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Editorial

I have a pleasure to welcome you to issue number 44 of the *International Journal of Management and Economics*. This issue includes six papers covering very interesting research topics. The majority of papers are based on empirical research, both in economics and management. There are also other perspectives represented. The issue starts with a conceptual work and ends with a methodologically focused article.

The first article, "Capability Building and Learning: An Emergent Behavior Approach," is by Rafael Andreu, Josep Riverola, Josep Mª Rosanas, Rafael de Santiago. The research problem is grounded in a critique of conventional economic models with their assumptions suggesting that “firms have identical production functions, their efficiency improves at the same pace, and that managers are rational, have complete information, and maximize profits.” The authors abandon these conventional assumptions and determine how managers’ decisions “affect the time-wise performance of companies when firms can develop their own capabilities”. They are interested in the trade-offs between short and long-term objectives and the effect of different forms of learning and knowledge accumulation over time. They developed a model demonstrating the consequences of specific management decisions on the aggregate behavior of a population of firms. In this model, managers decide what projects to undertake, taking into consideration the fact that each of them will contribute differently to learning, capability building, and eventually to firm performance.

The second article, by Willem Molle, "Competitiveness, EMU and Cohesion Experiences in the Past (2000–2013); Assessment of the Present (2014–2020) and Lessons for the Future (2020 and Beyond)," is focused on highlighting the main issues in three EU policy fields: competitiveness, EMU, and cohesion. The author describes the past experiences in coping with inter-related problems within the EU (2000–2013), assesses the present situation (2014–2020), and develops two scenarios for post-2020 development (2020 and beyond).

The effects of firm size, competition, and access to finance on a firm’s innovation performance are explored by Zeina Alsharkas in the article “Firm Size, Competition, Financing and Innovation. The paper is based on the Business Environment and Enterprise Performance Survey (BEEPS). The data were analyzed to evaluate the Schumpeterian hypotheses on the relationship between competition, firm size, access to financing, and innovation behavior. Regressions for the three logit models using pooled time series analysis and the cross section analysis were applied. To address the endogeneity problem, the lagged values were used. Some research findings are in line with Schumpeter’s hypothesis, while some others coincide with Schumpeter’s predictions.
The fourth article – “Effect of Celebrity Endorsement in Advertising Activities by Product Type” – was written by Grzegorz Karasiewicz and Martyna Kowalczuk. The authors objective was to determine “the impact of a celebrity’s image on evaluation of the advertised product”. They used a quasi-experimental method involving four groups of university students. Four questionnaires illustrating four combinations of products (watches, juices) and endorsers (celebrity, model) were developed. The research was conducted through an online survey. Data analysis supported the major, final conclusion suggesting that “the use of celebrity endorsements is justified only in the case of those product categories where physical attractiveness and social status can be transferred onto brand attributes and thus strengthen the brand image”.

“Impact of Insurance Market on Economic Growth in Post-Transition Countries,” was researched by Jaba Phutkaradze. The author’s objective is to determine whether the development of an insurance market was related to economic growth in ten former transition countries over the 2000–2012 period. To test the hypothesis suggesting the positive relation between these two variables a multiple regression analysis and a fixed effect model were employed. The findings did not confirm the hypothesis, showing a negative and statistically non-significant correlation between insurance market and GDP growth.

The objective of the sixth article, “Validating DART Model”, by Jolanta Mazur and Piotr Zaborek, was to quantitatively test the DART model developed by Prahalad and Ramaswamy. This model focuses on company’ capabilities necessary to effectively work with customers. It specifies the four main building blocks or groups of competencies that companies should develop to effectively engage in value co-creation with customers, i.e., Dialog, Access, Risk Assessment, and Transparency. As the co-creation concept has so far been studied primarily using qualitative methods, the authors spotted a gap in its quantitative validation, which would test the model’s usability for survey research. A multiple measurement scale was developed and employed in interviewing managers of Polish SMEs. The statistical evidence for adequacy of the model was obtained through CFA with AMOS software. The findings suggest that the DART model may not be an accurate representation of co-creation practices in companies.

The current issue of the International Journal of Management and Economics is supplemented with the book review by Włodzimierz Januszakiewicz. The book ”International Competitiveness of the Economies of Belarus, Russia and Ukraine” was written by Krzysztof Falkowski.

At the end of this issue we present the list of the reviewers who assessed the submissions considered for publication in issue numbers 41, 42, 43 and 44. I would like to thank them very much for their time and expertise in keeping our academic standards high, which helps us to build our Journal’s reputation.

I hope that the variety of topics and research approaches applied in the articles will make the current issue interesting for the readers.
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### Capability Building and Learning: An Emergent Behavior Approach

#### Abstract

Economics-based models of firms typically overlook management acts and capability development. We propose a model that analyzes the aggregate behavior of a population of firms resulting from both specific management decisions and learning processes, that induce changes in companies’ capabilities. Decisions are made under imperfect information and bounded rationality, and managers may sacrifice short-term performance in exchange for qualitative outcomes that affect their firm's future potential. The proposed model provides a structured setting in which these issues –often discussed only informally– can be systematically analyzed through simulation, producing a variety of hard-to-anticipate emergent behaviors. Economic performance is quite sensitive to managers’ estimates of their firms’ capabilities, and companies willing to sacrifice short-run results for future potential appear to be more stable than the rest. Also, bounded rationality can produce chaotic dynamics reminiscent of real life situations.
**Introduction**

Conventional economic models assume that firms have identical production functions, that their efficiency improves at the same pace, and that managers are rational, have complete information and maximize profits. With these assumptions microeconomic theory shows that profit maximization (or, in modern terms, firm value maximization) also achieves maximum social welfare (see Jensen [2000] for a brief statement of this argument).

The profit maximization hypothesis has been severely criticized as being “too difficult, unrealistic and immoral” [Anthony, 1960], as have been formulations based on maximizing firm value. According to Senge, by maximizing profit in the short-run one is liable to ignore complex feedback dynamics. “This is why manipulating profits over the short-term is much easier than building wealth over the long-term. Thus, whether intentionally or not, firm value maximization will almost always become, by default, short-term profit maximization” [Senge, 2000]. Simon [1983] calls the maximizing approach “the Olympian model” that serves perhaps “as a model of the mind of God, but certainly not as a model of the mind of man.” Canals [2010] shows the limitations of the value maximization approach from the point of view of implementation and achievability. Jack Welch, who popularized the notion of shareholder value in the 1980s, said in 2009 that this was “a dumb idea” and that value maximization is “a result, not a strategy” [Welch, 2009]. Analysts have tried to take into account qualitative factors (such as quality and depth of management, or strategic credibility), but they recognize that “the information on strategic plans and planning provided by management is of generally low quality” [Chugh, Meador, 1984].

The need for a better approach to firms and their relationship with the environment is clearly felt, especially in a post-crisis world [Zollo, Freeman, 2010]. However, dropping economics-based assumptions to make models more realistic complicates the analysis and is seldom done, thus leaving management action out of the picture.

In this paper we depart from these conventional assumptions by analyzing how management decisions affect the time-wise performance of companies when firms can develop their own capabilities. By having a number of companies develop in parallel, we estimate their transient behavior. In our model, managers decide what projects to undertake, being aware that different projects will contribute in different ways to learning, capability building and, eventually, to firm performance. This allows us to explore in detail how management decisions affect the trade-off between short and long-term objectives (in a way reminiscent of the classical distinction between exploration and exploitation, cf. March [1991])
and the effect of different forms of learning and knowledge accumulation over time, both in firms and in management, as aggregate information about how projects contribute to the economy’s performance becomes “publicly available.”

The paper is organized as follows: section 2 highlights the model’s most relevant features (a formal description is presented in the appendices); section 3 describes the simulation strategy; and section 4 identifies several cases of emergent behavior. In section 5 we discuss the managerial implications of our finding and in section 6 our conclusions analyze the limitations of the model, and we put forward suggestions for further research.

Model Overview

Our model focuses on the evolution of a population of independent firms over an arbitrary number of time periods. Firms act and evolve driven by management decisions and learning. They should be considered a sample that allows population-based expectations to be computed when the system is not in a steady state. Firms have “profiles” determined by whether or not they possess certain capabilities. These profiles evolve over time as companies acquire or lose capabilities. At the beginning of each time period, and in all companies independently, firm managers chose which project to undertake. They do so with two potentially conflicting goals in mind: on the one hand, they seek economic results; on the other, they seek to develop a “better” profile for their firm, so that the firm is able to undertake more demanding projects in the future.

By “better” profiles we mean profiles that are more in line with managers’ preferences. This is done in the following way. Managers have their own preferences regarding the ideal type of firm they would eventually like to have. When deciding whether to accept a project, managers consider how the project fits the firm’s current profile and how undertaking such project could result in learning that will bring the firm closer to their ideal firm profile. Capability building has been discussed in the context of a resource-based view of the firm [Wernerfelt, 1984; Amit, Shoemaker, 1993; Barney, 1991; Dierickx, Cool, 1989; Teece et al., 1990], including the role of management in the learning process [Andreu, Ciborra, 1996]. Argawal and Helfat [2009] explain that capability development has enough potential “to substantially affect (a firm’s) long-term prospects”. The next section and the appendices describe how this is implemented.

To make the model more realistic, we include bounded rationality in managers’ decision-making process, as well as imperfect information. By bounded rationality we mean that when choosing projects, managers do not identify the project that is best in terms of their objectives but, rather, are satisfied when they find a project that is good enough. While an optimizing decision rule (evaluating all candidate projects and choosing the best) is at one extreme of the spectrum, choosing the first project that comes in is at the
other extreme. By setting an acceptance threshold, we control how demanding (i.e., how close to optimizing) managers are.

The imperfect information assumption is modeled in the following, twofold way:

1) Managers do not have perfect knowledge of the actual capabilities (the true profile) of their own firms. (This captures the idea that it is hard to know the true state of an organization.) Instead, managers have a prior probability distribution over all possible profiles, which is updated as managers observe company results. For instance, managers may choose to undertake a project because they think the company has some capability; once they see the project’s results, however, they may realize that the firm probably did not have that capability. This leads managers to update their beliefs about the company’s profile.

2) Managers’ imperfect knowledge (regarding how likely the firm is to achieve economic success when undertaking a project) is modeled through probability distributions estimated from aggregate information available in the sample.

Treating the dynamic evolution of a firm under the above conditions analytically is very complicated. Most well-known tools are inadequate for this purpose. We therefore resort to simulation techniques to systematically explore the model’s transient behavior. Simulation has been successfully used in management research and economic dynamics, for example, by Davis, et al. [2007, 2009], Harrison, et al. [2007], Gilbert [2008], Miller and Page [2007], and Coen and Maritan [2011].

One characteristic of the resulting model is that the interplay between capability building, learning, bounded rationality and uncertainty results in difficult-to-anticipate “emergent behavior” in which transient phenomena are often more informative than the final state achieved by the economy. Emergent behavior happens when simple rules can expand into sophisticated behavior that cannot be attributed to any individual agent, but rather to the system’s structure. It appears when a number of agents interact with each other without a central planner and generate complex conducts that are not explicitly “programmed” in simple rules. Emergent behavior is hard to predict because the number of interactions increases in a combinatorial way with the number of agents, often making it impossible, even for a computer, to exhaustively examine all the potential states of the system, thus allowing unexpected types of behavior to emerge [see, for example, Gilbert, 2008].

The remainder of this section describes how the model actually works.

**Firm Profiles**

We characterize firms according to whether they have, or lack, a set of capabilities that consists of Unity (U), Attractiveness (A) and Effectiveness (E). In the model’s current implementation the only conceptual difference between U, A and E is that we impose a “probabilistic hierarchy” on them, meaning that U is harder to develop (to learn) than A, which is in turn harder to develop than E. Also, U may be more easily lost than A, which may be more easily lost than E (see Appendix 1).
We thus denote a firm's profile by the triplet \( (U, A, E) \), where the variables \( U \), \( A \), and \( E \) indicate whether the firm has the related capability or not. If it does, the variable is set to 1, and if it does not the variable is set to 0. For example, profile \( (0,1,1) \) indicates that the company has attractiveness and effectiveness but lacks unity.

We use all-or-nothing levels for these capabilities for several reasons. First, subdividing a single level into \( N \) levels seems to lead to very similar behavior. Second, using \( N \) levels requires the specification of a transition law, with at least \( N \) times more probabilities. Finally, the abstract nature of the capabilities makes it difficult to characterize each level in terms of its properties, and therefore in terms of its transition probabilities. It is easy to split a single transition probability into \( N \) parts, but it does not add much. We therefore prefer the binary characterization.

While carrying out a project, a company's profile may change as a result of learning. If at the beginning of period \( t \) a company's profile is \( (1,0,1) \) and by period \( t+1 \) its new profile is \( (1,1,1) \), this means that it has gained attractiveness. If, instead, the new profile is \( (0,0,1) \), the company has lost unity. If the new profile is unchanged \( (1,0,1) \), no learning has occurred. Below we explain in more detail how profile changes are modeled.\(^2\)

**Project Types**

Project types are specified in terms of the same three capabilities as company profiles, and are also represented as \( (U, A, E) \) triplets. The fact that a project type requires a particular capability is to be understood in two complementary ways. First, a firm that has a capability required for a particular project type has a better chance of succeeding in that project type than a firm that lacks it. Second, a firm that lacks a capability required for a particular project type but undertakes that type of project may acquire such capability; conversely, a company that has a particular capability may maintain that capability even when undertaking a project for which the capability is not required.

The learning process that leads to changes in a company’s profile is therefore probabilistic. For example, if a firm has a \( (0,0,1) \) profile and its managers would like to develop attractiveness and unity, they can try to do so by choosing a project that requires such capabilities—a \( (1, 1, 1) \) project, say—hoping that, in the process of carrying out the project, workers will learn. We set the probabilities according to the above mentioned “probabilistic hierarchy” (i.e., setting the probability of learning Effectiveness higher than that of acquiring Attractiveness, and the probability of learning Attractiveness higher than that of acquiring Unity). Also, since we assume Unity to be easier to lose than Attractiveness, we also set those probabilities accordingly. A detailed account of how this is done in terms of the model parameters is given in Appendix 1.

**Project Evaluation**

Managers use two criteria to evaluate and choose projects. On the one hand, they consider a project’s economic value. This is a rational, short-term, purely financial criterion.
As a proxy we use the project’s probability of success. Note that success coincides with the expected return if we assume, without loss of generality, that every project has a unit margin.

On the other hand, managers consider capabilities as an intangible asset which, if developed, will enable the company to succeed in projects that otherwise it could not have succeeded in. Trying to develop capabilities is a long-run oriented, aspirational criterion in the sense that it depends on the type of company managers aspire to have in the future.

Generally speaking, managers are interested in developing capabilities through learning because it gives their companies a better chance of future success. If developing capabilities requires giving up short-term objectives in order to make long-term goals more likely, there will be trade-offs.

Given a specific project, we model these trade-offs as follows. Based on managers’ estimates, we compute: (i) a proxy for the probability that the company will succeed in the project; and (ii) a proxy for the probability that the company will acquire or maintain (through learning) each capability. See Appendix 2 for details.

We then combine these two proxies linearly, as depicted in Figure 1, where the parameter $\alpha$ (a value between 0 and 1) which we call “Sacrifice,” is the weight assigned to the proxy that accounts for the learning potential. The closer $\alpha$ is to 1, the more willing managers are to forego immediate performance in order to develop future capabilities. When $\alpha$ is zero, managers try to maximize financial results only.3

**FIGURE 1. Project evaluation procedure**

![Diagram](source: own elaboration)

**Project Selection**

An important feature of the model is that managers choose projects with bounded rationality. There are many ways of implementing bounded rationality [Rubinstein, 1998]. Perhaps the simplest one is Simon’s [1955] original formulation, schematically depicted in Figure 2, where bounded rationality is implemented by setting a threshold for the project’s value. There is no need, therefore, to evaluate all projects; the first one that exceeds the threshold is selected. The order in which a firm evaluates projects is important for the firm’s development. Initially, we have chosen a random order. (Changing it, however, has been included as an option in the current implementation).
Influence of Projects on Firms’ Learning

One of the consequences of executing a project is that the firm's profile may change (the firm learns). In order to avoid simple deterministic patterns, we assume that management decisions do not necessarily lead to the same results, even if they take place at the same moment in time and in the same place.\(^4\)

We thus assume that firm profiles evolve through probabilistic transitions. Figure 3 summarizes the logic of the corresponding probabilities for the case of Attractiveness (the logic is analogous for the other two capabilities). Part (a) illustrates how transitions
occur if the chosen project has Attractiveness; part (b) shows the transitions when the project does not have it.

Thus, as Figure 3 (a) shows, if a firm with a certain capability undertakes a project that also has that attribute, the firm maintains the capability with probability 1 (no change). If a firm without that capability undertakes such a project, it will develop the capability with probability \( \lambda_A \), or not develop it with probability \( 1 - \lambda_A \). (The equivalent probability for Effectiveness is named \( \lambda_E \), and for Unity \( \lambda_U \)).

Conversely, in Figure 3 (b), if a firm that lacks a certain capability undertakes a project that lacks that capability, the company will continue to lack the capability with probability 1. If a firm that has a certain capability undertakes a project that does not have it, the firm will lose that capability with probability \( \mu_A \) or keep it with probability \( 1 - \mu_A \). As above, \( \mu_E \) and \( \mu_U \) are the corresponding probabilities for Effectiveness and Unity.

Further learning in the model takes place in the following two areas:

1) Managers learn about the success potential of different projects when undertaken by firms with different profiles by observing the aggregate information regarding past performance that becomes available.

2) Managers refine their (imperfect) knowledge about the true profiles of their companies using success information about the projects they have undertaken.

The first type of learning is an example of “rote learning”, which is the simple accumulation of information directly from the environment. The second type may be called “reasoned or logical learning” and it is based on the ability to change one’s beliefs about the world as observations are collected, interpreted and assimilated.

Rote learning [Klein, 1996] follows from simple observation of a random phenomenon, even if its probabilistic structure is unknown. We implement it by means of a neural network [Haykin, 2009]. We thus assume that the “brain” of the decision maker can be modeled as a neural network that estimates the success probability of different projects by observing a series of real world successes and failures.

Logical learning is implemented in the model by successively updating managers’ prior probability distributions over profiles, using Bayes’ Rule (see Appendix 2). We thus assume that managers can change their initial beliefs by observing information. Although a manager may not know how to apply Bayes’ rule explicitly, it has been shown that quick and dirty reasoning based on logical Bayes-like rules is often used to anticipate the value of a random phenomenon [Pearl, 1998].
Simulation Structure and Strategy of Analysis

This section presents the structure of the discrete-time simulation program that we have developed for experimenting with the model described above. An overview of its structure is depicted in Figure 4.

FIGURE 4. Overall structure of the simulation program

The initial step requires the modeler to: (i) set the value of the basic parameters that will remain unchanged throughout the simulation, such as the transition probabilities $\lambda$ and $\mu$, the threshold, and the sacrifice parameter $\alpha$; and (ii) provide the parameters to generate a number of firms, each endowed with a set of capabilities, managers’ preferences, managers’ initial knowledge about the true profile of their own firm, and so on.

At each discrete step each firm selects a project and then executes it. Next, the results (success or failure, and the effect on each firm’s profile) are collected. These results are used
to update: (i) managers’ knowledge about the true profile of their firms; and (ii) estimates of the success probabilities of the different projects.

The process is repeated for the number of periods set by the modeler. As time goes by, the program shows the changes in firms’ profiles and the changes in the number of successful projects.

**Strategy**

In the simulation literature models are used in different ways, depending on the type of experiments designed by the modeler. There are three main approaches:

1) *The discovery of behavior.* In this approach the model is used to observe a small set of trajectories, aiming to identify their main behavioral characteristics. The basic idea is that simple models often present complicated behavior that is difficult to anticipate from the models’ structure. A close scrutiny of behavior is therefore key for the analysis. This is a complicated approach because trajectories are functions, not values, meaning that the observed effects are functional behaviors which are not easy to detect with present-day observation techniques. This approach has been promoted and used mainly by the Santa Fe group [Gilbert, 2008].

2) *The response surface approach.* This is a classical approach that does not focus on trajectories, but rather on certain parameters of the results. A steady state is typically assumed to exist and to closely represent the state of affairs. This approach is widely used (see, for instance, Wagner [1995]) because it is simple to implement. It is just a matter of running a large number of scenarios and using appropriate statistical techniques to build a response surface for the desired parameters. No emergent behavior can be discovered with this approach, which is plagued with technical problems (lack of smoothness of the response function, presence of catastrophic behavior, and even difficulties with statistical techniques).

3) *The analysis of purposeful behavior.* This approach is a combination of the previous two. It allows the modeler to carry out a multi-parameter simulation and introduce properties of the trajectories in the model (by means of some sort of “optimization”, so that a large number of non-optimal states can be quickly discarded). Once an optimal behavior has been identified, by analyzing its neighborhood one can concentrate on the properties of the optimal trajectory. This is “Simulation Optimization” [Gosavi, 2010].

Approaches 2 and 3 implicitly assume that a good grasp of the model’s plausible behavior is at hand, which is not true in our case even after having conducted a theoretical analysis of it. In this work, therefore, we have taken the first approach.

**Baseline Parameters**

In the analysis of the model that follows, we concentrate on two parameters: the “degree of sacrifice” (represented by α); and the “threshold” (represented by T).
The sacrifice $\alpha$ represents the importance that managers attach to the long-run. As already mentioned, it gives an indication of how willing managers are to forego immediate results in order to develop capabilities for the future.

The threshold $T$ represents the satisficing level related with bounded rationality. It is also a number between 0 and 1. The larger the value of $T$, the more demanding managers will be in terms of project selection. If $T=0$, managers will choose the first project they come across; if $T=1$, managers will optimize by evaluating all projects and choosing the best one.

As both parameters lie between 0 and 1, we explore the effects of different pairs of values ($\alpha, T$) on the unit square. We start with an initial population of $N=1,000$ companies, which interact for at least 300 periods. We assume that all projects take one period to be completed, that they have the same economic value and that they require the same investment. As a consequence, the number of successful projects in a simulation round is a measure of the aggregate economic value generated by the firms.

We observe the evolution of the economy by looking at the distribution of company profiles. Note that there are seven meaningful types of firms, namely, $(0,0,1)$, $(0,1,0)$, $(1,0,0)$, $(0,1,1)$, $(1,1,0)$, $(1,0,1)$, and $(1,1,1)$. Profile $(0,0,0)$ is not meaningful for obvious reasons, as it would imply a firm with no capabilities at all. It could be included for completeness, but its interpretation would be awkward. At each time step we keep track of the proportion of companies with each profile, and we plot the corresponding trajectories.

At the end of each round, the distribution of company profiles is an indicator of the economy's capacity to successfully tackle more challenging projects in the future. As companies with a $(1,1,1)$ profile have the highest capacity to successfully undertake future projects, the reference point in measuring an economy's potential is typically the proportion of type $(1,1,1)$ companies.

For simplicity we make the following additional assumptions in our analysis.\(^{10}\)

1) The initial distribution of firms is uniform;
2) All management teams have the same preferences regarding the type of profile they would like to have in the future;
3) All management teams have the same prior probability distributions, representing the same initial perception about the true profile of their own firms.

Firm profiles change from period to period according to the transition probabilities $\lambda_E$, $\lambda_A$, $\lambda_U$, and $\mu_E$, $\mu_A$, $\mu_U$, introduced in the previous section. We assume that these probabilities are the same for all companies (they are set by the market environment). In what follows, we use the following values for the transition probabilities:

$$\lambda_U = 0.3, \lambda_A = 0.2, \lambda_E = 0.1;$$
$$\mu_U = 0.7, \mu_A = 0.8, \mu_E = 0.9.$$
Types of Behavior

In general the model is monotonous in the sense that (1,1,1) dominates all other states. Therefore, it seems that all companies should have trajectories that attain (1,1,1) as fast as possible and stay there forever. Surprisingly, this is not quite true.

By running multiple simulations for different values of $\alpha$ and $T$, we have identified three main types of behavior, which we call selective, diffusive and catastrophic.

Selective Behavior

This type of behavior is the behavior to be expected given monotonicity. It is characterized by profiles “disappearing” one by one, from the total population until a profile emerges as the winner. The typical winner is profile (1,1,1), meaning that all companies become excellent. An example of this behavior can be found in Figure 5, obtained for $\alpha=0.1$, $T=0.9$.

These parameter values mean, first, that firms are not willing to forego immediate results (with $\alpha=0.1$, managers evaluate projects by mainly taking into account immediate financial performance). At the same time, firms are rather demanding as to the kind of projects they choose (with $T=0.9$, they pick projects in an almost optimizing way). As can be seen in Figure 5 (a), the population of firms is quickly dominated by the (1,1,1) profile. In part (b) of the same figure we show the evolution of performance, measured by the number of successful projects. The proportion of successful projects gets to 100% because (1,1,1) firms can undertake any type of project successfully. We say that (1,1,1) companies are selected from the population, hence the name given to this type of behavior.

Selective behavior is a type of “Darwinian behavior” in which the fittest profile, namely (1,1,1), sweeps all others away. An additional characteristic of these trajectories is their low level of randomness (the variance at each point of time).

Not surprisingly, by swapping the values of $\alpha$ and $T$ we obtain the same type of behavior (see Figure 6, where $\alpha=0.9$ and $T=0.1$). In this case, firms do not optimize much in terms of project selection, but they are quite willing to forego short-term performance in exchange for future potential. If we plot all possible combinations ($\alpha,T$) in a unit square (see Figure 11), we can see that points above the downward sloping diagonal have selective behavior.

By observing the decisions that managers make at each iteration we can, in fact, see the strong dominating properties of the (1,1,1) profile, which quickly starts creating a cluster of companies of the same type.
FIGURE 5. Selective behavior \((\alpha=0.1, T=0.9)\)

Source: own elaboration.

FIGURE 6. Selective behavior \((\alpha=0.9, T=0.1)\)

Source: own elaboration.
Diffusive Behavior

In diffusive behavior the proportions of each company type stabilize after an initial transient period. As can be seen in Figure 7, no profile disappears. Diffusive behavior emerges when the degree of sacrifice ($\alpha$) and the threshold ($T$) are below the downward sloping diagonal of the unit square (Figure 11). In the particular case of our current example (Figure 7), firms that only have efficiency and lack the other two capabilities (i.e., type (0,0,1)) end up being around 40% of the population. Firms of type (0,1,0) end at 25% of the total. The proportion of firms in each profile fluctuates in the long run, never reaching a steady state, an effect that seems to be due to the learning process. In general, these trajectories look like sample paths of diffusion processes, hence the name.

FIGURE 7. Diffusive behavior ($\alpha=0$, $T=0$)

As time increases, profiles coexist in regular (and roughly cyclical) proportions. A limiting distribution for profile types does not exist in a simple sense. No complete extinction takes place, all profiles coexisting in roughly constant proportions. In graph (b) we see that about 43% of the projects are successful.

Figure 7 represents an extreme case because $T=0$ means that managers accept the first project they come across (i.e., they choose projects randomly), and $\alpha=0$ means that managers are completely unwilling to forego immediate results in order to develop better firms for the future. With these values of ($\alpha$, $T$), the model translates into a Markov...
Decision Problem [Sobel, 1993], which can be solved analytically. The solution is in close agreement with the simulation. Note that companies with a (1,1,1) profile represent only 1% of the population.

If the value of T increases while keeping $\alpha$ constant, a sort of selective behavior appears during the first periods before settling into a diffusive pattern (see Figure 8 below). In this figure, the proportion of (1,1,1) companies increases to 72% during the initial periods and then declines, showing the typical pattern of diffusive behavior in the long run. As the value of T gets closer to 1, the drop in the proportion of (1,1,1) companies takes longer to happen.

FIGURE 8. Diffusive behavior ($\alpha$=0.5, $T$=0.43)

Catastrophic Behavior

Figure 8 hints at a third type of behavior that is more interesting than the previous ones. We call it catastrophic because it is represented by sudden drops in the proportions of certain company types, as in Figure 9 ($\alpha=0.72; T=0.275$). This behavior occurs for a range of parameters clustered in a seemingly irregular band around the downward sloping diagonal of the unit square, where $\alpha+T=1$.

During a long initial phase, all companies become (1,1,1) and performance is optimal, with 100% of successful projects. After that, the proportion of (1,1,1) companies suddenly
falls to almost 20%, and remains there for another long phase, after which the behavior turns into a diffusive pattern, with a majority of type (1,0,0) companies. The overall performance after the sudden drop falls to approximately 60% (part (b) of the figure).

**FIGURE 9.** Catastrophic behavior ($\alpha=0.72$, $T=0.275$)

Analogous behaviors result from different combinations of values ($\alpha,T$). When we increase the value of $T$ for a given value of $\alpha$, the general behavior is roughly the same (although the shapes of the trajectories are different). This phenomenon illustrates some interesting features, such as the importance of the transient periods that precede stability, as well as the appearance of catastrophic drastic changes in the composition of the firm population.

A simple, approximate explanation of this catastrophic behavior is as follows. First, in a world where all companies are (1,1,1), project success gives managers little additional information, because if all companies are (1,1,1), all projects will be successful with probability 1. Mistakes may occur, however, when managers select projects under bounded rationality, which will result in negative learning. When $T$ is small, for instance, project selection is more random, which may lead some managers to choose inferior projects. Once this happens, the imitation effect produced by a relatively high value of $\alpha$ sweeps through the entire population. The “ideal” world is over and one returns to a messy, diffusive behavior. This is a variety of the story in which a butterfly flapping its wings...
in Japan can cause a hurricane in California. These arguments can be made rigorous in the mathematical sense under strong restrictions.\textsuperscript{14}

FIGURE 10. **Catastrophic behavior** ($\alpha=0.61$, $T=0.385$)

To further illustrate this outcome, Figure 10 depicts another situation with a different transient evolution. As one can see in the upper part of the graph, the proportion of (1,1,1) companies goes up to 100% and remains there for a long period. A first catastrophe occurs around period 900, and a second one around period 1300. The first catastrophe almost eliminates all (1,1,1) firms, while the second one cuts down the number of (1,1,0) firms. The causes of such behavior are not straightforward.

The results of the simulation experiments are summarized in Figure 11 below, which shows the tessellation of the unit square. The combinations of $\alpha$ and $T$ are roughly divided into two triangles, labeled with the dominant behavior that is displayed in each one. The two triangles are separated by a thin set of catastrophic behavior, marking the transition from the diffusive to the selective areas. The selective area is more homogeneous than diffusive one. In almost all experiments performed, moving around the selective area results in behaviors that look alike.
Managerial Implications

Below we summarize several insights that emerge from our work with the model.

1) First of all, in a complex situation, intuition cannot predict the evolution of a single company. Quick estimates based on a general (qualitative) appraisal of capabilities may lead to the wrong conclusion. In real life, the probability of surviving a catastrophe such as those produced in the model is near zero. Therefore, after a chaotic period many companies will not survive. And, surprisingly, the crisis could be caused by logical changes in the mental attitudes of managers.

2) Performance seems to be very sensitive to managers' estimates about the true profile of their own company. Even companies with a (1,1,1) profile can be very unstable if their management has a distorted knowledge of their profile. This sounds like common sense, but the model offers an additional insight. Initially, the manager has a prior on the company’s profile; unless this prior is concentrated around the true profile, the prior distribution will give weight to other profiles. Because managers make their decisions based on expectations, an erroneous prior (which could be due to fluctuations in learning) may lead managers to make wrong estimates about the expected value of the available projects and, therefore, to choose projects that are only second-best (or worse). This would give a positive probability of losing capabilities. Once lost, capabilities are difficult to recover, thus reducing the probability of the (1,1,1) state. When managers consider only Effectiveness, ignoring Attractiveness and Unity, things get worse. From all this we conclude that stability is highly dependent on managers’ ability to estimate the true profile of their companies. The old Greek aphorism “Know
Thyself “is crucial for success, but it has a consequence that is not at all trivial: if you seek only efficiency, your future looks bleak.

3) The recipe for an economy’s (or company’s) success is to keep both $\alpha$ and $T$ large. Companies that are willing to accept sacrifices in the short-run in order to increase future potential (high $\alpha$) and, at the same time, try to follow a more rational decision-making process (high $T$) appear to be more stable than others. The attitude of such companies makes them more likely to succeed in more projects. This is a golden rule, which requires a certain lack of short-term greed and a degree of trust within the company structure.¹

4) In addition, the analysis provides clues on how to change attitudes. Imagine a company that changes its managing team because it wants to evolve from a greedy, profit-oriented firm to a future-oriented one (i.e., from the Diffusive zone to the Selective zone). Our analysis recommends doing this as fast as possible because “crossing the diagonal” is dangerous and should be done quickly. Managers should be prepared to see peculiar behavior that could discourage the attempted change, pushing them back into the Diffusive zone. Once in the Selective zone, the company still has a substantial probability of failing; but long-run profitability requires that they cross over. Companies could thus be trapped in a paradox that is difficult to solve.

5) Being persistent in choosing (1,1,1) projects seems a good recommendation, even if the projects’ success probability is not that high or the cost of choosing them is large. Type (1,1,1) projects help managers develop their employees, giving the company the opportunity to reach a (1,1,1) profile. If this is achieved, the company could undertake a greater number of challenging projects and could remain optimal. Suppose that, at a given stage, type (1,1,1) companies abound and that a given firm, by an “imitation effect” would like to imitate the leaders. What happens if that company is not (1,1,1)? By the imitation effect, it will tend to select (1,1,1) projects and will therefore experience failures. If after a few mistakes managers become “demoralized” and think that (1,1,1) projects are too complex for their company, they will never achieve excellence. Thus, unless managers have an accurate knowledge of their company’s profile, a blind tendency to “follow the leader” runs the risk of overreaching.

Limitations and Further Work

We have presented a model that simulates the aggregate behavior of a population of firms resulting from specific management decisions. The model features a learning process that produces changes in company capabilities. Decisions are made under bounded rationality (satisficing behavior), and managers can sacrifice short-term performance
in exchange for qualitative variables that affect their firms’ future potential. The model provides a structured setting in which these issues can be rigorously analyzed.

Another relevant feature of our approach is that it illustrates how a complicated process of enterprise evolution based on managers’ attitudes and values can be modeled. A fairly simple and parsimonious description of reality leads to emergent behaviors that provide scope for the analysis of feedback phenomena involving learning.

We believe that the model includes the minimum number of features necessary to characterize learning enterprises. We have tried to simplify the model by removing some of the features, but this quickly brings it into well known, simple behavior. The model shows that features like learning, bounded rationality, concern for others’ welfare, uncertainty and so on, can be modeled and analyzed simultaneously. No harm arises from this and the explanatory power of the model increases noticeably. All this comes at the price of relying on simulation for the analysis, which to some extent decreases understanding of the deep relationships in the system. Even so, we believe it is important to shed light on transient behaviors.

Bounded rationality plays an important role in the results obtained. Without it, the optimal behavior would quickly converge to (1,1,1) profiles, which would consistently dominate the others. Although the model has proved useful for exploring a series of relevant phenomena, it also has a number of limitations that are worth pointing out.

1) One difficulty stems from the fact that, in the model’s current form, it is not easy to anticipate the behavior that will result from specific parameter values, other than in terms of the approximate tessellation shown in Figure 11. The only safe way to learn about behavior is by running the model and observing the outcome. There is work to be done in order to explain behavior as the logical consequence of the processes underlying the model dynamics.

2) It is difficult to interpret the meaning of specific parameter values (what is the meaning, for example, of an increase in the threshold from T=0.2 to 0.4?) In its current form, the model essentially performs “qualitative simulation” [Kuipers, 1994], which may provide qualitative insights into the consequences of learning, decision making, etc. but not clear, measurable results.

Regarding future research there are at least five main areas for further work.

1) Understanding better the effects of changes in the parameters that define the environment: transition probabilities, characteristics of the pool of projects, probabilities of project success, initial distribution of firms’ profiles, manager preferences, and different prior distributions.

2) Explore the effect of heterogeneous groups of firms (until now we have only studied the evolution of homogeneous groups) by allowing firms with a given number of failures to go bankrupt and disappear; and exploring different implementations of bounded rationality (for example, by using “bounded evaluation capability”).
3) Explore the “unavoidable” character of learning. With the present formulation of the model and due to bounded rationality, any firm may learn as a consequence of undertaking projects that do not exactly match their profile. There could be firms, however, that decide not to learn (and to collect short-term financial results). Although these could find appropriate projects, this is an option that the model does not currently consider.

4) Allow more than one economy in an “international” setting, and explore the results of different management decisions. For example, more advanced economies could generate more and more demanding projects that firms in other economies would not be able to undertake with the same probability of success, thus unveiling a need for change in management practices in underperforming economies.

5) Investigate a more advanced characterization of the difference between capability types, as suggested in Appendix 1. The idea is to compute the probabilistic hierarchy out of the dynamic evolution of Unity, Attractiveness and Effectiveness suggested by motivation and other human resources theories.

Appendix 1. Capabilities Names and Transition Probabilities

As indicated in Section 2, in our model the capabilities that define a firm’s profile are called Effectiveness (E), Attractiveness (A), and Unity (U). The reason for choosing these names is that we plan to continue working on a more elaborate capability scheme, which will better describe the capability development process, giving the capabilities a more specific meaning and thus depicting a richer development process closer to the actual learning dynamics in organizations.

Our plan is to work with the following specific capabilities: Effectiveness (E), defined as the degree to which a company is able to achieve measurable (typically financial) results; Attractiveness (A), or the degree to which employees develop professionally and enjoy their jobs; and Unity (U), or the degree to which employees identify with the organization’s goals and values, as well as with other members of the organization. (See Pérez López [1993] and Rosanas [2008]).

To give some indication of what we have in mind for the future, we conceive these capabilities as originating in the different types of motivation a person may have. The distinction between “intrinsic” and “extrinsic” motives comes from the literature of the ’50s and ’60s. (See, for example, Saleh, Hyde [1969] and Lawler [1969]). More recently, Ryan and Deci [2000] and Lindenberg [2001] distinguish between “intrinsic motivation, which refers to doing something because it is inherently interesting or enjoyable, and extrinsic motivation, which refers to doing something because it leads to a separable outcome”. Frey [1998], Osterlo and Frey [2003] and Gottschalg and Zollo [2007] consider that intrinsic
motivation may have a hedonic component of “enjoyment”, while at the same time there is a normative intrinsic motivation out of a sense of “obligation”.

Our approach will parallel the above distinctions, with the additional notion that obligation may also be enjoyable (this is the case, for example, when we do something we dislike in itself, not because it is an obligation but rather because we are happy to satisfy someone else’s needs). This is what Perez López [1993] and Rosanas [2008] call “transcendent” motives.

Simon [1997] notes that the constituency that predominantly has a direct interest in the firm’s objectives are the firm’s customers, whereas employees are directly interested in the rewards offered by the firm, both tangible and intangible, extrinsic and intrinsic. For employees to really pursue the firm’s objectives, they must identify with them [Simon, 1997]. What we call Unity (identification of the organization’s members with the organization’s objectives) is essential for the firm’s survival in the future and is based on transcendent motives.

The three capabilities are interrelated. For instance, attractiveness plays an important role in obtaining the desired output, although it may sometimes shift attention to the satisfaction of employee needs, rather than customer’s needs. At the same time, effectiveness will be important in satisfying extrinsic motives. Several authors have recently touched upon some of these aspects from different perspectives. Giancola [2001] discusses issues close to the notion of attractiveness. The arguments of Shuck and Wollard [2010], Choi and Wang [2009] and Hekman et al. [2009] are reminiscent of our concept of unity.

For the purposes of this paper, though, we treat E, A, U capabilities in a much simpler way, though consistent with the meanings stated above. Changes in firm profile (i.e., changes in a firm’s capabilities) are modeled in a probabilistic way, which in terms of the model parameters is described in Figure 3. In order to make the corresponding probabilities consistent with the assumptions discussed above, we set the following constraints on probabilities \( \lambda \) and \( \mu \).

**TABLE A 1.1. Constraints on probabilities \( \lambda \) and \( \mu \)**

\[
\begin{align*}
\lambda_U & < \mu_U \\
\land & \\
\lambda_A & < \mu_U \\
\land & \\
\lambda_E & < \mu_U
\end{align*}
\]

Source: own elaboration.

The columns indicate that acquiring Unity is harder (less likely) than acquiring Attractiveness, which in turn is harder than acquiring Effectiveness. Also, Unity can be more
easily lost than Attractiveness, which in turn is more likely to be lost than Effectiveness. Horizontally, the table reads that we assume it to be harder to acquire a capability (learning) than to lose one (unlearning).

Appendix 2. Formal Model Structure

We use the letter $x$ to designate a generic firm, $x = (x_1, x_2, x_3)$, with the three basic capabilities ($x_1$ represents unity, $x_2$ represents attractiveness, and $x_3$ represents effectiveness). The “state of the economy” can then be described by the number of companies of each type. Projects are also characterized in terms of unity, attractiveness, and effectiveness, and are represented by $y = (y_1, y_2, y_3)$.

Each management team has preferences regarding the type of company they would like to have in the future. These preferences are described by

$$\gamma = (\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6, \gamma_7),$$

where each component represents the relative importance that managers assign to each of the seven company types. The values of these parameters remain fixed throughout successive rounds.

Managers have uncertainty regarding:
1) The company’s actual profile;
2) Whether a certain project will succeed if undertaken by a given firm; and
3) A project’s potential to develop a particular capability if a given firm were to undertake that project.

We assume that managers allocate their time, resources, and efforts in such a way that the results satisfice (but do not necessarily maximize) managers’ goals, and that managers are willing to forego short-term results in exchange for learning and future potential. While the target profile remains fixed throughout the simulations, the knowledge mentioned in (1) and (2) above may evolve through time, so that companies and managers can and do learn $\gamma$. Managers learn about their own company type, but they also learn about the success probability of each type of project.

The process by which managers select projects depends on three elements: the type of company they would like to be in the future; the (incomplete) knowledge they have about the company’s profile, which is updated along the way; and the (incomplete) knowledge they have about the success probability of a project, which also is updated along the way.
Updating Managers’ Knowledge About Their Own Company’s Profile

A key element of the model is the way in which managers form their beliefs about the profile of their own company. Because managers do not know the true profile, they have a prior probability distribution \( \pi \), defined as follows:

\[
\pi(x) = \pi(x_1, x_2, x_3) = P(\text{true profile of the company is } (x_1, x_2, x_3))
\]

We assume that the initial distribution is uniform over all possible profiles, which is a non-informative prior distribution. This is a reasonable assumption in decision-making under uncertainty (and is easily modified at a later stage). As new information becomes available, the probability distribution is updated in a Bayesian way.

Probability of Succeeding When a Given Project Is Undertaken by a Firm

Another important element is the way in which managers form their beliefs about the possibility of success if they undertake a particular project. Denote by \( P_T(x, y) \) the “true” probability of success, defined for all pairs \( (x, y) \) as:

\[
P_T(x, y) = P(\text{success} | \text{company} = x, \text{project} = y).
\]

The subjective perception that managers have of (2) will be denoted by \( P_S(x, y) \). Note that while managers make their decisions based on \( P_S(x, y) \), the actual frequency of successes and failures in the simulations happen according to \( P_T(x, y) \). The process by which managers form their subjective perceptions is modeled by means of a neural network. In particular, the market makes public all quadruples

\{Initial firm profile; Project type; Success or failure; Final firm profile\}

generated during each simulation round. Based on this information, managers update their knowledge. For simplicity we assume that the learning process is the same for all companies in the sense that it is the same type of neural network that processes the information in all firms. We thus deal with three probability measures:

1) \( P_T(x, y) \), the “true” probability that a company with profile \( x \) succeeds when it undertakes a project with profile \( y \). This probability is assumed to be a feature of the “environment,” determined by the modeler.

2) \( P_S(x, y) \), the subjective estimate that a company of type \( x \) will succeed if it undertakes a project of type \( y \). This measure is updated as new information is generated by the environment in each round and should converge to \( P_T(x, y) \).

3) \( P_F(x, y) \), a frequency. It tells us how often a project of type \( y \) has actually succeeded when undertaken by a company of profile \( x \) during the different rounds. As time goes by, it should converge to \( P_T(x, y) \).
Evolution of Firm Profiles

Another characteristic of the model is the fact that, after working on a project, a company may develop a desired attribute or it may lose it (because its choice of project was excessively short-sighted or simply inappropriate).

The modification of profiles is modeled by a transition matrix that specifies with what probability a company evolves from one profile to another (in one period) as a consequence of undertaking a particular project. Consider a company with profile \( x = (x_1, x_2, x_3) \) that undertakes project \( y = (y_1, y_2, y_3) \). The profile at the end of the round will be denoted by \( x^+ = (x_1^+, x_2^+, x_3^+) \):

\[
(x_1, x_2, x_3) \xrightarrow{(y_1, y_2, y_3)} (x_1^+, x_2^+, x_3^+).
\]

The new profile is modeled by drawing from the probability distribution

\[
P \left[ x^+ = (x_1^+, x_2^+, x_3^+) \mid x = (x_1, x_2, x_3), y = (y_1, y_2, y_3) \right],
\]

where we explicitly assume that the new value of each attribute is independent of the new value of the other attributes. The probability that after one round \( x_1^+ = 1 \) (that is, that after having worked on a project, the company has acquired unity) will be denoted by \( g_1(x_1, y_1) \). In an analogous way, \( g_2(x_2, y_2) \) and \( g_3(x_3, y_3) \) will denote the probability that the company has acquired attractiveness \( (x_2^+ = 1) \) and effectiveness \( (x_3^+ = 1) \). In general,

\[
g_i(x_i, y_i) = P \left( x_i^+ = 1 \mid x_i, y_i \right), \tag{3}
\]

where \( g_i \in [0,1] \). Given the independence of the attributes, if a company chooses to undertake project \( (y_1, y_2, y_3) \), each attribute of the company \( (x_i) \) will evolve according to a controlled Markov chain [Chung, 1982; Taylor, Karlin, 1998; Heyman, Sobel, 2003] with transition matrix \( A_i \):

\[
A_i = \begin{bmatrix}
P(x_i^+ = 0 \mid x_i = 0, y_i) & P(x_i^+ = 1 \mid x_i = 0, y_i) \\
P(x_i^+ = 0 \mid x_i = 1, y_i) & P(x_i^+ = 1 \mid x_i = 1, y_i)
\end{bmatrix}.
\]

Using (3), this matrix can be written as

\[
A_i = \begin{bmatrix}
1 - g_i(0, y_i) & g_i(0, y_i) \\
1 - g_i(1, y_i) & g_i(1, y_i)
\end{bmatrix}. \tag{4}
\]

Note that it is the project that determines the matrix, and recall that the matrix is unknown to managers (i.e., its components are a feature of the environment, determined by the modeler).
In order to simplify notation, we let $\lambda_i$ denote the probability that a company lacking an attribute may acquire it after working on a project with that attribute. That is, for $i=1,2,3$,

$$\lambda_i = g_i(0,1) = P(x_i^+ = 1| x_i = 0, y_i = 1).$$

Likewise, we let $\mu_i$ denote the probability that a company may lose an attribute after working on a project that does not have that attribute:

$$\mu_i = 1 - g_i(1,0) = P(x_i^+ = 0| x_i = 1, y_i = 0),$$

for $i=1,2,3$. We impose the following conditions on these parameters:

1) **Invariance**, which means that a capability cannot change when both the company and the project have it, or both lack it. In other words, for $i=1,2,3$,

$$g_i(1,1) = P(x_i^+ = 1| x_i = 1, y_i = 1) = 1,$$

and

$$g_i(0,0) = P(x_i^+ = 1| x_i = 0, y_i = 0) = 0.$$

2) **Entropy**, which means that a weak project attribute is less determinant of the final result than a weak company attribute. That is, for $i=1,2,3$, we assume that

$$g_i(0,1) \leq g_i(1,0) \leq g_i(0,1) \leq g_i(1,0).$$

3) **Difficulty**, which has already been discussed in Appendix 1 (i.e., acquiring unity is harder than acquiring attractiveness, etc.). As we have seen in Table A1.1, we write:

$$\lambda_1 \leq \lambda_2 \leq \lambda_3 \quad \text{and} \quad \mu_1 \geq \mu_2 \geq \mu_3.$$

**Decision Making**

Two criteria are used to choose projects and assign them to firms. One captures the idea that managers would like to choose the project that maximizes expected NPV. This, however, would require them to compute the success probability $P_T(x,y)$, which is not observable. A solution would be to use the subjective perception $P_S(x,y)$, but the problem is that managers do not know the true profile of their firm. We thus consider the following version of the Expected NPV,

$$V(y) = \text{NPV}(y) \cdot \sum_{all\; x} P_S(x,y) \cdot \pi(x).$$

As we are assuming that the financial value of all projects is the same, we may assume NPV$(y) = 1$ for all $y$, which yields
\[ V(y) = \sum_{x} P_s(x, y) \cdot \pi(x). \]

The other criterion has to do with managers’ aspirations (goals) regarding the type of company they would like to have in the future, thus modeling the idea that managers are also interested in projects that will bring their firm closer to their goal. We proceed in two steps. First, we take into account the wishes or desires of the management team, represented by \( \bar{\gamma} \); second, such desires are tempered by the “imitation effect”, which is the attraction that managers feel toward projects that successful companies chose in the past.

To start, note that

\[ \sum_{\text{all projects } y \text{ undertaken by } x} P_T(x, y) \]

is an estimate of the success of a company with profile \( x \). As \( P_T(x, y) \) is not observable and \( P_s(x,y) \) is different for each company, we use the frequency measure \( P_F(x,y) \). If one considers the expected net present value of a project to be a measure of success, since all projects are alike, the above expression is a proxy for the total value earned by a company in a given simulation round. In an analogous way,

\[ G(x) = \sum_{\text{all companies of type } x} \sum_{\text{all projects } y \text{ undertaken by } x} P_F(x, y) \]

is a proxy for the total value earned by all companies of type \( x \). The function \( G \) is used to model the inclination to imitate other companies. Note that \( G(x) \) can be computed from the data generated by the system in each round.

Managers’ preferences regarding future company profiles are given by (1), where the components \( \bar{\gamma}_x \) represent the relative importance that the managers assign to each company type. These preferences, which remain fixed throughout successive rounds, should be combined with the fact that managers are not blind to what goes on in their environment (imitation effect, which goes beyond the concept of mimesis in neo-institutional theory [Di Maggio and Powell, 1983]). How to combine the two variables is open to discussion, but in line with the tradition of System Dynamics (see, for example, Meadows [2008]), we adopt a multiplicative approach. We therefore define \( \gamma_x = \bar{\gamma}_x \cdot G(x) \), so that

\[ \gamma = \left( \bar{\gamma}_1 G(1), \bar{\gamma}_2 G(2), \bar{\gamma}_3 G(3), \bar{\gamma}_4 G(4), \bar{\gamma}_5 G(5), \bar{\gamma}_6 G(6), \bar{\gamma}_7 G(7) \right). \]
The second criterion used by managers to choose projects is thus

\[ W(y) = \sum_{x^*} \gamma_{x^*} \cdot P(x^* | y) = \sum_{x^*} \gamma_{x^*} \cdot \sum_{x} P(x^* | x, y) \cdot \pi(x), \]

where the probability is to be understood as an (observed) frequency.

We have developed two indices, \( V(y) \) and \( W(y) \), for each project \( y \). It is easy to see that both indices take values in \([0,1]\). The first index is related to the project’s efficiency (its capacity to generate short-term profits), while the second one captures how closely the project is aligned with managers’ preferences regarding the future of the company. We combine the two indices as follows:

\[ D(y) = (1 - \alpha) \cdot V(y) + \alpha \cdot W(y), \]

where \( \alpha \) is managers’ willingness to sacrifice short term profits in exchange for a better company profile in the future. Obviously, \( 0 \leq D(y) \leq 1 \).

In the process of project selection, managers do not maximize this index. Rather, they fix a threshold \( T \) and choose the first project for which \( D(y) \geq T \).

If \( \alpha = 1 \) (complete willingness to sacrifice immediate profits), the decision criterion becomes \( D(y) = W(y) \), meaning that the weight in the decision making process is carried by the managers’ long-term vision of the type of company they would like to be in the future.

If \( \alpha = 0 \), the decision index would be \( D(y) = V(y) \), meaning that managers exclusively seek short-term profits. Figure A 2.1. shows a detailed diagram of the model consistent with the preceding discussion.
FIGURE A 2.1. Detailed model structure

Notes

1 Because of this, one cannot appeal to ergodic theorems to get long-run averages by computing averages along single paths.
2 Since we treat the three profiles as probabilistically independent, one could simulate each profile separately instead of aggregating them in triplets. In our view, however, this would make the model more difficult to understand.
3 We are assuming implicitly that managers can keep their jobs no matter the sacrifice they make to forego immediate results. This may not be the way things oftentimes work in practice, in the sense that managers who are “exclusively” concerned about the long-run may not be around to celebrate the future success of the company. However, one of the objectives of this paper is precisely to explore the impact of decisions of managers who are concerned, in varying degrees, about the long-run consequences of their actions. We thus assume implicitly, as a necessary simplification at this stage, that such managers can keep their jobs. It is a simplification that could be relaxed in further research.

4 Without randomness, the model’s behavior would be rather simple and uninteresting. For instance, a deterministic evolution in a {0,1} space only allows transitions that either always go to 0, or always go to 1. This results in four types of transitions. In addition, the time to reach a state is either 0 or 1 steps, which is not a very exciting behavior! In a deterministic scenario, all companies would evolve in the same way if they happened to start in the same state (picking the same projects and undergoing the same changes in profiles).

5 A neural network is an object with exogenous inputs and outputs. Some of the inputs and all the outputs are used for learning. They are supplied with the actual data and result of an experiment, and the internal structure of the network is modified to provide the best fit for the new observation. Whenever a prediction is needed, inputs are supplied and the network uses its internal structure to compute the prediction. The internal structure is essentially a nonlinear least squares model, recalculated for each new piece of evidence. The same least squares structure provides the computational machinery for the prediction.

6 See Appendix 2 for a detailed description of the model. The software we use has been written in Delphi, an object-oriented programming language, and has roughly 5000 sentences.

7 We normally generate 1,000 companies, as this is sufficient to obtain a significant sample without slowing down the process. Changing the number of companies can be easily done. In our experience, good quality results can be obtained with as few as 300 firms.

8 Sometimes the only way to understand the roots of the system’s behavior is by tracing it, following the computer program step by step. We often had to resort to this technique. In a sense this is a rather new approach to the analysis of simulation experiments, that is not normally found in the literature.

9 Experience with our type of model is small, and so far we have only a few pointers on how the model may evolve as a function of its structure. In this sense we are still trying to obtain some solid knowledge of its evolution. The exploration (simulation) phase is technically challenging, but a necessary step before additional theoretical refinements can be included in the model.

10 These assumptions can be easily changed in the model implementation, and we plan to do so in the future.

11 When we say that a company profile “disappears,” we mean that companies with that particular profile evolve (they acquire or lose capabilities) in such a way that, after a number of periods, there are no companies left with that profile among the total population of 1,000 firms.

12 So far this is not a formal proof, just an observed result in our experiments.

13 It does exist in more sophisticated approaches, in which paths may be averaged over time. When the averaging option of the program is active, the paths follow smooth patterns that converge to a steady state.

14 A fully rigorous mathematical analysis is still under way, although the nature of the problem seems to make it intractable. In any case, a detailed mathematical analysis falls well beyond the scope of this paper, which is centered on exploiting the model’s emergent behavior properties by means of experimental techniques.

15 We are aware that keeping T large means a higher cost of screening projects. However, those that are chosen will bear a higher performance. This is a true managerial trade-off that ought to be resolved in each particular case.

16 Note that the summation has seven terms, for there are only seven company profiles.

17 Currently, projects of different types are successively “offered” to each company in a random order.
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Competitiveness, EMU and Cohesion Experiences in the Past (2000–2013); Assessment of the Present (2014–2020) and Lessons for the Future (2020 and Beyond)

Abstract

The European Union has adopted several strategies to cope with a set of inter-related problems. The best known is the Europe 2020 strategy with its focus on smart, sustainable and inclusive growth. Another is fostering balanced macro growth via a strengthening of the EMU. Finally the cohesion policy has to cope with spatial unbalances. The objective of this paper is to highlight the main issues in three policy fields: competitiveness, EMU and cohesion. Two scenarios for post 2020 development are described, which show the need for further strengthening of EU policies and of the quality of government at all levels.

Keywords: European Union, Competitiveness, EMU, Cohesion, Scenarios beyond 2020
JEL: E52, O14, O33, R11,12

Introduction

This paper focuses on the spatial dimension of the conditions for growth. We distinguish between three large geographical areas of the EU; North, South and East, paying particular attention to the East and Visegrad four countries.

For each policy field, we describe the issues and the relevant policy solutions for two periods: the recent past (2000–2013) and the present (2014–2020).
In the last section of the paper two future alternative scenarios are posed; one pessimistic, and the other optimistic. This juxtaposition of possible outcomes highlights the challenges ahead; notably, the need to further strengthen the European architecture and quality of governments on national and regional levels.

A short conclusion will round off the paper.

Competitiveness

Past: 2000–2013

Competitiveness is defined as the ability of countries, regions, cities or social groups to generate (while being exposed to external competition) relatively high income and employment levels. We distinguish the main drivers of competitiveness (and hence growth):\(^3\)

- industrial structure (specialization in high-value-added activities, new products and services; clusters of related activities);
- innovation (research and development institutes; knowledge-based firms);
- accessibility (telecommunication networks; transport infrastructure, urban services);
- environmental quality (environmental damage can be a barrier to development);
- human resources (employment rate, educational level, training and teaching facilities, adaptability of the labor force, entrepreneurial talent); and
- good governance (the rule of law; reliability and effectiveness of public sector services, absence of corruption).

For some time, an EU priority has been to improve competitiveness, as reflected by the Lisbon Strategy. In 2010, this goal was articulated in the Europe 2020 Strategy as smart, sustainable, inclusive growth. The competitiveness drivers listed above can easily be related to these three main Europe 2020 objectives. Smart growth is largely determined by developing the first three of these drivers; sustainable growth by the fourth driver; and inclusive growth by the fifth. The last driver cited – institutional and administrative system quality – is a precondition for effectiveness of all other drivers.

The various components of competitiveness have been measured on the national, regional and urban level and amalgamated into one composite indicator (Figure 1).

This indicator reveals the following fairly simple geographical structure; Northern countries are to the right; Southern and Eastern countries are to the left, mostly Eastern countries (and Greece) are in the extreme left, and the V4 countries are in the middle of figure 1 (together with a number of the more developed countries from the South). And the capital cities of each country occupy the best position.\(^4\)

There are no comparable figures available for describing the past development of the patterns of competitiveness on the lower spatial levels. However, partial data suggest that
over the past decade Eastern countries have made significant gains; and so have most of their regions. By contrast, Southern countries (and, in particular their ‘problem’ regions) have suffered considerable losses, which have been set in long before the crisis.

**FIGURE 1. Competitiveness index by member state, region and capital city (2013)**

Source: adapted from: Annoni and Dijkstra [2013].

**Present: 2014–2020**

The *national* dimension of competitiveness has been studied by the European Commission over time. Since 1997, the EC has published an annual Competitiveness Report, which quantitatively assesses the development of the main determinants of competitiveness of EU industries by country. These reports show that differences between EU countries are large and rather persistent. Moreover, similar patterns for the indicators of the various drivers of competitiveness are discerned. The latest report underscores the importance of the ‘availability of adequate funding’ and ‘good government’ to the growth of firms, and advocated policy reforms to reduce barriers to competitiveness.⁵

Although systematic information for the *regional dimension* of competitiveness is not available, regional competitiveness is a focus of the Europe 2020 targets. For those targets that correspond to a competitiveness driver, the gap between current conditions and aspirational goals has been assessed, and relevant data amalgamated in a comprehensive weighted index. These figures show that, by region, the largest problems are posed in the southern regions of Portugal, Spain, Italy, and portions of the Balkans. These results are not new.⁶
Within countries, the main urban centers tend to outperform all other regions. This suggests that in countries where the rift between the two categories is particularly deep, specific efforts will be needed to close the gap between first tier cities and other regions.7

EMU

Past: 2000–2013

The EMU started in 2000. However, not all EU member states participated in it. Some could not join because they were not ready, and others did not want to join because they thought that participation would not benefit them. Notably the UK and Denmark negotiated an opt-out from the EMU. Membership in the EMU does not coincide with the divisions in the large geographical areas that we have adopted for this study. In the North one sees that not all countries participate (i.e., the UK). In the South, all countries of that group did participate. In the East, only a minority of mainly smaller member states participate in the EMU.

The EMU has such positive effects as greater macro-economic stability and a lowering of interest rates. However, it has also had some negative effects. The EMU permitted Southern European countries to borrow cheaply and invest in unproductive ventures. When the financial markets were in crisis, a number of these countries risked a sovereign default. Interlinkages between the financial sectors of different countries resulted in immediate contagion, and even well run countries were infected, resulting in an unprecedented crisis. Rescue packages for banks and austerity measures for public budgets have since been put in place in all EU countries to remedy the problems. Growing imbalances and the ensuing crisis have numerous effects, some negative, and others positive.8

Negative consequences include:

- Long-term loss of competitiveness (evident from balance of payments deterioration);
- Slack economic growth, which washed away the public’s capacity to recover as tax revenues decreased;
- Increased unemployment (e.g., unemployment rates in Portugal and Spain reached high double digit figures);
- Increased wealth disparities between EU countries, erasing a decades long efforts to foster cohesion (see next section);
- Severely impaired quality of institutions and administrations in problem countries; and
- Deep mistrust between partners, undercutting European solidarity that had gradually developed over decades.
Among the positive points to be mentioned are:

- The internal market is intact. The crisis has not shaken the ‘acquis communautaire’; no country reacted nationally in economic terms (as has been the case in previous crises);
- Independence of ECB has been crucial;
- EMU and EU solidarity prevented the crisis from becoming even more devastating by, among other things, buffering exchange rates from undue turbulence (currency crises);
- EMU design failures have been addressed under heavy strain;
- Cohesion policy has been maintained; and
- Decisions on further integration of complementary policies have been undertaken.

The economic and systemic crises of the EMU have had very different impacts on the three EU areas. In the North, countries were severely shaken but have now largely absorbed those shocks. However, policies designed to control budget deficits have slowed growth. For most countries in the South, the effects have been devastating. Decades of cohesion were eviscerated, tax bases eroded, black economic activities increased, and unemployment and poverty accentuated, along with the concomitant deterioration in the quality of governance systems. Recovery is, on average, painfully slow. The situation in the East is very different. There, the system has proven to be fairly resistant to shock waves, for both EMU and non-EMU members. Accordingly, the Eastern countries have continued to grow.

Present: 2014–2020

A deep crisis could happen due to the incomplete construction of the EMU and “the failure of Member States to empower it with strong instruments and to put sufficient effort into the processes.” [Molle, 2011, p. 326]

In the recent past, quite a few systemic weaknesses of the EMU have been corrected. This was done through greater EU involvement in such areas as control of fiscal policy, banking surveillance, etc. These efforts have resulted in the creation of new devices such as the European Semester, National Stability Programs and the Excessive Imbalance Procedure. Institutionally, major changes have also been made – one example being the European Stability Mechanism. Together, these actions represent an unprecedented acceleration in the EU integration process. Some tend to overlook these achievements – perhaps because they were accomplished in a setting of turmoil, political instability, unsatisfactory compromises, and nationalist discourses. As the dust of that process is blown away, these large changes in the architecture of the European building will have become apparent.9

The main challenge for the EU now is to complete the EMU. Proposals have been made to create a so-called Genuine Economic and Monetary Union (GEMU), that would add three steps to the present set-up:10

- Completion of the Banking Union;
- Mutualisation of (a part of) the public debt; and
- Creation of a Fund to deal with asymmetric economic shocks.
There is considerable controversy about the need for these changes, the conditions necessary to make them feasible, and the precise form that each of these three measures should take. Notwithstanding these open questions, it does seem clear that all three aspects of the GEMU would have pro-cohesion effects and enhance the capacity of the weakest EU countries to return to balanced growth.

Cohesion

Past: 2000–2013

The primary objective of EU cohesion policy is the convergence of wealth levels. Table 1 illustrates the evolution of the relative GDP/P levels of the large geographical groups of countries since 2000, during the pre-crisis and the crisis periods.

TABLE 1. GDP/P (index EU28 = 100), by countries’ group, 2000–2020

<table>
<thead>
<tr>
<th>Region/year</th>
<th>2000</th>
<th>2007</th>
<th>2012</th>
<th>2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>North</td>
<td>121</td>
<td>116</td>
<td>116</td>
<td>115</td>
</tr>
<tr>
<td>South</td>
<td>105</td>
<td>102</td>
<td>95</td>
<td>90</td>
</tr>
<tr>
<td>East</td>
<td>45</td>
<td>56</td>
<td>65</td>
<td>72</td>
</tr>
<tr>
<td>V4</td>
<td>53</td>
<td>61</td>
<td>70</td>
<td>77</td>
</tr>
<tr>
<td>EU 28</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>CoV (countries)</td>
<td>.51</td>
<td>.46</td>
<td>.42</td>
<td>.34</td>
</tr>
</tbody>
</table>

PPP = purchasing power parities. CoV Coefficient of variation.

Table 1 shows that there are important differences between the three geographical areas. One is that throughout the presented period, the North was above average, the East was significantly below average, and the South was close to average.

Another is that in the pre-crisis period North countries were characterized by relatively low growth figures, and that continued the past trend towards convergence. Post-crisis, these countries were less severely impacted than many other EU countries, with the result that the convergence flattened off between 2007 and 2012.

The Eastern countries present the opposite picture. Their integration in the EU – and consequent institutional stabilization and increased market access – brought about high growth rates, which resulted in a strong tendency of convergence.11 This trend was not significantly impacted by the crisis; the major Eastern countries had maintained their
monetary autonomy and were able to adapt to the new competitive and macro-economic environment. The V4 countries very much contributed to this tendency.

In the South, the data very clearly shows that this group of countries performed relatively poorly pre-crisis, losing out in wealth levels relative to the EU average. The consequence is quite dramatic; the trend towards convergence that had dominated the previous period was actually reversed. One reason for this development was that these countries had specialized in traditional industries that were very vulnerable to increased competition from developing countries (globalization) and new EU member countries. Moreover, these countries have not in time developed new competences in other industries and services. On the contrary; much of the investment went into the wrong projects.¹²

Eurozone membership permitted them to borrow cheaply and postpone adaptation. However, when the crisis hit the countries in this group were forced to operate very drastic restructurings, with a strong negative effect on GDP and, hence, GDP per head. This process played out with a particular strength in Greece, but also in Spain and Portugal and to a lesser extent in Italy and Ireland. Table 1 shows that effect: the index figure for this group dropped some 7 points between 2007 and 2012.

To cope with these disparities the EU has developed an elaborate cohesion policy. Its basic objectives and main systemic features have been relatively stable over time. After each enlargement, new member countries with relatively low income levels benefitted from that policy – most recently for member states in Central and Eastern Europe. The policy has been reoriented to deal with major new challenges; in the past this applied in particular to the Lisbon strategy for growth and competitiveness.¹³

Present: 2014–2020

Notwithstanding decades of EU and national efforts, table 1 demonstrates that disparity persists; suggesting that a continued effort is needed. Assuming that this effort is as effective in the future as it has been in the past, suppositions about the likely development of the GDP/P in the period up to 2020 can generally be made.¹⁴

In particular, the three large EU geographical zones should continue prior growth trends (see the last column of table 1), with the North stabilizing, the East converging further, and the South diverging further. The evolution of the coefficient of variation (based on individual country figures) shows that overall, the convergence trend observed in the past decade is likely to continue, mainly due to the dynamics of the East, which is very much driven by the V4.

These potential trends indicate that a significant policy effort is still needed. For the 2014–2020 period, essentially five main changes have been made in the system.¹⁵ These are:

1. Integration of cohesion policy with the objectives of strategy Europe 2020; this is to be facilitated by minimum allocations of funds for specific objectives;
2. Clear formulation of quantifiable results by beneficiaries of place specific targets, to focus solutions of specific local problem by integrated delivery on the ground;
3. More binding relations between various government layers, in the form of partnership agreements;
4. More conditionality concerning effective policy implementation and macro-economic conditions. In order to make them effective the whole policy is integrated in the European Semester. Conditionality here means that disbursement of funds is made dependent on fulfilment of conditions; and
5. Efficiency measures: the practical rules for the delivery of the policy by the diverse Structural and Cohesion Funds (SCF) have been made uniform to decrease administrative burdens.

A combination of considerable financial resources with a very elaborate system of coordinated regulation has to lead to a mutual reinforcement of the effectiveness of the three policy domains: Europe 2020, Macro stability and cohesion. This system puts very high demands on the capacity of governments and the quality of their institutions, so a reinforcement of this systemic aspect is essential – as recently stressed in the EU’s latest Cohesion report [EC 2014c].

**Future: Opportunities and Risks Beyond 2020**

**Optimistic Scenario; New Balanced Growth**

We have assumed in previous sections that the EU will use the present period (2014-2020) to recover from the crisis and restart growth. In this section, we assume that those efforts will lead to a new period of sustained and balanced growth.

We base this assumption on historical parallels. After the double energy crises of the 1970s, new initiatives were taken to complete the Internal Market and to design the EMU. What sort of subjects would such a new élan cover this time? We can assume that it will involve first completion of the EMU (in terms of both design and accession of the presently non-euro area members in the East). We can next assume that this reinforced EMU will create the conditions of stability under which a new dynamism can occur.

We further assume that the EU faces with determination the main challenges of the period beyond 2020. Persistent social and environmental problems will require the continued pursuit of smart, sustainable and inclusive growth. External openness to competition from emerging market countries (that produce high technology goods and services) will force the EU to focus on competitiveness.

We assume that actions to improve competitiveness (e.g., education, quality government, innovation, etc.) are successful. This implies that: 1) the Structural Funds are effectively used to profoundly modernize the EU’s production system; 2) the quality of government is improved (most of all in the countries with the highest deficiencies); and
3) macroeconomic stability is maintained by a Genuine Economic and Monetary Union (GEMU). The consequences of this scenario, in terms of disparities, are positive. The North continues its position. The South picks up again. The East embarks on a trajectory to join the North: competitiveness is expanded to high value added goods.

**Pessimistic Scenarios; New Mistakes**

But the last crisis has shown that situations may occur which are not foreseen by standard models. It is therefore necessary to develop alternative scenarios, taking into account other, even ‘undesirable,’ developments to be able to prepare for the worst. We develop in schematic form two such scenarios and discuss briefly the chances that they will materialize.

A ‘Doom scenario’ could develop in case the EMU (even with the latest and planned adaptations) cannot survive without a Political Union. Assuming that EU Member States are unwilling to take this last step in the integration process, the EMU will prove to have been step too far, and the EU may have to retreat to the stage of a Common Market plus. This scenario will place Europe in uncharted territory. However, history suggests that the EU, which has consistently overcome past problems (however cumbersome and unorthodox the solutions), will do so again. Indeed, the cost of breaking up is so high that one may assume the EU will have no choice but to overcome a new EMU/EPU crisis by developing new original organizational solutions to shape its future.

An alternative is the ‘Mistake scenario’, in which we assume that the Eastern countries fall in the same trap as the Southern countries did in the period before the crisis. It means a significant loss of competitiveness of this group of countries. The drivers of this development would be the usual ‘suspects’ – increased labor costs, real estate bubbles, poor government functioning (including rampant corruption), too much concentration in capital cities and a number of ‘dangerous liaisons’ between private and public sectors. The negative effect of these factors would likely be aggravated by aid dependency, unproductive investment and macro-economic disequilibria. In principle, the new EU policy architecture should minimize the risk that this alternative scenario develops. But the past has shown that hidden dangers may become apparent only in periods of crisis. So the scenario is not unrealistic.\(^{16}\)

What would be the effects of this scenario? If growth figures for the Eastern countries resembled those of the South in the 2007–2012 period, a quite different cohesion picture than the one from the previous scenario emerges. Convergence between countries and groups of countries practically comes to a halt. Clearly then, a focus on all factors determining competitiveness and the correct use of cohesion money, in particular the quality of government, is essential because it is the cement that keeps the structure together.\(^{17}\)
Conclusion

Severe problems persist in three policy areas (competitiveness, EMU and cohesion). For all three the situation of the North has been more or less stable; the situation of the South has dramatically deteriorated, while the situation of East has improved.

The EU has drawn a number of lessons from its mistakes of the past and has adapted its policy architecture to the challenges of the period up to 2020. These adaptations consist essentially of an increased focus on competitiveness, completion of the EMU, better focused cohesion efforts on Europe 2020 objectives, and a further integration of three main policy domains by strengthened coordination and conditionality.

We have explored the future and in particular the future of the countries of the Eastern group. Under a positive scenario improved conditions would lead to a further catching up of the East with the EU mean. Under a pessimistic scenario the new systems in place will not be sufficiently strong, causing countries in the East to replicate the past mistakes of the Southern countries.

In all cases the improvement of competitiveness, economic stability and cohesion is critically dependent on the improvement of the quality of government.

Notes

1 This division is inspired by the famous triade of arguments for policy intervention: allocation, stabilization and redistribution (equity) made by Musgrave and Musgrave (1989).
2 The North groups all countries in the North and Northwest of the EU. The South consists of the Mediterranean countries (Portugal, Spain, Italy, Greece, Malta and Cyprus). The East groups the Member States of Central and Eastern Europe. In interpreting the data, one has to bear in mind that these groups differ in size: the North has about half of the EU’s population; the South and the East have each about one quarter.
3 See for clarification of the concept and its main drivers: Camagni (2002), Kitson et al. (2004), Bristow (2010) and Martin et al. (2012). The concept is used on all government levels; the EU, countries, regions and cities.
4 Of course, various EU member countries are at different stages of development. In the more advanced stages represented by the right hand group, factors like innovation are more important than at a lower stage of development (e.g., the left hand part, where the cost of production factors play a larger role). Moreover, the interdependencies of countries at different stages in development can be a stimulus for growth and reform.
5 See: EC (2014a) in particular chapter 4. The findings of the series of EC reports are corroborated by those of a similar series of studies by the World Economic Forum that place competitiveness in the Europe 2020 perspective; see e.g.: WEF (2014).
Competitiveness, EMU and Cohesion Experiences in the Past (2000–2013)

7 For cities a competitiveness divide (between Northern and Western Europe on the one hand, and Southern and Eastern Europe on the other hand) is likely to be maintained through 2025 (EIU, 2013, 19).
8 In the past, these countries could regain competitiveness by devaluing their currency; an option no longer available under the EMU.
10 The proposals have been made by the heads of the EU executive institutions; they are discussed in detail in Begg et al. (2014, chapter 5).
11 See: e.g. Epstein (2014).
12 See for the illusion of cohesion that his created Fernandez-Villaverde et al. (2013).
13 See for development of the policy Bachtler et al. (2013) and Molle (2007, 2015).
14 The 2020 forecast figures (right hand column of Table 1) have been constructed in two stages. The 2015 figures have been taken from the forecast of the European Commission for each member country (EC 2014b). The 2015–2020 evolution has been forecast using the average longer term growth forecast for each member country made the IMF (2014) and the OECD (2012a,b). These forecasts take into account a large number of factors, but seem in general to assume that the factors determining the dynamics of each of the member countries are fairly stable over the long-term.
16 See Camagni and Capello (2014). Similar considerations are voiced in EBRD (2013). See for further considerations that can lead to a failure of countries to stand up to challenges: Acemoglu and Robinson (2012) and Fukuyama (2014).
17 For evidence on the need to go along this way and the modalities of a possible implementation see: Molle (2012).

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## Firm Size, Competition, Financing and Innovation

### Abstract

This paper investigates the effects of firm size, competition and access to finance on the innovation performance of that firm. After a review of the relevant literature, three logit models are proposed and tested. The empirical analysis is based on the business environment and enterprise performance survey (BEEPS) for 1053 enterprises from twenty-six countries in years 2002 and 2005. Our results suggest a positive and statistically significant relationship between firm size and innovation. We also find a positive relationship between both competition and access to finance with innovation.

**Keywords:** access to financing, firm size, innovation and competition  
**JEL:** G21, O31, L25

### Introduction

The relationship between a firm’s size, financing and market structure is considered a central issue in both industrial organization (IO) and the endogenous growth theory. Schumpeter [1942], who was a pioneer in studying this relationship, argued that large firms, which operate in concentrated markets, are the central drivers of technological progress and, hence, economic growth. He explained why innovation increases disproportionately to, and more than, because large firms can better spread the risks of R&D, have better access to external finance, and have sufficiently large sales to fund the fixed costs of R&D. Taken together, these attributes of size, market structure, and access to financing encourage innovative behavior.

Empirical work has not been conclusive on Schumpeter’s hypotheses. Some authors point to a positive correlation; others, to a negative one. An inverted U relationship has
been reported by Scherer, F.M. [1965a, b] Hence, while the hypotheses are relatively straightforward, but support for them has been less so.

In terms of product market competition (PMC), some of the industrial organization literature predicts a negative correlation between innovation and competition. Schumpeter hypothesizes that innovation is higher in concentrated markets using the following reasoning: firms with market power have more incentive to innovate as they can easily appropriate the returns from innovation (due to little imitation); in addition, since concentrated markets tend to be more profitable, they are more able to finance R&D from their own profits. However, some researchers – such as Blundell, Griffith and Van Reenen [1999] and Maiti [2011] point to a positive correlation between competition and innovation. Other researcher, such as Aghion et al. [2006], assert that the relationship between innovation and competition is non-linear, as there exists an inverted U relationship: innovation increases as competition increases up to a critical level of competition, after which it gradually falls.

Regarding the relationship between innovation and financing, the empirical research by a number of researchers generally point to a positive correlation between financing, size, and innovation. This supports Schumpeter’s view.

The present paper is a contribution to understanding the link among innovation, firm size, market structure and access to finance starting from the basic Schumpeterian paradigm. We estimate this link using data concerning a panel of 1,053 enterprises for two years, 2002 and 2005, based on the Business Environment and Enterprise Performance Survey (BEEPS). We run three different models using a pooled time series specification and controlling for country and industry effects. The use of pooled regression was necessary as we do not have data for a sufficient number of years. We then run a cross section analysis for our models. Endogeneity problems are a feature of the equations and are addressed by using lagged values.

The paper starts with a literature review of Schumpeter’s specific hypotheses as to how competition, firm size, and financing affects innovative activity. Then we present our data sources and a descriptive analysis of the data. In this same section, we present an explanation of the variables that are used in our empirical model. Later we discuss and analyze the results. Finally, we present a few concluding remarks and suggests directions for future research.

**Literature Review**

This section presents the literature drawn from industrial organization (IO) and endogenous growth theory on the link between innovation and a variety of firm-specific, industry-specific, and institutional characteristics. The section covers both empirical and
theoretical contributions in three areas: the link between competition and innovation, firm size and innovation, and financing and innovation.

**Competition and Innovation**

The relationship between product market competition (PMC) and innovation has received much attention from economists. Both the theory of IO and endogenous growth theory have grappled with this issue. In the Schumpeterian paradigm of growth theory innovation, which plays an essential role in sustaining economic growth, is motivated by the expected monopoly rents from resulting patents or licenses that guarantee successful the innovator monopoly power over its inventions [Tirole, 1988]. Empirical work by Blundell, Griffith and Van Reenen [1999] has found a positive correlation between PMC and innovation, i.e., more competition and more innovation are correlated. Several analytical approaches have also augmented the Schumpeterian growth model by demonstrating the convergence between theory and evidence1.

One such attempt was made by Aghion, Dewatripont and Rey [1999], which introduced Hart’s [1983] framework2 into a Schumpeterian growth model, considering competition as an incentive to innovate. In this approach, the relationship between product market competition and innovation is monotonic with a positive correlation if firms are administered by managers who care about the firm’s survival. In other words, competition (and the concomitant threat of liquidation) are disciplinary devices that reduce managerial slack and foster technological adaptation and, therefore, growth. The inverse relationship holds when most of the firms are value-maximizing due to a Schumpeterian effect in their model.

This expansion of the basic Schumpeterian model allows all firms to innovate in order to reduce production costs. Both the technological leader and followers in this model invest in R&D. “Step-by-step” innovation means that the laggard firm must innovate (once) to catch up with the leader before it can innovate (again) to become a (cost) leader in the future. This structure is known as a quality ladder or a vertical innovation model, which states that growth is generated by a sequence of quality improving innovations that result from research activities by firms, which (if successful) will grant them monopoly power. New innovations make the prior technology obsolete.

In this framework, competition has two different effects: a Schumpeterian effect and an escaping competition effect. The former implies that a leader gets “monopoly” rents from the innovation if it pulls ahead. The latter; that a laggard firm gets nothing (where the firms are Bertrand competitors), and therefore, innovates in order to “escape” symmetric competition. This suggests an inverted-U relationship between PMC and innovation, which relies on step-by-step innovation to dampen excessive incentives to innovate for extreme industry structures: as the leader innovates, the follower will automatically copy the leader’s technology and a one step gap remains. Hence, the leader will have no more incentive to innovate once it has pulled ahead “once,” as profits depend on a gap between the leader and the follower that can only be so large. Similarly, the follower can only be
so far behind, so it does not get “discouraged” and can instead always maintain a realistic hope of pulling ahead through some new innovation.

An important feature of the Aghion et al., framework is that innovation incentives hinges on the difference between post-innovation and pre-innovation rents, while in the basic Schumpeterian model incentives to innovate depend only on the post-innovation rents. The increase of PMC may, then, promote innovation because PMC reduces pre-innovation rents more than it reduces post-innovation rents. Innovation progresses along a quality ladder on which successful innovation raises quality, and short-term monopoly power compensates for the fixed costs of that innovation. In this case, the escape competition effect is stronger when firms compete neck-and-neck. An example of neck-and-neck competition is the homogeneous product – Bertrand Industries- where the firm’s profit is zero. By contrast, in asymmetric industries where there is a leader and a follower, increased competition might reduce innovation because of a possible decrease in the laggard’s reward for catching up. In other words, the Schumpeterian effect dominates.

This model has been investigated empirically by Aghion, Bloom, Blundell, Griffith and Howitt [2002]. They confirm the existence of an inverted U-shaped relationship between PMC and innovation. For lower levels of competition, the escape competition effect dominates. Accordingly, innovation rises with competition, while under the Schumpeterian innovation falls as competition rises. This result has been confirmed in related work by Polder and Veldhuizen [2012], who empirically investigate the relationship between competition and innovation using industry-level data from the Dutch National accounts. They find an inverted U-shaped relationship when using Profit Elasticity as a measure of competition; however, this U-shaped relationship is not found when they use one minus PCM.

**Firm Size and Innovation**

A substantial body of literature has focused on the relationship between innovation and firm size. The most important hypothesis is that firm size has a positive correlation with innovation [Symeonidis, 1996]. Empirically speaking, Schumpeter [1942] has found that large firms, which operate in a concentrated market, are the essential engines of technological progress. As a variety of measures of innovation have been used in the literature, this part of our review will be divided according to the classification of innovation measurements. First, we consider innovation inputs such as R&D. We then consider innovation outputs, such as the number of significant innovations and the number of patents.

Considering R&D investment and firm size, previous studies such as Fisher and Temin [1973] described a positive relationship between firm size and R&D investment activities that enhance innovation. By contrast, Shefer and Frenkel [2005] encountered a negative and significant correlation between firm size and R&D investment rate in a large number of small firms investing in R&D activities. Hence, there is little certainty whether larger firms invest more (or less) on R&D. However, Tether et al. [1997] found a non-linear
relationship between size and innovation, as both small and large firms might reflect high innovation propensities. Additionally, Scherer’s [1965a, b] regressions show an inverted U-relationship between R&D investment and firm size.

Regarding innovation output, Rothwell and Dogson [1994] found the early stages of an industry’s life cycle is more favorable for small firm innovation, whereas during more mature stages the situation favors larger firms. Acs and Audretsch [1987] found that small firms are more innovative in competitive markets while large firms do better in more monopolistic markets.

Zona et al. [2013] use the total number of directors as a measure of size. Their regression analysis using Italian firms identifies a positive and statistically significant relationship between firm size and innovation.

In brief, Schumpeter’s hypothesis says that larger firms innovate more because of their ability to access to funds and spread R&D risk. However, the empirical evidence is mixed. Firm size is just one factor that influences innovation, and how salient that size is in a given case overall depends on other factors. Those other factors, in turn, include industry life cycle and, as we have seen above, product market competition. Accordingly, the finding of a size-innovation relationship will depend heavily on what controls are included in the equation. Moreover, innovation measures also matter to the findings. For example, if small firms tend to be more successful at innovating even though they spend less, one measure of innovation could generate the opposite results to the other measure in empirical work.

**Financing and Innovation**

Innovation is considered an expensive process, as significant resources must be invested in R&D until the innovation process is complete, while the outcome and the returns of this process are uncertain [Mowery, Nelson, 2006]. The availability of financial resources therefore determines whether a firm can undertake R&D activities.

Schumpeter assumed that available resources are completely utilized in a stationary circular flow, and that the creation of new products and new processes requires reallocation of these resources, as the entrepreneur cannot be financed by the returns of established activities. He noticed that entrepreneurs introduce innovations financed through bank credit (creation of credit) rather than savings or the existing stock of money or goods [Schumpeter, 1934]. He pointed out the role of commercial banks in producing new purchasing power that is used as a demand driver, a situation that creates the preconditions for innovation by entrepreneurs. He also characterized the role of large companies, which have the resources and the capital to invest in R&D, as agents that drive innovation.

Hall [1992] found that more R&D-intensive firms have relatively less debt in their capital structure than less R&D-intensive ones. Further, she found that financial constraints hinder R&D activities. Her results show a positive relationship between cash flow and R&D investment, suggesting that R&D is financed out of free cash flow.
Of course, acquiring external resources may be costly. One reason, according to Myers and Majluf [1984] is asymmetric information between lenders and borrowers, which might lead firms to prefer financing risky projects using debt. On the other hand, moral hazard concerns may cause banks to not finance innovation using debt. That reticence could be reflected in the financing of innovation out of retained earnings, or other non-debt sources, which suggests using cash flow as the main financing for R&D, in line with some of the regressions cited above. Another issue is the agency problem. Jensen and Meckling [1976] pointed out that this issue arises when the managers do not pursue shareholder interests, leading firms to pay a premium for external financing. Agency issues are generally not fully present in Schumpeter’s work and can drive a wedge between empirical results and Schumpeter’s theory.

In sum, our literature review indicates that while Schumpeter’s theory yields relatively straightforward predictions, the empirical implementation has revealed a wide variety of results. This motivates our work, which revisits the issue with a data set that is useful for studying Schumpeterian hypotheses. We now turn to this data set and our methods of exploiting it.

**Data Description**

The paper is based on the Business Environment and Enterprise Performance Survey (BEEPS), which is a joint work of the European Bank for Reconstruction and Development (EBRD) and the World Bank Group.

The survey is based on a stratified random sampling procedure using the size of the economy and sector as strata. This survey consists of firm level data collected in five rounds (1999, 2002, 2005, 2009 and 2013). The survey provides information about innovation behavior of enterprises through data on whether the firm has introduced new or significantly improved products or processes. This allows a distinction to be made between product and process innovation. In addition to that, the survey includes information about the number of competitors, firm age, firm size, ownership, exports, legal status, education of work force, corruption, obstacles faced by the enterprise and financing obstacles. As such, it is a rich and unique data for investigating innovation correlations, specifically those suggested by Schumpeter. Information is, however, self-reported, so that items like “number of competitors” represents the firm’s view and is not an externally-validated figure.

Due to data shortages for 2003 and 2004, we assess a balanced panel of 1,053 enterprises in two years only – 2002 and 2005.
Descriptive Analysis of Data

Table 1 shows that most innovative firms face a high number of competitors but, to a similar degree, do most of non-innovative firms. As previously noted, Aghion et al. [2006] argued that innovation can be driven by escaping competition, as well as by the Schumpeterian effect. The first result reported here can be explained by Aghion’s work and the Hart model (in which competition works as an incentive to innovate). The second result is consistent with Schumpeter’s hypothesis, according to which firms innovate optimally in concentrated markets. Considering all size categories in our data, innovation is higher when facing a higher number of competitors, which suggests that the “escape innovation” effect may dominate.

Tables 1,2 and 3 are based on cross tabulation and three-way tabulation.

TABLE 1. Different innovation activities according to size and number of competitors

<table>
<thead>
<tr>
<th>Innovation behaviour</th>
<th>Number of competitors</th>
<th>1 to 3</th>
<th>4 or more</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>15</td>
<td>110</td>
<td>704</td>
</tr>
<tr>
<td>Product innovation</td>
<td>15</td>
<td>172</td>
<td>689</td>
</tr>
<tr>
<td>Process innovation</td>
<td>19</td>
<td>223</td>
<td>958</td>
</tr>
<tr>
<td>Both</td>
<td>21</td>
<td>251</td>
<td>1,082</td>
</tr>
</tbody>
</table>

Innovation/Size

<table>
<thead>
<tr>
<th>Number of competitors</th>
<th>None</th>
<th>1 to 3</th>
<th>4 to more</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>8</td>
<td>70</td>
<td>564</td>
</tr>
<tr>
<td>Product innovation</td>
<td>5</td>
<td>88</td>
<td>425</td>
</tr>
<tr>
<td>Process innovation</td>
<td>6</td>
<td>122</td>
<td>593</td>
</tr>
<tr>
<td>Both</td>
<td>7</td>
<td>136</td>
<td>689</td>
</tr>
</tbody>
</table>

Medium

| No innovation         | 3      | 25     | 91      |
| Product innovation    | 4      | 45     | 161     |
| Process innovation    | 6      | 57     | 228     |
| Both                  | 7      | 64     | 245     |

Large

| No innovation         | 4      | 15     | 49      |
| Product innovation    | 6      | 39     | 103     |
| Process innovation    | 7      | 44     | 137     |
| Both                  | 7      | 51     | 148     |

Source: own elaboration.
TABLE 2. Proportions of firms involved in different innovation activities according to age and size

<table>
<thead>
<tr>
<th>Innovation/Size</th>
<th>AGE(^7)</th>
<th>Young N=2344</th>
<th>Middle N=303</th>
<th>Old N=213</th>
<th>Very Old N=32</th>
</tr>
</thead>
<tbody>
<tr>
<td>No innovation</td>
<td>Small</td>
<td>26.87</td>
<td>33.65</td>
<td>22.73</td>
<td>0.00</td>
</tr>
<tr>
<td>Product innovation</td>
<td>Medium</td>
<td>18.07</td>
<td>16.83</td>
<td>14.77</td>
<td>33.33</td>
</tr>
<tr>
<td>Process innovation</td>
<td>Large</td>
<td>25.30</td>
<td>23.08</td>
<td>29.55</td>
<td>33.33</td>
</tr>
<tr>
<td>Both innovations</td>
<td></td>
<td>29.76</td>
<td>26.44</td>
<td>32.95</td>
<td>33.33</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
<td>100.00</td>
</tr>
</tbody>
</table>

As firm age and size tend to coincide, we follow the approach of some authors – such as Maiti and Singh [2011] – in controlling for age in order to study the effect of size. Table 2, illustrates that very old firms and large firms are the most innovative in all size categories. Process innovation is weakly dominant over product innovation in all size and age categories. The highest proportion of non-innovative firms is found in small and middle age and young firms.

Table 3 shows that the number of firms innovating (considering all innovation categories) is higher when access to finance does not form an obstacle. Considering the case of product innovation, 39.49 percent of product innovative firms face no such obstacle. This percentage is 40.06 when considering process innovation alone and 40.41 when considering both product and process innovation.

In conclusion, our data review generally supports Schumpeter’s view in the sense that innovation is optimal in concentrated markets (the Schumpeterian effect). However, there was also a noticeable escape competition effect; a situation explained by Aghion's
work [2006]. In regards to firm size, the findings coincide with Schumpeter’s hypothesis that large firms innovate more than smaller ones. In addition, financial resources seem to play a vital role in innovation.

### TABLE 3. Proportions of firms under different innovation behavior facing access to financing obstacle

<table>
<thead>
<tr>
<th>Innovation</th>
<th>No</th>
<th>Minor</th>
<th>Moderate</th>
<th>Major</th>
</tr>
</thead>
<tbody>
<tr>
<td>No innovation</td>
<td>40.89</td>
<td>19.01</td>
<td>20.49</td>
<td>19.62</td>
</tr>
<tr>
<td>Product innovation</td>
<td>39.49</td>
<td>18.66</td>
<td>20.34</td>
<td>21.52</td>
</tr>
<tr>
<td>Process innovation</td>
<td>41.06</td>
<td>18.16</td>
<td>20.57</td>
<td>20.21</td>
</tr>
<tr>
<td>Both innovations</td>
<td>40.41</td>
<td>18.56</td>
<td>20.36</td>
<td>20.67</td>
</tr>
</tbody>
</table>

Source: own elaboration.

### The Dependent Variable

Our dependent variable is a measure of innovation. The BEEPS classifies a firm as an innovator if the firm has either introduced a significantly new product, or a significantly new process.

In order to capture innovation, we construct a set of binary variables based on Schumpeter’s innovation categories [1934]. Maiti and Singh [2011] also maintain this dissection of innovation as a dependent variable in a similar analysis of innovation sources.

We will run our regression so that “any” type of innovation on the left hand side is included. Hence, the dependent variable would be 1 if either process or product innovation or both innovations types occur, and zero if no innovation of any type occurs.

### Explanatory Variables

#### Size

The previous literature review indicate that larger firms are more likely to be more innovative than smaller firms, using a variety of measures such as R&D expenditure, sales revenue and employees as a proxy of size. Therefore, for robustness purposes we will do two different runs; the first using the number of employees and the second using R&D expenditure in the previous year.

#### Competition

A main hypothesis of the Schumpeterian model is that firms operating in concentrated industries tend to be more innovative. As we saw in the literature review, this has been empirically controversial, with some finding the reverse correlation and more recent
literature finding a non-linear relationship in the form of an inverted U. Accordingly, we construct a measure of competition to test the relation between product market competition and innovation.

**Access to Financing**

We introduced a dummy variable to measure access to financing constructs as obstacle for the firms. In Schumpeter's work, financial resources and firm size influence innovation. The more access a firm has to financial capital the more innovative it would be, and the bigger the firm the higher the propensity to innovate.

**Control Variables**

We will include the following variables into our regression to see the contribution of each of them to the results.

**Ownership and Age**

Following Maiti and Singh [2011], we added an ownership dummy variable and log of age. Their results suggest that private and large firms are more innovative than others. We have already commented that agency issues may be of concern and so ownership controls are appropriate. Concerning age, the log of age does not have a consistent sign in Maiti and Singh's results, but empirically large and old firms tend to coincide. Looking at the probability of innovation after including the age of the firms into our regressions helps us to understand the dynamics of the industries. Some researchers, such as Huergo and Jaumandre [2004], confirm econometrically that the evolution of innovation behavior across ages is complex in the sense that two opposite results always show up. On one side, entrant firms on average present a high probability of innovating. On the other side, old firms tend to show a lower probability of introducing an innovation than entrant firms in their first year. Theoretically, the effect of age on innovation has two opposite forces. On one hand, knowledge accumulation positively affects a firm's ability to catch up and improve its innovation rate because current technological achievements depend on the previous work [Nelson, 1991]. On the other hand, aging might lead to rigidities in communication flows within the boundaries of the firm, and rivalry might lead to more advances in the surrounding environment; therefore, firms will produce less innovations as they age [Sorensen, Stuart, 2000], and age should be controlled for in a study of the effect of firm size on innovation.

**Legal System**

We introduced a dummy variable indicating whether the legal system is able to uphold contracts and property rights. This variable was constructed according to each firm's survey response.
Exports

According to Maiti and Singh [2011], exports create an incentive to innovate. Or it might be the case that more able innovators tend to export more. To capture these effects, we included a continuous variable that indicates exports as a percentage of the total sales in the previous year.

Industry

Cohen and Levin [1989] argued that the importance of controlling for industry effects arises from the fact that size is likely correlated with industry-level variables such as technological opportunity, which affects innovation positively. Therefore, controlling for industry-specific characteristics prevents bias in the estimation.

All the variables used are detailed in the appendix.

The Empirical Model

Our research goal is to investigate the effect of firm size, competition and the access to financial sources on innovation. Since our dependent variable is a binary variable, we employ a logit model. Our estimation procedure involves three different models. Model 1 examines the effect of size on innovation. Model 2 examines the effect of competition on innovation and Model 3 examines the effect of access to finance on innovation. In order to capture non-linearity in PMC and size in models 1 and 3, we used a categorical competition variable. Hence, the non-linearity we wish to uncover is included by using dummy variables for each category.

First we estimate the following models using a pooled time series specification. The estimates are carried out including control variables such as for country and sector effects. The use of a pooled regression was necessary as we do not have sufficient history of data over the years. We can get more precise estimates and test statistics with more power by pooling samples from the same population but at a different point of time.

Model 1.

\[
\text{Innovation} = \alpha_1 + \beta_1 \text{LogofAge} + \beta_2 \text{Exports} + \beta_3 \text{Legalsystem} + \beta_4 \text{Ownership} + \\
+ \beta_5 \text{SizeDummy} + \beta_6 \text{CountryDummy} + \beta_7 \text{SectorDummy} + \epsilon
\]  

Model 2.

\[
\text{Innovation} = \alpha_2 + \beta_8 \text{LogofAge} + \beta_9 \text{Exports} + \beta_{10} \text{Legalsystem} + \beta_{11} \text{Ownership} + \\
+ \beta_{12} \text{CompetitionDummy} + \beta_{13} \text{CountryDummy} + \beta_{14} \text{SectorDummy} + \epsilon
\]  

Model 3.

\[
\text{Innovation} = \alpha_3 + \beta_{15} \text{LogofAge} + \beta_{16} \text{Exports} + \beta_{17} \text{Legalsystem} + \beta_{18} \text{Ownership} + \\
+ \beta_{19} \text{FinancingDummy} + \beta_{20} \text{CountryDummy} + \beta_{21} \text{SectorDummy} + \epsilon
\]
Endogeneity problems, which are a feature of the previous equations, are dealt with later in this paper.

Results

This section reports the results of the regressions for the three models using both the pooled time series analysis and the cross section analysis.

Pooled Time Series Analysis

Table 4 presents our analysis with innovation as a dependent variable, which takes a value of one if either process and/or product occur, and zero if no innovation of any type occurs. We run three different regressions using the pooled time series estimate. In particular, column 1 is the estimation of the equation (1) above which considers the size dummies. Small size is the omitted category in the regression. Both medium and large firms have a positive and statistically significant effect at the 1 percent level. The odds of a firm being innovative rather than not increase by a factor of 3.480 when the firm is large rather than small. The relative probability of innovating rather than not is 2.102 higher when a firm is medium rather than small sized. This finding is consistent with Schumpeter’s theory that larger firms will be more innovative. Considering the second size measure, we included R&D expenditure instead of size categories. The results indicate robustness, as we found a statistically positive effect.

The second column focuses on the degree of competition. We find a negative marginal effect when the number of competitors is 4 or more. When the number of competitors is between 1 and 3, the odds of innovating rather than not is greater by 1.519. This relative probability of innovation rather than not is also positive when the number of competitors is 4 or more, and greater than no competitors at all by 1.242. However, both degrees of competition are not significant at any level. This might result from the lack of the data in our estimate. The middle category seems to have the greatest innovative potential with less difference between low and high levels of concentration. Indeed, since the coefficient of the high competition dummy is less than the middle level, this is evidence of non-linearities in the relationship between competition and innovation. Aghion’s [2006] model of macroeconomic growth and innovation specifies that the escaping competition effect dominates for some industries and he Schumpeterian effect dominates for others where the optimal innovation rate happens at intermediate levels of concentration.

The third column captures firm access to the financial resources. It was expected that the probability of innovating is higher when the firm does not face a problem in accessing finance. However, the results were not significant in our regression. This insignificant result may reflect a lack of data used in our research or, perhaps, financing issues are so tied to the controls that they do not stand out as an independent effect.
The effects of the control variables bear mention. In all three models, the probability of innovation is higher in firms that export. This can be explained by the fact that exports create the profit incentive to innovate. On the other hand it could be a selection effect in the sense that more able innovators tend to be more likely to innovate. This result is consistent with Maiti and Singh’s [2011] findings. The probability of innovation is at least 0.26 percent higher when the legal system is able to uphold property rights, as we might expect. Privately-owned firms are more likely to innovate than state-owned ones with a positive and statistically significant coefficient. Evidence generated by Lerner et al. [2011] supports our result that private firms are more innovative than public ones. Ferreira et al. [2012] suggest that public firms normally exploit existing ideas while private firms take more risk in exploring new ideas, explaining that situation private firms are less transparent to outside investors as compared to public ones. Therefore, insiders in private firms are more able to deal with failure, and are hence more willing to invest in innovation than public firms because they can choose an early existing strategy if they receive bad news. For example, in public firms the price of securities react to both good and news, which leads insiders to invest (or refrain from investing) in conventional projects.

In most of the regressions, we see that age is not significant in explaining innovation. However, in the first logit model, the probability of innovation appears to decrease as the firms get older with a 10-percent level of significance. Some authors, such as Sorensen and Stuart [2000], explain that aging leads to rigidities in the flow of communication within the boundaries of the firm, and to rivalry towards technical advances in the surrounding environment, so that firms will produce less innovation as they get older.

**TABLE 4. Logit model of innovation activity (Pooled time series analysis)**

<table>
<thead>
<tr>
<th>Dep.Var: Innovation</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOG of Age</td>
<td>-0.173*</td>
<td>-0.0118</td>
<td>-0.0176</td>
</tr>
<tr>
<td></td>
<td>[0.0942]</td>
<td>[0.0659]</td>
<td>[0.0878]</td>
</tr>
<tr>
<td>Exports</td>
<td>0.0141***</td>
<td>0.0157***</td>
<td>0.0175***</td>
</tr>
<tr>
<td></td>
<td>[0.0041]</td>
<td>[0.00325]</td>
<td>[0.00407]</td>
</tr>
<tr>
<td>Legal system</td>
<td>0.230*</td>
<td>0.227**</td>
<td>0.265**</td>
</tr>
<tr>
<td></td>
<td>[0.128]</td>
<td>[0.101]</td>
<td>[0.128]</td>
</tr>
<tr>
<td>Private</td>
<td>0.591**</td>
<td>0.25</td>
<td>0.354</td>
</tr>
<tr>
<td></td>
<td>[0.238]</td>
<td>[0.173]</td>
<td>[0.231]</td>
</tr>
<tr>
<td>Large</td>
<td>1.247***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.289]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>0.743***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.191]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Dep.Var: Innovation | (1) | (2) | (3)
---|---|---|---
Competition 3 | 0.18 |  | 
| [0.295] |  |  
Competition 2 | 0.378 |  | 
| [0.308] |  |  
Access to finance |  | −0.116 |  
|  | [0.129] |  |  
Country F.E | Yes | Yes | Yes 
|  |  |  |  
Sector F.E | Yes | Yes | Yes 
|  |  |  |  
Observations | 2,084 | 2,084 | 2,084 

Standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1
Model 1 examines the effect of size on innovation, model 2 examines the effect of competition on innovation, and model 3 examines the effect of access to finance on innovation.

Source: own elaboration.

Cross Section Analysis

In this section we re-run the previous regressions, considering each year separately. Table 5 replicates the same regressions using a cross section analysis for the year 2005, while Table 6 considers cross section analysis for year the 2002. In the first model large firms appear to have a slightly higher probability to innovate as compared to medium and small sized firms. This finding coincides with our finding in the pooled time series regression and with Schumpeter’s hypothesis. The second model indicates that the probability of innovation is higher when a firm faces low or no competition, which is more in line with the Schumpeterian effect than the escaping competition effect. In addition to that, the results show that the intermediate level of competition is the most conductive for innovation, which is consistent with Baldwin et al.’s [2000] empirical finding. The third model focuses on the effect of financial resources on innovation. It is expected that the probability of innovating is higher when a firm does not face a problem in accessing finance. We capture this positive relationship only in year 2002, meaning the probability of undertaking innovative efforts in 2002 is higher in firms that do not face an obstacle in accessing finance. This fits with the Schumpeterian hypothesis in which financing and size interact to generate innovation.

Observed impacts of the legal system are consistent with what we found in the pooled time series regression. Moreover, firms that export are more likely to be innovative in all of the regressions. Private firms seem to be more innovative than public firms, which also mirrors the results observed in our pooled time series regression.

Overall, the results seem to be consistent with Schumpeter’s hypothesis that bigger size firms with greater access to finance enhance innovation. The competition results indicate
that firms facing lower competition are more likely to innovate, which is also consistent with Schumpeter’s view.

### TABLE 5. Logit model of innovation activity (Cross section analysis 2005)

<table>
<thead>
<tr>
<th></th>
<th>Dep.Var: Innovation</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOG of Age</td>
<td>–0.102</td>
<td>0.049</td>
<td>0.0525</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.104]</td>
<td>[0.0949]</td>
<td>[0.0927]</td>
<td></td>
</tr>
<tr>
<td>Exports</td>
<td>0.0106*</td>
<td>0.0142**</td>
<td>0.0144***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.00569]</td>
<td>[0.00562]</td>
<td>[0.00473]</td>
<td></td>
</tr>
<tr>
<td>Legal system</td>
<td>0.269*</td>
<td>0.326**</td>
<td>0.376**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.148]</td>
<td>[0.146]</td>
<td>[0.148]</td>
<td></td>
</tr>
<tr>
<td>Private</td>
<td>0.533*</td>
<td>0.229</td>
<td>0.249</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.275]</td>
<td>[0.263]</td>
<td>[0.258]</td>
<td></td>
</tr>
<tr>
<td>Large</td>
<td>1.520***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.347]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>0.689***</td>
<td>0.163</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.207]</td>
<td>[0.322]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competition 3</td>
<td></td>
<td>0.363</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.339]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competition 2</td>
<td></td>
<td>–0.375**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.154]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Access to finance</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Country F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Sector F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,044</td>
<td>1,044</td>
<td>1,044</td>
<td></td>
</tr>
</tbody>
</table>

Standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1
Model 1 examines the effect of size on innovation, model 2 examines the effect of competition on innovation, and model 3 examines the effect of access to finance on innovation.

Source: own elaboration.

In order to compare the coefficients within the two cross-section models, we conduct a Chi-square test. The Chi-Square test for the equality of the medium and large size coefficients across the two years are equal to 16.89 and 24.22, respectively at two degrees of freedom; hence we reject the hypothesis of the equality of the two coefficients at p value 0.05. Conducting a Chi-square test for the equality of the competition variables provides us with values of 1.15 for competition 2 and 0.28 for competition 3 at two degrees of freedom. Hence there is no statistical difference in the two models of different years.
considering competition variables. Chi-square value is 2.89 when testing the equality of the two models at one degree of freedom. Hence, there is no statistical difference in the two models.

Overall, we find the behavior to be the same in 2002 and 2005 as there is no statistical difference in the coefficients. Hence, we can take the pooled regressions as a “good model” and we can take our conclusions from each individual year seriously.

**TABLE 6. Logit model of innovation activity (Cross section analysis 2002)**

<table>
<thead>
<tr>
<th>Dep.Var: Innovation</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOG of Age</td>
<td>-0.184*</td>
<td>-0.085</td>
<td>-0.0806</td>
</tr>
<tr>
<td></td>
<td>[0.103]</td>
<td>[0.0967]</td>
<td>[0.0989]</td>
</tr>
<tr>
<td>Exports</td>
<td>0.0151***</td>
<td>0.0170***</td>
<td>0.0172***</td>
</tr>
<tr>
<td></td>
<td>[0.00512]</td>
<td>[0.00516]</td>
<td>[0.00466]</td>
</tr>
<tr>
<td>Legal System</td>
<td>0.176</td>
<td>0.164</td>
<td>0.139</td>
</tr>
<tr>
<td></td>
<td>[0.148]</td>
<td>[0.147]</td>
<td>[0.148]</td>
</tr>
<tr>
<td>Private</td>
<td>0.394</td>
<td>0.298</td>
<td>0.285</td>
</tr>
<tr>
<td></td>
<td>[0.259]</td>
<td>[0.255]</td>
<td>[0.245]</td>
</tr>
<tr>
<td>Large</td>
<td>1.520***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.347]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>0.644**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.28]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competition 3</td>
<td></td>
<td>-0.168</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[1.146]</td>
<td></td>
</tr>
<tr>
<td>Competition 2</td>
<td></td>
<td>0.123</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[1.153]</td>
<td></td>
</tr>
<tr>
<td>Access to Finance</td>
<td></td>
<td></td>
<td>0.251*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[0.148]</td>
</tr>
<tr>
<td>Country F.E</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Sector F.E</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>1,044</td>
<td>1,044</td>
<td>1,044</td>
</tr>
</tbody>
</table>

Standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1
Model 1 examines the effect of size on innovation, model 2 examines the effect of competition on innovation, and model 3 examines the effect of access to finance on innovation.

Source: own elaboration.
Addressing Endogeneity

Endogeneity is a serious problem that can arise when we use a single equation model to study the relationship between innovation and market structure, firm size, or financial access because the relation may not be a simple one-way causal relationship. Innovation activity may affect market structure and firm size [Symeonidis, 1996]. At the same time market structure, size and financial access may affect innovation activity. Regarding firm size, Scherer [1992] emphasizes the reverse causation between size and innovation: innovation affects firm growth and hence firm size, so that size in the current year is influenced by innovative activity in the previous year.

Some authors, such as Machin and Van Reenen [1996] argue that the use of instrumental variables could solve this problem, while others, such as Levin and Reiss [1988], have estimated simultaneous equation systems in which both innovation and each of market structure, size or financing are each treated as endogenous.

Since we have data for two years, we could potentially use earlier values (year 2002) for firm size, competition and financial access variables and later values (year 2005) for the dependent variable, which is innovation. The idea would be that the competitive situation, size or financial access for firms in an earlier year might give rise to innovation in later years, but not the reverse. If three years lag is a long enough period to minimize reverse causality, it might give us at least an adequate idea of the magnitude of the effect endogeneity may be having on our results.

Table 7 shows the results of estimating the same three previous models after addressing the endogeneity problem using lagged values. In comparison with the results of the estimation of the pooled time series, we generally see an increase in the coefficient after treating the endogeneity problem. This outcome is expected and suggests that endogeneity is probably an issue; likewise, we would normally expect some bias to arise if endogeneity is present.

In more detail, the first column shows that size generally does not have a large effect and is generally in line with the sort of bias we might expect due to endogeneity. Regarding the other variables, the coefficients increased slightly. Moving to column 2, all the variables have experienced a small increase in their magnitude. After treating for endogeneity, the coefficient of innovation decreases with competition. This change might be due to endogeneity, but we also have to consider the possibility that there is a lag structure to the interaction between competition and innovation. In other words, by using lagged values as instruments we might be instead picking up a different problem with the base model: we might not be capturing lags. If innovation occurs quickly, the instrument strategy might make sense. For innovation that takes longer, it may simply mean that the lag structure of innovation is three years. We cannot separate out these possible explanations with the current choice of instrument. Furthermore, as our data assembles a wide variety of innovation types (process and product) and, as the innovation measure is based on an evaluation process that might, in itself, carry (such that one would only evaluate oneself
as innovative some time after having achieved innovation), the lag structure might not be consistent across the data.

**TABLE 7. Logit model of innovation activity (Using the lagged values to address the endogeniety problem)**

<table>
<thead>
<tr>
<th>Dep.Var: Innovation</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[9.054]</td>
<td>[8.303]</td>
<td>[8.278]</td>
</tr>
<tr>
<td>Exports</td>
<td>0.0176***</td>
<td>0.0188***</td>
<td>0.0190***</td>
</tr>
<tr>
<td></td>
<td>[0.0047]</td>
<td>[0.00465]</td>
<td>[0.00464]</td>
</tr>
<tr>
<td>Legal System</td>
<td>0.256*</td>
<td>0.247*</td>
<td>0.247*</td>
</tr>
<tr>
<td></td>
<td>[0.148]</td>
<td>[0.148]</td>
<td>[0.148]</td>
</tr>
<tr>
<td>Private</td>
<td>0.456**</td>
<td>0.335</td>
<td>0.325</td>
</tr>
<tr>
<td></td>
<td>[0.216]</td>
<td>[0.251]</td>
<td></td>
</tr>
<tr>
<td>Large</td>
<td>0.921***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.313]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>0.315</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.204]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competition 3</td>
<td></td>
<td>0.124</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[1.051]</td>
<td></td>
</tr>
<tr>
<td>Competition 2</td>
<td></td>
<td>0.271</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.206]</td>
<td></td>
</tr>
<tr>
<td>Access to Finance</td>
<td></td>
<td></td>
<td>0.0449</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[0.149]</td>
</tr>
<tr>
<td>Country F. E</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Sector F. E</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>1,044</td>
<td>1,044</td>
<td>1,044</td>
</tr>
</tbody>
</table>

Standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1
Model 1 examines the effect of size on innovation, model 2 examines the effect of competition on innovation, and model 3 examines the effect of access to finance on innovation

Source: own elaboration.

**Conclusion**

In this paper we evaluate the Schumpeterian hypotheses with detailed firm-level data on the relationship between competition, firm size, financial access and innovation behavior. Several findings are of note. First, size is positively related to innovation, which
is in line with Schumpeter’s hypothesis. Our results suggest that the probability of large firms to innovate is higher than small and medium sized firms. Second, the relationship between competition and size appears to be non-linear. As the number of competitors increases, the probability to innovate first increases, and then decreases. Intermediate levels of competition seem to be the most conductive for innovation. The third finding is that firms with no obstacles to accessing financial resources are more likely to innovate, which also coincides with Schumpeter’s predictions.

Our results are robust for different measurements of size and innovation and as to some different divisions of the data, such as year of measurement. We made a first attempt to address the endogeneity problem using lagged values as instruments, which also confirmed our initial results.

Regarding drawbacks of our analysis, our dataset covered only two years as a panel. Hence, this analysis could be extended in two directions. The first would be to examine more carefully competition variables using a larger sample of data. The second would be to address endogeneity using alternative instruments to permit more definitive conclusions concerning innovation policy.

Notes

1 See P.A. Geroski (1995) and S.J. Nickell (1996). Their research also pointed to a positive correlation between competition and innovation.

2 The Hart model (1983) formalized the fact that both competition in the product market and the capital markets play an important role in limiting managerial slack. He proved that managerial slack is lower under competition than for a single “non-profit” maximizing monopolist.

3 Quality ladder here is not an explicit measure of quality but rather a cost ladder where higher quality is equivalent to lower production costs.


6 J. Sutton (1991) provides significant support for this view of R&D as a large sunk cost.

7 Age is categorized into four groups: young, middle, old and very old. A firm is young if it has been operating for less than 20 years, middle if it has been operating between 20 and 50 years, old if it has been operating between 50 and 100 years, and very old if it has been operating for more than 100 years.

8 Our model is based on Maiti and Singh (2011) in the use of the main variables (size, competition and financing). We used some control variables other than those in Maiti and Singh (2011) in order to construct a balanced panel. Maiti and Singh run different regressions considering different types of
innovation. In our case, we only run our regression using one dummy variable indicating 1 when any type of innovation occurs and zero otherwise. Maiti and Singh run a cross section while, in our case, we will run both pooled time series and a cross section. Hence, our paper complements and extends Maiti and Singh’s work.

9 Technological opportunities vary across industries as the scientific environment provides more productive grounds for advances in some industries than in others. Hence, technical improvement is higher in some industries than in others (Baldwin et al., 2000).

10 We run three regressions using three different measurement of innovation as explained in the descriptive analysis of the data. The results show robustness across all innovation categories. The results have not been reported.

11 We have not reported the regression table while considering R&D expenditure for abbreviation purposes. We did not find any difference between the two measurements of size.

12 Independent variables were taken from the 2002 data set to be used as instruments to treat the endogeneity bias, whereas the dependent innovation variable is from the 2005 data set.

References


### Appendix
**Description of Dependent and Explanatory Variables for Logit Model**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>DEPENDENT</strong></td>
<td></td>
</tr>
<tr>
<td>Innovation</td>
<td>Process with product innovation</td>
</tr>
<tr>
<td></td>
<td>Product Innovation</td>
</tr>
<tr>
<td></td>
<td>Process Innovation</td>
</tr>
<tr>
<td><strong>EXPLANATORY</strong></td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td></td>
</tr>
<tr>
<td>Small</td>
<td>Less than 99 employees</td>
</tr>
<tr>
<td>Medium</td>
<td>100 to 499</td>
</tr>
<tr>
<td>Large</td>
<td>500–9999 employees</td>
</tr>
<tr>
<td>R&amp;D</td>
<td>R&amp;D expenditure in the previous year</td>
</tr>
<tr>
<td>Competition</td>
<td></td>
</tr>
<tr>
<td>Competition 1</td>
<td>No competitors</td>
</tr>
<tr>
<td>Competition 2</td>
<td>1 to 3 competitors</td>
</tr>
<tr>
<td>Competition 3</td>
<td>More than 4 competitors</td>
</tr>
<tr>
<td>Access to financial resources</td>
<td>Obstacle</td>
</tr>
<tr>
<td></td>
<td>No Obstacle</td>
</tr>
<tr>
<td>Ownership</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Private-owned</td>
</tr>
<tr>
<td></td>
<td>State-owned</td>
</tr>
<tr>
<td>LOG of Age</td>
<td>Age: number of years that the firm has been operating</td>
</tr>
<tr>
<td>Exports</td>
<td>Percentage of exports in sales</td>
</tr>
</tbody>
</table>
## Variable Description

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Legal system</td>
<td>The legal system able to uphold contracts and property rights. Yes No</td>
</tr>
<tr>
<td>Country</td>
<td>Bulgaria, Albania, Croatia, Belarus, Georgia, Tajikistan, Turkey, Ukraine, Uzbekistan, Russia, Poland, Romania, Kazakhstan, Moldova, Azerbaijan, FYR Macedonia, Lithuania, Armenia, Kyrgyz Republic, Estonia, Czech Republic, Latvia, Hungary, Slovak republic, Slovenia, Bosnia and Herzegovina.</td>
</tr>
<tr>
<td>Sector</td>
<td>Mining and quarrying, Construction, Manufacturing Transport storage and communication, Wholesale and retail trade, Real estate, renting and business services, Hotels and restaurants, Other services</td>
</tr>
</tbody>
</table>

*Source: own elaboration.*
Effect of Celebrity Endorsement in Advertising Activities by Product Type

Abstract

This article seeks to answer two related questions: are celebrity endorsements more likely to result in a higher evaluation of the product being advertised than use of an anonymous individual (e.g. a typical consumer); and, if present, do these positive effects vary by product category? To answer these two questions research was conducted on a 237 student sample employing a quasi-experiment consisting of four groups (two product categories and two types of endorsers) using data collected through an online survey. The results indicate that celebrity endorsements do have a positive impact on the evaluation of durable goods, but do not affect the evaluation of frequently purchased products. This finding largely confirms the assumptions of the match-up model, the meaning transfer model, and the ELM model.

Keywords: celebrity endorsement, endorser, advertising, brand.
JEL: M37

Introduction

The use of celebrity endorsements in advertising first appeared in the 19th century, and was further developed in the 20th century with the emergence of new advertising media: the radio (1930s); television (1950s); and the Internet (1990s) [Erdogan, 1999,
p. 292; Racula, 2012, p. 75]. This advertising technique is now one of the most ways to reach consumers. [Agrawal, Kamakura, 1995, p. 58; Ding et al., 2011, p. 148]. It is estimated that more than 25% of advertising campaigns in the USA used celebrities [Erdogan, 1999, p. 292; Erdogan et al., 2001, p. 39], and about 10% of advertising budgets were allocated to paying celebrities [Agrawal, Kamakura, 1995, p. 58].

According to definition, “a celebrity endorser is an individual who is known by the public for his or her achievements in areas other than that of the product class endorsed” [Friedman, Friedman, 1979, p. 63]. The use of celebrities in advertising: (1) attracts attention of the surrounding world (consumers, traders); (2) strengthens the advertising message; (3) refines brand image, giving it a new and better meaning; (4) is an opportunity to enter other geographical markets through the use of celebrities globally. [Erdogan, 1999, pp. 295–296; Racula, 2012, pp. 77–78; Abdussalam, 2014, pp. 80–82]

The use of a celebrity’s image does not, however, guarantee success; as with every most managerial decisions, this advertising technique poses risks, including: (1) a mismatch between the celebrity and the product advertised; (2) brands being obscured by an overwhelming celebrity; (3) the overuse of a particular celebrity by too many brands, leading to conflicting advertising messages; (4) that a celebrity working under a long-term advertising behaves badly, drawing negative publicity that undermines brand reputation; (5) a decreased interest in the brand when a celebrity loses importance or the public’s attention; (6) the general impact of significantly increased advertising campaign costs [Erdogan, 1999, pp. 295–296; Racula, 2012, pp. 77–78; Abdussalam, 2014, pp. 80–82].

Employing a pros and cons analysis of celebrity endorsements, a publication aims at answering the following questions: do celebrity endorsements achieve better results (i.e., product evaluation) than the use of anonymous individuals (e.g., typical consumers) and do these effects vary by product category?

### Theoretical Models

The literature dealing with celebrity advertising impacts identifies five models that describe celebrity endorsement. The purpose of each is to clarify the relationship between the product (brand), celebrity, and process by which a celebrity’s characteristics are transferred to the brand (endorsement process) [McCracken, 1989, pp. 310–312; Ergodan 1999, pp. 297; Mittelstaedt et al.2000, pp. 56–57; Hung et al., 310–312; Ergodan, 1999, pp. 297; Mittelstaedt et al., 2000, pp. 56–57; Hung et al., 2011, pp. 610; Racula, 2012, pp. 76–77; Carrilant et al., 2013, pp. 16–17; Hung, 2014, pp. 155–158]. These five models are:

1. The source model – based on the assumption that recipients will believe and accept an advertising message if the celebrity is trustworthy (defined as the perceived willingness of the source to make valid assertions), is an expert (defined as the perceived ability of the source to make valid assertions) and/or is attractive (a celebrity's popularity, physical
attraction). This model is based on research carried out in that social psychology field that defines two source model elements – trustworthiness and expertness [Hovland, Weiss, 1951, pp. 635–650]. The third component of this model, i.e., attractiveness, which also relies on theories derived from social psychology [McGuire, 1985, p. 264], was discovered and empirically verified by Weiner and Mowen [1986, pp. 306–310].

The source model assumes that using a celebrity with certain characteristics (trustworthiness, expertness and/or attractiveness) in advertising activities relating to any product category will bring positive effects.

2. The match-up model (the Product Match-up Hypothesis / celebrity-brand congruence model) is based on the hypothesis [Kamins, 1990, pp. 5–6] that the effects of using a celebrity in marketing communications depends on the degree of perceived fit between the brand (product name, symbol, image, benefits and attributes) and image of the celebrity. This model is consistent with the social adaptation theory [Kahle and Homer, 1985, pp. 954–955], which postulates that adaptive significance of information determines its impact on recipients, thus contributing to positive effects of advertising activities. Celebrity choice is based on the assumption that not every celebrity will effectively advertise every brand in any product category. This accentuates the risks of (1) too many brands using the same celebrity and (12) his or her potential for controversial behavior in the future. The model’s limitation is its inability to define and measure celebrity characteristics that are important for individual product categories and brands.

3. The meaning transfer model was developed by McCracken, and consists of three stages showing the transfer of characteristics/meanings [1989, pp. 313–318]. At the first stage – “culture” – a celebrity is defined by all characteristics that correspond to his or her image in the media through work performed, statements, roles played, etc. At the second stage – “endorsement” – various associations with the celebrity are transferred to the product (brand) advertised by him or her. The key issue at this stage is to determine the symbolic properties of the brand to be strengthened or created through advertising activities, and to then select a celebrity who is consistent with desired symbolic properties. At the third stage – “consumption” – the desired meanings linked to a celebrity are passed on from the product (brand) to the recipient (consumer). In this situation, the process of consumption or use is given a broader context as the consumer becomes a part of a larger whole, gains self-appreciation and strengthens his or her own self-image through the transfer of such meanings. The choice of celebrity to advertise a brand should take into account the relationship of the celebrity’s image with the desired image and perceived benefits and attributes of the brand. This model is a significant extension of the match-up model because it emphasizes not only the celebrity-brand match-up but also the choice of meanings to be transferred from the celebrity to the advertised brand. An elaboration of this approach is the model proposed by Misra and Beatty [1990, pp. 159–173], who imply
that meanings are not transferred in one direction only, i.e., from the celebrity to the
brand, but also from the brand to the celebrity. This is particularly pertinent when
a celebrity becomes the face of the brand. Necessary conditions include long-term
cooperation of the celebrity with the company (brand) and application of the exclu-
sivity rule (a celebrity advertising one brand only).

4. The Elaboration Likelihood Model (ELM) is based on the assumption [Petty, Cacio-
to an advertising message (including use of a celebrity) in various ways depending on
situational factors (resulting from the importance of a product category, and thus the
type of purchasing decisions, medium, message reception time, etc.). On this basis, two
situations related to an advertising message reception may be distinguished: high and
low involvement. In the first case, the reception of an advertising message is elaborate
and systematic, which can lead to a permanent change in the recipient’s attitudes.
Because recipients pay attention to the arguments contained in the advertising message
and then the celebrity should, first and foremost, be an expert in a given field. In the
second situation, the reception of an advertising message is peripheral and heuristic,
which weakens its influence on attitudes. Recipients with low involvement focus on
superficial characteristics of the message. Thus, a key element is that the celebrity be
attractive.

5. The Dual entertainment path model has, as a starting point, the following entertain-
ment [Valkenburg and Voort, 1994, pp. 334–337; Vorderer et al., 2004, pp. 393–403]
and transportation theories [Green et al., 2004, pp. 312–324; Green and Brock, 2000,
pp. 701–702]. Unlike the ELM model, which is based on a cognitive approach, this
model focuses on the recipient’s experience [Hung, 2014, pp. 155]. Similarly to the
ELM model, two situations are distinguished: the high and low involvement of the
recipient. In the first situation, aspirational motives are the key: the consumer wants
to be the same as the celebrity and imitate his or her lifestyle. A strong parasocial
bond with the celebrity then appears, which is determined by emotional investment.
The second situation is connected with playful motives. This means a weaker paraso-
cial bond with the celebrity. The key for building the recipient’s attention is avoiding
boredom and creating the fiction of escaping from real life through imagination and
dreams [Hung, 2014, pp. 156–159].

Previous Studies’ Overview

Empirical studies using these five celebrity endorsement models are presented in Table
1. The largest group of studies applied the match-up model. Determining communica-
tion effects of celebrity endorsement (attitude towards the brand, purchase intention,
degree of brand awareness, degree to which an advertisement is remembered, etc.) was the predominant purpose. Relatively few studies refer to financial results, including the company’s value for its owners; these include: Agrawal and Kamakura [1995, pp. 56–60], Ding, Malchanov, Stork [2010, pp. 147–163]. Most studies are based on a research design involving experiments or quasi-experiments carried out in two or more groups. Examples include one of the first studies on celebrity endorsement effects conducted by Friedman, Friedman [1979, pp. 63–71] and another one – the most frequently cited study by Kamins [1990, pp. 4–19]. Polish studies have not, however, been conducted in an experiment form [Woźniczka, 2011, pp.14–22].

Friedman and Friedman [1979, pp. 63–71] analysed three products: biscuits, a vacuum cleaner, and imitation jewellery. They were promoted through advertisements using different messaging sources: a housewife, an expert, and a celebrity. In addition, a “placebo” advertisement was introduced without any message source (endorser). The experiment design comprised twelve groups. For each group, an identically laid out advertisement was prepared, and all products had the same name – “Majestik”. The study sample included housewives living in Brooklyn. With respect to each group, 30 randomly selected respondents were interviewed. The total study sample consisted of 360 people [pp. 65–66]. The study results showed that different products should be advertised by different types of endorsers for the message to reach recipients in accordance with the intended purpose. Imitation jewellery of dubious quality was rated as a more attractive product when advertised by a celebrity, but less highly evaluated when presented by other endorsers – a housewife and an expert (in the jewellery industry) [pp. 66–70].

The second study, carried out by Kamins [1990, pp. 4–19], concerned advertisements of two products: a computer and a luxury car, presented by two well-known actors – one belonging to the “attractive” and the other to the “less attractive” categories. The experiment design consisted of four groups. The study sample included students, each of whom was randomly assigned to one of the groups, and the total study sample size was 89 respondents [pp. 7–9]. The study results indicate that the “attractive” actor fits a luxury car advertisement better. Respondents who were presented with the luxury car advertisement featuring the “attractive” actor evaluated the actor himself as more trustworthy and the advertised car as being of better quality than in the luxury car advertisement featuring the “less attractive” actor. The opposite effect was observed for the personal computer, which was better evaluated in the advertisement featuring the “less attractive” actor, who himself was more trustworthy according to respondents [pp. 9–10].

Research by Woźniczka [2011, pp. 14–22] was also carried out on a student sample. The total sample size was 145 people. The research involved the presentation of single shots of 10 TV commercials to respondents. Each commercial referred to a different consumer product. Five commercials used “ordinary people” and other five “celebrities”. For each commercial, respondents were to answer questions relating to commercial recognition, brand recognition, attitude towards the commercial, attitude towards the spokesperson,
and the impact of the commercial on their future purchase intentions [pp. 17–19]. The results of this research indicate that celebrity use does not lead to clear differences in communication effects, with the exception of attitudes towards the advertisement and the persons appearing in it [pp. 19–22].

**TABLE 1. Overview of previous studies**

<table>
<thead>
<tr>
<th>Study</th>
<th>Model</th>
<th>Conclusions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Friedman, Friedman, 1979</td>
<td>Source Match-up</td>
<td>The celebrity was more effective than the expert or typical-consumer endorser in sustaining recall of the advertisement and the brand name of the product, regardless of product type. Attitude towards brand and intention to purchase depended on the type of products. Celebrity endorsers were appropriate where products purchased involved high social and psychological risk.</td>
</tr>
<tr>
<td>Petty, Cacioppo, Goldman, 1981</td>
<td>ELM</td>
<td>Found that the quality of arguments contained in a message has a greater impact on persuasion under high involvement conditions, whereas under low involvement conditions peripheral cues – source attractiveness, credibility – have a greater impact on persuasion.</td>
</tr>
<tr>
<td>Petty, Cacioppo, Schumann, 1983</td>
<td>ELM</td>
<td>The manipulation of argument quality had a greater impact on brand attitudes under high than low involvement, but the manipulation of the product endorser had a greater impact under low than high involvement.</td>
</tr>
<tr>
<td>Khale, Homer, 1985</td>
<td>Source</td>
<td>Attitudes and purchase intentions changed due to celebrity source attractiveness, consistent with social adaptation theory</td>
</tr>
<tr>
<td>Speck, Schumann, Thompson, 1988</td>
<td>Source</td>
<td>Found that expert celebrities produced a higher recall of product information than non-expert celebrities; but the difference was not statistically significant.</td>
</tr>
<tr>
<td>Kamins, Brand, Hoeke, Moe, 1989</td>
<td>Source</td>
<td>Indicated the effectiveness of a two-sided, as opposed to one-sided, celebrity spokesperson appeal.</td>
</tr>
<tr>
<td>Kamins, 1990</td>
<td>Match-up</td>
<td>Found that physically attractive celebrities enhance credibility and attitudes for attractive products. The physical attractiveness of a celebrity endorser may only enhance both product-ad-based evaluations if the brand’s characteristics “match-up” with the image conveyed by the celebrity.</td>
</tr>
<tr>
<td>Misra, Beatty, 1990</td>
<td>Match-up</td>
<td>Found that advertising recall, then transfer affects from spokesperson to brand, and affect toward the brand are significantly higher when the spokesperson is congruent with brand.</td>
</tr>
<tr>
<td>Langmeyer, Walker, 1991</td>
<td>Meaning transfer</td>
<td>Found that celebrities embody various meanings that are passed on to brands with endorsements.</td>
</tr>
<tr>
<td>Ohanian, 1991</td>
<td>Source</td>
<td>Perceived expertise of the celebrities was a significant factor explaining the respondents’ intention to purchase the product. Attractiveness and trustworthiness of the celebrities had an insignificant impact on the intent to purchase the product.</td>
</tr>
<tr>
<td>Study</td>
<td>Model</td>
<td>Conclusions</td>
</tr>
<tr>
<td>--------------------------</td>
<td>-------</td>
<td>--------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Kamins, Gupta, 1994</td>
<td>Match-up</td>
<td>Found that the higher level match-up between spokesperson and product resulted in increased believability, attractiveness of the spokesperson, and positive attitudes toward the product.</td>
</tr>
<tr>
<td>Lynch, Schuler, 1994</td>
<td>Match-up</td>
<td>Found that the congruence in advertisements between spokesperson characteristics and product attributes is related to observed variations in source credibility, product evaluations, perceived product gender, and other measures of advertising and communication effectiveness.</td>
</tr>
<tr>
<td>Agrwala, Kamura, 1995</td>
<td>-</td>
<td>Positive impact of announcing celebrity endorsements on stock returns.</td>
</tr>
<tr>
<td>O’Mahony, Meenaghan, 1997/1998</td>
<td>Match-up</td>
<td>The study confirmed that consumers expect congruence between the perceived image of the celebrity endorser and product types. Celebrities must possess expertise in product categories consistent with their public image.</td>
</tr>
<tr>
<td>Till, Busler, 1998</td>
<td>Match-up Source</td>
<td>Found that expertise is more important than physical attractiveness for matching a brand with an appropriate endorser.</td>
</tr>
<tr>
<td>Mittelstaedt, Riesz, Burns, 2000</td>
<td>Match-up</td>
<td>Indicated that matches between endorsers and products, rather than the nature of the products or the endorsers themselves, affect the perceived effectiveness of endorsements.</td>
</tr>
<tr>
<td>Till, Busler, 2000</td>
<td>Match-up</td>
<td>Found that the variables “fit” or “belongingness” are important to understanding the match-up effects between celebrity and brand.</td>
</tr>
<tr>
<td>Stafford, Stafford, Day, 2002</td>
<td>Match-up</td>
<td>Found that the effectiveness of a celebrity will probably vary on the basis of whether the service is utilitarian or hedonic. Celebrities create trust and expertise for a hedonic service and a positive affect for utilitarian services.</td>
</tr>
<tr>
<td>Silvera, Austad, 2004</td>
<td>Match-up Source</td>
<td>The resulting model indicated that brand attitudes were predicted by inferences about the linking of endorser’s and the product and attitudes toward the endorser.</td>
</tr>
<tr>
<td>Biswas, Biswas, Das, 2006</td>
<td>Source</td>
<td>For high technology – oriented products, an endorsement by a person perceived to be an expert for that product is more effective in reducing perceived risk than an endorsement by a celebrity or by a non-celebrity non-expert.</td>
</tr>
<tr>
<td>Liu, Chen, Jiang, 2007</td>
<td>Match-up Source</td>
<td>Found that the attractiveness of a spokesperson can affect purchase intentions, particularly when match-up is low.</td>
</tr>
<tr>
<td>Lee, Thorson, 2008</td>
<td>Match-up</td>
<td>Found that celebrity endorsements with moderate product mismatch have more favorable purchase intentions than extreme match or extreme mismatch, and that the effects of celebrity-product congruence are more pronounced among participants with higher product involvement than those with lower product involvement.</td>
</tr>
<tr>
<td>Lord, Putrevu, 2009</td>
<td>Source ELM</td>
<td>Found that the celebrity expertise and trustworthiness are the primary determinants of informational motivation, while attractiveness is the principal variable driving transformational motivation.</td>
</tr>
</tbody>
</table>
Effect of Celebrity Endorsement in Advertising Activities by Product Type

<table>
<thead>
<tr>
<th>Study</th>
<th>Model</th>
<th>Conclusions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheeler, 2009</td>
<td>Match-up ELM</td>
<td>Found that a celebrity who is closely connected to a non-profit organization through experience and proper fit will generate greater source credibility than others; the source credibility generated by the connected celebrity will directly affect the intention to volunteer time and donate money; the ad subject involvement plays a significant role in determining the level of source credibility and intention.</td>
</tr>
<tr>
<td>Ding, Malchanov, Stork, 2010</td>
<td>–</td>
<td>Announcing celebrity endorsements do not experience positive abnormal returns (net discounted cash flow to be close to zero). Positive impact of endorser on abnormal returns: group (e.g., a soccer team), athlete, celebrity-brand congruence, multiplicity (multiple celebrities to advertise brand/company).</td>
</tr>
<tr>
<td>Spry, Pappu, Cornwell, 2011</td>
<td>Source</td>
<td>Found that endorser credibility has an indirect impact on brand equity when this relationship is mediated by brand credibility. This mediating relationship was moderated by type of branding.</td>
</tr>
<tr>
<td>Woźniczka, 2011</td>
<td>Source</td>
<td>Found that the celebrity endorsement creates a better ad and brand attitude than typical consumer, and there was no statistically significant difference between celebrity and typical consumer in ad recognition, brand awareness and brand purchase intention.</td>
</tr>
<tr>
<td>Hung, 2014</td>
<td>Dual entertainment path</td>
<td>Found links between entertainment motives (aspirational and playful) and experiences (celebrity fantasy and emotional investment) influence endorsed brand attitude. Fans are driven by both aspirational and playful motives to engage in celebrity-induced entertainment experiences. Non-fans are driven predominantly by a playful motive.</td>
</tr>
</tbody>
</table>

Source: own elaboration.

Research Methodology

The starting point for designing the research methodology was to define the research problem and hypotheses. The research problem was formulated as: determining the impact of a celebrity’s image on evaluation of the advertised product. The research used a quasi-experimental method involving four groups. This solution is typical for research on celebrity endorsements in advertising.

Four advertisements were prepared for the experiment – they were not used in the real world and featured generic (non-branded) products. The advertisements were full page press ads. An actress (Alicja Bachleda-Curuś) and an unknown model were selected as endorsers. These two persons were of similar physical attractiveness, such that the celebrity effect could be separated from the influence of the attractiveness of the endorsers on respondent assessments.¹
Two products were used during the study. The first – colorful watches – is a product often considered tacky. The study’s intended purpose was to verify whether the presence of a celebrity can boost a product’s prestige and increase the interest of the respondents, as indicated by Friedman and Friedman (effect for imitation jewelry) [1979, pp. 63–71]. The second featured product was fruit juice, an uncomplicated product frequently purchased without much thought. It does not reflect the status of the buyer, is inexpensive and consumed at home, similarly to the biscuits described by Friedman and Friedman [pp. 63–71].

The research employed four questionnaires that differed in terms of the advertisement being shown (a combination of two advertised products and two endorsers) and, depending on the product advertised, asked several different questions. In the questionnaire, information about the research being conducted was followed by a display of the advertisement to be watched by respondents and questions to be answered. The first version of the questionnaire referred to the following situations: one, a celebrity and a speciality good (Watches A); two, an attractive but unknown model and a speciality good (Watches B); three, a celebrity and a convenience good (Juice A), and four, an attractive but unknown model and a convenience good (Juice B). For watches, in both cases the advertising slogan “fashionable watches” was used. For juices, the slogan used was “delicious juice”. The attractiveness of the source and the advertisements was measured on a 5-item Likert scale (strongly disagree, disagree, neither agree nor disagree, agree, strongly agree).

With regard to the problem so defined and the research design, three hypotheses were specified:

- **H1**: The celebrity will be evaluated as more attractive than the model.
- **H2**: The celebrity will be better evaluated as an endorser than the model (likeability, credibility, trust).
- **H3**: The celebrity will have a positive impact on product evaluation.

The research was conducted through an online survey among students of four higher education institutions in Warsaw, i.e. the University of Warsaw, the Warsaw University of Technology, the Warsaw School of Economics, and the University of Medicine. The research involved 256 respondents: 149 women and 107 men. The answers given by respondents who did not fully complete the questionnaire were not taken into account. In total, there were 14 such partially completed questionnaires. The numbers of people in each of the advertisement options were as follows:

- **Watches A** – 72 people (44 women and 28 men),
- **Watches B** – 72 people (43 women and 29 men),
- **Beverages A** – 57 people (32 women and 25 men),
- **Beverages B** – 55 people (30 women and 25 men).

Since the paper analyses the celebrity effect, questionnaire with a celebrity included a question intended to verify whether respondents recognised the celebrity appearing in the advertisement. People who responded that they did not recognise the endorser
in the Watches A and Beverages A questionnaires were excluded from the research. Thus, final respondent numbers in the two groups with a celebrity were:
- Watches A – 62 people (40 women and 22 men) – 10 persons did not recognise the celebrity,
- Beverages A – 48 people (31 women and 17 men) – 9 persons did not recognise the celebrity.

The research was conducted in 2014. A link to the questionnaires was published in a social networking service on 04.04.2014 and the survey was closed on 13.04.2014. Respondents were randomly redirected to one of the four questionnaires. Hence, respondents were not aware of other questionnaire versions used in the research. The research sample consisted of students, to reduce the costs of the experiment. Use of a representative nationwide sample is much costlier (a randomized quota selection would require a sample size of approximately 1300 respondents). Student samples have therefore been used in international studies on celebrity endorsement in advertising. Moreover, the high homogeneity of such a sample fairly permits the study results to generally be extended to the larger student population even when a relatively small sample is used. Finally, use of a student sample facilitates the use of an online survey, which is very most cost-effective. That communication pathway is, however, still problematic for much of the remainder of Poland’s population.

To statistically analyze the collected material, the Student’s t-test was used for two populations with unknown standard deviations. Although use of the Student’s t-test for the ordinal-scale analysis of assessments has sometimes been criticised. Norman [2010, pp. 625–632] indicates that the results mirror more sophisticated statistical tests that are theoretically more appropriate for such data.

**Results Analysis – Hypothesis 1**

In order to verify this assumption, the questionnaires included a question about the endorser’s attractiveness. Figure 1 shows respondents’ overall average evaluations of perceived celebrity and non-celebrity attractiveness referring to watches and juices. Cumulative results for both questionnaires are presented, by endorser.

A comparison of the average perceived attractiveness of the celebrity and non-celebrity is shown. This comparison indicates that the average rating of the celebrity’s attractiveness was statistically significantly higher than the rating of a non-celebrity ($p = 0.000$). This effect was also observed among the respondents describing advertisement with “watches” ($p = 0.000$), but not among respondents describing advertisement with “juices” ($p = 0.249$). This suggests that the observed differences in attractiveness evaluation may actually result not exclusively from the celebrity’s greater physical attractiveness, but from some qualities of the advertised products which, in combination with the celebrity characteristics, lead to a higher evaluation of her attractiveness.
FIGURE 1. Perceived attractiveness of product endorsers in advertisements

<table>
<thead>
<tr>
<th>Endorser Type</th>
<th>Total Rating</th>
<th>p Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-celebrity total</td>
<td>3.98</td>
<td>0.000</td>
</tr>
<tr>
<td>Celebrity total</td>
<td>4.37</td>
<td></td>
</tr>
<tr>
<td>Non-celebrity – watches</td>
<td>3.89</td>
<td>0.000</td>
</tr>
<tr>
<td>Celebrity – watches</td>
<td>4.45</td>
<td></td>
</tr>
<tr>
<td>Non-celebrity – juices</td>
<td>4.09</td>
<td>0.249</td>
</tr>
<tr>
<td>Celebrity – juices</td>
<td>4.27</td>
<td></td>
</tr>
</tbody>
</table>

p < 0.05 means that the differences between the groups studied are statistically significant.

Source: own elaboration.

Results’ Analysis – Hypothesis 2

The next step in the analysis of the celebrity effect in advertising is to find out how product endorsers were evaluated and whether differences in these evaluations are statistically significant. For this purpose, the figures below compare total average ratings for the celebrity and non-celebrity (see Figure 2), in groups with watches (see Figure 3) and in groups with juices (see Figure 4).

FIGURE 2. Total endorser ratings

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Total Rating</th>
<th>p Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Is the endorser likeable?</td>
<td>3.89</td>
<td>0.167</td>
</tr>
<tr>
<td>Is the endorser credible?</td>
<td>3.08</td>
<td>0.226</td>
</tr>
<tr>
<td>Would you trust a recommendation by</td>
<td>2.57</td>
<td>0.430</td>
</tr>
<tr>
<td>the endorser?</td>
<td>2.59</td>
<td></td>
</tr>
</tbody>
</table>

p < 0.05 means that the differences between the groups studied are statistically significant.

Source: own elaboration.
FIGURE 3. **Endorser ratings in watches questionnaires**

- **Is the endorser likeable?**
  - Non-celebrity: 3.82, p = 0.030
  - Celebrity: 4.06

- **Is the endorser credible?**
  - Non-celebrity: 2.88, p = 0.302
  - Celebrity: 2.97

- **Would you trust a recommendation by the endorser?**
  - Non-celebrity: 2.33, p = 0.417
  - Celebrity: 2.37

p < 0.05 means that the differences between the groups studied are statistically significant. Source: own elaboration.

FIGURE 4. **Endorser ratings in juices questionnaires**

- **Is the endorser likeable?**
  - Non-celebrity: 3.98, p = 0.308
  - Celebrity: 3.90

- **Is the endorser credible?**
  - Non-celebrity: 3.13, p = 0.291
  - Celebrity: 3.23

- **Would you trust a recommendation by the endorser?**
  - Non-celebrity: 2.87, p = 0.495
  - Celebrity: 2.88

p < 0.05 means that the differences between the groups studied are statistically significant. Source: own elaboration.

Hypothesis 2 assumed that the celebrity would be evaluated by respondents as more likeable, more credible and more trustworthy than the non-celebrity in both advertisements. The results obtained show that a statistically significant evaluation difference, with the celebrity rated higher in the watches survey regarding likeability (see Figure 3).
In other cases there were no statistically significant differences between the ratings for the celebrity and non-celebrity, which undermines hypothesis H2. It should be recalled, however, that the celebrity was earlier considered as significantly more attractive in two of three analyzed comparisons (see Figure 1).

**Results’ Analysis – Hypothesis 3**

Hypothesis 3 concerned the determination of the celebrity’s impact on product evaluation in selected product categories. To carry out this analysis, five questions from the research questionnaires were used.

For the “watches” product category (see Figure 5), the results indicate that the assumed hypothesis held true in two dimensions. Watches evaluation is statistically significantly better in the questionnaire with the celebrity in the second question \((p = 0.040)\), concerning willingness to use the product, and the third question, which refers to the product quality \((p = 0.008)\). The higher rating in the third question may also indicate that the the celebrity adds prestige to the advertised product. The result obtained for the first question is close to the limit of statistical significance of 0.05 \((p = 0.077)\). Therefore, celebrity endorsement in advertising may also contribute to a higher overall evaluation of the “appeal” of the product.

**FIGURE 5. Ratings for watches**

<table>
<thead>
<tr>
<th>Question</th>
<th>Celebrity</th>
<th>Non-celebrity</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Did you find the advertised product appealing?</td>
<td>2.21</td>
<td>2.45</td>
<td>0.077</td>
</tr>
<tr>
<td>Would you like to use the advertised product?</td>
<td>1.90</td>
<td>2.21</td>
<td>0.040</td>
</tr>
<tr>
<td>Is the advertised product high quality?</td>
<td>2.26</td>
<td>2.63</td>
<td>0.008</td>
</tr>
<tr>
<td>Would you consider purchasing the advertised product?</td>
<td>1.86</td>
<td>1.98</td>
<td>0.233</td>
</tr>
<tr>
<td>Is the advertised product fashionable?</td>
<td>3.03</td>
<td>3.18</td>
<td>0.201</td>
</tr>
</tbody>
</table>

\(p < 0.05\) means that the differences between the groups studied are statistically significant.

**Source:** own elaboration.
In the fourth and fifth questions, differences in product ratings do not show significant statistical differences ($p = 0.233$ and $p = 0.201$). Respondents considered the watches to be equally fashionable in both celebrity and non-celebrity endorsed advertisements, which may be due to the fact that the advertisement used the slogan “fashionable watches,” giving equal ratings in both groups.

With respect to the “juices” product category, the research hypothesis that a celebrity affects product evaluation was rejected. No statistically significant differences between the groups studied were identified as regards all questions asked to evaluate the product (see Figure 6).

**FIGURE 6. Ratings for juices**

<table>
<thead>
<tr>
<th>Question</th>
<th>Non-celebrity – juices</th>
<th>Celebrity – juices</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Did you find the advertised product appealing?</td>
<td>3.45</td>
<td>3.29</td>
<td>0.315</td>
</tr>
<tr>
<td>Would you taste the advertised product?</td>
<td>3.44</td>
<td>3.52</td>
<td>0.612</td>
</tr>
<tr>
<td>Is the advertised product high quality?</td>
<td>3.11</td>
<td>3.10</td>
<td>0.975</td>
</tr>
<tr>
<td>Would you consider purchasing the advertised product?</td>
<td>3.38</td>
<td>3.25</td>
<td>0.481</td>
</tr>
<tr>
<td>Does the advertised product taste good?</td>
<td>3.27</td>
<td>3.04</td>
<td>0.103</td>
</tr>
</tbody>
</table>

$p < 0.05$ means that the differences between the groups studied are statistically significant.

*Source: own elaboration.*

**Conclusions and Managerial Implications**

1. Recipients of advertising consider celebrities to be of higher attractiveness than unknown models, depending on product category. In this study, the celebrity was perceived as more attractive in the case of the watches than juice. This allows us to formulate the first marketing implication: only in product categories where the physical attractiveness of an endorser is important (e.g., cosmetics) can that attractiveness be transferred onto the brand image and strengthen the brand’s key attributes or perceived benefits. This finding is in accordance with the meaning transfer model by McCracken [1989, pp. 310–321] (celebrity endorsement in advertising can bring
better communication results than the use of ordinary persons, experts or anonymous models), and with the research of Kamins [1990, pp. 1–19], who concluded that physical attractiveness of the communication source is significant for product categories associated with this characteristic.

2. Higher attractiveness of an endorser (in this study, the celebrity) is not reflected in the assessment of this person's likeability, trustworthiness, and credibility (word-of-mouth). Therefore, it can be assumed that when the purpose of marketing communication is to create positive brand attitudes, the use of a celebrity endorsement is not justified. It should be noted that a celebrity is a relatively expensive source of communication and may generate conflicting messages when he or she endorses various brands.

3. In the case of celebrity influence on certain elements of the assessment of advertised products, impact was stronger for the watches than for the juice. These results are consistent with the previous research conducted by Friedman and Friedman [1979, pp. 63–71], who indicated that celebrity endorsement brings better results when the advertised products are associated with higher levels of social and psychological risk. An important implication for marketers is that the use of celebrity endorsements is justified only in case of those product categories where physical attractiveness and social status can be transferred onto brand attributes and thus strengthen the brand image.

The research results are consistent with the match-up model (not every product can be advertised by a particular celebrity) and the meaning transfer model (possibility of transferring of elements of the celebrity's image onto selected brand attributes) and, to some extent, with the ELM model (based on the different effects of celebrity endorsement in the case of high and low involvement).

**Limitations and Directions of Further Research**

The research conducted was characterised by the limitations. First, the research sample size and structure (sample consisting of students only) do not allow any inferences to be drawn concerning the total population. Second, the way in which respondents were contacted may have influenced the results. That is, the possibly low involvement of some respondents in answering the research questions and the possibility that the advertisements evaluated were displayed improperly. Third, the research results may have been influenced by the wrong choice of product categories (watches and juices) from the point of view of the population studied and types of purchase decisions (degree of consumer involvement). Fourth, the results of the advertised products and endorsers evaluation may be distorted by differences in the evaluation of attractiveness of the celebrity and model.

These limitations suggest directions for further research. One is to perform similar experiments with other socio-demographic groups. The research results presented here
may also be verified through studying other advertised product groups (including financial services, for which celebrities are routinely used in Poland). Third, endorser categories studied may be expanded to include an expert (in addition to the celebrity and ordinary consumer studied here).

Notes

1 It was addressed in the first research hypothesis.
2 It is possible that persons who responded to the survey also included individuals who were not students of these schools but visited their social networking service when the research was being conducted.

References


Impact of Insurance Market on Economic Growth in Post-Transition Countries

Abstract

The purpose of this work is to identify whether the development of an insurance market is linked to economic growth in former transition countries. A multiple regression analysis is employed to estimate the insurance-growth relationship, using a cross-country panel dataset analysis tracking annual total insurance penetration in 10 countries over the 2000–2012 period, and applying a fixed effect model to test the hypothesis that this linkage is demonstrably positive. The results show a negative and statistically non-significant correlation between insurance and GDP growth, suggesting a lack of evidence that insurance promotes economic growth in post-transition economies.

Keywords: insurance sector, GDP, total insurance penetration, economic growth, post-transition countries
JEL: E44, G22, O11, P27, P34

Introduction

In a worldwide practice there is a vast literature on factors affecting economic growth and different factors supporting this process. Most of the literature is, however, concentrated on specific problems related to the bank industry or capital markets and possible solutions to overcome challenges they pose. In the last decades a strong consensus has emerged that there is a significantly positive correlation between banking/financial industry development and a country’s economic growth [Levine, 1997; Levine, Loayza, and Beck, 2000; Merton and Bodie, 1995].
Apart from the main determinants of economic growth (such as components of GDP, the banking sector, government policies, etc.) insurance markets may fairly be considered as being closely related to economic growth and general financial stability of a country. The insurance sector contributes to economic development through issuing insurance policies, efficiently changing savings to finance real investment projects. In addition, insurance is considered to be a complementary to the banking system, and a facilitator of growth enhancing financial advancement of the country [Grace, Rebello, 1993].

The bulk of the literature on the insurance-growth nexus theory focuses on analysis of a few nations over a various times [e.g. Catalan et al, 2000; Ward and Zurbruegg, 2000]. Only limited scholarly attention has been devoted to the insurance sector in transition economies, and there are only a few econometric works on the interaction between the insurance sector expansion and economic growth in those countries, which have now completed their initial transition stage. It is important to better understand this relationship in those economies because insurance industry development is a core regulatory and policy issue that may meaningfully impact growth.

Our focus here is on the causality connection between income expansion and a deepening of the banking and the insurance sectors, particularly in the transition states of Central and Eastern Europe (CEE), which became the New EU Member States (NMS) in 2004 and 2007, respectively. Eight countries (Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, and Slovenia) became members of the European Union on 1 May 2004, while Romania and Bulgaria joined on 1 January 2007. An analysis of the area of the so-called countries of the Eastern Bloc has become especially important after the collapse of Communism in the Central and Eastern Europe and progression of those countries towards the EU.

Despite various political and economic difficulties associated with transformation, these countries have made significant progress in development and successfully accomplished the transition period. However, economic growth and systemic stability are still far from optimal in those countries, as compared to “old” EU member countries. Accordingly, further examination of various aspects of economic growth in the New EU Member States may provide lessons for future reforms to accelerate their economic progress.

This study attempts to verify the insurance-growth assumption utilizing recent panel data. A fixed effect model is employed, which applies cross-country and time-series techniques for the analysis. The study tests whether development of the insurance sector is an important determinant of economic growth in the former transition countries by empirically regressing economic growth on measures of total insurance penetration. Annual data for 10 former transition countries during the period of 2000–2012 are examined in this analysis.
Literature Review

The role of insurance markets in a country’s economic activity has been a subject of much discussion and analysis. Initially, economists were considering insurance primarily as a technique to minimize and manage risk. Later insurance impacts were linked to financial stability, government security programs, facilitation of trade and commerce, and a country’s general economic growth [Skipper, 2001]. Arena [2006] notes, when summarizing an earlier study by Skipper [1997], that “… evolution of insurance industry can influence economic growth by: (a) mobilizing domestic savings, (b) allowing different risks to be managed more efficiently, thereby encouraging the accumulation of new capital; (c) boosting financial stability and decreasing anxiety; (d) facilitating trade and commerce; (e) supporting to reduce or mitigate losses; and (f) fostering a more efficient allocation of domestic capital…” p. 2.

The idea that a formation of a national insurance market is essential for economic growth was first developed in 1964, during the initial conference of UNCTAD [Kugler, Ofoghi, 2005]. Kugler and Ofoghi [2005] have shown a positive correlation between the development of an insurance market and the economic growth of a country. However, Ward and Zurbruegg reached a different conclusion in their research conducted in 2000. Their study found no evidence of this correlation in the long-term in some OECD countries. In reaching this conclusion, the authors used the total amount of insurance premiums as an indicator of insurance activities.

It is worth mentioning that the majority of empirical researches on financial/economic growth concentrates on interdependencies between the stock market and banking sector with GDP growth. More recently, the role of financial industry on economic growth has become an additional important subject for empirical research. The works conducted by King and Levine [1993] and Rousseau and Wachtel [1998] may serve as examples. Many studies show a positive correlation between finance sector development and economic growth. Levine and Zervos [1998] used cross sectional methodology to estimate the role of stock market and the banking sector with regards to GDP growth. Similarly, Beck and Levine [2001] performed analyses based on panel data techniques. These (and other) works confirmed that growth in both areas (banking and stock market) have independent and positive impact on economic growth. The impact of the bond market on economic growth has also been extensively researched [e.g., De Fiore and Uhlig, 2005]. It was evidenced that the development of the bond sector stimulated economic growth as well.

Favara [2003] observed that there are limited empirical studies examining the role of other financial vehicles on economic growth. Most of the attention is dedicated to the banking sector, bonds and stock markets, often ignoring insurance market and its linkages to economic growth. Given the growing interaction of insurance companies within the financial industry, it would be reasonable to anticipate the rising interest of economists and
government agencies in establishing efficient regulatory policies. Such works could be particularly helpful to developing countries when seeking strategies to stimulate GDP growth.

Browne and Kim [1993] performed regression analyses to assess variables that may influence demand for life insurance around the globe. Data for 45 different countries on the consumption of life insurance per capita were collected for the years 1980 and 1987. Variables included: religion, national income, dependency ratios, life expectancy, the share of the young adult residents pursuing tertiary education, social security payments, expected inflation rates, and policy loading charges or the prices of insurance. Three types of log linear equations were developed. In the first version of the model premium was employed whereas in the second and third versions life insurance was used. As it was anticipated inflation, income and dependency ratio were positive and were statistically significant indicators in every model. Education and religion demonstrated a negative sign, which also was expected, but lacked significance in some trials. Social security and price, both with a positive signs, were also statistically significant. Life expectancy was not significant. One of the main findings of Browne and Kim was that in Muslim countries there is lower demand for life insurance, relative to other countries. It should be emphasized that similar findings were made by Hofstede [1995] and Fukuyama [1995], who suggested that social origins and religion influence insurance consumption.

In 1996, Outreville published a cross-sectional analysis for the year 1986 by concentrating on data from 48 developing countries. His primary goal was to estimate a correlation of life insurance with GDP. The result was, however, unexpected. Outreville assumed that life insurance premiums had no impact on financial development. This research contradicts earlier results derived by Outreville [1990], when he evaluated a cross-section of 55 developing countries and identified the relationship between property-liability insurance premiums and economic and financial development. A positive relationship between the logarithm of property-liability premium per capita and GDP per capita was found. Although the coefficient for price was not statistically significant, Outreville reported a positive linkage between demand for insurance and financial enhancement. Furthermore, income elasticity was greater than one.

ZhiZhuo [1998] attempted to understand whether income per capita and consumer price index (CPI) are linked with insurance utilization in China, for which he conducted both: cross-regional (for the year 1995) and time-series analyses for the years 1986–1995. Both analyses appeared to be positive – GDP and CPI are significantly correlated with insurance.

Webb, Grace and Skipper [2002] applied a cross-country analysis for 55 countries for the 1980–1996 time-periods to test the relationship between banks, life insurance, non-life insurance, and economic growth. The authors applied the Solow-Swan neoclassical growth model and the three-stage-least-squares instrumental variable approach (3SLS-IV) to test their hypothesis of interest. Insurance penetration was used as a measure of insurance sector development. This work indicated that banking and life insurance, taken as
exogenous components, strongly predict economic growth. However, when the interaction
terms between banking and life insurance and between banking and non-life insurance
were included, the individual variables lost explanatory power, suggesting the presence of
complementarities among financial intermediaries. As can be seen from the analysis, insur-
ance activities should have a positive impact on economic growth. However, this impact
may vary across different countries and across different lines of the insurance business.

A regression model and cross-country panel data analysis were used by Haiss and
Sümegi [2007] to examine the role of insurance in economic growth for 29 countries. The
authors divided observed countries into two groups: in the first group were included EU-15
member countries, Switzerland, Iceland and Norway; while the second group consisted
of new EU member states (the CEE countries) and EU membership candidates – Turkey
and Croatia. Croatia, Lithuania and Latvia were omitted due to insufficient data. GDP
was utilized as a measure of economic growth, whereas total, life and nonlife insurance
premiums were used as insurance activity indicators. The research was performed for the
years 1992–2005. According to their findings, the “overall picture is mixed”. There was
a positive correlation of life insurance and GDP growth in the EU-15 countries, and short-
run impact for the CEE/NMS countries for non-life insurance. The authors concluded
that, like the banking industry, the impact of the insurance sector depends on the level
of economic development.

Almost a decade earlier, Holsboer [1999] had reached a different conclusion. His study
focused on alterations in external settings for insurance companies in European countries,
and suggested that the significance of the insurance industry in the economy is reliant
on rising competition between financial sectors. Holsboer underlined the bi-directional
relationship between the insurance sector and economic growth of a country, and sup-
ported the notion that a developed insurance sector facilitates financial sector growth
and, therefore, growth of the economy in general (and vice versa).

Arena [2008] conducted empirical research about the interdependence among insur-
ance and economic growth in 56 countries, which were developed or developing during
the period 1976–2004. Insurance activity was measured as attracted premiums of total,
nonlife and life insurance. The author found that only in developed countries did life
insurance impact economic growth, but the impact of nonlife insurance is positive and
significant for both developed and developing economies (though smaller in developing
countries than in developed ones). Arena’s overall conclusion was that nonlife and life
insurance positively impacted economic development.

Kjosevski [2011] also examined the impact of insurance on economic growth, with
empirical analysis for the Republic of Macedonia. He used data for the period 1995–2010
and employed multiple regression approach to test his hypothesis. The author used
three different insurance indicators life insurance, nonlife insurance and total insurance
penetration. Insurance development was measured by insurance penetration. Kjosevski
[2011] found positive and significant correlation between insurance sector development
and economic growth. The growth promoting role of insurance was confirmed in terms of non-life insurance, and total insurance, while the results for life-insurance demonstrated negative impact on economic growth.

Recently, Richterkova and Korab [2013] also attempted to examine the potential correlation between insurance and economic growth. Their study was based on a relatively new meta-analysis, which was initially adopted in 1980s. [Havranek, Irsova, 2010a]. The meta-analysis is a statistical method for aggregating results from independent studies, enabling researchers to estimate findings with a higher number of observations and better accuracy [Richterkova, Korab, 2013]. As in almost all previous studies, Richterkova and Korab used total insurance premiums as a variable determining insurance activity. The findings indicated a positive influence of insurance markets on economic growth.

Although one may argue that there is a theoretical explanation for the positive correlation between insurance industry and GDP growth of a country, empirical studies report results that differ across countries and regions. Most economists agree that the development of insurance markets stimulates economic growth, however, the number of empirical works is rather small generally, and particularly so regarding the insurance-growth linkage in post-transition economies. Given the growing involvement of insurance companies in the larger financial industry, government bodies in those economies will need to be increasingly vigilant in trying to assure the proper functioning of this sector, requiring regulatory policies that are responsive to actual conditions. Revealing those conditions is the primary goal of this work.

**Empirical Model**

The empirical approach presented in this study attempts to explain the trend in economic growth and its variation over time in post-transition countries. Since vast majority of the economic literature states that developed insurance market promotes economic growth of many countries, we seek to confirm this pattern for post-transition countries. Thus, we test whether trends in economic growth of the country are correlated with tendencies in insurance market. Hence, it has to be ensured that the estimates of economic deepening accounts for the sway of the exogenous element of insurance.

The empirical specification attempts to check the economic development based on 13 time periods, using time-series and cross-country data for the 2000–2012 periods. The standard approach within this framework is to use annual data for estimation purposes. Using such data, however, has a drawback; it ignores the possibility that annual data may not characterize long-lasting equilibrium statistics for any particular period, due to the slow adjustment to changes in the variables. To avoid this problem, our model allows partial adjustments through a log-linear equation for economic development.
A fixed effect estimation model is implemented, as it is more appropriate compareto OLS to account for the country-specific effects. The least squares dummy variable (LSDV) method is used to test the hypothesis. In the model there is a standard specification in levels, where economic development is persistent (i.e., it is a function of its own past values). Thus, the empirical model has the following form:

\[
(GDP \text{ growth})_t = \alpha_i + \gamma t + \beta_1 (\text{Total insurance penetration})_t + \beta_2 (\text{GDP per capita})_t + \beta_3 (\text{Private credit})_t + \beta_4 (\text{Export})_t + \beta_5 (\text{Investment})_t + \beta_6 (\text{Government spending})_t + \epsilon_{it}
\]

\(\alpha\) and \(\gamma\) are intercept parameters, which differ across countries and years, \(\beta\) is the coefficient of the explanatory variables and \(\epsilon_{it}\) is an error term. According to the fixed effect model, intercept parameters embody all observable effects and specify an estimable conditional mean, assuming the same slopes and constant variance across countries. The fixed effect approach takes intercept parameter to be a group-specific constant term in the regression model, which can be correlated to other regressors.

### Data, Measurement, and Sources

In this research focusing on the insurance market development and economic growth a data set for the period 2000–2012 is used. Statistics used in the analysis originate from a variety of sources. Insurance penetration figures are taken from Insurance Europe (CEA) website. Real income per capita, private credits provided by the banking sector, government expenditures, total exports, and gross capital formation are from the World Development Indicators (WDI) database.

Economic expansion is calculated as the growth rate of GDP per capita. Indicators employed as control terms that could clarify economic boost are: total insurance penetration, GDP per capita, private credit, government spending, export, and investment.

As a corresponding measure of the insurance sector, annual data of total insurance penetration was used. Total insurance penetration is a frequently utilized measure of insurance activity. It is expressed as total gross written premiums relative to GDP. It is expected that this variable will have positive influence on economic growth.

Initially, real income per capita was also introduced into the model, since higher income is assumed to stimulate economic activity and, thus, generate a disproportionate rise in demand for insurance. This factor is included in the empirical formula to indicate on the convergence effect, or the propensity of the speed with which economic growth equalized across various states. Annual data on real GDP per capita is obtained from the World Development Indicators based using 2005 US prices. The caution here is that inclusion of additional variables into the macroeconomic specification raises the number of moment conditions, which could carry additional bias. Hence, GDP per capita is
treated as an exogenous variable in the regressions. Data scrutiny indicates the occurrence of unit root in GDP per capita figures. To deal with the problem of non-stationarity, data for GDP per capita were first differenced. Based on the theory the anticipated sign of the initial level of economic expansion measure is positive.

Various researches [Demirguc-Kunt, Maksimovic, 2002; Levine, 1999; Levine, Zervos, 1998; Beck, Levine, 2004; Demetriades, Andrianova 2004] have shown that advanced financial system positively affects economic growth. Banking sector development is employed here (specifically, private credits provided by the banking sector) as a proxy for the financial development. This indicator is expressed as percentages of GDP. The data source is the World Development Indicators dataset (WDI), which contains annual information for a large panel of countries. It is widely accepted that private credit is the most essential banking development indicator, because it illustrates the level of likelihoods that new entrants will get bank funding. Consequently, higher levels of this indicator were interpreted as signs of higher levels of financial services for the private sector, and as a result, greater credit accessibility. In general, economists expect credit provided by the banking sector to positively impact economic growth. Thus, we expect positive signs for credit in this analysis.

We use exports as a proxy for economic growth and consequently the share of exports of goods and services in GDP is utilized. According to traditional Keynesian theory, exports can be a significant facilitator of economic growth. Studies conducted by Marin in 1992 and Vohra in 2001 empirically verify that positive role. In research on the relationship between insurance industry expansion and economic growth international trade is also included as a supplementary explanatory term [e.g., Webb, Grace, Skipper, 2002; Arena, 2008]. The expected sign of the coefficient is positive.

Another control term in the hypothesis formula is investment, which we measure as gross capital formation, defined as follows: “Gross capital formation (formerly gross domestic investment) consists of outlays in addition to the fixed assets of the economy plus net changes in the level of inventories. Fixed assets include land improvements (fences, ditches, drains, and so on); plant, machinery, and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings. Inventories are stocks of goods held by firms to meet temporary or unexpected fluctuations in production or sales, and ‘work in progress.’ According to the 1993 SNA, net acquisitions of valuables are also considered capital formation” [The World Bank]. Investments are expected to be positively associated with economic growth.

The government plays a key role in establishing an environment for private sector expansion in any country. Nevertheless, various theoretical and practical studies propose that greater government consumption negatively affects development of the financial sector of a country generally and, in particular, with the insurance sector. For instance, Beenstock, Dickinson and Khajurja [1986] established an inverse relation between life
insurance premiums and social security coverage. According to Skipper and Kwon [2007], if the government plays an active role in providing security protection for property damages, disability, retirement and health care, people are not motivated to acquire insurance to address those risks. Economists in general agree that high government consumption decreases the efficiency of government investments since investment decisions are influenced by political and social factors [e.g., Webb, Grace, Skipper, 2002; Dorfman, 2008]. Thus, government expenditures is typically applied as a control indicator when describing economic growth in banking and insurance investigation papers [Levine, 1998; Levin, Loayza, Beck, 2000; Ahlin, Pang, 2008; Ward, Zurbruegg, 2000; Arena, 2008]. In this analysis, government expenditure is measured by its share in GDP. It is anticipated government expenditures negatively correlate with economic growth.

**Empirical Results**

The main outcomes of the study are summarized in Table 1, which contains the estimates of economic growth regressions using a fixed effect estimator in which Total Insurance Penetration as well as other independent variables is treated as exogenous. To start with, it is important to note that the value for F-test for this model is significant, meaning that all the coefficients of the model are not equal to zero. On the basis of the F-test it can be observed that the model is well fitted. In addition, all coefficients are statistically different from one. Furthermore, based on the Hausman test \( \chi^2(2) = 34.09 \) [Prob\(>\chi^2 = 0.0000\)], the null hypothesis stating that a random effect model is better than its counterpart is rejected. Therefore, it may be concluded that a fixed effect is a suitable estimator and is relied upon for delivering statistical inference.

**TABLE 1. Fixed-effects regression Total Insurance Penetration and GDP in post-transition countries, dependent variable: logarithm of GDP**

| Variable                | Coef.   | Std.Err | z      | P>|z| | [95% Conf. Interval] |
|-------------------------|---------|---------|--------|------|---------------------|
| Total Insurance Penetration | -.5003374 | .8959353 |−0.56   | 0.578 | −2.278292 1.277617   |
| GDP per capita           | .0005674 | .0001715 | 3.31   | 0.001 | .000227 .0009079    |
| Private Credit           | -.1402303 | .0212325 |−6.60   | 0.000 | −.1823656 −.0980951 |
| Exports                 | .248303  | .0438888 | 5.66   | 0.000 | .1612072 .3535989   |
| Government Expenditures  | -.2831441 | .1082442 |−2.62   | 0.010 | −.4979511 −.068337  |
| Capital Formation        | .5738759 | .0728128 | 7.88   | 0.000 | .4293813 .7183704   |
| Interaction Term         | −7.025615 | 5.645966 |−1.24   | 0.216 | −18.22985 4.178621  |

Notes: Number of observations 114; Sample period 2000–2012; Number of time periods (T) =13; Number of countries (N) = 10; \( R^2 = 0.7389 \); F-Test (6,98) =46.23 (Prob>F=0.000)

*Source:* author’s estimations.
Table 1 shows that the estimated coefficient of Total Insurance Penetration is negative, but lacks significance at the 5 percent significance level. This means that the insurance variable is a statistically insignificant determinant of economic growth, where GDP growth is employed as a proxy for economic development. Though inconsistent with theory, these findings are in line with the outcomes obtained by various authors [Webb et al. 2002; Haiss, Sümegi, 2006]. While empirically studying all EU countries during the period 1992–2004, Haiss and Sümegi also found the signs for total premium income negative and insignificant. Webb et al., as well as Haiss and Sümegi [2006] found coefficients to be negative and not significant for non-life insurance.

We also calculated coefficients and signs for Total Insurance Penetration in combination with private credit provided by the banking sector (a proxy for the financial development). The sign for Private Credit is negative and significant, meaning financial development negatively affects economic growth. This could indicate the shrinking strength of the bank-growth-nexus over the last decade, consistent with Rousseau and Wachtel [2005], who found weaker links using more current data. This observation is also generally consistent with other studies showing negative, with low significance, coefficients of banks and the insurance sectors in the latest studies indicating both sectors having to face similar transformation.

An alternative explanation for this unexpected negative correlation of insurance market development and the banking sector on economic growth may be found in regional differences that are aggregated in our data set (treatment of the region as a whole). There are significant differences in the structure and level of development of both the insurance and banking sectors among the CEE countries studied. For instance, according to a CEA annual report [2009] the only state in the CEE area with a life insurance sector developed at European level is Poland, which accounts for more than 50 percent in life gross written premiums among the CEE countries. Differences are also apparent in the banking sector. Based on EBF databases [2009] four countries – Poland, the Czech Republic, Hungary, and Romania – account for more than 75 percent of total bank assets in the CEE region, and Poland alone holds more than 25 percent of those total assets. Hungary and Romania showed a decline in total bank loans in 2009. Furthermore, the distribution by bank loan categories differs from country to country (Romania shows large consumer credit, while Slovenia relies more on the corporate sector credit).

As for other independent variables the outcomes seem to demonstrate that the level of Exports are significant at 5 percent level, and therefore facilitate economic growth, while Government Expenditures negatively correlate to GDP growth as predicted by the theory and previous findings in this area [Levine, 1998; Levin, Loayza, Beck, 2000; Webb, Grace, Skipper, 2002; Arena, 2008]. As was expected, the coefficient of Capital Formation is positive and significant.

Based on our data, the assumed positive and significant impact of the insurance sector on economic growth in post-transition countries is not confirmed by the data set. Thus, the
results from the testing propose that the Total Insurance Penetration is not a statistically significant determinant of economic growth. Although these findings are comparable to the findings of Grace and Skipper [2002], Haiss and Sümegi [2006] and other researchers, a general lack of consensus in this area suggests that more research is necessary to investigate the various channels through which insurance can affect economic growth. Above mentioned studies as well as studies conducted by Catalan et al. [2000], Davies and Hu [2004] and Boon [2005] have also separately analyzed life and non-life insurance sectors and their impact on economic growth. Grace and Skipper [2002], Haiss and Sümegi [2006] found out that though signs for total insurance premium and non-life business are negative and non-significant, coefficients for life insurance are positive and significant. Thus, investigating each insurance branch and its impact on economic growth individually can shed more light on the insurance-growth nexus in former transition countries.

Concluding

Most studies exploring the relationship between total insurance penetration and economic growth have uncovered a positive links between them. However, these links have received less attention in the transition countries of Central and Eastern Europe (CEE), which became New EU Member States (NMS). The significance of the insurance in the overall financial intermediation has increased over time; however, the vigor of the finance-growth-relationship seems to have weakened in recent years. The key purpose of this research was to better understand the function of the insurance sector in the finance-growth-nexus, and answer the question how insurance affects economic development, concentrating on the post-transition countries. Investigation of this notion is important since results could guide to numerous policy suggestions and sequencing of changes in transition states.

We used a log-linear equation for economic growth which includes a lagged dependent measure. Employing a panel data set of 10 countries over the period 2000–2012 and a using fixed effect estimator the empirical investigation shows that the total insurance penetration is statistically not a significant determinant of GDP growth. The results of the analysis are inconsistent with the insurance-growth hypothesis; however, they support the previous studies proposing a negative and non-significant influence of insurance and the banking sectors on the economic growth in the EU members. Thus, the obtained figures do not confirm that execution of incentives for advancement of the insurance would facilitate faster economic growth in the former transition countries.

The lack of empirical evidence in support of the insurance-growth nexus points to the need to further research these relationships, analyzing non-life and life insurance separately. This approach may help policy makers better determine whether, and to what extent, insurance regulations may most contribute to economic growth.
Impact of Insurance Market on Economic Growth in Post-Transition Countries

Notes

1 According to the World Bank, „the transition is over” for the 10 countries that joined the EU in 2004 and 2007.

2 OLS estimation can lead to biased outcomes in analyzing panel data as it assumes a single set of slope coefficients and one intercept.


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**Validating DART Model**

**Abstract**

The primary objective of the study was to quantitatively test the DART model, which despite being one of the most popular representations of co-creation concept was so far studied almost solely with qualitative methods. To this end, the researchers developed a multiple measurement scale and employed it in interviewing managers. The statistical evidence for adequacy of the model was obtained through CFA with AMOS software. The findings suggest that the DART model may not be an accurate representation of co-creation practices in companies. From the data analysis it was evident that the building blocks of DART had too much of conceptual overlap to be an effective framework for quantitative analysis. It was also implied that the phenomenon of co-creation is so rich and multifaceted that it may be more adequately captured by a measurement model where co-creation is conceived as a third-level factor with two layers of intermediate latent variables.

**Keywords:** DART, co-creation, measurement scale, survey, Polish companies  
**JEL:** C1, C4

**Introduction**

In the knowledge intensive economy the capacity to serve individual customers is becoming a major source of competitive advantage. Therefore the operational instruments
enabling the managers to understand and implement new business models enhancing the capacity of value co-creation are welcome. Despite its importance, research on co-creation with customers is still at an early stage. In particular, there is a dearth of quantitative evidence, obtained through research methods other than case studies and other qualitative approaches. The DART model is considered to be an important step forward and a valuable attempt to indicate the range of companies’ capabilities necessary to effectively work with customers. It specifies the four main building blocks or groups of competencies that companies should develop to effectively engage in value co-creation with customers. Those blocks include Dialog, Access, Risk Assessment and Transparency, which taken together form the DART acronym. However, despite its theoretical appeal DART was not met with the adequate effort at quantitative validation. For this reasons, the present paper is focused on the task of developing a measurement system usable for survey approach and employing it to test the merits of the DART model.

The main body of the paper begins with an overview of the pertinent literature on value co-creation, followed by the presentation of the research method and sample structure. Discussion of survey findings comes next and the final section is dedicated to conclusions and limitations of the study.

Literature Review

The concept of co-creation emerged out of the core competences theory [Prahalad and Hamel, 1990] adding new elements to the resource based model [Barney, 1991]. The present paper is grounded in the literature demonstrating changing nature of competition and value creation process by C.K. Prahalad, V. Ramaswamy, M.S. Krishanan, [Prahalad, Ramaswamy, 2004; Prahalad, Krishanan, 2008]. Those authors suggested that digitization, connectivity and globalization impacts all the industries by radically changing the nature of value creation. They asserted that “value is based on unique, personalized experiences of consumers. Firms have to learn to focus on one consumer and his/her experience at a time, even if they serve 100 million consumers” [Prahalad, Krishanan, 2008, p. 11]. The recently emerged stream of publications concerning the concept of service dominant logic (SDL) proposed by Vargo and Lush [2004] was the source of another vital element of theoretical background to the current paper. SDL was designed in opposition to the goods dominant logic rooted in the pre-service era environment. According to the authors of the concept, the shift to the postindustrial knowledge economy required switching the focus to value creation. According to SDL, customers were value co-creators, as “value cannot be embedded in either the factory or the distribution process” [Vargo, Lush 2006, p. 49]. Other worth mentioning attempt at developing coherent conceptualizations of co-creation was that by von Hippel [2005].
The immediate theoretical foundation for the present paper was provided by the DART model, by Prahalad and Ramaswamy [2000, 2004a, 2004b, 2004c]. The DART model was not the only framework proposed to conceptualize co-creation processes. Another was developed by Payne for service organizations. It supported understanding customer behavioral and cognitive processes and goals. The third model by Grönroos distinguished value co-creation during customer and supplier interactions from value creation by customer alone. Grönroos suggested that firms should facilitate value creation by customers and make efforts to create opportunities to engage themselves with customer processes. [Mukhtar, Ismail, Yahya 2012; Grönroos, 2009]. All three aforementioned models employed the perspective of a supplier. There was also an attempt to look at the co-creation process from a customer perspective by developing a measurement scale for customer involvement in value co-creation. The scale comprised two dimensions: customer participation behavior and customer citizenship behavior [Yi and Gong, 2013].

In the recent marketing literature the DART model remains the most popular framework to conceptualize and guide implementation of customer value co-creation. The approach proposed by Prahalad and Ramaswamy was driven by recent advances in communications technology, that empowered customers to make more informed purchase choices and offered them the possibility to get involved in long-term relationships with suppliers. Prahalad and Ramaswamy suggested that technological advances in communication between suppliers and retail customers should be used by the firms to enhance customers’ role in innovation processes and value creation. In particular they indicated the need to migrate from products and services to individual experience environments. As the experiences were the result of interactions, the interactions through different channels should be managed. In their view, implementing co-creation in practice called for a new business model.

The DART framework contains the following four constituent components (its building blocks) [Prahalad and Ramaswamy, 2004a]:
1. **Dialogue** represents interactivity between two equal problem solvers, eager to act and to learn.
2. **Access** implies facilitating co-creation by offering the right tools for communication between customers and suppliers; it also entails those marketing solutions that result in increased freedom of choice for customers.
3. **Risk assessment** is referring to the customers’ right to be fully informed about the risks they face from accepting the value proposition.
4. **Transparency** represents resigning from information asymmetry between the customer and supplier and practicing the openness of information.

In terms of available empirical evidence the issues of co-creation and the DART framework are a clearly underdeveloped area. The only aspect of co-creation that is currently supported by a more substantive body of research is the involvement of customers in innovation creating processes (so called innovation co-creation or co-creation for others
versus experience co-creation or co-creation for use [Gustafsson et al., 2012]. An extensive overview of literature presenting empirical findings on this topic can be found in Boger et al. [2010]. A few more recent examples of research on the role of users as innovators are presented by Gustafsson et al. [2012], Russo et al. [2012], Skibstedt and Bech Hansen [2011], Reay and Seddighi [2012].

In contrast, there are only a few studies that were centered on the co-creation for use, which is also the main focus of the DART model. The most likely reason for that are difficulties with operationalizing variables for quantitative, questionnaire-based approach. As a result most of the research projects on the topic were following case study methodology, quite often with only a single company being investigated, which might have benefits regarding internal validity but also seriously limits possibilities for generalizing the outcomes. One of such case studies concerned the Swiss Federal Railway operator (SBB), presenting the company’s migration from value facilitation to value co-creation with customers [Gebauer et al., 2010].

Another example of research involving case study analysis and directly employing DART as a theoretical framework was a project investigating co-creation processes at five leading consumer product companies running the so called temporary shops in Milan, Italy [Russo Spena et al. 2012]. The authors found that the temporary shops offering customers direct multisensory interactions were an effective implementation of the DART concept resulting in intense involvement of customers in co-creating usage experience. Another study, not invoking directly DART but rather trying to operationalize the whole notion of service dominant logic, was performed in Singapore with the aim to compare two Internet-based travel planning system designs: one driven by service dominant logic and one informed by goods centered approach characteristic for traditional marketing. The authors operationalized service and goods dominant mindsets proposed by Lush and Vargo [2008] to arrive at a set of metrics which were used to collect data on user experiences from interacting with two different journey planning applications. The main finding was that the design guided by the service dominant mindset was superior in quality of customer experiences and customer satisfaction, in part due to its enabling intense co-creation.

There were only a few attempts to study any form of co-creation in Poland. Mazurek [2012] studied Internet impact on suppliers’ and customers’ roles. Relying on survey data he noticed that Internet was not only used for transmitting information to customers but also served as a tool for interacting with them in a dialog. Even though the study did not employ DART framework some of its aspects served as an inspiration in developing the present project.

The closest in scope and topic to the current paper was a study by Albinson et al. [2011] which sought to develop a questionnaire multi-item scale for measuring the application of the DART model by consumer product companies. The Likert type scale was developed through a series of depth and focus-group interviews and validated by a survey of university students. The 23-item scale was verified by confirmatory factor analysis to possess
adequate levels of validity and reliability. The four constructs of DART were also found to be positively correlated with a sense of shared responsibility but with the exception of ACCESS they did not display any significant correlation with loyalty towards the provider of goods or services.

The original objective of the current study was to make use of the outlined literature sources to propose and test a comprehensive measurement system for survey research that would allow for effective evaluation of the firms’ involvement in various aspects of co-creation represented by the DART framework. However – as it transpired during the analysis – the gathered empirical evidence pointed to possible intrinsic conceptual flaws in DART, which consequently became the main focus of the investigation.

Research Method and Sample Structure

The scale employed in the study was developed through a four-stage process. As an initial step we specified the domain of the scale following the suggestion by Churchill [1979]. Through a literature review, involving works exploring the DART model as well as titles pertaining to more general co-creation topics (referenced in the previous section of the current paper), we established broad operational definitions of each component of the framework and developed sets of Likert scale statements to encapsulate all relevant aspects of each component. Next, the items were examined and debated in a seminar with doctoral students in marketing who were not otherwise involved in the study. The refined list of statements was presented to a group of managers who discussed it in a manner akin to the focus group interview. Finally, the appropriateness of wording was verified in a pilot survey administered in the same way as the main survey through telephone interviews. The complete list of the 30 Likert-type scale items was given below.

<table>
<thead>
<tr>
<th>TABLE 1</th>
<th>Statements used in the study for measuring firm’s involvement in the four aspects of the DART model</th>
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<tbody>
<tr>
<td><strong>DART component 1: DIALOG</strong></td>
<td></td>
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<tr>
<td>Dialog 1: We maintain a multichannel dialog system engaging our customers in production and distribution processes</td>
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<tr>
<td>Dialog 2: We encourage customers to enter dialog leading to enhancing their experiences with our products/services</td>
<td></td>
</tr>
<tr>
<td>Dialog 3: We give our customers ample opportunities to share with us their ideas for increasing their satisfaction with product/service experience</td>
<td></td>
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<tr>
<td>Dialog 4: We substituted dialog with customers for one-way promotion</td>
<td></td>
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<tr>
<td>Dialog 5: We support a dialog with our customers to foster their preference for our products/services over products/services of competitors</td>
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</tbody>
</table>
Dialog 6: We enhance our credibility by holding a dialog with customers who are not satisfied with our products/services

Dialog 7: Our employees are actively involved in discussions on internet forums and in social media (e.g., on Facebook)

Dialog 8: We actively support user groups of our products/services

Dialog 9: We have open and sincere dialog with all our partners

**DART component 2: ACCESS**

Access 1: We provide our customers with technical capabilities to share with us their opinions and experiences

Access 2: We immediately respond to questions and comments from our customers

Access 3: We maintain an Internet forum where our customers can exchange opinions among themselves and with us

Access 4: We support dissemination of information about our company on third-party owned web sites

Access 5: In Internet media there is more information about our offerings than competitors’

Access 6: Our customers can communicate with us easily

Access 7: Our customers are free to place their orders through a channel of their preference

Access 8: Our customers are free to choose their preferred delivery method of our products/services

Access 9: Our customers are free to choose their preferred time of receiving our products/services

Access 10: Our customers are free to choose their preferred location of receiving our products/services

**DART component 3: RISK ASSESSMENT**

Risk Assessment 1: We provide our customers with all relevant information about our products/services, so they could assess the benefits of our offerings on their own

Risk Assessment 2: We freely inform our customers of possible risk from using our products/services

Risk Assessment 3: We encourage our customers to learn about safety warnings and other kinds of risk from using our products/services

Risk Assessment 4: Our offerings are safe for everyone so informing of risk is unnecessary

Risk Assessment 5: We discourage from purchasing those customers who could be harmed by our products/services or dissatisfied with them

Risk Assessment 6: We advise our customers on how to use our products/services to avoid various kinds of risk

**DART component 4: TRANSPARENCY**

Transparency 1: We make available to customers all relevant information that facilitate their use of our products/services and/or inspire them with new ideas for consumption/application

Transparency 2: We put no constraints on our customers’ access to information about prices of our products/services and costs that we have incurred

Transparency 3: Partner relationships with our customers encourage us to supply them with information that can augment their experience

Transparency 4: Information that we provide to our customers is up-to-date, which fosters the best possible experience with our products/services

Transparency 5: Our customers know about us as much as we do ourselves

Source: own elaboration.
As was already noted the main inspiration in devising the above indicators was co-creation literature, in particular the original presentation of the DART framework by Prahalad and Ramaswamy [2004a] and later works by these authors [2004b, 2004c, 2008] supplemented by several other papers with DART references. Here, we provide a more detailed rationale for using particular statements as measures of respective DART components.

**Dialog Indicators**

Explaining their understanding of Dialog, Prahalad and Ramaswamy [2004a] used such terms and phrases as: engagement, propensity to act, interactivity, shared learning, maintaining community of loyal customers and firms and customers being two equal problem solvers. Accordingly, the indicators developed to measure Dialog reflected those aspects and characteristics. In particular:

- Engagement was embedded in the Dialog 1 indicator,
- Increasing propensity to act in Dialog 2,
- Interactivity in Dialog 3,
- Relying on one-way communication instead of dialog in Dialog 4, to better control validity of other metrics,
- Shared learning in Dialog 7,
- Maintaining community of loyal customers in Dialog 8,
- Firms and customers taking on roles of equal problem solvers in Dialog 9.

In addition, Dialog 5 and 6 were aimed at identifying managers’ perceptions of the changing nature of competition, shifting from the transactional model into value co-creation which strongly relies on dialog. Since DART is one approach to conceptualizing co-creation, this choice of statements seems to be justified.

**Access Indicators**

Not many guidelines are offered in the DART conceptual articles on how to define and operationalize Access; and what is offered there could be summarized by the phrase that “Access begins with information and tools” [Prahalad and Ramaswamy, 2004b].

Consequently, subsequent research by other authors did not employ a consistent outlook on this element of the framework. In one such paper, Russo Spena et al. [2012] stated that “Access covers how interaction empowers customer access to knowledge, tools, information and experience”. Our view is similar in that we believe in defining Access by emphasizing availability of tools, procedures and routines that empower customers to gather information and enter into interactions, which result in enhanced experience. Accordingly, Access 1, 3 and 4 were designed to represent the use of various Access tools, while in items 2, 5 and 6 we tried to capture the functional aspects (or quality) of those tools, understood as reaction speed, amount of available information and the general ease of use, respectively.

The original DART concept do not extend the Access category beyond sharing information and knowledge. However, its authors stressed that “...co-creation experience
occurs where individuals exercise choice, and where value is co-created.” [Prahalad, Ramaswamy, 2004b]. In line with this suggestion, we decided to broaden Access scope to include elements of the distribution system beyond communication processes (Access 7 through 10). This idea was strongly influenced by the work of Albinson et al. [2011], who used similar approach in their DART survey scale.

**Risk Assessment Indicators**

Risk Assessment was originally defined as “the probability of harm to the consumer” [Prahalad and Ramaswamy, 2004b]. The main idea seems to be enabling customers to make informed choices. Hence, the consumer has the right to be aware of the risks involved in accepting the offer (items 2, 3, 5 and 6), as well as benefits it generates (item 1). The insights on harm probability allows the consumer to make an in-depth value proposal assessment. Item 4 was included to clearly identify those companies whose offerings (by perceptions of their managers) do not carry significant risks to consumers and thus informing on them may not be relevant.

**Transparency Indicators**

According to Prahalad and Ramaswamy [2004c] Risk Assessment and Transparency are two building blocks of trust. Thus their suggested motto for smart companies was “When in doubt, disclose”. To their mind, Transparency was meant to promote the end of information asymmetry, so that customers had easy access to comprehensive, timely and accurate information resources on offered value propositions. The commitment of companies to removing information asymmetry was examined with items 1, 3 and 5, while item 4 was centered on the quality of offered information.

Using the above scales, the data were collected through a combination of CATI and CAWI interviews, in which company managers gave their answers by telephone while seeing the web based version of the questionnaire. This interviewing mode allowed for using more complex questions and scales due to enhanced communication between respondents and field workers as compared to the ordinary CATI. It total 440 managers participated in the survey in July and August 2013. The final response rate, defined as the ratio of completed to attempted interviews, amounted to 39%; a comparison of the sample and population distributions on known characteristics, such as profitability, size and ownership status, did not reveal significant differences, which suggests that obtained reply rate should not be problematic in generalizing results. The study sample encompassed in equal halves service and manufacturing companies directing their offers to mass retail markets. In particular the following industries were investigated: production of food (35.9% of the sample size) and beverage (7.8%), cosmetics manufacturing (6.8%), hotels and accommodation (20.7%), catering (20.5%) and other tourism services (8.9%). The sample included almost equal number of small (10–49 employees) and medium (50–250 employees) firms. Focusing the research on these types of companies lessened heterogeneity
and thus offered a certain level of control over extraneous variables that could not be studied due to constraints on the length of the interview but could possibly have confounding effect on substantive covariance patterns. Overall, the random selection of firms for the study from a representative database of Polish companies allowed an adequate level of external validity, permitting generalizations to the pertinent industry groups in Poland.

Validation of the DART Measurement Model

The primary objective of the study – investigating relevance of the DART model for the Polish service and manufacturing companies – was approached with confirmatory factor analysis (CFA) as the main methodology. The CFA, implemented in AMOS 22 program, allows the evaluation of a whole measurement model with a single statistical test and also provides specific metrics for assessment of particular parameters of the model.

The first step in the analysis was running CFA for a solution including the whole array of 30 indicator items assigned to the four factors in accordance with the designations provided in Table 1. The graphical representation of the model together with estimated standardized regression weights, correlations and squared multiple correlations is shown in the Figure 1.

The graphical model uses standard symbols and shapes to depict elements of the CFA path diagram, in particular:

- Ellipses represent latent variables or constructs (in the present case the four building blocks of the DART model)
- Rectangles denote observed variables or indicators
- Circles stand for measurement error terms that in addition to actual measurement errors also represent all other factors (other than the model latent variables) that explain the variance of particular indicators not accounted for by the model
- One-headed arrows pointing from construct variables to indicator variables depict regression paths
- Two-headed arrows correspond to correlations between latent variables to account for the fact that the latent variables in the DART model, due to partially overlapping conceptualizations, may not be independent and show statistical associations.

In addition, the graph contains three kinds of statistics:

- Numbers attached to double-headed lines describe correlations between latent variables
- Numbers next to one-headed lines represent standardized regression weights that show how strongly latent variables affect particular indicators
- Numbers to the left of rectangles provide squared multiple correlations, which indicate what percentage of variance in an indicator is explained by the latent variables in the model
FIGURE 1. The CFA model of DART structure with all 30 indicators

Source: own elaboration.
Following the above explanations it is quite clear that the model is not a particularly
good representation of the collected data. What is most striking is the considerable num-
ber of indicators which variance is explained only in a small fraction (e.g. Access_3 only
1% of variation, Access_2 4% and Access_5 7%). Those indicators, with small regression
coefficients and negligible amounts of variance attributed to the model, do not contribute
valuably and probably solution's parameters will be improved should they be removed.

Deeper insights into the model adequacy can be obtained from the overall goodness
of fit measures of the model, which typically include chi-square statistic ($\chi^2=2246.229$;
df=399; $p<0.0005$), relative chi-square ($\chi^2/df=5.630$), goodness-of-fit index (GFI=0.718),
comparative fit index (CFI=0.631) and root mean square of approximation (RMSEA=0.103;
LO 90=0.099; HI 90=0.107).

To aid in interpreting the goodness-of-fit metrics Garson (2012) gives the following
guidelines for cutoff points to accept a CFA model:
- Model chi-square should be statistically insignificant at 95% confidence level to con-
sider the model consistent with empirical data
- Relative chi square: <2 for good fit, <3 for acceptable fit
- GFI: ≥0.9
- CFI: ≥0.9
- RMSEA: ≤0.05 for good model fit; ≤0.08 for adequate fit; in addition, the upper 90%
  confidence limit (HI 90) should be no more than 0.08 for a well-fitting model

Using the above criteria it was apparent that the CFA model is of too low quality
to consider it a good approximation of the observed covariance structure (which serves
as an input for CFA). First of all, chi-square test was statistically significant at a p level
of 0.0005. Given that the null hypothesis for the test was that there were no significant
differences between the observed covariance matrix and the one reproduced from the
model, the p score of the test suggested poor model fit. However, the chi square test is
thought to be unreliable, particularly for large sample sizes, often giving too large values
signaling the need to reject otherwise adequately fitting models [Byrne 2010, pp. 76–77].
For that reason a number of additional indexes were developed for assessing the reliability
and validity of a CFA solution relying on different features of model fit and using various
assumptions about data. In fact, “although the chi-square value should always be reported
it is widely considered acceptable to conclude that a model fits the data well, even when
the value is statistically significant, if other preselected fit indices meet their established
criteria for fit” [Bowen, Guo 2012, p. 142]. Following this set of recommendations on
model verification it was clear that none of the four other measures of the solution quality
was adequate, thus the hypothesized model should definitely be rejected.

The next steps in the analysis were focused on modifying the initial configuration of
the model to try and achieve a solution with an acceptable fit with the sample data. As
the starting point, the exploratory factor analysis (EFA) was performed four times: once
for each group of indicators assumed to be correlated with each DART component. The
EFA was set up so that to extract only one factor from each group of indicators. It was consistent with the assumption that DART components are unidimensional constructs and accordingly their indicators are expected to have high factor loadings (i.e. correlation coefficients) only on one latent variable. As such, indicators that did not associate closely with an extracted factor were assumed to describe different construct and hence removed from further analysis. As the cutoff point for acceptable factor loadings served a value of 0.5 following suggestions in Hair et al. [2009, pp. 120–121]. Therefore, the EFA was used as a data reduction tool to retain only those observed variables that were highly associated with DART components and served as their reliable measures. To ensure that the EFA procedure was consistent with the CFA, the factors were extracted with the maximum likelihood method. In consequence, the total number of indicators was reduced from 30 to 13 so that DIALOG was represented by 4 variables, ACCESS by 3, RISK by 3 and TRANSPARENCY also by 3. With this configuration of observed variables the CFA was repeated to yield the following path diagram (Figure 2).

FIGURE 2. The CFA model of DART structure with 13 indicators

Source: own elaboration.
The adequacy measures for the new model were: (1) chi-square=280.48; df=59; p<0.0005; (2) relative chi-square=4.754; (3) GFI=0.912; (4) CFI=0.896; (5) RMSEA=0.092; LO 90=0.082; HI 90=0.103. The diagnostics indicated that the second model was a better representation of the sample data compared with the initial solution, however chi square test was still significant (though at a lower value) and fit indexes (apart from GFI) were outside the acceptance range. What was noticeable in relation to the starting model (Figure 2) was the lack of indicators with very low regression weights; here all indicators have factor loadings above 0.5 which suggests no further candidate variables for deletion.

To try to attain an even better data fit two avenues were available: to either modify the model by including correlations of error terms or reduce the sample to achieve a higher level of homogeneity of constituent companies. Given that introducing substantively and statistically justified correlations of error terms is thought to be less arbitrary than sample manipulation this is what was done in the next step. Using the modification indices provided in the AMOS output it was possible to identify the error terms that if correlated offered the most substantial gains in the model fit as measured by drops in the model chi-square value. In total three new covariance terms were brought in to arrive at a model (Figure 3.).

FIGURE 3. The CFA model of DART structure with 13 indicators and correlated intra-construct error terms

Source: own elaboration.
The third model yielded the following set of data fit metrics: (1) chi-square=204.297; df=56; p<0.0005; (2) relative chi-square=3.648; (3) GFI=0.935; (4) CFI=0.930; (5) RMSEA=0.078; LO 90=0.066; HI 90=0.089. The modified model showed an improved fit across all indices with GFI and CFI at an acceptable level and a borderline score on RMSEA. However, Chi square test still gave significant outcomes, suggesting poor fit.

**FIGURE 4.** The CFA model of DART structure for 220 manufacturers with 13 indicators and correlated intra-construct error terms

Source: own elaboration.

To further improve model parameters an attempt was made to exclude from the analysis certain groups of companies with a rationale that a more homogeneous dataset may yield more distinct correlation patterns, though at the cost of constraining external validity (i.e. after leaving out specified companies the generalizability will be only possible to a target population of firms that were left in the data set). Given the study sample composition the most natural choice was to run separate CFA for manufacturing and services companies on the assumption that their inherent similarities would result in better fitting models. It transpired that the service providers yielded a solution that was considerably worse on all of the diagnostic metrics than the earlier model. This suggests that the DART framework can be more effective at explaining aspects of co-creation in manufacturing firms, possibly
because its development was apparently driven by data from case studies of manufacturing companies [Prahalad, Ramaswamy, 2004]. As a consequence, the next structural model was centered solely on the manufacturers subsample (Figure 4.).

The solution obtained for manufacturers was characterized by the following diagnostics: (1) chi-square=109.944; df=57; p<0.0005; (2) relative chi-square=1,929; (3) GFI=0.932; (4) CFI=0.945; (5) RMSEA=0.065; LO 90=0.047; HI 90=0.083.

As it stands, the model including only manufacturing companies and following the same specification as the previous structure (the only small exception being the lack of one error covariance which was deleted due to its insignificance in the new sample) provides acceptable data fit on 4 out of 5 criteria. Bearing in mind earlier remarks about unreliability of the chi-square test, the model can be accepted as providing adequate data fit.

When model generation strategy is guided by modification indices it is important to be able to substantively justify the addition of new parameters to the model. Furthermore, even though the indices may suggest introducing new parameters (or “freeing up parameters”, as it is also termed in the literature) the researcher can decide against it in the interest of the rule of parsimony. The rule of parsimony in science is a principle that advises the simplest possible model design to avoid the risk of over-specification, which can result in a well-fitting model to the observed data but with no relevance for other data sets [see the discussion in Mulaik 2009, pp. 342–345]. Over-specification occurs because model components are developed by leveraging unique features of the studied data that may not repeat in other data files, i.e. through capitalizing on chance. Mulaik [2009, pp. 381] cautions against too liberally adding parameters to a model following the values of modification indices by noting that “if the lack of fit is not due merely to a misspecified parameter in a correctly specified model structure, this can be misleading. The problem could lie in a misspecified model structure, omission of important latents, and no amount of freeing up parameters in the current model could lead to a correct model, even though the resulting model might fit acceptably”. As the existent DART literature doesn’t provide theoretical grounds to modify the model structure by introducing new latent variables or adding new regression paths, and heeding the rule of parsimony, the fourth model appears to be the best representation of the DART concept for the research data. However, to possibly reveal potential limitations of DART, further analysis was performed to attempt to achieve the maximum fit level even at the risk of overspecification. The employed procedure involved sequentially adding and deleting covariances of error terms (not only within factors but also between indicators assigned to different factors) based on the changes in significance levels and effect sizes, although without altering the general structure of the solution. The outcome of this model building strategy was presented in Figure 5.
Every adequacy metric for the solution (chi-square=62.713; df=52; p=0.147; relative chi-square=1.206; GFI=0.958; CFI=0.989; RMSEA=0.031, LO 90=0.000, HI 90=0.005) is not only substantively better than for any previously considered alternative but also well within the range of acceptable values indicating a very close match with the data set of 220 manufacturing firms. However, the improvement in goodness-of-fit from the previous solutions was achieved due to the introduction of six covariances between errors of observed variables assigned to different constructs. The new covariance parameters rendered statistically insignificant the two error covariances between pairs of indicators within DIALOG and TRANSPARENCY factors, which were consequently removed from the model.

As was already explained, the error terms in regression analysis are taken to represent all variance in indicators that was not accounted for by latent variables. The variance could originate from random factors, measurement errors or – what is typical of misspecified models – other latent variables that were not included in the model [Hoyle 1995, pp.172–173]. Hence, the presence of so many statistically significant correlations between indicators from different factors suggests that the observed variables are influenced by more than four factors, which in turn strongly implies that the DART model is incomplete and ought to include more than four latent variables. The conclusion is corroborated by relatively low multiple correlation coefficients, that inform about percentage of variance in each indicator explained by the constructs present in the model. In fact, 8 out of 13 observed variables are explained in less than 50% by the DART components.
Another finding is that DART may not be a unidimensional structure as was assumed by the conceptual work of Prahalad and Ramaswamy [2000] and the survey by Albins-son et al. [2011]. As explained by Kline [2011, p. 115], unidimensional measurement is defined by (1) each indicator loading (correlating) on one factor and (2) independent error terms. Accordingly, a measurement model which contains indicators substantially correlated with two and more factors suggests multidimensionality. The same is indicated by the correlated error terms, reflecting the assumption that the pairs of corresponding indicators share something in common that is not explicitly represented in the model [Kline 2011, p. 115]. Thus, the source of multidimensionality is likely to be an unknown construct or constructs from outside the model. The present study enables to observe both causes of multidimensionality: (1) correlated error terms of indicators point to the existence of other explanatory latent variables, while (2) multiple factors loading on more than one indicator hint that the constructs are not independent since their substantive scopes markedly overlap. Table 2 provides more evidence to support this line of argument. It contains linear combinations of regression coefficients for all indicators in the model which could be used for estimating values of each of the DART components.

<table>
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<tr>
<th>TABLE 2. Regression weights between factors and observed variables</th>
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<tr>
<td>TRANSPARENCY</td>
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<tr>
<td>RISK</td>
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<tr>
<td>ACCESS</td>
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<tr>
<td>DIALOG</td>
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Source: own elaboration.

It can be seen that, with the exception of ACCESS, the factor scores were best predicted by a combination of indicators from within and without their respective domains (highlighted in grey). In fact, some indicators attributed in the model to a particular factor were less useful as predictors in comparison to indicators nominally assigned to other factors (a case in point being TRANSPARENCY, where Risk_3 and Dialog_2 had stronger impact on the construct score than Transparency_2; it was likewise for the constructs RISK and DIALOG). On the other hand, looking at the table column-wise, it is obvious that most indicators were associated with more than one factor, e.g. Transparency_1 and Transparency_2 loaded substantially on TRANSPARENCY, RISK and DIALOG, while dialog_2 was related in varying degrees to all factors. As it was already noted, only
ACCESS, which comprised three aspects of Internet applications in communication with customers, was truly independent of other constructs, and consequently its indicators did not load on other latent variables. The cross-loading of the indicators was symptomatic of questionable convergent validity of the DART model. On the other hand, high correlations coefficients (see Figure 5) between DIALOG and TRANSPARENCY and RISK and TRANSPARENCY, respectively 0.72 and 0.82, were an evidence of low discriminant validity (i.e. the same indicators measure two factors simultaneously).

Conclusions and Limitations

The findings of the study highlight possible shortcomings of the DART concept. First of all, it may imply that DART is too simplistic in that it assumes unidimensional structure with only four factors. The analysis necessitated exclusion of 17 indicators from the data set, that were coherent with various conceptualizations and exemplifications of DART found in extant literature sources, to be able to achieve an acceptable match to the actual observations with the remaining 13 variables. Regardless, the final CPM model seemed to display clear evidence of multidimensionality even in the reduced group of 13 observed variables. Apparently, to attain higher relevance of the model to the business practice it would be useful to overhaul the DART structure to arrive at a selection of constructs that do not overlap so markedly and possibly add new elements that are able to better address those aspect of co-creation that were captured by the discarded indicators. It is rather conceivable that the four DART constructs could actually be second level latent variables affecting indicators not directly but through the first level constructs serving as mediators.

In the extant literature there has not been a single widely accepted approach to measuring businesses’ involvement in co-creation. The most common method assumed that value co-creation is a first level, one-dimensional construct with rather compact Likert-type measurement scales encompassing three [Auh et al., 2007], four [Grissemann, Stockburger-Sauer, 2012] or five [Zhang, Chen, 2008] component items. Consequently, the individual statements on the scales were phrased quite generally and seemingly did not include all designators of the concept of co-creation, which had very similar definitions across most pertinent papers. On the other hand, there was an attempt to employ a more complex measurement system [Yi, Gong, 2013], treating co-creation as a third-level construct directly affecting two second level-factors of customer participation and customer citizenship behavior, which in turn were reflecting on four first-level factors each. That operationalization when tested through a survey on a group of consumers was demonstrated to have acceptable reliability and validity. Although definitions of particular first and second level constructs as well as phrasing of individual Likert-scale items could be disputed, this outlook of having two intermediate layers of effects between co-creation and actual scale items is coherent with the perspective of the authors of the present study.
based on the conclusions from the analysis of the measurement model for DART. The positive validation of the quoted alternative conceptualization of value co-creation seems to lend credence to the authors’ observation that the DART model, to closer mesh with actual practice, should be enhanced with an additional layer of hidden variables to form a three-level factor structure.

One has to admit though that the study has several limitations that could attenuate the appeal of its findings. Firstly, the final model was built entirely on data collected from a few consumer oriented manufacturing industries in a single Central-European country. As a result, any generalizations beyond the strictly defined target population of the study should be performed cautiously. Secondly, in addition to the limitations in external validity, it is possible to raise concerns about certain aspects of internal validity. Even though the authors did not have any particular reason to harbor doubts, it is not entirely certain if relying solely on managers’ replies for data was not affected with measurement bias. Though in the data collection process as well as in further analysis nothing was indicative of existence of such a problem, it would be revealing to be able to tap into other sources of information about companies to achieve triangulation effect and thus enhance reliability and validity of findings.

References


Validating DART Model


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Book Review
Krzysztof Falkowski – „Międzynarodowa konkurencyjność gospodarek Białorusi, Rosji i Ukrainy” („International Competitiveness of the Economies of Belarus, Russia and Ukraine”),
Warsaw School of Economics,
Warsaw 2013, p. 248

Polish economists have long been interested in our Eastern neighbours’ economies, which are among our largest foreign trade and, more widely, economic partners. Falkowski has been observing, researching, and analyzing economic processes in Belarus, Russia and Ukraine for many years and has published a number of papers and publications on this interesting subject. This work about the ability of these countries to compete and innovate, is a welcome addition to the author’s own body of work on that region, as well as the more general, worldwide discussion about innovation and competition now taking place among economists.

The book consists of an introduction, four chapters, a conclusion, a bibliography and a rich statistical annex, including 18 tables. In the introduction, the author explains the genesis of the book, and defines an economy’s international competitiveness. The remainder of the book is a careful elaboration of his analysis of the three countries economies using country-specific features in the context of cogently explained data limitations.

Chapter I presents the theoretical aspects of international competitiveness of economies, i.e., the relevant definitions, the nature of international competitiveness of an economy and the factors determining it. In so doing, he discusses the different views of several of the most renowned specialists in the field of competitiveness both in Poland
In Chapter II, the author analyzes in detail the competitiveness of Russia and Ukraine in 2006–2012 based on the most reputable world rankings, but does not do so for Belarus, which is outside that data set. The World Economic Forum data ranks both Russia and Ukraine in very low and steadily deteriorating positions (Russia – 133 and Ukraine – 132 among 144 analyzed countries). The author rightly suggests that without “…quick and comprehensive systemic changes in how the public sphere as well as the business operate in these countries” this situation and negative trend is unlikely to be reversed, anytime soon. However, given their current political situation, it seems improbable – if not impossible – that these changes will be implemented quickly.

Chapter III analyzes the competitiveness of the countries in question with regard to foreign trade using a variety of schemes. The last chapter of the book deals with selected international competitive determinants of Belarus, Russia and Ukraine. Here, the author demonstrates his wide knowledge of the current economic situations in these countries, which are used to great effect in formulating insights of real value.

There are points in the book where a reader wants more data inputs and, perhaps, somewhat greater clarity in terminology and the uniform use of particular terms. For example, the data limitations cited by the author concerning Belarus could have been at least partially remedied by including the UNO report entitled „International World Economic Situation and Prospects”, issued yearly in New York. A discussion of the consequences of Belarus’s growing negative trade balance, and an analysis of services turnover in Russia (which has undoubtedly affected Russia’ balance of payments since in 2013, Russia ranked 8th on the list of largest importers of services, accounting for 2.8% of the world import) would have been welcome. And, on occasion, subtle language- related issues arise concerning such terms as “sectors”, which does not translate well, as applied, from English to Polish.

None of which materially detracts from the author’s primary purpose- that is, to not only answer the question “how it is”, but to also explain why it has happened. And that, after all, is the crux of all good economic research.

In conducting that research, the author provides readers with solid evidence. There are 113 notes and over 65 bibliographic entries, four of which are the author’s own publications.

This book fills a gap in the contemporary economic literature. It is the first comprehensive attempt at describing the international competitiveness of Belarus, Russia and Ukraine and the breadth of problems and deliberations presented on that issue – especially given the context of the current political events in Ukraine – make it a useful read not only for university students but also for business practitioners and politicians who are actively shaping Poland’s economic relations with these three countries.
A final suggestion or, rather, request. In this work, the author’s opinion about the future of these states was rendered before the outbreak of full-scale war by Russia with Ukraine. Given the depth of Falkowski’s region understanding, a future work describing Russia’s invasion of Ukraine influence on both economies would be met with great interest of readers.
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