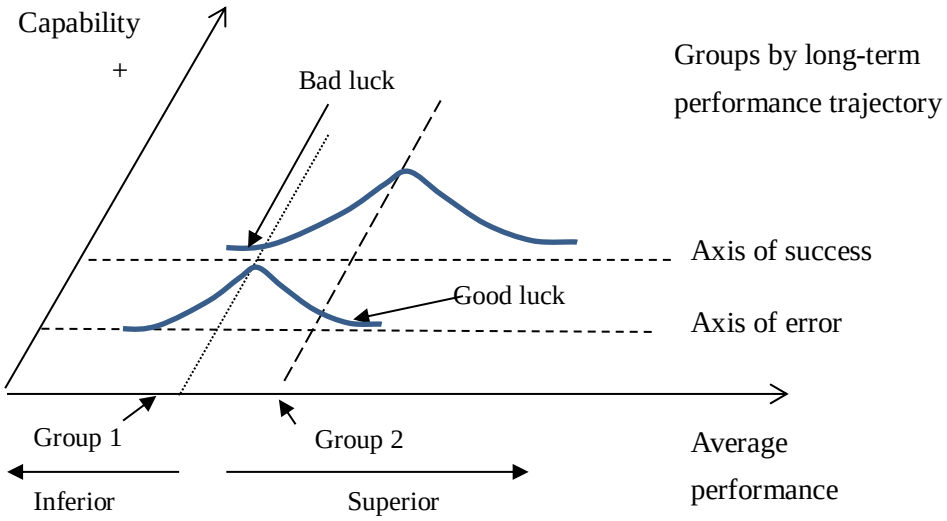

Figure 2. Distributions of performance at two axis of competition

We need a methodology to classify firms at different levels of capability provided that the grouping variable is unobservable. The latent class growth analysis (LCGA) can serve this purpose.

3.2 *Latent Class Growth Analysis*

LCGA is a group-based, multi-parametric approach. LCGA models the probability of membership in the observed distinct (performance) trajectory groups where the grouping variable is unavailable or unknown (Jung and Wickrama 2008; Nagin 2001; 2005; Nagin and Tremblay 1999). LCGA is a special type of growth mixture model, which is particularly useful for topic areas with the need to identify and understand unobserved subpopulations and recognizing the unobserved heterogeneity in measurement functioning in organizational research (Wang and Hanges 2011). In this latent variable modeling framework, the random effects on individual differences are reconceptualized as continuous latent variables. Between-class differences are measured by the intercept and the slops of the growth functions.

LCGA groups individuals in a way that the longitudinal individual response trajectories within

groups are homogeneous but those of different groups are heterogeneous (Jung and Wickrama 2008; Sturgis and Sullivan 2008). LCGA fits each group with a different model and assigns different parameter values across unobservable subpopulations (Jung and Wickrama 2008). It is particularly useful to identify and model the probability of membership in identical trajectory groups where grouping variables are unobservable (Jung and Wickrama 2008; Nagin 2001; 2005; Nagin and Tremblay 2001).

For persistent performance analysis, LCGA can identify groups of firms with homogenous growth trajectories based on observable financial indicators (observable consequence variables). Each firm has some estimated probability of membership in each trajectory class. These are referred to as *posterior probabilities* (Feldman, Masyn, and Conger 2009). Each firm's estimated performance trajectory is a function of the probability of membership in each of the classes. The group trajectory representing within-group members' long-term performance pattern provides a framework for post-hoc identification and description of differences in change between groups.

3.3. *Latent trajectories of performance groups*

LCGA is used to group individual growth parameters rather than observed outcomes (Jones, Nagin and Roeder, 2001). It identifies *K* latent classes (the latent trajectory groups) with distinct developmental trajectories depicted with different growth parameters (Sturgis and Sullivan, 2008). The growth trajectory identified for each group is based on the vector $Y_i = (y_{i1}, y_{i2}, \cdots, y_{iT}), i = 1, \ldots, n,$ describing the longitudinal sequence of firm *i*'s performance over *T* points in time for *n* firms. In our case, the elements of *Y* are binary values indicating the presence or absence of superior performance in a given period. LCGA assumes that there are *K* unobserved trajectory subpopulations of firms within an industry, differing in parameter values. The maximum likelihood method is used to estimate these unknown parameter vectors that determine the shapes of the trajectories (Jones, Nagin, and Roeder 2001; Jones and Nagin 2007; Haviland, Jones, and Nagin 2011). The form of the likelihood function can be selected to conform to three types of data: count data, psychometric scale data, or binary data. For binary data, which we use in the present study, the

likelihood function is based on the Bernoulli distribution.

LCGA allows one to incorporate variables other than time, including both time-dependent covariates and time-invariant predictors (Jones, Nagin, and Roeder 2001). In the present study, we include lagged performance (Bollen and Curran 2004; 2006, Sec. 7.5) and the annual economic growth rate, both time-varying variables, in order to partial out the effects of cumulative advantage and environmental changes. The adjusted latent trajectories of the firms better reflect the latent factors driving the performance changes over time. We use the binary logit model to fit the dichotomous data (superior performance or otherwise) resulting from the 'above the industry average' criterion. Specifically, letting Y_{ijk} be the binary performance response (1 = superior; 0 otherwise) for firm *i* at time *t* in group *k*, we have

$$\Pr(Y_{itk}=1)=p_{itk}=\frac{\exp\left(\beta_{0k}+\beta_{1k}Time+\beta_{2k}Time^{2}+\ldots+\delta_{1k}Y_{i,t-1}+\delta_{2k}ecog_{t}\right)}{1+\exp\left(\beta_{0k}+\beta_{1k}Time+\beta_{2k}Time^{2}+\ldots+\delta_{1k}Y_{i,t-1}+\delta_{2k}ecog_{t}\right)}, \tag{3}$$

where β_{0k}, β_{1k}, and β_{2k} denote the latent intercept, latent linear trajectory, and latent quadratic trajectory for group *k* respectively. The observable variable $ecog_t$ is the economic growth rate at time *t*. The parameters δ_{1k} and δ_{2k} are the random coefficients associated with Y_{t-1} and $ecog_t$ for group *k*. The degree of the polynomial logit model is determined by trying different models and choosing the degree that best fits the data. The ellipsis in the formula represents these higher-order terms.

Grouping is based on the adjusted latent trajectories (reflecting the categorical latent variables) of the firms. Moreover, the entry status, a time-invariant variable, is included to examine and to delineate its effect on the groups formed by using the multinomial logit model given by

$$\Pr\left(C_i=k\left|ENTRY_i=entry_i\right.\right)=\frac{\exp\left(\theta_k+\lambda_k entry_i\right)}{\sum_{k=1}^{K}\exp\left(\theta_k+\lambda_k entry_i\right)} \tag{4}$$

where $C_i = k$ means that firm i belongs to group k. θ_1 and λ_1 are taken to be zero for identifiability (Jones, Nagin, and Roeder, 2001).

4. Empirical study

Our sample are commercial banks, savings institutions and credit/loan providers, covered in the Compustat North America Database by SIC code 6020, 6022, 6035, 6036, 6156, and 6163. This is the competing industry with a great many banks disappearing (died or acquired by other bans) in the space of last decades. There are 2,129 such banks in the Compustat database from 2000 to 2013. This period also covers at least two phases of the industry business cycle, if the five-year period depicted by McGahan and Porter (1999) and Rumelt (1991) is accurate. The research selected return on average assets (ROAA) to indicate firm performance and deleted banks with data less than five years, 87 banks are kept in the final dataset. In the following section, median is used to present average in order to avoid distortion by outliers.

4.1 ***The results***

The ROAA identified two trajectory groups (Table 1). The first group, which includes 60 banks (69% of the population), fit an upward linear growth pattern. The second group, which consists of 27 banks, (31%) presents a constant trajectory higher than that of the first group. The capability levels are identical for firms classified in the same group and are heterogeneous for firms in one another. The second group presents a higher level of capability since its performance trajectory is constantly higher than the first group. The long-term average ROAAs in the study period for the group at high-level of capability is 3.2%, which is higher than the other group (2.0%). In the low-level capability group, 10 out of the 60 banks have long-term average ROAA higher than the average for firms at the high-level capability: the membership of performance trajectory of these banks might be driven by good luck. There are only 2 out of the 27 banks at the high-level capability have long-term ROAA lower than the average for firms at the low-level capability: the membership of trajectory of these banks might be from bad luck.

Table 2 presents the performance indicators of the two trajectory groups. They are identical in terms of efficiency ratio but are heterogeneous in terms of productivity of personnel.

Table 1. Membership grouping and shapes of trajectories by ROAA

Group	Parameter	Estimate	Error	Parameter=0	Prob > |T|
1	Intercept	-2.153	0.232	-9.279	0.000
	Linear	0.130	0.030	4.268	0.000
2	Intercept	1.387	0.154	9.004	0.000
	Group membership				
1	(%)	68.52836	5.18367	13.22	0
2	(%)	31.47164	5.18367	6.071	0

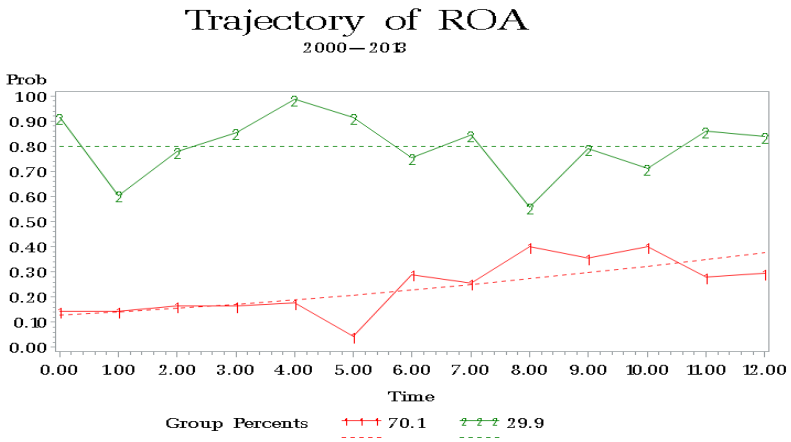

Figure 3. Performance trajectories of latent groups

Table 2. Performance indicators of trajectory groups

Trajectory group	Frequency	ROA	Efficiency	Productivity
1	60	0.0026	0.5872	0.0142
2	27	0.0033	0.5846	0.0175

Note: Efficiency Ratio = Total Non-interest expenses / Total Net Interest Income (before provisions) plus Total Non-Interest Income; Productivity= Personnel expenses / Employee

5. Discussion and conclusions

This research aims to identify performance driven by luck from those driven by latent managing factors such as capabilities or resource employment in the banking sector. Banks are classified into two groups using the observed annual return data. The LCGA identified two heterogeneous groups, which presents the unobserved factor that driving the observed trajectories of

the annual performance. The group with high long-term average return is defined as successful firms competing at the high-level axis and the other group is defined as competing at the low-level axis. Good luck is then defined as the situation that firms at the high-level axis performed worse than the average return of the firms competing at the low-level axis. Bad luck is defined as the situation that firms at the low-level axis performed better than the average return of the firms competing at the high-level axis. The results show that ten banks which successful performance trajectories of at the low-level axis were driven by good luck and those of two firms at the high-level axis were driven by bad luck. This implication supports the proposition of equifinality: even without knowing their underlying strategic differences, firms can be grouped simply by their observed performance (von Bertalanffy, 1968; Katz and Kahn, 1978).

The research is different from prior literature by distinguishing good luck from bad luck. It is also unique to identify subpopulations and the heterogeneous performance trajectories in the banking industry. In addition, the performance driven by good luck or bad luck should be excluded when researchers investigate the sources of superior performance. There are several potential extensions for future research. Organizational variables, such as brand value, knowledge accumulation of employees, and organizational culture can be added to the research model to investigate the effects of these latent factors on long-term performance trajectories whenever they are available. Further, the LCGA assumes homogeneous within groups, that is, variation within groups is zero. the LCGA groups can be used as a basis for growth mixture models or other growth models, in order to examine the common factors within groups and heterogeneous factors between different groups. This extension of the model would help identify sources for the observed differences in performance trajectories.

References:

Barney, J.B. (1986). "Strategic factor markets: Expectations, luck and business strategy," *Management Science*, 32 (10), pp 1231-1241.

Barney, J.B. (1991). "Firm resources and sustained competitive advantage," *Journal of Management*, 17(1), 99–120.

Boisot, M. and A. Canals (2004). "Data, Information and Knowledge: Have We Got It Right?," *Journal of Evolutionary Economics*, 14(1), 43-67.

Brock, W.A. and C. H. Hommes(1997). "A rational route to randomness," *Econometrica* 65(5), 1059-1095.

Bollen, K. A. and P. J. Curran. 2004. Autoregressive latent trajectory (ALT) models: A synthesis of two traditions. Sociological Methods & Research 32, no. 3: 336-383.

Bollen, K. A. and P. J. Curran. 2006. Latent curve models: A structural equation perspective. Hoboken, NJ: Wiley.

Camerer, C.F. (1989). "Does the Basketball Market Believe in the 'Hot Hand,'?," *American Economic Review* 79(5), 1257-1261.

Coff, R.W. (1999). "When competitive advantage doesn't lead to performance: The resource-based view and stakeholder bargaining power," *Organization Science*, 10(2), 119-133.

Denrell, J. (2004). "Random walks and sustained competitive advantage," *Management Science* 50(7), 922-934.

Fama, E.F. (1980). "Agency Problems and the Theory of the Firm," *Journal of Political Economy* 88(2), 288-307.

Frecka, T. J. and C. F. Lee (1983). "Generalized financial ratio adjustment process and their implications," *Journal of Accounting Research*, 21(1), 301-316.

Feldman, B. J., K. E. Masyn, and R. D. Conger. 2009. New approaches to studying problem behaviors: A comparison of methods for modeling longitudinal, categorical adolescent drinking data. Developmental Psychology 45, 652–676.

Gilovich, T., R. Vallone and A. (1985). "TverskyThe hot hand in basketball: On the misperception of random sequences," *Cognitive Psychology* 17(3), 295–314.

Grant, R. (1991). "The resource-based theory of competitive advantage: implications for strategy formulation," *California Management Review* 33, 114-135.

Henderson, A.D., M.E. Raynor and M. Ahmed. (2012). How long must a firm be great to rule out chance? Benchmarking sustained superior performance without being fooled by randomness. *Strategic Management Journal* 33(4), 387-406.

Hendricks, D., J. Patel and R. Zeckhauser (1993). "Hot hands in mutual funds: short-run persistence of relative performance 1974-1988," *Journal of Finance* 48(1), p93-130.

Haviland, A., B. Jones, and D. S. Nagin. 2011. Group-based trajectory modeling extended to account for nonrandom participant attrition. Sociological Methods & Research 40, no. 367–390.

Jagannathan, R., A. Malakhov and D. Novikov (2010). "Do hot hands exist among hedge fund managers? An empirical evaluation," *Journal of Finance* 65(2), 217-255.

Jose, M.L. and C. Lancaster (1996). "Stability of excellence: Revealed patterns in Tobin's q-ratios," Journal of Applied Business Research 12(2), 83-92.

Jung, T. and K. A. S. Wickrama. 2008. An introduction to latent class growth analysis and growth mixture modeling. Social and Personality Psychology Compass 2, no. 302–317.

Jones, B. L., D. S. Nagin, and K. A. Roeder. 2001. A SAS procedure based on mixture models for estimating developmental trajectories. Sociological Methods & Research 29, no. 374–393.

Jones, B. L. and D. S. Nagin. 2007. Advances in group-based trajectory modeling and an SAS procedure for estimating them. Sociological Method and Research 35, no. 542–571.

Katz, D. and R. L. Kahn. 1978. The Social Psychology of Organizations. 2nd ed., New York: Wiley.

Kuhn, T.S. (1974).*The Structure of Scientific Revolutions*. University of Chicago Press, Chicago, IL.

Lee, C. F. and C. Wu (1988). "Expectation formation and financial ratio adjustment process," *The Accounting Review,* 63(2), 292-306.

Lev, B. (1969). "Industry averages as targets for financial ratios," *Journal of Accounting Research*, 7(2), 290-299

Levinthal, D.A. (1991). "Random walks and organizational mortality," *Administrative Science Quarterly*, 36(3), 397-420.

Liou, F.M. (2011). "The effects of asset-light strategy on competitive advantage in the telephone communications industry," *Technology Analysis & Strategic Management*, 23(9), 951-967.

Lippman, S.A. and R.P. Rumelt (1982). "Uncertain imitability: An analysis of interfirm differences in efficiency under competition." *The Bell Journal of Economics*, 13(2), 418-438.

McGahan, A. M. and M. Porter. 2003. The emergency of and sustainability of abnormal profits. Strategic Organization 1, no. 79–108.

McGahan, A. M and M. Porter. 1999. The persistence of shocks to profitability. The Review of Economics and Statistics 81, no. 143–153.

Nagin, D. S. 1999. Analyzing developmental trajectories: a semi-parametric, group-based approach. Psychological Methods 4, no. 139–157.

Nagin, D. S. 2005. Group- based modelling of development. Cambridge, MA: Harvard University Press.

Nagin, D. S. and R. E. Tremblay. (2001). "Analyzing developmental trajectories of distinct but related behaviors: A group-based method," *Psychological Methods*, 6, 18–34.

Nelson, R., S.G. Winter (1982). *An evolutionary theory of economic change*. Harvard University Press, Cambridge, MA.

Pettway, R. and, J. Sinkey (1980). Establishing on-site bank examination priorities: An early warning system using accounting and market information. *Journal of Finance*, 35(1), 137-150.

Porter, M.E. (1985). *Competitive advantage: Creating and sustaining superior performance*. Free Press: NY.

Porter, M.E.and M.R. Kramer (2011). "Creating shared value." *Harvard Business Review* 89(1/2), 62-77.

Peteraf, M.A. (1993). "The cornerstones of competitive advantages: a resource-based view," *Strategic Management Journal*, 14(3), 179−191.

Powell, T.C. (2001), "Complete advantage: logical and philosophical considerations," *Strategic Management Journal* 22(9), 875-888.

Powell, T.C. (2002), "The philosophy of strategy," *Strategic Management Journal*, 23(9), 873-880.

Powell, T.C. (2003), "Strategy without ontology," *Strategic Management Journal*, 24(3), 285-291.

Powell, T.C. and J.L. Arregle (2007). Firm performance and the axis of errors. *Journal of Management Research*, 7(2), 59-77.

Powell, T.C., D. Lovallo and C. Caringal (2006). "Causal ambiguity, management perception, and firm performance," *Academy of Management Review* 31(1), 175-196.

Rabin, M. and D. Vayanos (2010). "The gambler's and hot-hand fallacies: theory and applications," *Review of Economic Studies* 77, 730-778.

Reed, R. and R.J. DeFillippi (1990). "Causal ambiguity, barriers to imitation, and sustainable competitive advantage," *Academy of Management Review* 15(1), 88-102.

Rumelt, R. P. 1991. How much does industry matter?. Strategic Management Journal 12, no. 167–185.

Singh, S. (1999). *The Code Book: The Science of Secrecy from Ancient Ehypt to Quantum Cryptography*. New York, NY: Anchor Books.

Sivia, D.S. (1996). *Data analysis: a Bayesian tutorial*. Oxford University Press: Oxford, UK.

Sturgis, P. and L. Sullivan. 2008. Exploring social mobility with latent trajectory groups. Journal of the Royal Statistical Society: Series A 171, 65–88.

Tang, Y.C. and F.M. Liou (2010), "Does firm performance reveal its own causes? The role of Bayesian inference," *Strategic Management Journal*, 31(1), 39-57.

Teece, D. J., G. Pisano, and A. Shuen (1997). "Dynamic capabilities and strategic management," *Strategic Management Journal* 18, 509–533.

Tippetta, M., and G. Whittington (1995). "An Empirical Evaluation of an Induced Theory of Financial Ratios," *Accounting and Business Research*, 25(99), 208-218.

von Bertalanffy, L. 1968. General system theory. New York: Braziller.

Whittington, G., and M. Tippett. (1999). "The components of accounting ratios as co-integrated variables." *Journal of Business Finance and Accounting* 26(9-10), 1245-1273

Williamson, O. (1981). "The economies of organization: The transaction cost approach," *American Journal of Sociology*, 87(3), 548-577.

Wang, M. and P. J. Hanges. 2011. Latent class procedures: applications to organizational research. Organizational Research Methods 14, no.24-31.

出國報告書

專題研究計畫：熱手：績效是來自運氣還是能力?」(102-2410-H-263 -008-)
出國地點：日本東京
出國期間：7/24 – 7/27, 2014
會議名稱：The Global Business, MIS, Economic and Finance Research Conference
論文名稱：How Sustainable is Sustained?: The Latent Trajectory of Performance in Baking Industry

一、 參加會議經過

本研討會於日本東京舉行，共有來自台灣、日本、法國、波蘭、以色列、緬甸等國學術人士參加。本篇文章安排於 7/25 上午進行口頭發表。

二、 與會心得

各領域學者發表論文涵蓋國際競爭力、消費者行為、人力資源管理等。部份論文為質化析，部份則為量化分析。

三、 發表論文全文

研討會議程及發表論文全文詳見附件。

五、攜回資料名稱及內容

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論文全文

How Sustainable is Sustained?: The Latent Trajectory of Performance in Baking Industry

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How Sustainable is Sustained?: The Latent Trajectory of Performance in Baking Industry

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ABSTRACT

This paper introduces a new methodology, Latent Class Growth Analysis (LCGA), to identify firms with sustained competitive advantage. LCGA models the probability of membership in the observed distinct (performance) trajectory groups where the grouping variable (the latent factor) is unavailable or unknown; it provides an appropriate procedure to capture information about interindividual differences in intraindividual change. In our paper, the trajectory of performance is defined by market-to-book ratio (MTB), a common indicator approximating Tobin's q, to measure the competitive advantage of the firm. Using MTB as the performance indicator, we apply LCGA to US banking industry in the last 15 years and distinguished three performance-difference groups. The latent trajectory groups identified by MTB are heterogeneous in their dynamic capabilities. This paper contributes to the strategic management research by showing how one may predict the status of sustained competitive advantage from a series of historical performance.

INTRODUCTION

Historical financial performance is widely used to examine the existence of sustained competitive advantage. A firm is said to have sustained competitive advantage if it has achieved long-term persistent superior performance, that is, persisting profits above the norm. Previous studies have used long-term series of performance data from accounting books to detect persistent superior performance (e.g., ~~Henderson, Raynor, and Ahmed, 2012;~~ McGahan and Porter, 1999, 2003; Powell, 2003; Powell and Lloyd, 2005; Powell and Reinhardt, 2010; Ruefli and Wiggins, 2003; Wiggins and Reufli, 2002, 2005). These studies do not pay attention to the random-walk process associated with financial indicators under study. If a financial performance indicator follows a random-walk process, whether the yearly performance is driven by an antecedent (such as competitive advantage) or simply by luck is undetermined (Denrell, 2004). Therefore, the methodology used to identify persistent superior performers should be able to distinguish performance driven by firm specific factors such as capabilities from other random factors such as luck (Denrell, Fang, and Zhao, 2013; Henderson, Raynor, & Ahmed, 2012). Prior studies either ignore the heterogeneity within an industry or do not address the sequence of ordering of performance. The Latent Class Growth Analysis (LCGA), a methodology new to the management field, can be used to identify the group of outperformers without the constraints in the prior literature.

LCGA, which is widely used in social and psychological sciences, is a person centered multi-parameter approach (Nagin, 1999, 2005). It models the probability of membership in the observed distinct (performance) trajectory groups where the grouping variable is unavailable or unknown (Jung and Wickrama, 2008; Nagin, 1999, 2005; Nagin and Tremblay, 2001); thus it provides an appropriate procedure to capture information about interindividual differences in intraindividual change (Nagin, 1999). It can be used to identify growth patterns that describe continuity and change among members of different subpopulations (Jung and Wickrama, 2008).

We apply LCGA to the banking industry and successfully identify three subgroups with distinct latent performance trajectories. Entry status and lagged performance are included in the models to examine the effects of luck and cumulative advantage on the model (Denrell, 2004; Denrell, Fang, and Zhao, 2013; Henderson, Raynor, and Ahmed, 2012). We also control for economic growth, which is believed to be positively correlated with performance for all firms. Hence, each latent trajectory identified by the model reflects the average dynamic capability of a group of firms to improve or sustain a specific performance indicator.

LITERATURE REVIEW

Persistent performance

A firm that out-performs its rivals in an industry in terms of abnormal returns (Barney, 2001; Peteraf, 1993; Porter, 1985; Denrell, Fang, and Winter, 2003) or superior returns to their rivals or industry average (Besanko et al.,

2000; Ghemawat and Rivkin, 1999; Brandenberger and Stuart, 1996) in a long time is said to have sustained competitive advantage. Although persistent performance is defined as "the tendency of abnormally high or low profits to continue in subsequent periods" (McGahan & Porter, 2003), there is no universal accepted operational definition about persistent or sustained superior performance. While competitive advantage is usually measured with a selected financial indicator, sustained competitive advantage is often identified by methodologies such as modeling and grouping approach. Autoregressive model is the most commonly used methodology for examining the persistence of profits. Other methodologies, including full information maximum likelihood; panel unit root tests; structural equation modeling; trend analysis, including polynomial time trends and structural time series; and Bayesian approach (Denrell, Fang and Zhao, 2013) have been used to examine the persistence of profitability ~~(Liou and Ding, 2014)~~. These methodologies utilize parametric and non-parametric approaches, both of which have limitations in identifying superior performers.

When examining sustained superior performance, the autoregressive model has several limitations. First, the cardinal data it uses are not directly comparable across time periods, and the model requires assumptions about the true form of the unobserved performance distribution (Powell and Reinhardt, 2010). Second, it statistically neutralizes the differences between firms and fails to account for their unique characteristics (Hansen, Perry, and Reese, 2004). Third, it estimates just one growth pattern to describe the entire population, which oversimplifies the diversity of growth patterns found in real industries that describe continuity and change among members of different subpopulations with heterogeneous performance (Jung and Wickrama, 2008). For ordinal (rank-based) approaches, the investigation of persistent profits does not specify the time sequence of shifts in ranking or wins, which is essential for recognizing growing outperformers (Liou and Ding, 2014). The LCGA does not have the constraints described above; it captures time-ordering performance trajectory for each heterogeneous group of firms.

Persistent performance in banking industry

Several studies examine the persistence of long-term performance of banks. For example, using a sample of large US banks observed over the period 1986-1991, Levonian (1993) found that despite restraints on competition imposed by bank regulation, abnormal profits tend to be temporary, rather than permanent. The speed of convergence, however, is slower than that suggested by most manufacturing studies. Roland (1997) tested the persistence of profit for US bank holding companies, using the quarterly data for the period 1986-1992. They found that persistence is stronger for banks with below-average performance. Berger et al. (2000) developed non-parametric methods to examine the persistence of bank profit. The strength of persistence has been found to differ between banks initially located in the top and bottom deciles of the distribution of banks by performance. Knapp et al. (2006) reported persistence estimates for a sample of US banks, suggesting that profits take about five years to converge towards average industry norms.

Bertrand and Schoar (2003), Malmendier and Nagel (2011), and Malmendier, Tate, and Yan (2011) pointed out that banks learned from their performance in the 1998 crisis; thus they performed better in the latter crisis. Fahlenbrach et al. (2012) showed that a bank's poor performance in stock returns during the 1998 crisis was significantly related to its stock return performance in 2014 and probability of failure during the2008 financial crisis.

THE LATENT CLASS GROWTH ANALYSIS

LCGA is a multiple-group approach based on semi-parametric group-based trajectory analysis (Jones, Nagin, and Roeder, 2001). It is a statistical methodology developed by Nagin and Land (1993) in criminology and is adopted by other social science research for longitudinal data analysis (Bushway and Weisburd, 2006). This approach is a special case of growth mixture model in which the growth parameters are assumed to be invariant within classes (Jung and Wickrama, 2007, Muthén and Muthén, 2000). The latent class analysis approach has been proved useful in modeling the developmental path of individual characteristics and behavior for the heterogeneous population (e.g., McLeod and Fettes; Sturgis and Sullivan, 2008; Syed and Seiffge-Krenke, 2013; Van den Akker et al., 2013; Zheng, Tumin, and Qian, 2013; Nagin and Odgers, 2010 for an overview).

It groups individuals in a way that the individual response trajectories within groups are homogeneous but those of different groups are heterogeneous (Jung and Wickrama, 2008; Sturgis and Sullivan, 2008). LCGA fits each group with a different model and assigns different parameter values across unobservable subpopulations (Jung & Wickrama, 2008). It is particularly useful to identify and model the probability of membership in distinct trajectory

groups where grouping variables are unobservable (Jung & Wickrama, 2008; Nagin, 1999, 2005; Nagin & Tremblay, 2001).

The classes derived from the latent trajectory analysis can be examined for their antecedents and their consequences (McLeod and Fettes, 2007). The antecedents can be the background variables as a predictor of class membership such as the unobserved strategy, organizational taxonomy, dynamic capabilities, or resources configurations while the consequences can be the class membership as a predictor of firm performance.

LCGA is different from the dummy variable approach, which is commonly used to indicate group membership. The dummy variable approach, which assigns dummy variables for group membership to evidence population heterogeneity and assumes invariant intercept and slope variances across groups. Alternatively, LCGA fits each of the different groups with different models and assigns different parameter values across unobserved subpopulations using latent trajectory classes (Jung and Wickrama, 2008). Hence, LCGA is more flexible over the between-group parameter constraints than the dummy variable approach (McArdle and Hamagami, 1996).

LCGA is applied to variation individual growth parameters, rather than to the observed outcomes themselves, to identify the latent trajectory group variable (Jones et al., 2001). It identifies *k* latent classes (the latent trajectory groups) with qualitatively distinct developmental trajectories with different growth parameters estimated for each of the *k* latent classes (Sturgis and Sullivan, 2008).

For competitive advantage analysis, LCGA can identify groups of firms with homogenous growth trajectories based on observable financial indicators (observable consequence variables). The group trajectory representing within-group members' long-term performance pattern is driven by unobservable antecedents such as dynamic capabilities (Teece, Pissano, and Shuen, 1997).

LCGA groups individual growth parameters rather than observed outcomes (Jones, Nagin, and Roeder, 2001). It identifies *K* latent classes (the latent trajectory groups) with distinct developmental trajectories depicted by different growth parameters (Sturgis and Sullivan, 2008). The growth trajectory identified for each group is based on the vector $Y_i = (y_{i1}, y_{i2}, \cdots, y_{iT}), i = 1, \ldots, n,$ describing the longitudinal sequence of firm *i*'s performance over *T* points in time for *n* firms. In our case, the elements of Y are binary values indicating the presence or absence of superior performance in a given period. LCGA assumes that there are K unobserved trajectory subpopulations of firms within an industry, differing in parameter values. The maximum likelihood method is used to estimate these unknown parameter vectors that determine the shapes of the trajectories (Jones, Nagin, & Roeder, 2001; Jones & Nagin, 2007; Haviland, Jones, and Nagin, 2011). The form of the likelihood function can be selected to conform to three types of data: count data, psychometric scale data, or binary data. For binary data, which we use in the present study, the likelihood function is based on the Bernoulli distribution. The likelihood for each firm *i*, conditional on the number of group *K* (Jones and Nagin, 2007; Haviland, Jones, and Nagin, 2011),

$$P\left(Y_i \middle| k; \beta^k\right) = \sum_{k=1}^{k} \pi_k p^k\left(Y_i\right) \tag{1}$$

where p^k is the probability of belonging to class k with corresponding parameter(s); β^k is the unknown parameter vector which determines the shape of the trajectory of group k; π_k is the group membership (in k) probability, which is not estimated directly but instead are estimated by a multinomial logit function:

$$p_k = e^{\theta_k} \Big/ \sum_{1}^{K} e^{\theta_k} \tag{2}$$

where θ_1 is normalized to 0, which ensures that each probability p^k properly falls between 0 and 1.

The model assumes that conditional on membership in group *k*, the random variables y_{it}, *t*=1,2, …, T, are independent. Thus,

$$P^k\left(Y_i \middle| k;\beta^k\right)=\prod^{T} p^{kt}(y_{it}) \quad . \tag{3}$$

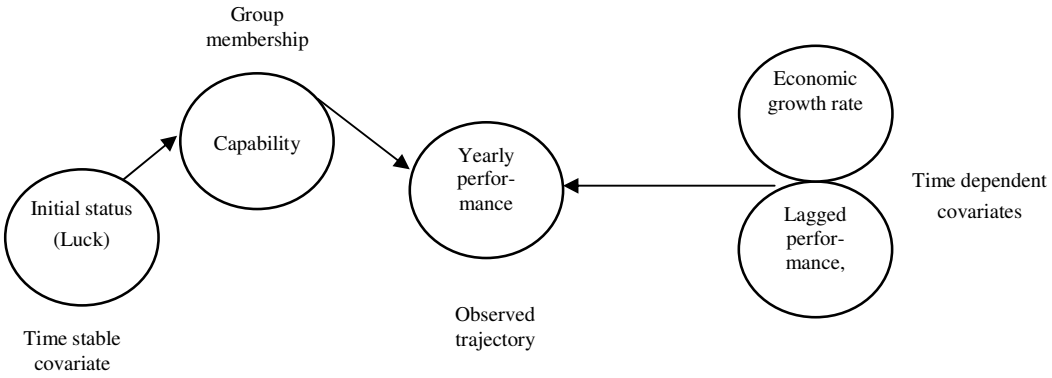


Figure 1: Framework of latent class growth analysis in competitive advantage study

LCGA allows one to incorporate variables other than time, including both time-dependent covariates and time-invariant predictors (Jones, Nagin, and Roeder, 2001). In the present study, we include lagged performance (Bollen and Curran, 2004; 2006, Sec. 7.5) and the annual economic growth rate, both time-varying variables, in order to partial out the effects of cumulative advantage and environmental changes. The adjusted latent trajectories of the firms reflect their dynamic capabilities better. We use the binary logit model to fit the dichotomous data (superior performance or otherwise) resulting from the 'above the industry average' criterion. Moreover, we include the entry status (luck), a time-invariant variable, to examine and to delineate its effect on the groups formed by using the multinomial logit model. Figure 1 presents the framework of latent class growth analysis applied to the study of competitive advantage.

Since entries and exits of firms are common in the free market, attrition and truncation of the performance series are unavoidable in the longitudinal data. Banks that delisted from the stock market because of bankruptcy, mergers, acquisitions, or went private disappeared from the dataset partway through the study period while newly listed banks are entered the dataset. In LCGA, all periods with missing performance values are retained. It is reasonable to include subjects with missing longitudinal data in the analysis of competitive advantage, because these firms account for a significant portion of activity in the industry and should not be ignored (McGahan and Porter, 2003).

To conduct LCGA, we need to determine the number of trajectory groups and the shapes of the trajectories. SAS Proc Traj software allows estimating up to a fourth-order polynomial. Regarding the number of trajectory groups, no "correct" solution is available, yet it can be determined by statistical and/or theoretical criteria (Greenbaum et al., 2004; Muthén, 2004; Nagin, 2005). The trajectory procedure in SAS (Jones, Nagin, and Roeder, 2001) uses the Bayesian information criterion (BIC) to determine the model. The model with the smallest BIC is the one that best fits the data and is therefore considered the best model.

EMPIRICAL STUDY

Our sample firms are commercial banks with a period of 15 years from 1998 to 2012 because the market value is available during this period for many banks. We identify these banks in the Compustat North America Database by SIC code including commercial Banks (6020), savings institutions (6035 and 2036), and Functions related to deposit banking (6009). This industry shows three cycles during the study period. The number of banks

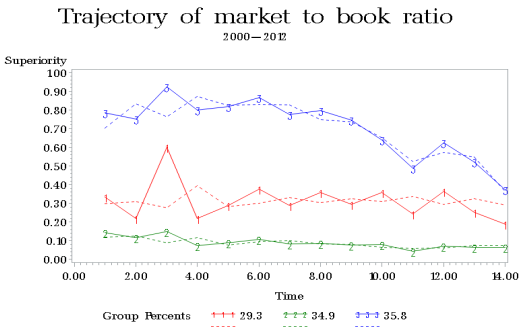
increased from 823 in 1998 to 915 in 1999 and decreased to 674 in 2012. We include banks with incomplete series but exclude those with less than 10 years of data. Thus we retained the data from 443 banks.

Most studies in the strategy literature define superior performance operationally using the binary criterion that a firm's financial return is higher compared to the industry's average. We further define sustained competitive advantage as a persistent pattern of superior performance during the study period. We use market-to-book ratio (MB) to measure sustained competitive advantage as a proxy of Tobin'q (Amit, Livnat and Za-rowin, 1989)), which indicates the intangible resources of a firm (Villalonga, 2004).

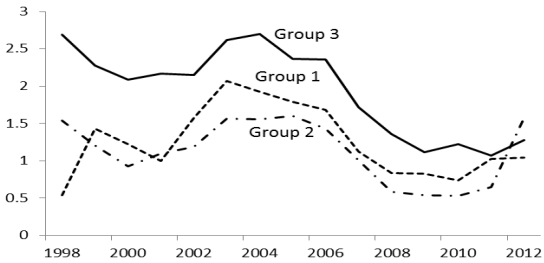
We turn MTB into a binary yearly time series. A bank is defined as superior (value 1) if it meets two criteria: (1) MTB is above the industry average and is greater than one in that specific year; and (2) the earnings of that specific year is positive. Its value is set as 0 otherwise. We then fit the LCGA model to these series to identify the developmental trajectories of the different groups. The performance in the previous year and the US annual economic growth rate, measured as the percent change of gross domestic product relative to the preceding period (U.S. Department of Commerce, 2001 to 2012) are used as time-variant covariates to control for the effects of cumulative advantage and external environmental changes on the trajectories. Furthermore, the firm's first observed performance is used as a risk factor to examine the effects of entry status on group membership. The full trajectory period is 19 years, since we lose the first period in order to include the lagged performance. We test several LCGA models with different group numbers and polynomial degrees, and select the one with the lowest BIC value.

The Result

Figure 2(a) shows the performance trajectories (dynamic capabilities) identified by the best LCGA model for MTB. The solid lines present the average superior performance dummies within the group and the dashed lines are the predicted trajectories. Figure 2(b) displays the average values of the original financial indicators within each LCGA group. Table 2 reports the estimated parameters of the best model for each performance indicator, including the types and shapes of the trajectories. The effects of entry status on the trajectory memberships, lagged performance, and economic growth rate are also reported. The percentage of firms classified and the average number of years that each group achieved above-average performance relative to the number of observed years are listed in the last two rows in Table 1.



(a) Performance trajectories



(b) Average MTB

Figure 2: Performance trajectories and average market-to-book ratio of the LCGA groups

Table 1: Summary of LCGA grouping

	Group 1	Group 2	Group 3
Estimated parameters			
Intercept	-1.28***	-3.71***†	-3.01***
Linear			1.91***
Quadratic			-0.49***
Cubic			0.05***
Quartic			-0.002***
Time-varying covariate			
Lag MTB	1.39***	4.03***	2.62***
Economic growth	-0.67	11.2	18.18***

Time-stable covariate			
Initial status	-	-1.19	2,01***
Group percent	29.3%	34.9%	35.8%
Times above average/year counts	4.5 / 13.5	1.1 /13.4	10.4 / 14.0

MTB identifies three trajectory groups, Groups 1 and 2 have a pattern that is independent of time while Group 3 shows a quartic pattern (Table 1). This result is consistent with the findings in prior studies that persistent performance is stronger for banks with the inferior performance (Berger et al., 2000; Roland, 1997). Group 3, which includes 35.8% of the population, achieved superior performance 10.4 times out of an average of 14.0 observed years. This group also enjoyed the highest MTBs consistently over time (Figure 1(b)) although its superiority presents a downward trend (Figure 1 (a)). Many banks in Group 3 rank on Forbes' 2014 best 100 banks, with all top 10 banks are included. They are Prosperity Bancshares, Signature Bank, State Street, Bank of Hawaii, First Republic, SVB Financial Group, Bank United, Bankunited, East West Bankcorp, and Commerce Bancshares (the forth ranking bank, Commerce Bancshares is not included because of data shortage).

In contrast, firms in Group 2 (34.9%) achieved superior performance only 1.1 times on an average over 13.4 sample years; they operated on the axis of errors (Powell and Arregle, 2007). Group 1 (29.3%) achieved superior performance 4.5 times out of an average of 13.5 years.

Performance in the previous year has significant positive effects on the annual performance (the observed trajectory shown in Figure 3(b)) of all three groups, supporting the effects of cumulative advantage on superior performance in the banking industry. In addition, the effect of economic growth is positively significant on the performance trajectories of Groups 1 but not Group 1 and 2. This result indicates that firms in Groups 1 and 2 fail to employ resources available to all firms (Powell, and Arregel, 2007), that is, they are unable to draw the opportunities during economic prosperity. Finally, the initial status does not affect the trajectory membership between Group 2 and Group 1 but it significantly influences the trajectory membership between Group 3 and Group1. The following section discusses several findings and implications for theory and management in strategic field.

DISCUSSION AND CONCLUSIONS

We adopt a group-based, multi-parametric approach to capture the heterogeneity of firms' performance trajectories in the banking industry. This approach lets us identify the long-term superior performing firms from the grouping results where competitive heterogeneity among groups is latent and unobservable. The LCGA identifies groups of banks based on the underlying factors embedded in the series of annual performance. Since we partial out the cumulated advantage (performance of the previous year) and luck (the initial status of performance), the performance trajectories of the memberships are likely to present the dynamic capabilities.

For all groups, LCGA identifies one complete cycle from 2001 to 2010, a downward cycle from 1998 to 2001, and an upward cycle from 2010 to 2012, which is consistent with the S&P 500 index. The average MTBs of all groups follow an upward trend since 1998, a downward trend since 2006, and a rebound in 2011/2012. Among the groups, the average MTB of Group 1 has been higher than the other two groups except 2011. Although the yearly performance fluctuated severely, the probabilities of being superiority of Group 1 has sustained throughout the study period. However, gaps in the probability of superiority between Group 1 and the other two groups are narrowing, signifying a much more severe competition than before in the banking industry.

First mover in terms of early entry or innovation is one of the advantages of firms to generate superior performance (Lieberman and Montgomery, 1988). The finding that the initial status positively affects trajectory membership in the banking system supports the notion of the first-mover advantage. This finding is consistent with the findings of a prior study conducted in financial services industry (e.g., López and Roberts, 2002).

Our research can be extended to various purposes. First, this paper uses MTB to measure the superiority of banks and identifies 175 banks with persistent superior performance. Other performance indicators such as return on assets, return, on equity, earnings per share, and price-earnings ratio can be used to measure the superiority of a firm. Since each performance indicator signifies a respective aspect of capability, these indicators can be used to infer the persistent superior performance. The long study period can also be divided into phases corresponding to economic environmental shocks. Second, the LCGA groups can be used as a basis for growth mixture models or other growth

models, in order to examine the common factors within groups and heterogeneous factors between different groups. This extension of the model would help identify sources of the observed differences in performance trajectories.

ACKNOWLEDGEMENT

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REFERENCES

Amit, R., Livant, J., and Zarowin, P. (1989). A Classification of Mergers and Acquisitions by Motives: Analysis of Market Responses. Contemporary Accounting Research, 6, 143-158.

Barney, J. B. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17, 99-120.

Berger, A. N., Bonime, S. D., Covitz, D. M., and Hancock, D. (2000). Why are bank profits so Persistent? The Roles of Product Market Competition, Information Opacity and Regional Macroeconomic Shocks. Journal of Banking & Finance, 24, 1203-1235.

Bertrand, M., and Schoar, A. (2003). Managing With Style: The Effect of Managers on Firm Policies, Quarterly Journal of Economics, 118, 1169-1208.

Besanko, D., Dranove, D., Shanley, M., and Schaefer, S. (2007). Economics of Strategy. 4th ed., Hoboken, NJ, John Wiley & Sons.

Bollen, K. A., and Curran, P. J. (2006). Latent Curve Models: A Structural Equation Perspective. Hoboken, NJ: Wiley.

Brandenburger, A., and Stuart, H. (1996). Value-based Business Strategy, Journal of Economics & Management Strategy, 5, 5-24.

Bushway, S., and Weisburd, D. (2006). Acknowledging the Centrality of quantitative Criminology in Criminology and Criminal Justice. The Criminologist,31, 1-4.

Choi, J., and Wang, H. (2009). Stakeholder Relations and the Persistence of Corporate Financial Performance. Strategic Management Journal, 30, 895-907.

Connolly, R. A., and Schwartz, S. (1985). The Intertemporal Behavior of Economic Profits. International Journal of Industrial Organization, 3: 379-400.

Denrell, J., Fang, C., and Zhao, Z. (2013). Inferring Superior Capabilities from Sustained Superior Performance: A Bayesian Analysis. Strategic Management Journal, 34, 182-196.

Fahlenbrach, R., Prilmeier, R., and Stulz, R. (2012). This Time Is the Same: Using Bank Performance in 1998 to Explain Bank Performance during the Recent Financial Crisis. The Journal of Finance, 67, 2139-2177.

Ghemawat, P., and Rivkin, J. (1999). Strategy and the Business Landscape. Reading, PA, Addison-Wesley.

Greenbaum, P. E., Del Boca, F. K., Darkes, J., Wang, C. P., and Goldman, M. S. (2005). Variation in the Drinking Trajectories of Freshmen College Students. Journal of Consulting and Clinical Psychology, 73, 229-238.

Henderson, A. D., Raynor, M. E., and Ahmed, M. (2012). How Long Must A Firm Be Great to Rule Out Chance? Benchmarking Sustained Superior Performance without Being Fooled By Randomness. Strategic Management Journal, 33, 387-406.

Hansen, M.H., Perry, L.T., and Reese, C.S. (2004). A Bayesian Operationalization of the Resource-Based View. Strategic Management Journal, 25(, 1279-1295.

Haviland, A., Jones, B., and Nagin, D. S. (2011). Group-Based Trajectory Modeling Extended to Account for Nonrandom Participant Attrition. Sociological Methods & Research, 40, 367-390.

Jones, B. L., Nagin, D. S., and Roeder, K. A. (2001). A SAS Procedure Based on Mixture Models for Estimating Developmental Trajectories. Sociological Methods & Research, 29, 374-393.

Jones, B. L., and Nagin, D. S. (2007). Advances in Group-Based Trajectory Modeling and An SAS Procedure for Estimating Them. Sociological Method and Research, 35, 542–571.

Jung, T., and Wickrama, K. A .S. (2008). An Introduction to Latent Class Growth Analysis and Growth Mixture Modeling. Social and Personality Psychology Compass, 2, 302-317.

Knapp, M., Gart, A., and Chaudhry, M. (2006). The Impact of Persistence and Mean Reversion of Bank Profitability on Post-Merger Performance in the Banking Industry. Journal of Banking & Finance, 30, 3503-3517.

Levonian, M. E. (1993). The Persistence of Bank Profits: What the Stock Market Implies. Working Papers in Applied Economic Theory, No. 93-15. San Francisco: Federal Reserve Bank of San Francisco.

Lieberman M. B., and Montgomery, D. B. (1988). First-Mover Advantage. Strategic Management Journal, 9, 41-58.

Liou, F. M., and Ding C. D. (2013). How Stained Is Stainable?: The Latent Class of Competitive Heterogeneity. Working Paper, Taiwan: Chihlee Institute of Techology.

López, L. E., and Roberts, E.B. (2002). First-Mover Advantages in Regimes of Weak Appropriability: The Case of Financial Services Innovations. Journal of Business Research, 55, 997-1005.

Malmendier, U., and Nagel, S. (2011). Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?. Quarterly Journal of Economics, 126, 373-416.

Malmendier, U., Tate, G. and Yan, J. (2011). Overconfidence and Early-Life Experiences: The Effect of Managerial Traits on Corporate Financial Policies, Journal of Finance, 66, 1687-1733.

McArdle, J. J., and Hamagami, F. (1996). Multilevel Models from a Multiple Group Structural Equation Perspective. In: G. Marcoulides and R. Schumacker (Eds.), Advanced structural equation modeling: Issues and techniques. Hillsdale, NJ: Erlbaum, 89–124.

McGahan, A. M., and Porter, M. (1999). The Persistence of Shocks to Profitability. The Review of Economics and Statistics, 81, 143-153.

McGahan, A. M., and Porter, M. (2003). The Emergency of and Sustainability of Abnormal Profits. Strategic Organization, 1, 79-108.

McLeod, J. D., and Fettes, D. L. (2007). Trajectories of Failure: The Educational Career of Children with Mental Health Problems. American Journal of Sociology, 113, 653-701.

Muthén, B. (2004). Latent Variable Analysis: Growth Mixture Modeling and Related Techniques for Longitudinal Data. In: D. Kaplan, (Ed.),Handbook of Quantitative Methodology for the Social Sciences, Newbury Park, CA: Sage, 345-368.
Muthén, B. and Muthén, L. (2000). Integrating Person-Centered and variable-Centered Analysis: Growth Mixture Modeling with Latent Trajectory Classes. Alcoholism: Clinical and Experimental Research, 24, 882-891.
Nagin, D. S. (1999). Analyzing Developmental Trajectories: A Semi-Parametric, Group-Based Approach. Psychological Methods, 4,139-157.
Nagin, D. S. (2005). Group-Based Modelling of Development. Cambridge, MA: Harvard University Press.
Nagin, D. S, and Land, K. C. (1993). Age, Criminal Careers, and Population Heterogeneity: Specification and Estimation of a Nonparametric, Mixed Poisson Model. Criminology, 31, 327-362.
Nagin, D. S., and Odgers, C. (2010). Group-Based Trajectory Modeling in Clinical Research. Annual Review of Clinical Psychology, 6, 109–138.
Nagin, D. S., and Tremblay, R. E. (2001). Analyzing Developmental Trajectories of Distinct But Related Behaviors: A Group-Based Method. Psychological Methods, 6:18-34.
Peteraf, M. A. (1993). The Cornerstones of Competitive Advantage: A Resource-Based View. Strategic Management Journal, 14, 179-191.
Porter, M. E.(1980). Competitive Strategy. New York: Free Press.
Powell, T. C, and Arregle, J. L. (2007). Firm Performance and the Axis of Errors. Journal of Management Research, 7,59-77.
Powell, T. C., and Reinhardt, I. (2010). Rank Friction: An Ordinal Approach to Persistent Profitability. Strategic Management Journal, 31, 1244-1255.
Roland, K. P. (1997). Profit Persistence in Large US Bank Holding Companies: An Empirical Investigation. Economics Working Paper, 97-2. Washington, DC : Office of the Comptroller of Currency.
Sturgis, P., and Sullivan, L. (2008). Exploring Social Mobility with Latent Trajectory Groups, Journal of the Royal Statistical Society: Series A (Statistics in Society), 171, 65-88.
Syed, M., and Seiffge-Krenke, I. (2013). Personality Development from Adolescence to Emerging Adulthood: Linking Trajectories of Ego Development to the Family Context and Identity Formation. Journal of Personality and Social Psychology, 104, 371–384.
Teece DJ, Pisano G., Shuen A. 1997. Dynamic capabilities and strategic management. Strategic Management Journal 18(7): 509–533.
Van den Akker, A. L, Dekovi´c, M, Asscher J. J., Shiner, R. L., and Prinzie ,P. (2013). Personality Types in Childhood: Relations to Latent Trajectory Classes of Problem Behavior and Overreactive Parenting Across the Transition into Adolescence. Journal of Personality and Social Psychology, 104, 750–764.
Villalonga, R. (2004). Intangible Resources, Tobin's Q, and Sustainability of Performance Differences, Journal of Economic Behavior & Organization, 54, 205-230.
Zheng, H., Tumin, D., and Qian, Z. (2013). Obesity and Mortality Risk: New Findings from Body Mass Index Trajectories. American Journal of Epidemiology, 178 , 1591-1599.

The Global Business, MIS, Economics and Finance Research Conference, Tokyo

June 16, 2014

Dr. Fen-may Liou
Dr. Chin-Hui Hsiao
Department of Finance
Chihlee Institute of Technology
313, Sec. 1, Wunhua Rd.,
Banciao District
New Taipei City, 22050
Taiwan, R.O.C

ACCEPTANCE

Dear **Dr. Liou and Dr. Hsiao:**

Your paper titled "**How Sustainable is Sustained: The Latent Trajectory of Performance in Baking Industry**" submitted for consideration for The Global Business, MIS, Economics and Finance Research Conference, Tokyo has been processed utilizing a two person referee blind process and upon their recommendation your paper has been accepted for oral presentation at the conference and publication in the journal as a complementary. The Global Business, MIS, Economics and Finance Research Conference will be held at Conrad Tokyo in July 2014.

The conference, GMEF, does not provide any financial support in any way and you will be responsible for your own travel expenses including airfare, ground transportation, hotel, meals and travel insurance. Please note that this letter is not a confirmation of attendance as confirmation of registration is sent separately.

Thank you for making The Global Business, MIS, Economics and Finance Research Conference, Tokyo a vehicle for your research interests.

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KEYNOTE SPEAKER

Dr. Steven Taylor
Professor of Marketing
Illinois State University, IL

*

The Global Business, Management Information System, Economics and Finance Research Conference, Tokyo

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SCHEDULE FOR SPECIAL EVENTS

THURSDAY, JULY 24, 2014

Arrival and Independent Research Meetings in Tokyo

FRIDAY, JULY 25, 2014
8:00 AM – 4:30 PM Registration

FRIDAY, JULY 25, 2014
8:00 AM – 12:00 PM ***Management, Marketing, Business, Information Technology, Economics***
Room: Balcony **Session Chairs:** Dr. Steven A. Taylor, Dr. Agnieszka Zakrzewska, Dr. Estelle Pellegrin, Dr. Krystyna Kmiotek

Identifying the Goal Structures of Undergraduate Students Vis-à-vis Ethical Decision Making. #66
Dr. Steven A. Taylor, Hinderliter Chair of Business, Illinois State University, Normal, IL
Dr. Woojung Chang, Illinois State University, Normal, IL
Dr. Chiharu Ishida, Illinois State University, Normal, IL
Leyla Orudzheva, Illinois State University, Normal, IL
Aaron Barton, Illinois State University, Normal, IL

Coopetition? Yes, but Who With? The Selection of Coopetition Partners by High-Tech Firms.
Dr. Agnieszka Zakrzewska – Bielawska, Lodz University of Technology, Poland

Cooperation in Business Education: What about Trust? #213
Dr. Herve Chappert, ISEM – Universite Montpellier 1, France
Dr. Thuy Seran, ISEM – Universite Montpellier 1, France
Dr. Estelle Pellegrin, ISEM – Universite Montpellier 1, France

Generation Y Approach to Flexibility of Employment.
Dr. Krystyna Kmiotek, Rzeszow University of Technology, Poland

Hot Money and Stock Prices in China. #198
Dr. Ching-Yi Lin, National Tsing Hua University, Taiwan 30013
Dr. Ling Feng, Shanghai University of Finance and Economics, Shanghai, P.R. China
Dr. Chun Wang, Brooklyn College, CUNY, Brooklyn, NY

Gene Selection in Microarray Using Sequential Forward Selection Strategy. #164
Dr. Hung-Yi Lin, National Taichung University of Science and Technology, Taichung, Taiwan, ROC
Dr. Po-Hsun Hou, Taichung Veterans General Hospital, Taichung, Taiwan, ROC

Employment Volatility and Bank Lending in Taiwan. #170
Dr. Shu-hen Chiang, Chung-Yuan Christian University, Taiwan (ROC)

The Influence of Consumers' Mood Elicited by Website Context on Advertising Attention and Effect.
Dr. Chiung-Wen Hsu, Kaohsiung University of Applied Sciences, Kaohsiung, Taiwan, R.O.C.

Green Building Game for Innovative Education.
Dr. Yi-Kai Juan, National Taiwan University of Science and Technology (NTUST), Taipei, Taiwan
Tseng-Wei Chao, National Taiwan University of Science and Technology (NTUST), Taipei, Taiwan

An Imperialist Competitive Algorithm for Minimizing the Makespan of Overlapped Jobs over Multiple Machines.
Dr. Sheng-Chung Tu, Hungkuang University, Taiwan (R.O.C.)
Dr. Jen-Ya Wang, Hungkuang University, Taiwan (R.O.C.)

Minimizing the Makespan of Overlapped Jobs with Release Times over Multiple Machines.
Dr. Jen-Ya Wang, Hungkuang University, Taiwan (R.O.C.)
Dr. Jr-Shian Chen, Hungkuang University, Taiwan (R.O.C.)
Dr. Fuh-Gwo Chen, Hungkuang University, Taiwan (R.O.C.)

The Influence of Impulse Purchases and the Positive–Approach Effect on Emotional Accounting. #260
Dr. Chien Shu-Hua, Professor, National Taichung University of Science and Technology, Taichung, Taiwan
Dr. Wu Jyh-Jeng, Professor, National United University, Miaoli, Taiwan
Dr. Wang Chun-His, National Taichung University of Science and Technology, Taichung, Taiwan
Chin-Lin Chuang, National Yunlin University of Science and Technology and Southern Taiwan University of Science and Technology, Taiwan

Logistic Competitiveness and Export Performance: The Case of Myanmar Fresh Produce.
Dr. Hla Theingi, Assumption University, Thailand

A Study of Social Network Based Recruiting Service Design.
Dr. Pin-Rui Hwang, National United University, Taiwan, R.O.C.

Insider Trading Direction and Optional Wage Design.
Dr. A. Can (John) Inci, Bryant University, Smithfield, RI

How Sustainable is Sustained: The Latent Trajectory of Performance in Baking Industry.
Dr. Fen-may Liou, Chihlee Institute of Technology, Taiwan, R.O.C
Dr. Chin-Hui Hsiao, Chihlee Institute of Technology, Taiwan, R.O.C

FRIDAY, JULY 25, 2014
12:00 PM – 12:30 PM
Room: Balcony

KEYNOTE SPEAKER

Dr. Steven Taylor
Professor of Marketing
Illinois State University, IL

Steven Taylor is a Professor of Marketing who joined the faculty of Illinois State University in the Fall of 1992. He received his Ph.D. in Marketing from the Florida State University (1992). Prior to entering academics, Dr. Taylor enjoyed managerial experiences with the US Navy (seven years), as well as the drug screening, pharmaceutical sales, and hospital management industries.

Dr. Taylor's areas of expertise concern Services Marketing, Relationship Marketing, and eBusiness with an emphasis on how the service quality, value, satisfaction, and loyalty constructs operate in consumer models of judgment and decision making. Professor Taylor has published 50 refereed academic journal articles in his academic career to date across numerous journal outlets such as the Journal of Marketing, Journal of Service Research, Journal of Retailing, Journal of Service Management, British Journal of Social Psychology, Journal of Business Ethics, Journal of Insurance Issues, Journal of Product and Brand Management, International Journal of E-Business Research, among numerous others. He has also published many refereed proceedings and invited book chapters. Most recently, Dr. Taylor has focused on attitude-based models of human decision-making in consumer contexts, including a series of articles investigating digital piracy behaviors.

In addition to regularly serving as an ad hoc reviewer for numerous marketing journals, Dr. Taylor also recently served for a decade as the Co-Editor of the Journal of Consumer Satisfaction, Dissatisfaction & Complaining Behavior, currently serving as an Associate Editor for the journal since 2014. Dr. Taylor has also been a long-term member of the Editorial Review Boards of the Journal of Service Research (founding member) and the Journal of Service Management. He has consulted across a wide variety of industries, including recent projects for insurance, retail, health care, and manufacturing concerns.

Professor Taylor was recently named the Hinderliter Chair of Business (2012-2013). He has previously been honored with the Outstanding Reviewer for the Journal of Service Research (2007), Illinois State University Outstanding Researcher (2013), Mannehan College of Business Outstanding Teaching Award (2001), Illinois State University Teaching Initiative Award (1997), the Illinois State University Caterpillar Scholar (1998, 2003), the Illinois State University College of Business Outstanding Researcher Award (1997, 2009), the Wilma Jean Alexander Technology Innovation Award (1997), and the Illinois State University Research Initiative Award (1995). Dr. Taylor has been married to his wife Michel for 30 years, and they have three children.

****LUNCH FOR PRESENTERS AT THE HOTEL ****
For Presenters and paid non-presenters only (12:30 PM – 1:30 PM)

FRIDAY, JULY 25, 2014
1:30:00 PM – 2:00 PM
Room: Balcony

KEYNOTE SPEAKER

FRIDAY, JULY 25, 2014
2:00 PM – 7:45 PM ***Management, Business, Information Technology, Economics, & Human Resources***
Room: Balcony **Session Chairs:** Tim Raffour, Dr. Jian Wu, Dr. Ze'ev Shtudiner, Dr. Wojciech B. Cieslinski

Applications of Exotic Options in Corporate Finance: A Panorama. #238
Dr. Jian Wu, Professor of Finance, Neoma Business School – Rouen Campus, Mont-Saint-Aigna

Can China Overtake the U.S. As The Global Economic Leader?
Dr. Bala Maniam, Professor of Finance, Sam Houston State University, Huntsville, Texas

Religious Souvenirs from the Holy Land – Is there a Deadweight Loss?
Dr. Ze'ev Shtudiner, Ariel University, Israel
Prof. Jeffrey Kantor, Ariel University, Israel

The Influence of Organizational Trust upon Affective and Calculative Commitment. #205
Professor Dagmara Lewicka, AGH University of Science and Technology, Poland

Model of Network Thinking in Management of Knowledge Flow Processes in Sports Enterprises. #192
Professor Wojciech B. Cieslinski, University School of Physical Education in Wroclaw, Poland
Professor Andrzej Rokita, University School of Physical Education in Wroclaw, Poland
Dr. Piotr Głowicki, University School of Physical Education in Wroclaw, Poland
Dr. Iwona Chomiak-Orsa, Wroclaw University of Economics, Poland
Jakub Mierzynski, Wroclaw University of Economics, Poland

The Effect of Destination Image on Tourist Loyalty in Kinmen Battlefield Tourism: The Mediating Role of Tourist Satisfaction and the Moderating Roles of Tour Guide Interpretation Performance and Perceived Value #157
Dr. Nien-Te Kuo, National Kaohsiung University of Hospitality and Tourism
Dr. Kuo-Chien Chang, Chihlee Institute of Technology, New Taipei City, Taiwan (R.O.C.)
Dr. Hui-Hsiung Huang, Chia Nan University of Pharmacy and Science, Taiwan
Jui-Chou Lin, Ming Chung University, Taiwan

An Efficient Clustering Method Based on Cuckoo Search for XML Documents. #184
Dr. Tsui-Ping Chang, Ling Tung University, Taiwan, R.O.C.
Kun-Jheng Jhong, Ling Tung University, Taiwan, R.O.C.
Dr. Shih-Ying Chen, National Taichung University of Science and Technology, Taiwan, R.O.C

Manpower Need and Vocational Training of Electrical and Electronics Industry.
Dr. Fu-Man Hsieh, National Taipei University
En-Kuang (Daniell) Lin, Wenzao Ursuline University of Languages, Taiwan R.O.C.
Hsin-Yi Chou, Wenzao Ursuline University of Languages, Taiwan R.O.C.
Kung-Hou Lin, Wenzao Ursuline University of Languages, Taiwan R.O.C.
Nai-Chung Chang, Wenzao Ursuline University of Languages, Taiwan R.O.C.

Using Conjoint Analysis to Discover Guest Preferences and Willingness to Pay for Bed and Breakfast in Taitung.
Dr. Chen-Te Lin, Kang Ning University, Taiwan
Dr. I-Hua Lin, Taiwan ShouFu University, Taiwan
Yi-Tsun Ho, Chang Jung Christian University, Taiwan
Dr. Chen-Hsien Lin, Overseas Chinese University, Taiwan

The Training Requirements and the Curriculum Design of the Meridian Therapy Industry Employees- A Case of San-Sui Tang Company.
Dr. Fu-Man Hsieh, National Taipei University
Meng Chen Yu, Wenzao Ursuline University of Languages, Taiwan R.O.C.
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Chiao -Yi Chiu, Wenzao Ursuline University of Languages, Taiwan R.O.C.

IPR Competition between Asymmetric Countries.
Dr. Chia-Chi Wang, Tatung University, Taiwan

The Linkages of Network Relationship among the Systems of Nursing Homes.
Dr. Chun-Yao Tseng, Tunghai University, Taiwan
Dr. Sue-Ming Hsu, Tunghai University, Taiwan

Worldwide GINI: Models, Pitfalls and Trends.
Dr. Ayman Amer, Mount Mercy University, Cedar Rapids, IA
Dr. John Robeson, Mount Mercy University, Cedar Rapids, IA

Business Intelligence Tools to Analyze Data of Nursing Information System to Improve Clinical Quality of Care.
Dr. Nan-Chen Hsieh, National Taipei University of Nursing and Health Science, Taipei, Taiwan
Chen-Chang Lan, National Taipei University of Nursing and Health Science, Taipei, Taiwan

Testing for Export Performance Differential and FDI Externalities: A Firm Level Analysis of Thai Manufacturing Plants.
Chayanon Phucharoen, Chulalongkorn University, Bangkok, Thailand

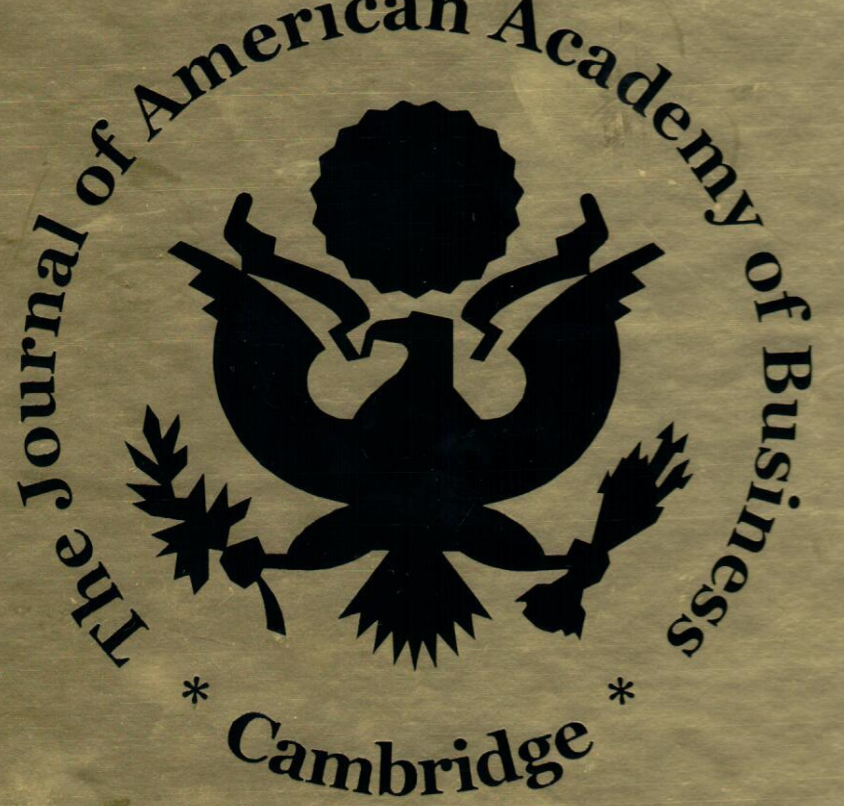
Is Corporate Governance a Moderator in the Relationship between Corruption and Economic Growth?
Tzu-Yun Tseng, Nien-Su Shih, Feng Chia University, Taiwan, ROC

The Global Business, MIS, Economics and Finance Research Conference, Tokyo - Research Scholars
Tim Raffour (CPA), Alcatel-Lucent Japan CFO, Tokyo, Japan

SATURDAY, July 26, 2014 and SUNDAY July 27, 2014

Independent Research Meetings in Tokyo, Japan

****HAVE A SAFE TRIP HOME! ****



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The Global Business, MIS, Economic and
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與研討會部分發表人合照

科技部補助計畫衍生研發成果推廣資料表

日期:2014/10/27

科技部補助計畫	計畫名稱: 熱手：績效是來自運氣還是能力?
	計畫主持人: 劉芬美
	計畫編號: 102-2410-H-263-008- 學門領域: 策略管理

無研發成果推廣資料

102 年度專題研究計畫研究成果彙整表

計畫主持人：劉芬美	計畫編號：102-2410-H-263-008-
計畫名稱：熱手：績效是來自運氣還是能力?	

成果項目			量化			單位	備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等）
			實際已達成數（被接受或已發表）	預期總達成數(含實際已達成數)	本計畫實際貢獻百分比		
國內	論文著作	期刊論文	0	0	100%	篇	
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		研討會論文	1	1	100%		
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（本國籍）	碩士生	1	1	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	7	7	100%		
國外	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	1	1	100%		
		專書	0	0	100%	章/本	
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（外國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		

其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)	撰寫論文投稿中。

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

科技部補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估

■達成目標

□未達成目標（請說明，以 100 字為限）

□實驗失敗

□因故實驗中斷

□其他原因

說明：

2. 研究成果在學術期刊發表或申請專利等情形：

論文：□已發表 □未發表之文稿 ■撰寫中 □無

專利：□已獲得 □申請中 ■無

技轉：□已技轉 □洽談中 ■無

其他：（以 100 字為限）

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限）

競爭優勢理論相關之實證研究中，如何區分管理相關因素創造之績效，或是由運氣帶來的績效，是驗證競爭優勢相關理論的重要議題。 S Strategic Management Journal 於 2004 年、2012 及 2013 年均刊登相關之研究論文。而據統計分析，產業間之廠商績效則為一厚尾之統計分配(Nicholas et al., 2012)。本研究首度將產業內之廠商績效視為一多母數母體，依據 Powell and Arrengel (2007)之主張，將廠商分為[成功]與[錯誤]兩軸競爭之次群體(subpopulations)，利用 latent class growth analysis 分成長期績效優及劣兩群，再分析[good luck]與[bad luck]驅動之績效。研究競爭優勢來源之研究，宜先排除運氣驅動之績效，再進行分析，以避免受到運氣因素之干擾，使研究結果更能反映實際狀況。