Essays on the Management of Innovation in Financial Services

by

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Submitted to the Sloan School of Management in partial fulfillment of the requirements for the degree of

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at the

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Abstract

The goal of this research is to establish a foundation for the exploration of the management of innovation in financial services. We explore several facets related to innovation in that field.

In the introduction we examine the literature associated to innovation in services. We note that, despite its importance, little work has dealt with the topic, and we present a guiding overarching framework for the study of the management of innovation in financial services. This is followed by a brief description of our empirical setting. The framework is thereupon examined in four related essays in as many chapters.

Chapter 1: A well-established stream of research indicates that innovative firms must carefully time their entry into new markets, and that there are advantages to early market entry. Such empirical regularity has not been extensively tested in financial services, despite the importance that timing order of market entry might have for financial innovations. Such importance derives from the weak appropriability regimes faced by financial service innovators. This characteristic leaves innovators with pioneering as an important approach toward appropriation. Analyzing three lines of financial products (credit cards, debit cards, and pension funds), we find important market share advantages to early entry in financial services innovations. Results are much in line with other research performed in other industries, particularly consumer products.

Chapter 2: Here we extend the insights gained in chapter one. We estimate entry effects when moderated by the strategic characteristics of the entering firm. Although the main effect of order of market entry on market share is remarkably strong, we find, when we control for firms’ strategic inclinations, that certain strategic typologies appear to fare better than others when pioneering new financial services. Such differences could help explain situations in which later entrants outperform pioneers.
Chapter 3: In this chapter we explore whether there are differences in the organizational structures for innovators and non-innovators in financial services. We hypothesize that financial service firms which are either highly rigid or highly flexible will exhibit the highest degree of innovation. We find, however, that firms with a product development orientation and with more formal procedures are apparently the ones which appear to have larger product arrays aimed at different markets. This product development orientation measure reveals itself more strongly through the interaction with measured organizational formality. Although no normative conclusions can be derived with the data available, such results, which are in line with other studies about innovation in financial services, seem to suggest that formalized and differentiated product development processes tend to be associated with successful innovative behavior in financial services firms.

Chapter 4: Finally, we turn our attention to the diffusion of financial innovations. Once a new financial product is introduced into the market, new producers are likely to enter as more users adopt the product. Because of the relatively simple process of user adoption in financial services, it is likely that strong system interdependencies will take place, and that new producers will enter the market influenced not only by the rate of producer adoption but also by the rate of user adoption. A model is developed to take into account such interdependencies. The model is helpful in determining user diffusion curves based on producer diffusion data, and it has good descriptive and forecasting capabilities when applied to two financial products.

We summarize and conclude by outlining the main findings of this work and linking them to salient managerial implications and also to suggestions for further research. We also discuss the limitations of the present study. This work suggests that research in the management of innovation in financial services can be fruitfully explored using ideas that have been derived from, and applied to, the study of industrial innovation. It also submits that the frameworks we have so far used to study industrial innovation can be enriched by studying the phenomenon in financial services.
Acknowledgments

Completion of this thesis was made possible by many people and institutions. My deepest gratitude goes to Ed Roberts, my thesis advisor. Ed’s constructive and detailed criticism tremendously improved the quality of this research. He generously spent time and effort reading countless versions of my essays. His contributions and insights had a considerable impact on the final result. Professor Roberts showed not only an interest in the thesis but also in my academic career and objectives. I have learned much from Ed’s advice.

I was also privileged to have professors Don Lessard and Scott Stern in my dissertation committee. Don was a continual source of valuable ideas and new approaches which significantly improved this thesis. Scott provided patient advice and innumerable suggestions.

I want to thank my friends Guk Hyun Cho, Alvaro Cuervo, Steve Freeman, J.J. de Groof, and Sandy Rothenberg who always gave support and encouragement. I am particularly grateful to Allan Afuah, Pek Hooi Soh, and Steven White for their help at crucial moments. My appreciation also goes to Mark Meyer for many research ideas and for his invaluable help.

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I gratefully acknowledge the financial support of CLACDS, FMECA, IDB, INCAE, ICRMOT, MIT, and MIT’s Center for Innovation in Product Development.

Finally I would like to thank my family. Our brothers and sisters were always there when we needed them. Our parents were constantly helping us in many ways.

This thesis is dedicated to my wife Mary and our children Alicia and Eduardo. Without their emotional support, love, and encouragement I wouldn’t have made it past the first semester of studies. They constantly reminded me that the really important things in life had nothing to do with a thesis or a doctoral program. Because of them, my time in Cambridge was immensely rewarding.

A mi esposa con todo el amor de siempre y a mis hijitos con mucho cariño.
Los quiero mucho.
# Contents

Abstract ................................................................. 3
Acknowledgments ......................................................... 5

Introduction .............................................................. 9

Chapter 1: First Mover Advantages in Financial Services Innovations .............. 23

Introduction and Review of the Literature ........................................... 24
Hypothesis ........................................................................ 36
Methods ........................................................................... 37
Results ............................................................................ 42
  Qualitative Analysis ....................................................... 42
    Pension Funds .......................................................... 42
    Debit Cards ............................................................. 48
    Credit Cards ............................................................ 54
Quantitative Data Analysis ............................................................ 59
Summary and Conclusion ............................................................ 76
References ..................................................................... 83
Appendix 1 ..................................................................... 87
Appendix 2 ..................................................................... 88
Appendix 3 ..................................................................... 89
Appendix 4 ..................................................................... 90

Chapter 2: Order of Market Entry and Competitive Strategy in Financial Services Innovations ........................................................... 93

Introduction and Research Background ............................................ 94
  Order of Market Entry and Strategy ........................................... 101
Hypotheses ........................................................................ 108
Methods ........................................................................... 109
Model and Measures ................................................................ 110
Chapter 3: Effects of Organization on Financial Innovation

Research Background
- Organizational Structure
- Innovation = Invention + Exploitation

Hypothesis

Methods
- Measures
- Predictor variables
- Outcome variable
- Sample

Data Analysis

Summary and Discussion

Chapter 4: Modeling the Diffusion of Financial Innovations

Literature review and model development

Proposed model

A pilot study
- Mutual Funds
  - Comparison to simpler model
  - Forecasting of demand
Introduction
Little academic research has dealt with the study of innovation and product development in services. As Roberts (1988, 13) indicates, "...academic research in the area of technological innovation and technology management has traditionally focused on product innovations aimed at industrial markets." Thus, research in the management of innovation and new product development has focused on physical products. The body of innovation research has not been extended broadly to services and products based on information (Meyer and Zack, 1996). As Utterback (1986, 129) suggests:

"...we must build a wider, more holistic appreciation of the phenomena involved. This requires moving beyond units of analysis such as the individual, group, project, or innovation to comprehend technological change at the level of the firm and to encompass changes in software, services and management within the framework as well."

And Roberts (1988, 13) adds:

"The overall management of technological innovation includes the organization and direction of human and capital resources toward effectively. (1) creating new knowledge, (2) generating technical ideas aimed at new and enhanced products, manufacturing processes and services; (3) developing those ideas into working prototypes; and (4) transferring them into manufacturing, distribution and use."

Moreover, from a practitioner's standpoint, the need to pay explicit and conscious attention to developing new products within a coherent product development strategy is probably just as important in non-manufacturing industries as it is in the goods-producing sectors. Practitioners may benefit from institutionalizing research and development - and innovation in general - as an important function within service firms, and from paying attention to the organizational arrangements that seem to be necessary for success in such function. In all industries Wheelwright and Clark (1992: 4-5) argue.
...rigorous international competition, the explosion of market segments and niches, and accelerating technological change have created a set of competitive imperatives for the development of new products and processes in industries as diverse as medical instruments and automobiles, textiles and high-end disk drives... (and) ...effective competition requires highly efficient engineering, design, and development activities.

In services, increased levels of competition require most industries actively to perform research and to develop new products. As Scheuing and Johnson (1989:25) indicate:

Most service industries have a need to develop a steady stream of service innovations. Competitive pressures are prompting a new-found aggressiveness that questions established service offerings and calls for new ways of identifying and satisfying buyers’ needs. Unfortunately, few service firms are adequately prepared to meet this challenge, and the literature concerning new service development is sparse at best.

Assessing the applicability to services of our understanding of product development practices and innovation should become increasingly important, particularly as economies become service-oriented. Today most people in advanced economies work in services.

By 1985 services accounted for almost 77% of total employment and about 70% of the GNP of the United States. By 1994 80% of the U.S. population worked in services (Quinn, 1992). A similar situation is present in other industrialized countries, and, as Table 1 shows, even in developing countries more than half of the population works in services. Table 1 suggests the increasingly important role services are playing in the world economy, and, as a result, we can infer that the creation of new knowledge and the generation of new products in services will become a crucial element in the performance
of economic systems. As Drucker (1991: 69) indicates, "the single greatest challenge facing managers in the developed countries of the world is to raise the productivity of knowledge and service workers." With this structural change becoming more evident and important, and with consumption of information products and services increasing relentlessly, the understanding and active management of innovation in services has to be addressed.

| Table 1 |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| Employment by industry in selected countries as a percentage of total employment |
|                | Year | Agriculture and other | Manufacturing | Services |
| U. S.          | 1985 | 4.0%             | 19.5%          | 76.5%          |
|                | 1994 | 3.5%             | 16.4%          | 80.2%          |
| Germany¹       | 1985 | 5.8%             | 31.8%          | 62.4%          |
|                | 1994 | 3.8%             | 28.7%          | 67.5%          |
| France         | 1985 | 7.7%             | 22.9%          | 69.4%          |
|                | 1994 | 5.0%             | 18.8%          | 76.2%          |
| Japan          | 1985 | 8.9%             | 25.0%          | 66.1%          |
|                | 1993 | 6.0%             | 23.7%          | 70.3%          |
| Spain          | 1985 | 19.2%            | 22.7%          | 58.1%          |
|                | 1993 | 10.6%            | 20.3%          | 69.1%          |
| Brazil         | 1985 | 30.2%            | 14.7%          | 55.1%          |
|                | 1990 | 24.2%            | 15.2%          | 60.7%          |
| Costa Rica     | 1985 | 27.3%            | 15.8%          | 56.9%          |
|                | 1994 | 21.6%            | 17.9%          | 60.5%          |

¹ Data refer to what was the Fed. Rep. of Germany before 9-30/1990


Few studies have dealt with the subject of innovation in the service industries both from a corporate strategy perspective and at the industrial level. Quinn (1992) explored the use of technology in services and the management of intellect in services. He stresses that managing intellect to create new products in services will revolutionize competition in all industries. However, as he indicates (Quinn, 1992: xiii)), there is a "...lack of fine-grain
data collection for services." Much work in this area is still exploratory and based on case studies. As a result, field work acquires an inductive slant, because the development, a priori, of a conceptual framework to be tested empirically is difficult.

Related research in the management of innovation in the goods-producing sector can be used as a foundation to circumvent these problems. The body of research on innovation of tangible goods is extensive, and many ideas can be used as the basis for developing a conceptual framework to guide research in service innovation. This alone is an important and necessary extension that can be made to studies in the management of innovation. Although, as Quinn and Guile (1988, 2) indicate, "... many of the principles that have proved so essential to innovation management in product or manufacturing environments are equally important in services," it has not been established that the frameworks used to explain innovation in product and manufacturing environments can be extended to explain processes of innovation in services. As a result, we have few tools to understand and manage product development and innovation in services. We know little about the patterns of new product development and product diffusion at the industry level. We do not know which organizational characteristics may be more suitable for nurturing innovation. Though we know much about scientists working in laboratories developing new industrial products, we don't know if the concept of research and development has applicability in services and what considerations should management follow for properly staffing such a function. All in all, we do not even know whether being an innovator and creating products which are intangible, perish at the moment of their consumption, are in many cases administered through human intervention directly on humans, and are very difficult to patent, is correlated with success.

Aside from the need to understand innovation in services per se, it is also clear that the process of technical industrial innovation should not be understood in isolation, as if it
were insulated from processes occurring in other realms. Technical innovation engenders upswings in the business cycle (Schumpeter, 1939), and as these upswings occur, firms enter the market in the search for returns from innovative activities. Such innovations and their subsequent diffusion may require a great deal of capital. Technical "real" innovations may provide no sustainable advantage unless paralleled by innovation in downstream industries. Allen and Gale (1994: 58) illustrate this with the example of the Soviet Union and its lack of innovativeness in financial services.

The former Soviet Union provides an interesting illustration of the role of financial innovation. Although technologically advanced in many ways, its economic system was unable to provide a high standard of living to its citizens because it was economically unsophisticated.

Or, as Quinn (1992: 6) points out, planned economies concentrated so much in "technical" advance that "...their countries today tragically cannot store, transport, distribute, finance, communicate about, or repair the products they could otherwise produce in abundance."

In this thesis we examine some aspects of innovation in services. The mere vastness of the service realm, and the latitude of potential possibilities and unanswered questions preclude efficiently encompassing the study of services as a totality. Therefore, we focus on financial innovations in commercial banks.

This work does not examine financial innovation from an economic perspective. It focuses instead upon the management of innovation. In doing so, we seek to extend some ideas that have good explanatory power when applied to technological innovation to

---

1There are several approaches to the study of financial innovation in the economic literature. Miller (1986) ascribes financial innovation to the impulse of tax and regulatory changes; Silber (1975, 1981 and 1983) and Ben Horim and Silber (1977) study processes of financial innovation as responses to financial constraints; Van Horne (1985) and Allen and Gale (1994) look at risk sharing opportunities provided by financial innovation; and Merton (1990) looks at the role of agency costs.
the financial innovation realm. The work on technological innovation in the goods-
producing sector is extensive. Numerous conceptual frameworks offer the opportunity to
increase and enrich our understanding of processes of financial innovation. The use of
these instruments and the potentially rewarding cross-fertilization has been limited, but
some incipient work suggests that this approach can be useful. For instance, Geoffron
(1992) has presented an analysis of the similarities and differences that can be found in the
processes of financial and "real" innovation. He stresses the importance of analyzing
innovations in the financial realm in the same terms as those used to understand "real"
innovations. To do this, he suggests transferring analytical frameworks from the realm of
traditional innovations to the sphere of financial innovations. This exercise could be, in
fact, important and necessary because, as Geoffron (1992:86) indicates, "...the matter of
innovation, -its motivations and associated mechanisms- are phenomena of similar nature
both in the goods-producing and in the service sectors, regardless of whether some
parameters have different 'values'."

Thus, as Geoffron suggests, it is possible to construct a wider conceptual
framework that comprises the phenomenon of innovation without limiting it to the
particularities of one industry. A framework like this would account for industry
variations by changing parameters in one model and not through the use of many different
models.

We contribute to these ideas by exploring various aspects associated with
innovation in services. The goal of this research is to contribute to an overarching
framework for examining and understanding several facets related with innovation in
financial services. A multi-essay approach built around independent but related research
questions is followed. The framework that serves as an overall guide for this research is
shown in Figure 1. Financial innovation is examined as an outcome of organizational
arrangements and firm strategy, and we establish links between innovations, their success, and the degree to which they diffuse within an economy. The framework is explored in four self-contained essays using data from the financial sector in Costa Rica.

![Diagram of framework](image)

**Figure 1. Framework for this study.**

In our first essay we look at financial products and explore whether there are any advantages to early entry into new financial markets. We elaborate on this point in the second essay, where we try to uncover plausible interactions between early entry and firm strategy. In the third essay we look at the interaction between organizational structure and innovation. Here the unit of analysis is the organization, and we try to establish whether certain organizational arrangements are associated with particular patterns of
innovative activity. Finally, in the fourth essay, we examine how financial innovations diffuse within an economy, and we try to establish the generalities of such patterns. Each essay has its own literature review according to the topic being treated and the conceptual framework under which the particular issue is analyzed. Similarly, each of the chapters has sections that describe methodological and analytical issues as well as a conclusion. The final chapter synopsizes and draws overall perspectives from these studies.

The empirical setting chosen provided a convenient and interesting quasi-experimental backdrop for studying the phenomenon of innovation in financial services for various reasons. First, studying financial services in a single country permitted us to control for environmental factors. All firms operated within a single jurisdiction (therefore under the same regulatory conditions), in the same markets, and within confined geographic boundaries. Second, in this country deregulation was increasing the level of competition. Before 1980 the commercial banking sector in Costa Rica was a heavily protected and regulated area dominated by 4 state-owned banks. Economic deregulation, particularly during the early eighties, dramatically changed the structure of the industry, and companies that were previously confined to restricted areas of activity started offering new services in fields that had traditionally belonged to banks. Private banks were allowed to receive funds from customers and, as a result, many aggressive private institutions started to enter the industry. The number of private banks went from 5 in 1980 to 17 in 1990 to 25 in 1996. In 1997 the industry was composed of 28 banks, which varied widely in their size, geographical coverage and organizational form (as can be seen in Table 2),
operating in a country with a population of less than 4 million people. As more banks entered, industry rivalry was increasing. Rojas (1993) shows that after 1980 all banks were forced to aggressively compete for customer share, and many did so by introducing new products and services.

Table 2. Some descriptive figures of the banks studied.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>min.</th>
<th>max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total assets</td>
<td>39.7</td>
<td>0.64</td>
<td>307</td>
</tr>
<tr>
<td>Number of employees</td>
<td>536</td>
<td>35</td>
<td>3200</td>
</tr>
<tr>
<td>Number of branches</td>
<td>15</td>
<td>0</td>
<td>125</td>
</tr>
</tbody>
</table>

Numbers for Total assets are in millions of monetary units.

Third, deregulation implied an increasing potential to access many new combinations of clients and products and financial institutions had to renew their products to remain competitive. As noted by one bank executive,

Credit growth is limited, and banks are under pressure to develop new products and financial services. To that respect, banks have started to look for new financial services that have not been their traditional line of business, and the tendency is, definitely, toward creating new products.
Such tendencies resulted in many products being adapted from practices observed in other countries and also in more indigenous market-oriented innovation. This provided an opportunity for observing the evolution and institutionalization of product development processes within firms.

Finally, other factors were also contributing to increase competitive rivalry and the need to develop new products. Corporate customers were becoming more sophisticated in raising capital by issuing stock and company-backed documents directly to the public. Individuals were also becoming more sophisticated. People avidly embraced new products (credit cards, debit cards, point of sale systems, electronic fund transferring) and started to actively invest in pension plans and mutual funds. A lethargic stock market was awakening from dealing almost exclusively with short-term bonds and government-backed securities to transacting more complex instruments. Simultaneously, the rapid advances in telecommunications and data-processing technologies had a large effect on these institutions, and technology became an important source of competitive advantage. Banks were in a position of using new technology to create new services.

In all, these institutions had to deal deal with an increasingly complex customer base in a very dynamic environment, the result of it being that "the financial system will look completely different and, without a doubt, the new game will result in increased competitive pressures for all banks" (Rodiles and Maldonado, 1996: 55). In this new game, the development of new products appeared to emerge in its own right as a formidable competitive weapon.
References


Chapter 1

FIRST MOVER ADVANTAGES IN FINANCIAL SERVICES INNOVATIONS
In this essay we try to answer one research question: Are there pioneering advantages in financial services? To answer this question we examine the relationship between order of market entry and long term market share for a set of financial products. Accordingly, the first part of the paper provides a review of the literature on pioneering. In the second part we formulate hypotheses and provide a research design for testing them. This is followed by data analysis and conclusions. Our findings indicate a negative relationship between order of market entry and market share. Using elapsed time since first entry as an independent variable permits qualifying in more detail such relationship.

**Introduction and Review of the Literature**

The empirical relationship between order of market entry and long term market share for new products is well-established. Kalyanaram and Urban (1992) analyzed 18 brand entrants in 8 different product categories of consumer packaged goods and found that later entrants into new markets suffer long-term market share disadvantages. For instance, as shown in Table 1, in the presence of 7 brands in the market, the pioneer captures 2.5 times as much share as the seventh entrant. These authors try to establish whether such advantages occur only through advantages in production costs, advertising, price, quality, distribution, and breadth of the product line, only to find after correcting for the effects of those variables, that such influences are not important, and to discover an apparently inherent penalty for late entry.
Table 1. Order of entry vs. market share (Taken from Kalyanaram and Urban, 1992).

<table>
<thead>
<tr>
<th># of brands in market</th>
<th>Asymptotic market shares for each order of entry.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1st</td>
</tr>
<tr>
<td>1</td>
<td>100</td>
</tr>
<tr>
<td>2</td>
<td>57</td>
</tr>
<tr>
<td>3</td>
<td>42</td>
</tr>
<tr>
<td>4</td>
<td>34</td>
</tr>
<tr>
<td>5</td>
<td>29</td>
</tr>
<tr>
<td>6</td>
<td>25</td>
</tr>
<tr>
<td>7</td>
<td>23</td>
</tr>
</tbody>
</table>

Associated empirical findings, primarily in the marketing literature, report a negative relationship between order of market entry and market share. Robinson and Fornell (1985) analyzed 371 mature consumer goods businesses and found first-movers to have higher market shares than later entrants. On average, first-movers had a market share of 20%, early followers' market shares were 17%, and late entrants held 13% of the market. Similarly, Robinson (1988) studied 1209 mature industrial goods businesses and found pioneers to have higher market shares than later entrants. They had, on average, a market share of 29% versus 15% for later entrants. First-movers also tended to have higher product quality, more comprehensive product lines, and served ampler markets. Along similar lines, other studies have focused on cigarettes (Whitten, 1979), start-up and adolescent businesses (Lambkin, 1988), prescription drugs (Bond and Lean, 1977), and new corporate ventures (Miller et al., 1989). Lambkin (1988) analyzed 2 subsamples of 129 start-up businesses (using data for their first four years of operation) and 187 adolescent businesses (data for their second four years of operation) and found that, generally speaking, pioneers attained an important market share advantage over later entrants (about 24% on average for pioneers vs. 9.7% for late entrants in the start-up subsample, and approximately 33% vs. 13% in the adolescent subsample).
Table 2. **A summary of some selected empirical studies on pioneering advantages**

<table>
<thead>
<tr>
<th>Study, year</th>
<th>Characteristics of the study and findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bond and Lean, 1977</td>
<td>Reviewed 11 new products in two prescription drug markets. Found that first entrants maintained market share leadership after more than 10 years in market. Later entrants needed to offer substantial additional benefits to surpass the first-mover.</td>
</tr>
<tr>
<td>Whitten, 1979</td>
<td>Studied 7 cigarette markets and found that pioneering brands held over 50% of the market several years after their introduction. These cigarette brands were also those which were actively promoted and widely distributed.</td>
</tr>
<tr>
<td>Robinson and Fornell, 1985</td>
<td>Analyzed 371 mature consumer goods businesses. On average, first-movers had a market share of 20%, early followers had a market share of 17%, and late entrants held 13% of the market.</td>
</tr>
<tr>
<td>Urban et al., 1986</td>
<td>Analyzed 129 entries across 34 product categories. Important penalties were reported for late entrants (see Table 1) controlling for product positioning and marketing activity.</td>
</tr>
<tr>
<td>Robinson, 1988</td>
<td>Analyzed 1209 mature industrial goods manufacturing businesses. The market pioneer holds 29% of the market on average. Early followers and late entrants retain 21% and 15% of the market respectively.</td>
</tr>
<tr>
<td>Lambkin, 1988</td>
<td>Considered 2 subsamples of 129 start-up businesses (data for their first four years of operation) and 187 adolescent businesses (data for their second four years of operation). Pioneers attained an important market share advantage over later entrants (23.96% for pioneers vs. 9.7% for late entrants in start-up subsample and 32.56% vs. 12.95% in the adolescent subsample).</td>
</tr>
<tr>
<td>Lilien and Yoon, 1990</td>
<td>The likelihood of success for first and second entrants was lower than the likelihood of success for the third and fourth entrants in a sample of 112 new industrial products from 52 French firms.</td>
</tr>
<tr>
<td>Golder and Tellis, 1993</td>
<td>Using an historical approach found that not all pioneering efforts ended in success. They report a 47% failure rate for pioneers.</td>
</tr>
<tr>
<td>Brown and Lattin, 1994</td>
<td>Modeled the effect of time in market on pioneering advantage. Found that time-in-market may exert a beneficial effect upon the pioneer.</td>
</tr>
<tr>
<td>Huff and Robinson, 1994</td>
<td>Re-analyzed Urban et al.'s (1994) data on 95 surviving brands in 34 product categories. Found that longer lead-time increases the pioneer's market share reward.</td>
</tr>
</tbody>
</table>
These, and many other investigations have contributed to establish a remarkably strong empirical regularity in both consumer products and industrial goods. The results appear to be quite consistent across many product lines, as can be seen in Table 2. Kalyanaram, Robinson, and Urban (1995) summarized some generalizations that applied to prescription anti-ulcer drugs and consumer packaged goods. These generalizations are reproduced in Table 3.

Table 3. Order of market entry and market share for consumer packaged goods and prescription anti-ulcer drugs.

<table>
<thead>
<tr>
<th>Entry order</th>
<th>Consumer Packaged Goods</th>
<th>Prescription Anti-Ulcer Drugs</th>
</tr>
</thead>
<tbody>
<tr>
<td>First</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Second</td>
<td>0.71</td>
<td>0.76</td>
</tr>
<tr>
<td>Third</td>
<td>0.58</td>
<td>0.64</td>
</tr>
<tr>
<td>Fourth</td>
<td>0.51</td>
<td>0.57</td>
</tr>
<tr>
<td>Fifth</td>
<td>0.45</td>
<td>0.53</td>
</tr>
<tr>
<td>Sixth</td>
<td>0.41</td>
<td>0.49</td>
</tr>
</tbody>
</table>

Taken from: Kalyanaram et al., 1995.

Little work has dealt with services. Tufano (1989) found, for a sample of 58 financial innovations, the existence of some first-mover advantages, particularly in the form of lower costs of trading, underwriting, and marketing. He showed that pioneers capture shares which are "...almost 2.5 times as large as the followers in those markets" (Tufano, 1989: 231). Such advantage seems to remain consistent in subsequent years of
the life of the product. The same firm is shown to capture substantially less share with imitations than with innovations. This can be observed in Table 4.

Tufano's data showed that pioneers did not charge higher prices for underwriting than later entrants, and, by charging similar or lower prices, generated larger market shares. Thus, pioneer advantages were reaped primarily from lower costs of trading and from secondary trades and not from increased revenues accrued through higher pricing. Tufano's (1989) study suggests that innovation provides banks with sources of information that allow them to reduce information search costs, thus reducing the difficulties involved in further pioneering. This suggests, in turn, that certain banks tend to be more innovative than others (as is also apparent in Table 4). The findings, however, have not been confirmed with additional studies.

Table 4. Percentage of the dollar value of offerings of 35 imitated financial innovations captured by investment banks in markets in which they underwrite the initial pioneering deal versus those in which they offer imitative products.

<table>
<thead>
<tr>
<th>Investment bank</th>
<th>Markets in which bank pioneers the product</th>
<th>Markets in which bank offers an imitative product</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of products innovated</td>
<td>Average share as pioneer (%)</td>
</tr>
<tr>
<td>Salomon Brothers</td>
<td>7</td>
<td>47.8</td>
</tr>
<tr>
<td>First Boston</td>
<td>6</td>
<td>54.4</td>
</tr>
<tr>
<td>Morgan Stanley</td>
<td>5</td>
<td>45.3</td>
</tr>
<tr>
<td>Goldman Sachs</td>
<td>4</td>
<td>35.5</td>
</tr>
<tr>
<td>Shearson Lehman</td>
<td>4</td>
<td>47.3</td>
</tr>
<tr>
<td>Merrill Lynch</td>
<td>3</td>
<td>37.4</td>
</tr>
<tr>
<td>Smith Barney Harris</td>
<td>2</td>
<td>54.7</td>
</tr>
<tr>
<td>Blyth Eastman Dillon</td>
<td>2</td>
<td>61.6</td>
</tr>
<tr>
<td>Drexel Burnham</td>
<td>1</td>
<td>69.2</td>
</tr>
<tr>
<td>Bear Stearns</td>
<td>1</td>
<td>11.7</td>
</tr>
<tr>
<td>Shearson Loeb Rhodes</td>
<td>1</td>
<td>62.2</td>
</tr>
</tbody>
</table>

Mean 47.9 15.4

Taken from Tufano (1989).
Studying innovation in services from the perspective of the pioneering literature should be enlightening. As economies become more service-oriented, the R&D function within service firms emerges. Practitioners should benefit from guidelines that can help to determine expected returns from products entering markets at different stages of market evolution.

Moreover, the need to explore these issues is particularly interesting in services because there are possibly important differences between services and consumer or industrial products. These differences occur along many dimensions. For example, all products are bundles of physical objects and intangible attributes. Many services, however, have a high degree of intangibility. This makes it difficult to assess the needs of the customer before creating a product and to measure objectively the satisfaction derived from purchasing a service (Bitran and Lojo, 1993). This thereby adds complexity to the design and testing of services, thus increasing the risk associated with new product development (Anderson, 1987). Moreover, some services must be delivered at the moment of their inception. For instance, customers must be present to receive services like transportation, hotel accommodation, health care, and the like. When such services are generated, they are consumed at once. The act of producing and consuming the product occurs, therefore, in many cases, simultaneously, and such services cannot be inventoried for later use. Although the assets necessary to generate a service can, of course, be kept ready to deliver, the product per se cannot be delivered except in real time (thus, yesterday's unused hotel room or airline seat is lost forever and cannot be inventoried for later usage).

It is also salient that many services have to be delivered by humans, have the customer as their primary input, or both. Health care, for example, is delivered by humans to humans. Patients are the "raw material" of very complex production processes. For
this reason, each delivery is, by definition, different. As Bitran and Hoetch (1990: 89) note, in some services "it is not sufficient to define quality simply as 'conformance to specifications', because the human encounter cannot be completely specified."

Finally, newly created service products or processes are very difficult to protect (although, of course, not impossible¹). Bitran and Lojo (1993) attribute this lack of appropriability to the intangible nature of services.

These differences do not necessarily imply a difference in the fundamental nature of innovation. The phenomenon of innovation, its motivations and related mechanisms, are, in all industries, events of similar nature that have some parameters that take on different values (Geoffron, 1992). In financial services in particular, two parameters are highly relevant to the dynamics of innovation: increased volatility with respect to the environment and, most importantly, a very weak appropriability regime. Marshall and Bausal (1992), for instance, argue that environmental factors have contributed to the creation of many new financial instruments during the last 20 years.² Among the factors responsible for such increase in environmental volatility are: frequent and abrupt changes in prices, the globalization of markets, regulatory changes, technological advances, advances in financial theory, and others (Marshall and Bausal, 1992). For instance, the augmented changes in the speed, frequency, and magnitude of price variations requires the creation of new financial schemes to manage the associated risk. This results in a more rapid diffusion and a reduced duration of the transient monopoly allowed to innovators. In this regard, Tufano (1989) reports, for a sample of 58 innovations in the securities industry, that rivals enter the market less than one year after the pioneer in 60% of the

¹There is an increasing interest in the possibilities of patenting financial innovations. See for example Petruzzi, Del Valle, and Judlowe (1988).
²Finnerty (1988), for instance, compiled a partial list of over 100 instruments created between the early seventies and 1988.
cases. The mean number of deals the pioneer is able to close before rivals enter is in all cases less than two.

The feebleness of appropriability regimes in services stems from several causes. First, little protection is allowed either in the form of copyright or trade secret laws. In financial services, for example, very few patents have been awarded for new products. When Merrill Lynch was awarded a patent for its Cash Management Account, the company was able to obtain it on the grounds that it was a novel computer program. Patents are awarded to tangible things. In financial services patents may only be given to systems (for example, mechanical or electronic systems) that make the product somehow different or that serve to operate it. In these weak appropriability regimes, new services are copied and improved after very short periods of time (Bitran and Lojo, 1993). In the case of financial services in the United States, the Securities and Exchange Commission (SEC) in many cases forces "inventors" to disclose detailed information about the products they create (Tufano, 1989). In spite of this, numerous financial instruments are created and marketed every year. As Miller (1986:459) indicates: "...the word revolution is entirely appropriate for describing the changes in financial institutions and instruments that have occurred in the past twenty years." These innovations include securities (zero coupon bonds, junk bonds), consumer-type financial instruments (debit cards, credit cards), process innovations (ATMs -automated teller machines, CMA -cash management accounts, EFTs -electronic fund transferring) and financial strategies (LBOs -leveraged buyouts, swaps, corporate restructuring) (Finnerty, 1988; Miller, 1986). In this regard, developing new financial products requires large financial outlays (Tufano, 1989). Clearly, financial innovation, which implies the commitment of a great deal of resources into the development process, is undertaken as a profit-maximizing activity (Tufano, 1989; Anderson and Harris, 1986). This is carried out despite imitators needing to invest only a
fraction$^3$ of the innovator's original investment to replicate a financial product and to sell it in the market, not worrying about infringing any patent law. As a result, in many services product life cycles in some industries are short, and in some, ephemeral. This is especially true in many types of financial services, as we saw for the case of securities (Tufano, 1989), where products are copied almost instantaneously and development cycles must be reduced to the order of months (Quinn, 1992).

Levin et al. (1987) argue that firms use alternative means to protect the competitive advantages of new or improved processes and products. They identify six mechanisms firms use to appropriate the returns of innovative activities: 1) patents to prevent duplication, 2) patents to secure royalty income, 3) secrecy, 4) lead time, 5) moving quickly down the learning curve, and 6) sales or service efforts.

Patents are not very effective as a means of protecting innovations except in very few industries. As Von Hippel (1988: 47) indicates:

The real-world value of patent protection to innovators is a much-examined question. A series of studies conducted by several authors over a span of nearly 30 years (1957 to 1984) have asked whether inventors find patents useful for excluding imitators and/or capturing royalty income. The answer uniformly found: The patent grant is not useful for either purpose in most industries.

Though generally ineffective, patents do appear to offer some protection in certain industries. For instance, patents are particularly effective in the chemical and pharmaceutical industries but ineffective or not more effective than some other alternatives in the electronics and the telecommunication industries.

Similarly, secrecy appears to offer little protection to innovators. Von Hippel reports the existence of informal know-how trading among specialists in a given discipline.

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$^3$25% to 50%, Tufano 1990
These specialists might find it economically reasonable to trade information that could be considered proprietary, even with rivals (Von Hippel, 1988).

Given the relative inefficiency of some forms of appropriation in certain contexts, firms probably utilize a combination of means of appropriation that is likely to be cost-effective. That is, depending on the industry, the relative inefficiency of some appropriation methods is likely to be balanced with a greater emphasis placed on other alternative methods. In financial services, patents and secrecy are nonexistent or ineffective. Moreover, products, once released, are relatively easy to imitate. Bitran et al. (1993) report that:

In the financial services industry, whenever an institution introduces a new type of account, others not only copy it very quickly, but often introduce an improved service since they have some time to assess the strengths and weaknesses of the original service. In order to be a leader in the service industry in terms of new product introduction, therefore, it is important to have the next service almost ready by the time the first one is introduced.

A plausible alternative way to protect and derive rents from innovative activity is to introduce products that are hard to copy. This is difficult in some financial services, as Bitran et al. (1993) indicate, because products are not intrinsically complex. The process of creation may be complex, involving high doses of creativity and the participation of specialists from different areas, but replication is easy. Tufano estimates that the cost of replicating a financial product is on the order of 50% to 75% less than the innovator.

Even products that require intricate technological or institutional networking that may render them a bit more difficult to replicate are not necessarily difficult to copy. As Morone and Berg (1993) indicate, "... the relative benefits of pioneering versus fast following are particularly open to question since information technology can often be
quickly copied, and later entrants often enjoy the benefits of lower-cost hardware."
Hence, adding complexity to products through a more intensive use of information
technology or other means will not necessarily cause delays in product diffusion or in
competitors' movement down the learning curve.

Given this, we would expect that, at least in financial services, pioneering should
be an important form of appropriation if not the dominant one. If patent-related
protection and secrecy are ineffective and, for all practical purposes, absent, and moving
down the learning curve occurs almost instantaneously because of the relative simplicity of
the products, then lead time (being first to market) and a quick response in introducing
new products might be the most effective methods of appropriating the returns of
innovation efforts in financial services.

No study, however, aside from Tufano's, has looked into this problem in depth.
The literature on pioneering advantages has primarily concentrated, as we saw, in
packaged goods aimed at consumer markets. For these types of products it has been
determined that, in general, market share is inversely (though not necessarily linearly)
related to order of market entry.

The literature on pioneering advantages does, however, contain a number of
problematic aspects. a) The dynamics of order of entry are sometimes evaluated
disregarding the characteristics of firms that launch the new products. Thus, whether
products fail because they lack strategic relation with other products in the firm's
portfolio, or for other reasons not related to order of entry, is seldom studied.

b) The literature sometimes identifies as first entrant a product that first "achieves
national distribution" (e.g., Urban et al., 1986) or requires that the product be supported
by national advertising (e.g., Whitten, 1979). "Hence, if a firm does not have national
advertising or national distribution in a national market, it does not qualify as an entrant."
(Robinson, Kalyanaram and Urban, 1994:2). This might be problematic because indirectly it means that the product that qualifies as an entrant has been launched by a firm that has an important set of complementary assets (i.e., being able to nationally advertise or distribute), thus precluding many products launched by smaller firms. By using this methodology one runs the risk of confounding "entry" with financial muscle. The method also censors entrants that have failed to stay in the market, thus overstating the effect of entry on the survivors.

c) Units of analysis tend to vary. Some studies center their attention on products while others analyze organizations. Making generalizations from the literature as a whole is difficult.

d) Censoring: Many studies cannot or do not consider the products' entire history, thus overestimating or underestimating pioneering.

c) A rapidly changing market may defy order of entry dominance, especially if subsequent entrants in a very volatile environment are able to incorporate into their products characteristics that take such changes into account.

f) Finally, premature market conditions (i.e., pioneering "too early") may also obscure the effect of order of entry. Pioneers may end up bearing the weight of educating future consumers or creating network externalities yet unconsciously level the field for others to invade it.

As a result, though empirical results appear strong, empirical generalization is controversial. Some of this controversy is discussed by Golder and Tellis (1993) who, using an historical approach, argue that moving first achieves no advantage. On the contrary, they show for a variety of products that almost all of those who have moved first have died in their youth. Golder and Tellis do not require the pioneer to reach any specified scale of commercialization and many of those pioneers do not have a meaningful
share of the market in the long run. In their methodology, Golder and Tellis gather information from articles some as far back as 1842 to prove their point. Though this historical approach solves the problem of reverse causality (i.e., high market share firms being identified quasi-automatically as pioneers), it can also overlook other entries into the market that are not well documented. Such aspects should be taken into account when choosing an appropriate methodology to study the phenomenon in financial services.

**Hypothesis**

On account of the aforementioned we hypothesize first mover advantages for financial services innovations:

H: There is a negative relationship between order of market entry and market share of financial services innovations, controlling for firm size and product interrelatedness.

This proposed relationship falls in line with the same empirical regularity that has been discovered in many consumer products, in particular the pharmaceutical industry and consumer packaged goods (Robinson, et al., 1994), but runs contrary to the findings of Golder and Tellis (1993).
Methods

The study is based primarily on historical analyses. Product histories for several financial products are assembled and reconstructed using archival records. These records are information available in published sources of information (which include primarily newspapers, trade journals, and research papers) and from other sources such as regulatory institutions. The historic information is then validated with data from informants in pertinent institutions and by others familiar with the industry.

For convenience of data gathering, the sample chosen is a set of financial services launched in Costa Rica within the past 15 years. A sample of 36 entries in three product lines (credit card, debit card, and pension fund) is used. Thus, through this choice of sample we are trying to minimize the problem of lack of fine-grain data. This study is part of a larger one in which product line histories of commercial banks were reconstructed for a sample of Costa Rican financial institutions. For the purposes of this paper, however, we included only those products whose histories were reconstructed in detail. This was done with the intention of a) correctly identifying pioneers, b) avoiding censoring, and c) choosing products which had been launched in roughly similar time-frames (to control for potentially different market effects when agglomerating the sample).

The sample of products was circumscribed purposefully to a small market under progressive deregulation, and, thus, historical information could be obtained to permit an accurate determination of pioneering and subsequent entries. Moreover, the industry in which these products have flourished provided an interesting case for studying service-related innovation. No more than 20 years ago, the commercial banking sector in Costa Rica was a heavily protected and regulated domain. Economic deregulation dramatically changed the structure of the industry since 1980 and companies that were confined to specific domains of activity were allowed to offer new services in areas that had
traditionally belonged to banks. All financial institutions have been forced to renew and offer a wider range of products in order to remain competitive. Over 15 years, innovation and the development of new products in the financial services industry have become increasingly important.

Our choice of sample includes products that have been created in the near past. This allows for a relatively simple process of information gathering from public records. It also permits us to gather first-hand information from people who participated in the launching of the products. Another important advantage is that we were able to assess the dynamics of the dependent variable, market share, over time. Moreover, we chose product-lines whose history could be reconstructed through comparison and contrast of several data sources. Thus, we were trying to avoid overreliance on single informants within organizations who may overstate pioneering status, or whose recollections might not be entirely accurate. To avoid these problems, multiple measures were collected both from organizational informants and from secondary sources, allowing us to cross validate and triangulate data from different origins (scholars, experts, journalists, etc.), particularly sources who were not interested in overstating the pioneering status of a particular firm.

An important disadvantage with the chosen sample of products is that we may in fact be censoring the dependent variable, since it is plausible that not enough time has elapsed for assessing the survival and performance of the different market entrants. In this case the long term may not yet be long enough.

Although historical analysis is little used in studies of pioneering carried out in the marketing field, it has been widely used in studies of technological innovations. Of particular interest are the studies done by Cooper and Schendel (1976), David (1986, 1992), and Utterback (1994). All these authors incorporate a strong historical component in their work.
The dependent variable in this study will be total market share of the nth entrant at the time of the study, measured as percentage of total customers using a particular financial instrument and, alternatively, as percentage of total portfolio of dollars committed to the financial instrument. Data sources for this variable included informants' reports and archival data. Archival data were obtained primarily from financial periodicals. A manual search of all the issues of the four most important local business, financial, and economic journals since 1985 (and a selective search of some older issues) was coupled to both electronic and manual searches of the countries' most important newspapers. We also searched several libraries in the country (for example universities' libraries, the Central Bank Library, the library of the Stock Exchange Commission, and several others) for sources of information which included books, unpublished theses and papers, and monographs. In all we were able to assemble over 100 articles or printed pieces of information which referenced the product lines under scrutiny. This information was validated with data provided by organizational level informants and three industry experts. For pension funds we contacted an incipient Pension Fund Regulatory Commission which required all pension fund operators in the country to report data on portfolio size, number of customers, and the like. When we found contradictory information we either sought a third piece of confirmatory evidence or asked an industry expert for clarification. Because the products were recent, confirmatory evidence was generally found with only a moderate degree of difficulty.

The order of market entry will be used as an independent variable. Pioneers are operationalized as the first entrant. Time of entry was obtained using primarily informants. Most organizations had personnel who were able accurately to recall the time of entry of their product. This was confirmed with archival data and, in the case of
pension funds, with the date reported to the Pension Fund Regulatory Commission as the first year of operation.

An additional independent variable will be the elapsed time delay since the first entry until the nth entry. The rationale here is that the impact of being the nth entrant will vary depending on the time elapsed since the first entry. Elapsed time was easily determined once we had dates of product introduction per institution.

The institution’s size, in terms of total number of employees at the time of the study, will be used as a control variable. Number of employees is highly and positively correlated with total assets. These size measures are a proxy for the bank’s ability to leverage existing resources to support a product in terms of advertising expenditures, reputation, and distribution channels. This information was obtained through informants within the organizations.

Relatedness with the rest of the institution’s products can also have a moderating effect upon the outcome variable. People may be inclined to switch to certain institution’s products because of the added convenience of carrying on all businesses with one organization. For this purpose a measure of strategic focusing was used. The dispersion of the point cloud on the client-product matrix of each institution was used as a measure of product interrelatedness. Institutions with larger/ampler arrays of products and clients may be better positioned to leverage new product offerings. An alternative measure, which quantified the change in the dispersion of each bank’s product cloud, was also used as a measure of interrelatedness (small values indicating small departures from current product offerings).

Finally, a dummy variable was used for assessing the regulatory effect upon the hypothesized relationship. This dummy was assessed with the help of three industry

\[\text{Please see Appendix 4 for details.}\]
experts who were independently asked which of the product lines was influenced by regulation (when operation required permission from the regulator, or when the regulator only permitted certain institutions to operate at the time of entry).

The model to be tested can be summarized as:

\[ S_{nc} = E_{nc}^{\alpha_1} T_{nc}^{\alpha_2} A_{nc}^{\alpha_3} R_{nc}^{\alpha_4} C_{nc}^{\alpha_5} \]

where,

\( S_{nc} \) = market share of the nth entrant in category c, in percent.

\( E_{nc}^{\alpha_1} \) = Order of entry of nth product in category c.

\( T_{nc}^{\alpha_2} \) = Elapsed time delay between nth entry and the first entry in category c, in months.

\( A_{nc}^{\alpha_3} \) = Relative size of institution that released the nth product in category c (measured as a ratio of total employees with respect to largest entrant in category).

\( R_{nc}^{\alpha_4} \) = Index of product relatedness for bank releasing product n in category c.

\( C_{nc}^{\alpha_5} \) = Regulatory variable (dummy variable, dichotomous).

Following a section of exploratory data analysis, we will fit a taxonomy of regression models.
Results

Qualitative Analysis

In general, all products examined here present different patterns of entry, exit, and seemingly different relationships between order of entry and performance. For some products, particularly those which only add features or are exclusively driven by changes in regulation, the effect of pioneering upon performance seems to be small. However, strategic products that enter the market in the absence of regulation reveal an apparent expected negative relationship between order of market entry and measures of performance.

Pension Funds.

Pension funds in this market had traditionally been administered by the state. Economically active people contributed a fixed percentage of their salaries to a national fund. In such environments, private pension funds tend to be successful if the state-operated pension system gives small pensions at high retirement ages. In such a case, customers would have an incentive to transfer to funds that offer more benefits. Problems with the state-administered fund opened an opportunity for other institutions to enter the market and offer complementary pensions. This industry operated with little or no supervision until July of 1995. In fact, before that time, private pension funds could not operate openly as such, but only as providers of additional coverage to that given by the state. Even so, the first private pension fund operator entered the market in August of 1988. In 1995 the funds were authorized to operate as such and also received an
additional impulse in the form of a tax break\(^5\). More operators entered the market between 1991 and September of 1996. Table 5 summarizes the order of market entry, the number of clients, and the size of the portfolio for the last three years.

Table 5. Raw data set for pension funds.

<table>
<thead>
<tr>
<th>Fund</th>
<th>Date of entry</th>
<th>Order of entry</th>
<th>Portfolio, Sept. 96 (m.u.) (^1)</th>
<th>Customers</th>
<th>Portfolio, Dec. 95 (m.u.) (^1)</th>
<th>Customers</th>
<th>Portfolio, Dec. 94 (m.u.) (^2)</th>
<th>Customers</th>
</tr>
</thead>
<tbody>
<tr>
<td>PF1 (B)</td>
<td>Aug 1988</td>
<td>1</td>
<td>20,000</td>
<td>52,000</td>
<td>11,580</td>
<td>45,000</td>
<td>8,335</td>
<td>37,714</td>
</tr>
<tr>
<td>PF2 (P)</td>
<td>Nov 1990</td>
<td>2</td>
<td>1,800</td>
<td>27,000</td>
<td>1,500</td>
<td>25,000</td>
<td>1,277</td>
<td>17,000</td>
</tr>
<tr>
<td>PF3 (I)</td>
<td>July 1991</td>
<td>3</td>
<td>1,208 (^1)</td>
<td>23,344 (^1)</td>
<td>1,800</td>
<td>18,000</td>
<td>665</td>
<td>15,187</td>
</tr>
<tr>
<td>PF4 (B)</td>
<td>Aug 1991</td>
<td>4</td>
<td>n.a. (^3)</td>
<td>2,250</td>
<td>610</td>
<td>2,000</td>
<td>243</td>
<td>1,015</td>
</tr>
<tr>
<td>PF5 (B)</td>
<td>Jan 1993</td>
<td>5</td>
<td>10,400</td>
<td>25,983</td>
<td>4,300</td>
<td>17,340</td>
<td>1,600</td>
<td>12,131</td>
</tr>
<tr>
<td>PF6 (B)</td>
<td>May 1993</td>
<td>6</td>
<td>2,600</td>
<td>41,500</td>
<td>1,400</td>
<td>38,000</td>
<td>528</td>
<td>24,046</td>
</tr>
<tr>
<td>PF7 (B)</td>
<td>Jan 1995</td>
<td>7</td>
<td>3,100</td>
<td>6,890</td>
<td>330</td>
<td>1,800</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PF8 (B)</td>
<td>Jan 1996</td>
<td>8</td>
<td>n.a. (^3)</td>
<td>920</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PF9 (B)</td>
<td>Mar 1996</td>
<td>9</td>
<td>850</td>
<td>1,100</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TOTAL</td>
<td></td>
<td></td>
<td>39,958</td>
<td>180,987</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^1\)April 1996 \(^2\)Millions of monetary units. \(^3\)No reliable data were found for these cells.


Different types of institutions entered this market. The most prominent participants are banks, but there is also one insurance company (PF3), and one company that exclusively operates the pension fund as its sole product (PF2).

Figure 2 is a scatterplot that shows order of market entry versus percentage of total market share (as of 1996) for all incumbents in the pension fund industry. Market share is measured as percentage of total customers. Inspection of this scatterplot reveals an apparent negative relationship between order of entry and market share. After an elapsed time of approximately seven years, the pioneer still holds the largest market share.

\(^5\) A portion of the funds saved could be deducted from income tax.
When % of market share is measured in terms of portfolio size (not shown on graph), the pioneer also appears to retain an important portion of the market.

Figure 2: Order of market entry vs. market share for pension funds. Market share is measured as % of total customers as of Sept. 1996.

Figure 3 shows a longitudinal history of total market shares (measured as % of total customers) for all participants. The pioneer in this market was able to operate alone in this market for a total of 23 months. Firms' market shares start leveling off after approximately 4 years since the first entry. According to these graphs and data, an early pension funds entrant gained a maximum market share over time that is approximately 50% of the pioneer's share. In this case, not considering the one apparently atypical data point (PF6), firms that entered the market within an elapsed time delay between 27 and 57
months eventually averaged 57% of the pioneer's share. Very late entrants appear to have stabilized with market shares that represent approximately 5% to 10% of the pioneer's share (8% in this case).

Figure 3: Order of market entry vs. market share for pension funds.

Other factors, however, particularly organizational size, seem to have an important effect upon market share. Figure 4 shows a scatterplot of order of entry vs. percentage of the pioneer's market share (measured as the relative size of its portfolio vs. that of the total market). The squares represent this percentage for the year of 1994, the triangles say the same for the year of 1995, and the circles represent this percentage at the end of August of 1996. Symbol size is an indication of organizational size (the larger the symbol, the larger the size of the institution measured in total number of employees). Inspection of this scatter plot reveals an apparent influence of size upon the dynamics of an incumbent's market shares. Notice that entrant number five, which is also the largest as measured by
symbol size, increases its market share noticeably in three years, signaling the possibility of combining the pension fund business with a larger platform of products, thus being able to offer more complete product packages to customers. A similar effect is observed in entrants 7 and 8, also banks, but it is not observed in entrant number three (which exclusively operates this pension fund) or number four (an insurance company). Size may also signal a greater ability to leverage sales efforts and achieve scale effects. The relationship between SIZE and market share is positive and significant for the years 1994 to 1996 (for 1996: $S_r=0.70$, $p<0.05$; for 1995 $S_r=0.63$, $p<0.1$; for 1994 $S_r=0.61$, $p<0.1$).

Figure 4: Order of market entry vs. pioneer's share for three years. Pension funds
Table 6 shows a matrix of Spearman-rank correlation coefficients for order of market entry and market share measured as a fraction of the pioneer's share (in terms of total customers) for the years ended in December of 1994, December of 1995, and August 1996.

Table 6: Spearman-rank correlations between the variable ENTRY and the variables SIZE and market share for various years (Market share measured as % of the pioneer's share in terms of total customers). Pension funds.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Spearman-rank correlation coefficient.</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIZE</td>
<td>-0.34</td>
</tr>
<tr>
<td>MARKET SHARE:</td>
<td></td>
</tr>
<tr>
<td>%PION96</td>
<td>-0.72*</td>
</tr>
<tr>
<td>%PION95</td>
<td>-0.81**</td>
</tr>
<tr>
<td>%PION94</td>
<td>-0.80**</td>
</tr>
</tbody>
</table>

**p<0.01,*p<0.05

As expected, a negative relationship between order of entry and market is fairly strong and statistically significant throughout (only last three years shown). Throughout these years the relationship conserves the expected direction, but its coefficient starts to decrease (from 0.8 to 0.72), presumably because other variables start exerting influence upon the outcome variable market share. Table 6 also suggests that there is no significant relationship between order of market entry and SIZE. Larger institutions (or smaller ones) are not, according to these data, the first ones or the last ones to enter the market.

These data on pension funds seem to indicate that there are some rewards for the pioneers. But these advantages are, however, quickly overcome by other factors associated with some organizational characteristics of subsequent entrants. Later entrants
into this financial market are not delayed by any sort of proprietary considerations, hence the pioneer enjoys only a relatively short period to operate as a monopolist.

Debit Cards

Debit cards were recently introduced into the financial system under study. This payment instrument requires the cardholder to have a checking account with the issuing institution, with the debit card serving to automatically and electronically deduct payments from the checking account. The product requires a fairly extensive network of affiliated businesses. Moreover, debit cards become more useful if they can also be utilized to obtain cash from automated teller machines or from bank offices. Hence, a priori, one would expect large banks, or banks with extensive geographical coverage to be more successful in this market.

Table 7: Raw data for debit card industry.

<table>
<thead>
<tr>
<th>Operator</th>
<th>Date of entry</th>
<th>Order of entry</th>
<th>Customers as of 10-96</th>
<th>Tot. assets, 12/95 (m.u.)¹</th>
<th># employees</th>
</tr>
</thead>
<tbody>
<tr>
<td>DC1</td>
<td>Aug-87</td>
<td>1</td>
<td>46,689</td>
<td>307</td>
<td>3,200</td>
</tr>
<tr>
<td>DC2</td>
<td>Dec-88</td>
<td>2</td>
<td>60,000</td>
<td>170</td>
<td>2,662</td>
</tr>
<tr>
<td>DC3</td>
<td>Jan-89</td>
<td>3</td>
<td>305,000</td>
<td>73</td>
<td>875</td>
</tr>
<tr>
<td>DC4</td>
<td>Oct-93</td>
<td>4</td>
<td>9,600</td>
<td>24</td>
<td>362</td>
</tr>
<tr>
<td>DC5</td>
<td>May-96</td>
<td>5</td>
<td>26,500</td>
<td>2.2</td>
<td>300</td>
</tr>
<tr>
<td>DC6</td>
<td>Jun-96</td>
<td>6</td>
<td>3,500</td>
<td>5.8</td>
<td>105</td>
</tr>
<tr>
<td>DC7</td>
<td>Sep-96</td>
<td>7</td>
<td>850</td>
<td>13</td>
<td>180</td>
</tr>
</tbody>
</table>

¹Millions of monetary units
The first debit card entered the market being studied in August of 1987. Six additional operators had entered the market by 1996 and another two were planning to enter soon. Table 7 summarizes some characteristics of these operators. All debit card institutions are commercial banks. The above data reveal a fairly short elapsed time between the pioneer and the next two entrants. A wave of new entrants occurs in 1996, caused by regulatory changes that allowed all banks to provide regular checking accounts. This change made it unnecessary for banks to circumvent this regulatory constraint, which they often did, through alternative and more creative means.

Figure 5 is a scatterplot that shows order of market entry versus percentage of total market share measured as % of customers for all participants in the debit card industry at the time of the study. Inspection of this scatterplot doesn't suggest the presence of a negative relationship between order of market entry and long term market share. The pioneer doesn't have any significant advantage. It is the third entrant who is able to capture market share. The pioneer's market share, in this case, is approximately one sixth of the third entrant's market share. A very late entrant (with a total elapsed time of 106 months after the pioneer's entry) appears to capture approximately 50 percent of the pioneer's share in a relatively short period of time.
Figure 5: Order of market entry vs. market share for debit cards. The size of the datapoints is an indication of the relative size of the institution.

No longitudinal data could be obtained for this product in particular. This notwithstanding, an examination, even a cursory one, is in order so that the effect of other factors may be inferred. It might be that this product has a much shorter life-cycle, and that additional factors have already overcome the effect of pioneering. In Figure 5 the size of the institution, determined by number of employees, is represented by the size of the data point. Obviously, the very large institutions entered this market first, perhaps suggesting that a minimum technological platform is necessary for firms to enter into this market because convenience to the customer drives the adoption of this product. Moreover, the product cannot be adopted in isolation. As a minimum, a checking account must be kept by the customer with the issuing operator. Convenience, however, may drive customers to adopt one or the other debit card, and this factor may quickly overcome the effect of early entry. Figure 6 shows, through the size of the data point, the number of ATMs each incumbent has. Entrant number three holds the largest number of
those by far, followed by entrant number five with 60% as many. Entrants 1 and 2 have nearly as many as entrant 5. Though this relationship evidently cannot be established with the cross-sectional information at hand, there is apparently a positive correlation between market share growth rates and # of ATMs.

![Figure 6: Order of market entry and market share as % of pioneer's market share for debit cards. The size of the data point is an indication of the number of ATMs each participant has.](image)

The effect of entry may also be influenced by the time elapsed since the pioneer's entry. The absolute order of market entry could hide nearly simultaneous entries or entries which are separated by long periods of time. In Figure 7 we have plotted total market share at the time of the study against elapsed time since the pioneer's entry. Two groups can be clearly recognized in the graph. One group of early entrants introduced debit cards into the market within a total elapsed time of 17 months. The next entry
occurred 58 months later, and more than eight years after the pioneer's entry we can observe a second group of institutions entering the market.

Figure 7: Elapsed time since pioneer's entry vs. total market share for debit cards.

Two observations are in order. First, the data on debit cards indicate the potential inconveniences of utilizing strict order of market entry as an independent variable. It might be preferable to moderate this strict order by coding entries as early entries, early followers, and so on. Alternatively, time elapsed since first entry could be used as an independent variable. Second, we can see that different motivations may stand behind different institutions entering a market. In this case, early entrants may well be termed as
strategic while the later wave of entrants may just be taking advantage of a regulatory change.

Despite this, we do observe for the case of debit card introduction a statistically significant relationship between order of market entry and long term market share. Table 8 shows a matrix of Spearman-rank correlation coefficients for several variables of interest. We have included for reference purposes the variable CLIENTS (which is indicative of total number of customers), the two variables that measure size (in terms of total assets and total number of employees), and the variables ELAPSED and %PION_SHR. Notice that market share (as a % of the pioneer's share) is negatively correlated with order of market entry (and similarly, given that we are using ranks, with time elapsed since first entry). In this case the large established players entered first (time elapsed is negatively correlated with both measures of entrant size: S-r = -0.86, p<0.01 for SIZE1 and -0.96 with p<0.001 for SIZE2). The observed positive relationship between market share and number of ATMs is statistically significant at p<0.01. Though the table generally supports a negative relationship between order of market entry and long term market share, it is also important to note that examination of statistical models alone, without further exploratory data analysis, may give an incorrect picture of the phenomenon under observation.

Finally, the data suggest, though in this case no firm conclusion can be drawn, that other factors come into play that eventually dilute the pioneering effect. In this particular case of debit cards we observe that entrants with larger coverage (in the form of a
network of ATMs) are apparently able to grow much more rapidly than pioneers. The data also suggest that, for this product, a much shorter transient monopoly existed than for pension funds. Three firms entered the market within a period of 17 months. A second wave of entry, presumably driven by changes in regulatory conditions, occurred 58 months after. Nonetheless, very late entrants appear to stabilize with market shares which are less than 8% of total.

Table 8: Spearman-rank correlation coefficients for variables of interest.

<table>
<thead>
<tr>
<th></th>
<th>ENTRY</th>
<th>CLIENTS</th>
<th>SIZE1</th>
<th>SIZE2</th>
<th>ELAPSED</th>
<th>%PION SHR</th>
</tr>
</thead>
<tbody>
<tr>
<td>ENTRY</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CLIENTS</td>
<td>-0.82*</td>
<td>0.61</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SIZE1</td>
<td>-0.86**</td>
<td>0.79*</td>
<td>0.89**</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SIZE2</td>
<td>-0.96***</td>
<td>-0.86**</td>
<td>-0.96***</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ELAPSED</td>
<td>1.00</td>
<td>-0.82*</td>
<td>-0.86**</td>
<td>-0.96***</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>%PION SHR</td>
<td>-0.82*</td>
<td>0.61</td>
<td>0.79*</td>
<td>-0.82*</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>ATMs</td>
<td>-0.56</td>
<td>0.88**</td>
<td>0.23</td>
<td>0.56</td>
<td>-0.56</td>
<td>0.88**</td>
</tr>
</tbody>
</table>

*p<0.05. **p<0.01. ***p<0.001

Credit Cards

The credit card is a relatively modern financial innovation but less modern than the debit card. The first successful large scale implementation of the credit card was done by Diners Club in 1956 (Mandel, 1990). In 1958 American Express and Carte Blanche entered the business in the so called Travel and Entertainment segment of the industry. Bank credit card programs came later. In the United States the first credit card plan adopted by a commercial bank appeared around 1950. Apparently, by 1953 there were more than 60 active plans in the United States (Gibson, 1967). In 1955 there were about
100 banks offering credit card plans (Mandel, 1990). By 1966 this number had risen to 200 (Gibson, 1967). In 1972 there were 8,574 banks with credit card plans (Federal Reserve Bulletin, 1973). In terms of the number of banks with cards in the United States: in 1967 less than one in ten banks had credit card plans (Gibson, 1967), by 1972 60% of all banks in the United States offered a credit card plan (Federal Reserve Bulletin, 1973), in 1979 71% of all banks had credit card plans; and in 1985 the figure had grown to 90% (Mandell, 1990). By 1976 there were two dominant organizations in the business (BankAmericard (later VISA) and Master Card). The growth of their total accounts is shown in Figure 8. Notice that explosive growth starts after 1975.

![Figure 8: Growth of Credit Card accounts in the US (VISA and Master Card). Taken from Krumme, 1987](image)

The first credit card plan in the financial system under study was created in 1976 by a commercial bank (this is a relatively early entrance even by U. S. standards). The second entrant appeared in the market after 108 months. In this environment pioneering advantages may have been obtained in terms of network externalities. Card operators
derive income from customer's interest payments and also from the commissions paid by vendors, thereby making it crucial to develop a large network of affiliated businesses. Figure 9 displays a scatterplot of total credit card market share for three years (1993, 1994, and 1995) versus total elapsed time since the first entry. As shown, the very early first entry doesn't sustain an above average market share over time. The second entrant (108 months after) captures approximately 45% of the market and retains it consistently. In this case it is not apparent that size of the institution or the plausible combination of this product with a more ample product platform is having any important effect. Moreover, it appears that large institutions (as indicated by symbol size) enter in a second wave of entry. In general, however, the observed scatterplot seems to support a negative relationship between order of market entry and market share.

![Figure 9: Elapsed total time in months since the pioneer's entry versus market share for credit cards. Market share measured as % of total customers.](image-url)
Figure 9 reports total market shares for the credit card market and Figure 10 market shares measured as a percentage of the pioneer's share (in both cases as percentage of total customers). Notwithstanding that the pioneer had a period of approximately seven years operating as a monopolist, it fails to reap long term market share advantages. In this case the second entrant became (and stayed) the market leader. After this period another three competitors entered the market during a three-year period.

Figure 10: Market shares for credit cards.

Notice also in Figure 11, that the pioneer retains the number of customers (in fact increases its number of customers somewhat consistently) despite losing market share. This may reflect different strategic intentions of the different firms. Moreover, the market is growing overall. This means that later entrants can grow without taking market share from other incumbents but rather from the intrinsic growth of the market, perhaps
attacking different market segments. This may explain in part the absence of erosion of any type in the early entrants' total number of customers. Figure 11 shows that the second and third entrants into this market do exhibit consistent growth in the total number of customers they attract.

Figure 11. Total number of customers for participants in Credit Card business. Only first four entrants shown.

Table 9 displays Spearman-rank correlation coefficients for several variables of interest. Notice, as observed in the scatterplots, the strong negative relationship between elapsed time since first entry and market share in the credit card business. There is also a negative relationship between order of entry and market share. Though this relationship is statistically significant throughout, the coefficient becomes smaller as time passes (S-r coefficients of -0.94, -0.90, and -0.69, p<0.001). Notice also the statistically significant negative relationship between size (measured by number of employees) and entry (S-r = -
0.69, p<0.001). As observed when exploring the scatterplots, large firms seem to enter later in this case. Finally, one can observe a positive relationship between all measures of market share for different years but, again, the sizes of the coefficients diminish. This could signal that the early entrants' market shares are starting to erode.

Table 9: Spearman-rank correlation coefficients for variables related to the credit card subsample.

<table>
<thead>
<tr>
<th></th>
<th>Entry</th>
<th>Size</th>
<th>Elpsdtot</th>
<th>mkt%95</th>
<th>mkt%94</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entry</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>-0.69***</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elpsdtot</td>
<td>1.00</td>
<td>-0.69***</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>mkt%95</td>
<td>-0.69***</td>
<td>0.43*</td>
<td>-0.69***</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>mkt%94</td>
<td>-0.90***</td>
<td>0.63**</td>
<td>-0.90***</td>
<td>0.81***</td>
<td>1.00</td>
</tr>
<tr>
<td>mkt%93</td>
<td>-0.94***</td>
<td>0.59**</td>
<td>-0.93***</td>
<td>0.74***</td>
<td>0.91***</td>
</tr>
</tbody>
</table>

***p<0.001, **p<0.01, *p<0.05

Quantitative Data Analysis

To complement the qualitative data analysis and to test our hypotheses more rigorously, we constructed a dataset with the datapoints collected in all three product categories. Thus, the data set includes observations for a total of 36 entries in three product categories with the following variables: ENTRY (numerical variable containing the order of market entry), SHARE (% of market share for nth entry measured as percentage of total customers), ELAPSED (elapsed time in months for particular entry since first entry in the particular category), SIZE (ratio that gives relative size of entrant with respect to the largest entrant in the product category, calculated based on total number of employees), INNOV (measures degree of dispersion of product offerings for that particular institution; calculation based on matrix of clients and products, providing a
measure of the firm's innovativeness as indicated in Appendix 4), and REGUL (dichotomous variable that indicates whether the particular product was driven by regulatory changes).

Our goal in this part of the paper is to build a sensible and efficient baseline model for the dependent performance variable SHARE, controlling for institution size, the effect of the institution's total product offerings, and the effects of regulation. We will then construct a model to include question predictors ENTRY and ELAPSED. Should a link exist between the question predictors and product performance, controlling for the aforementioned effects, practitioners could then design their product launching initiatives accordingly or, at least, qualify their perceptions about possible performance outcomes of financial products.

First, the raw data set and the distributions of all variables were examined. These are shown in Table 10.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>s.d.</th>
<th>Min.</th>
<th>Max.</th>
<th>Normality of distribution (*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SHARE</td>
<td>0.083</td>
<td>0.14</td>
<td>5.75E-04</td>
<td>0.67</td>
<td>No</td>
</tr>
<tr>
<td>ENTRY</td>
<td>8.31</td>
<td>5.92</td>
<td>1</td>
<td>21</td>
<td>Yes</td>
</tr>
<tr>
<td>ELAPSED</td>
<td>125.42</td>
<td>79.48</td>
<td>0</td>
<td>246</td>
<td>Yes</td>
</tr>
<tr>
<td>SIZE</td>
<td>0.27</td>
<td>0.34</td>
<td>0.0078</td>
<td>1</td>
<td>No</td>
</tr>
<tr>
<td>INNOV</td>
<td>4.49</td>
<td>1.67</td>
<td>1</td>
<td>7</td>
<td>No</td>
</tr>
<tr>
<td>REGUL</td>
<td>.19*</td>
<td>0.40</td>
<td>0</td>
<td>1</td>
<td>No</td>
</tr>
</tbody>
</table>

(*) Determined through Kolmogorov-Smirnov test (at the 5% level)
*Dummy variable: the mean is interpreted as the % of entries that are considered to be driven by regulation.
This initial examination shows some factors worth considering. Mean market shares for the sample of three financial product lines is fairly small (8.3%). If we couple this to the large average elapsed time since first entry (125.4 months), we can infer a possible negative relationship between elapsed time and share.

The average size of the institutions is approximately 27% the size of the largest institution in that product category. Given this, it is plausible that size will exert some influence on the outcome variable SHARE. Such presumption is reinforced with non-normalities observed for this variable.

In general, the non-normalities observed signal the presence of curvilinearity. A comparison of Pearson correlation coefficients with Spearman-rank correlation coefficients for the variables at issue rendered large differences for all bivariate relationships which included the variables SIZE and SHARE (as shown in Table 11), announcing the need for transformations.

<table>
<thead>
<tr>
<th>Variables</th>
<th>ENTRY</th>
<th>ELAPSED</th>
<th>SIZE</th>
<th>SHARE</th>
<th>INNOV</th>
</tr>
</thead>
<tbody>
<tr>
<td>ENTRY</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ELAPSED</td>
<td>-0.02</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SIZE</td>
<td>0.17</td>
<td>0.22</td>
<td>0.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SHARE</td>
<td>0.31</td>
<td>0.21</td>
<td>-0.43</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>INNOV</td>
<td>0.01</td>
<td>0.03</td>
<td>0.01</td>
<td>-0.17</td>
<td>0.00</td>
</tr>
<tr>
<td>REGUL</td>
<td>0.01</td>
<td>0.0</td>
<td>-0.02</td>
<td>0.09</td>
<td>-0.05</td>
</tr>
</tbody>
</table>
Further inquiry was performed by inspecting bivariate scatterplots of all variables. Selected scatterplots are included in Figure 12. In these plots the detected curvilinearities now become evident. A few other observations are in order. First, we can see the strong positive relationship between order of market entry and elapsed time. This relationship is not a straight line because of the different product categories present in the sample. Second, we can see that a group of notably larger institutions appear to have entered relatively early in the sample (though it is not clear whether such entries are prototypical for certain product categories). This clearly indicates the need to control for size in our analyses. Third, there appears to be a clear negative and curvilinear relationship between order of market entry and market share. Fourth, inspection of the scatterplot of INNOV versus ENTRY appears to indicate a strong negative relationship between the two variables. This could indicate that those firms which have wider product platforms (more products aimed at various markets, i.e., more innovative in this regard) tend to enter first. This graph, however, does contain a few seemingly atypical data points. Fifth, although the scatterplot of order of entry (ENTRY) vs. SIZE suggests that large firms tend to enter earlier, the graph of ELAPSED vs. SIZE suggests that this must be qualified if we consider real time. A similar thing happens when we look at the relationship extant between ELAPSED and INNOV. This suggests that different results could be obtained when using either variable as predictor, thus pointing to the need for differentiating any implications in terms of order of entry and timeliness of entry.
Figure 12: Scatterplots for selected bivariate relationships.
As suggested by the results of the exploratory data analysis, we performed transformations on the variables SHARE and SIZE. Using Tukey's ladder of transformations and the Rule of the Bulge, we presumed that natural logarithms would perform best for these cases. We nevertheless tried several possibilities (shown in Appendix 1). In fact, the natural log of both variables seems successfully to restore linearity in the relationship. Then we proceeded with our data analysis utilizing the transformed versions of the original variables (which will be designated here as SHARE* and SIZE*). Bi-variate scatterplots confirmed that the selected transformations were adequate (see Appendix 2). Various analyses were performed to assess the convenience of such transformations. Normal probability plots (coupled with Kolmogorov-Smirnov tests) showed that both variables had attained normality, as indicated in Figure 13.

Figure 13: Normal probability plots for SHARE* and SIZE*
A comparison of Spearman-rank correlation coefficients and Pearson correlation coefficients showed that the previously observed differences had been minimized (see Appendix 3). Once comfortable with the variables to analyze, we developed a table of bivariate correlations, estimated through Pearson correlation coefficients. This analysis, summarized in Table 12, revealed that the dependent variable SHARE* was strongly negatively correlated to both ENTRY (Pearson $\rho = -0.78$, $p<0.001$) and ELAPSED (Pearson $\rho = -0.69$, $p<0.001$). Moreover, the variable SIZE* is negatively correlated to ENTRY (Pearson $\rho = -0.68$, $p<0.001$) and ELAPSED (Pearson $\rho = -0.67$, $p<0.001$) and positively correlated to SHARE* (Pearson $\rho = 0.64$, $p<0.001$).

<table>
<thead>
<tr>
<th>Table 12. Pearson correlations (pair-wise deletion)</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ENTRY</td>
</tr>
<tr>
<td>ENTRY</td>
<td>1.00</td>
</tr>
<tr>
<td>ELAPSED</td>
<td>0.89***</td>
</tr>
<tr>
<td>INNOV</td>
<td>-0.45**</td>
</tr>
<tr>
<td>REGUL</td>
<td>-0.36*</td>
</tr>
<tr>
<td>SHARE*</td>
<td>-0.78***</td>
</tr>
<tr>
<td>SIZE*</td>
<td>-0.68***</td>
</tr>
</tbody>
</table>

***$p<0.001$, **$p<0.01$, *$p<0.05$, ~$p<0.1$

This confirmed the urgency of including SIZE as a control variable in the analysis. The variable INNOV has a strong positive correlation with SHARE (Pearson $\rho = 0.49$, $p<0.001$) and SIZE (Pearson $\rho = 0.53$, $p<0.001$), thus indicating that it might be relatively large institutions that enter earlier and attain larger market shares. With respect to REGUL, we noticed a barely significant relationship (Pearson $\rho = 0.30$, $p<0.1$),
suggesting that institutions with a larger array of products are not necessarily the ones that move first in the case of regulation-driven entries. This interrelation is of course not conclusive given the dichotomous characteristics of the dummy REGUL.

Following these analyses, we established two classes of control predictors and one class of question predictor. We estimated that "networking effects" could take place, defined as alterations in total market share from entrants which are able to push average SHARE* up or down on account of their size and ability to network with an ample platform of products. Thus we classified the variables SIZE* and INNOV as control predictors. The variable REGUL was classified as a control predictor of the level to which entries are driven by regulatory changes. The variables ENTRY and ELAPSED were established as question predictors in the analysis.

We noted that the relatively large correlations among practically all variables could result in multicollinearity problems. This will, evidently, become a problem in the case of the highly correlated and redundant variables, ELAPSED and ENTRY. It was decided, then, to build a sequence of nested models paying attention to the plausible occurrence of collinearity.

Three regression models were subsequently fitted and analyzed with the intention of creating an appropriate baseline model. First, SHARE* was regressed on ENTRY. Second, SHARE* was regressed on ELAPSED, and, finally, we used both variables as predictors in the regression analysis. The results are summarized in Table 13.
Table 13: Regression models in which market share, SHARE*, is predicted by order of market entry and elapsed time since first entry, ENTRY and ELAPSED, singly and jointly.

<table>
<thead>
<tr>
<th>Model</th>
<th>Intercepts</th>
<th>ENTRY</th>
<th>ELAPSED</th>
<th>R2 (%)</th>
<th>df Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-1.79***</td>
<td>-0.24***</td>
<td></td>
<td>61.59</td>
<td>34</td>
</tr>
<tr>
<td>2</td>
<td>-1.82***</td>
<td></td>
<td>-0.015***</td>
<td>47.47</td>
<td>34</td>
</tr>
<tr>
<td>3</td>
<td>-1.83</td>
<td>-0.25***</td>
<td></td>
<td>61.65</td>
<td>33</td>
</tr>
</tbody>
</table>

***p<0.001, **p<0.01, *p<0.05, ~p<0.1

For model 1 (in Table 13), the inspection of scatterplots of raw and studentized residuals did not reveal evidence of heteroscedasticity. Inspection of the normal probability plot and histograms of residual distributions reveal them to be normally distributed. Similar results were obtained for models 2 and 3, as illustrated in Figure 14. Comparison of the residuals of models 1 and 2 suggests that model 1 slightly overestimates share for intermediate values of entry. The introduction of both ENTRY and ELAPSED as predictors seems to correct this discrepancy. However, as shown in Table 13, the introduction of both predictors renders ELAPSED non-significant. This is caused by the already noted multicollinearity. A tolerance statistic (Tol = 0.20) and a Variance Inflation statistic (VIF) of 4.89 do indicate values approaching the usually accepted cut point of 5, thus indicating multicollinearity problems (particularly in a dataset of this size).
Two additional factors were considered in deciding upon the adoption of a sensible baseline model. First, and somewhat ancillary, we have units that have different dimensions and must be interpreted differently. Entry has a maximum value of 21 while ELAPSED has a maximum value of 246 (months). This results in very small Beta coefficients for ELAPSED when used as predictor of SHARE, thus rendering interpretation a bit more difficult. Second and more important, a difference in R-squared tests performed for models 1 and 2 with respect to model 3 shows that both models undergo a significant increment in the value of the R-squared statistic. Comparing the full with the reduced model number 1 ($F_{\text{observed}} = 5.16 > F_{\text{critical}} = 3.29$); and comparing the full with the reduced model number 2 ($F_{\text{observed}} = 12.20 > F_{\text{critical}} = 3.29$); we notice in both cases, but particularly in the second case, the real and important change in the magnitude of the R-squared statistic. However, the observed multicollinearity problems, and the potential interpretation difficulties urged us not to choose our baseline model as the most sensible one, but rather analyze models 1 and 2 separately.

After reaching a decision about the choice of question predictors, a taxonomy of multiple regression models was fitted. This taxonomy included the "networking effect"
control variables and the dummy variable REGUL, entered sequentially. Table 14 summarizes the results of these analyses.

An examination of this table shows that the control predictors do not exert any important influence upon the dependent variable SHARE*, either singly or jointly. Further inclusion of these variables into the model does not change the intercept and the coefficient of ENTRY. ENTRY remains negative throughout with a value close to -0.25 (p<0.001 in most cases). We observe that interactions of SIZE with the variables INNOV and ENTRY have no significant effect either. The interaction of SIZE and REGUL seems to have an important effect upon the outcome variable (Beta coefficient =0.49, p<0.05) which permits to reject the null hypothesis that the slope is zero in the population). Likewise, the interaction between ENTRY and REGUL does seem to exert an important influence upon the outcome variable. When this variable is introduced into the baseline model, both the intercept and the slope of ENTRY remain stable, but its own beta coefficient acquires a value of -0.24 with p<0.05 (which permits rejecting the null hypothesis that this slope is zero in the population). In both cases differences in R-squared tests support the inclusion of these variables into the baseline model (for model 10, $F_{\text{observed}} = 515.2 > F_{\text{critical}}=3.29$ and for model 12, $F_{\text{observed}}=520.5 > F_{\text{critical}}=3.29$). These interactions seem to make sense. It is perfectly plausible that regulation, size, and entry do not, through their additive terms, completely specify their effects upon the dependent variable SHARE* because synergies or other effects may be present. These interactions taken together would take the place of a good approximation of the combined effect of regulation, firm size and entry upon the dependent variable.
However, when both variables are included jointly they change signs and lose statistical significance. The Beta of SIZE_REG goes from 0.49 to -0.15 and the Beta of ENTRY_REG fluctuates from -0.24 to 0.2. This denotes that both variables are correlated (but "pointing" in different directions). In order not to lose valuable information, a composite was created to agglomerate the interaction using Principal Components Analysis. The composite thus created has been termed PC1 to denote the combined interactive effect of these three variables. To create the composite we first standardized variables SIZE_REG and ENTRY_REG. These two units of variances became subsumed into the single composite that ended up containing 98.7% of the total variance. We then calculated scores for the composite and used the scores to construct the variable at issue. Based on this, we fitted a final model adding the composite to the baseline model already chosen. The model is summarized in Table 15.

Table 15: Final fitted regression model in which the dependent variable SHARE* is predicted by ENTRY and a composite that captures the interactions of ENTRY, SIZE, and REGUL.

<table>
<thead>
<tr>
<th>Model</th>
<th>Intercept</th>
<th>ENTRY</th>
<th>PC1</th>
<th>R-sq (%)</th>
<th>dfE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Final</td>
<td>-1.65***</td>
<td>-0.25***</td>
<td>0.44*</td>
<td>67.52</td>
<td>33</td>
</tr>
</tbody>
</table>

***p<0.001  *p<0.05

A difference in R-squared test for this model again shows that there is a real and important change in the magnitude of the R-sq. statistic (Fobserved is, in this case, equal to 524.9 which is greater than the critical F value of 3.29). The model is parsimonious and appears to capture many of the variables of interest. An inspection of the scatterplot of studentized residuals for this model permits validating the assumptions about
independence of errors (see Figure 15). The assumption about normality of the residuals was validated through inspection of the normal probability plot (Figure 15). Furthermore, no evidence of multicollinearity was found when the model was tested through the tolerance statistic (Tol=0.95).

Figure 15. Plot of residuals and normal probability plot for final model.

Influence statistics were then estimated. Cook's D and Hat H were used to assess the impact of atypical data points. A scatterplot of these two statistics (Figure 16) shows the existence of two highly atypical data points (cases 15 and 16). A scatterplot of the two statistics shows that these points may have a very important impact upon the model. Therefore sensitivity analyses were carried out.
The analysis revealed the presence of one single data point (case 16) which was having a considerable impact on the fit. A sensitivity analysis performed to investigate the impact of this observation on the fit showed that its removal caused the R-squared value of the chosen model to climb from 67.52% to 68.46%. Case 15 was also identified to have an unusual impact on the model. These cases show unusually low values of the dependent variable SHARE for their relative sizes, thus causing them to show unusually high values on the created composite PC1, as shown on Table 16.
Table 16: Impact of atypical data points on fitted model

<table>
<thead>
<tr>
<th>Cases removed</th>
<th>Intercept</th>
<th>ENTRY</th>
<th>PC1</th>
<th>R-sq (%)</th>
<th>dfE</th>
</tr>
</thead>
<tbody>
<tr>
<td>-15</td>
<td>-1.65***</td>
<td>-0.25***</td>
<td>0.41~</td>
<td>67.25</td>
<td>32</td>
</tr>
<tr>
<td>-16</td>
<td>-1.64***</td>
<td>-0.25***</td>
<td>-0.21</td>
<td>68.46</td>
<td>32</td>
</tr>
<tr>
<td>-(15 and 16)</td>
<td>-1.60***</td>
<td>-0.24***</td>
<td>0.006</td>
<td>69.67</td>
<td>31</td>
</tr>
</tbody>
</table>

***p<0.001  ~p<0.1

Given these peculiarities and the results of the influence statistics, it appears that the two cases identified as atypical are very different from those of the rest of the sample (and in themselves worth studying), or that data available for those two cases are not accurate. Aside from the increase in the percentage of variability explained, and perhaps more interestingly, the sensitivity analysis also showed substantial changes in some of the β coefficients of the regression model. In particular, the β for PC1 goes from a significant 0.41 to zero! This poses of course a somewhat alarming note: that the presence of these two atypical points may have influenced the process of fitting the taxonomy of regression models. Hence, we went through the exercise of refitting a taxonomy of regression models for the reduced sample. No significant differences were found, except, of course, that the agglomeration of the interactions into one composite turned out to be unnecessary. It becomes evident that the real impact of our question predictor is unduly dampened by these two observations. Having done that and having refitted a taxonomy of regression models we were left with an unexpected result: Our best and chosen model is one that simply regresses SHARE* against ENTRY!

We chose that model as our final model. The assumption about normality of the residuals was validated through inspection of the normal probability plot and the
histogram of the residuals. Inspection of plots of raw and studentized residuals permitted validation of the assumptions about independence of errors as shown in Figure 17.

Figure 17. Plots of residuals and normal probability plot for final regression model.

The final model obtained is shown in Table 17.

Table 17. Fitted final model: Dependent variable SHARE*

<table>
<thead>
<tr>
<th></th>
<th>Intercept</th>
<th>ENTRY</th>
<th>R-sq (%)</th>
<th>dfE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-1.60***</td>
<td>-0.24***</td>
<td>69.67</td>
<td>32</td>
</tr>
</tbody>
</table>

***p<0.001

We then proceeded, in a similar fashion, to fit a model in which SIZE*, INNOV, and REGUL were included as control predictors and ELAPSED as a question predictor, controlling also for interactions among these variables. The second final and most

---

6 Including (with pair-wise deletion) the alternative measure for INNOV, which used the difference in chi square caused by the introduction of the new product into the bank's client-product matrix, did not cause any appreciable change to this final result.
parsimonious fitted model regresses SHARE* on ELAPSED (intercept = -1.82, p<0.001; coefficient of ELAPSED = -0.00154, p<0.001).

Summary and Conclusion

We wanted to assess the effect of order of market entry upon market share, controlling for some "networking effects". The goal was to determine whether innovation initiatives in the development of new financial services may render better performance if launched during certain time frames.

We found that a baseline model in which SHARE* was regressed against order of market entry (ENTRY) explained almost 70% of the variability in performance. Including control variables such as the firm's size and the amplitude of its product offerings did not have a sizable effect upon our baseline model. Our analysis turned out to be in line with most of the prior research work that has been performed in other industries, particularly consumer products.

Our analysis shows that financial industry practitioners may benefit from correctly timing the release of their new products. Figure 18 is a visual display of our model results for different orders of market entry. The visual display has been "untransformed" and results have been computed as a percentage of the pioneer's share to facilitate interpretation.
Figure 18. Results of final model of order of market entry versus market share for a prototypical case.

Our findings indicate a negative relationship between order of market entry and long term market share. A second entrant is likely to capture approximately 78% of the pioneer's eventual market share. A tenth entrant will only capture 11% on average. The results appear to be in line with those performed in other industries. Table 18 establishes such a comparison. It appears that our model slopes downward more rapidly and later entrants are penalized more heavily.
Table 18: Order of market entry and market share for consumer packaged goods, prescription anti-ulcer drugs, and financial services innovations.

<table>
<thead>
<tr>
<th>Entry order</th>
<th>Consumer Packaged Goods</th>
<th>Prescription Anti-Ulcer Drugs</th>
<th>Financial Products</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Urban et al. (1986)</td>
<td>Kalyanaram and Urban (1992)</td>
<td>Berndt et al. (1994)</td>
</tr>
<tr>
<td>First</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Second</td>
<td>0.71</td>
<td>0.76</td>
<td>0.70</td>
</tr>
<tr>
<td>Third</td>
<td>0.58</td>
<td>0.64</td>
<td>0.57</td>
</tr>
<tr>
<td>Fourth</td>
<td>0.51</td>
<td>0.57</td>
<td>0.49</td>
</tr>
<tr>
<td>Fifth</td>
<td>0.45</td>
<td>0.53</td>
<td>0.44</td>
</tr>
<tr>
<td>Sixth</td>
<td>0.41</td>
<td>0.49</td>
<td>0.40</td>
</tr>
</tbody>
</table>

Modified from Kalyanaram et al. (1995).

Using order of market entry alone, however, might render somewhat equivocal results because nearly simultaneous entries or entries separated by large periods of time are not evident. Results need to be moderated by a sense of real time between entries and, for such purpose, interpreting entry utilizing real elapsed time is very illustrative. As we can see in Figure 19, if subsequent entrants invade the market within short periods of time after the pioneer, pioneering advantages are scant. Shorter lead times mean pioneers have less time to establish their brand names. Early competitive rivalry favors later entrants’ market shares. From the pioneer’s perspective lengthening lead time by one year could represent, according to our data, as much as 2.5% of overall market share.
We can also observe that the use of order of market entry alone tends to average out elapsed time between entries. With our data such average comes out to approximately 15 months between entries. This means that the results for the second, third, fourth, and so forth entrants are roughly equivalent to entries occurring after 15, 30, and 45 months respectively in the second model.

Use of elapsed time since first entry also adds to a managerial interpretation of these models. We see that, for our sample of products, entrants which follow shortly after the pioneer may obtain substantial market shares relative to the pioneering brand; a result which is not obvious by looking at order of market entry alone.

Figure 19. Results of final model of elapsed time since first entry versus market share for a prototypical case.
In summary, several important results emerge from this research.

First, there are important advantages to early entry in financial services innovations. This result extends established generalizations to other industries and settings in a field that "relies heavily on North American manufactured goods that are included in either the Urban et al. Assessor data or the PIMS data" (Kalyanaram et al., 1995: 9).

Second, several outcomes of this research contribute more generally to the literature on order of market entry. On the one hand we observe that level of analysis matters. If we look at individual products, establish their longitudinal histories, and operationalize pioneering as the first entrant, we find that the pioneers do not necessarily retain an appreciable market share advantage. This is true in two of the three product lines explored. This is consistent with the exposition of Golder and Tellis (1993) although in our case the product histories are more concise because of the youth of the product lines studied. On the other hand, when our product sample is aggregated, an important early entry effect is observed. We get results which are in line with much other literature on pioneering advantages. Evidently by aggregating the data we can only assert to the advantages of early entry and not those of pioneering strictu sensu. History reveals a more detailed picture that cannot be completely captured in cross sectional studies.

Third, it appears to be useful and important to reframe the original research question here posited and to consider elapsed time since first entry when evaluating these models. These effects have been, to the best of our knowledge, explored only in two
studies. The study of Huff and Robinson (1994) determined that increasing the years of competitive rivalry (i.e., reducing the pioneer’s lead time) tended to reduce the pioneer’s market share advantage. Hurwitz and Caves (1988) examined 56 pharmaceutical products and their performance after patent expiration. They report that longer patent life (i.e., longer pioneer lead time) renders appreciable market share advantages. Evaluating order of entry in terms of elapsed time since first entry also ties to the industrial organization literature, particularly the work of Sutton (1995). Sutton posits that the presence of first-mover advantages may have important effects upon industry structure. Given enough lead time, a first-mover may spend more on advertising, thus preempting or relegating subsequent entrants to weak positions. Sutton’s (1995) empirical examples do indicate that such preeminence might be tightly linked to the time elapsed between first and subsequent entries. Because first mover advantages affect market structure, one could plausibly argue for a negative relationship between elapsed time and market concentration. Such elapsed time might obey to historical occurrences (history matters, as Sutton (1995) indicates). Moreover, it is interesting to speculate that in the absence of all sorts of exogenous influences, historical or otherwise, the phenomenon of innovation could render sequential entries with characteristic periods per industry. Variance in such “characteristic frequencies” could point to more or less difficulties in imitating products, establishing the necessary network externalities for products to diffuse rapidly and dominate the market, or both; thus establishing a firmer tie with the literature about product and process innovations and dominant designs. Moreover, it appears that such frequencies should be
related to characteristic life cycles of revenues whereupon entry at any point in time
should be evaluated in terms of its concomitance with the characteristics of such cycles.

Likewise, the idea of using the variation exerted by the new product (or brand)
into the firm's current product offerings (using our client-product matrix methodology or
similar ones) clearly deserves further evaluation over longer periods of time and with
larger samples of detailed data. Although in our case we did not find any significant
effect, it seems compelling to use such measures to proxy deviations in current strategy. If
in fact a firm is venturing to pioneering a product that appears too far away from its core,
pioneering may not be advantageous. In the case of banks, particularly where alternative
measures of hedging are not available, such occurrences could point to changes in the
institution's risk profile. These ideas are left here as suggestions for further research.
References


Appendix 1

Scatter-plot matrix report for various transformations of SHARE and SIZE
Appendix 2

Selected scatterplots after transformations.
Appendix 3.

Table Ap3-1: Difference between Pearson and Spearman correlations (pair-wise deletion)

<table>
<thead>
<tr>
<th>Variables</th>
<th>ENTRY</th>
<th>ELAPSED</th>
<th>INNOV</th>
<th>REGUL</th>
<th>SHARE*</th>
</tr>
</thead>
<tbody>
<tr>
<td>ENTRY</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ELAPSED</td>
<td>-0.021</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INNOV</td>
<td>0.007</td>
<td>0.027</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>REGUL</td>
<td>0.010</td>
<td>-0.003</td>
<td>-0.054</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>SHARE*</td>
<td>0.018</td>
<td>0.012</td>
<td>0.023</td>
<td>0.025</td>
<td>0.000</td>
</tr>
<tr>
<td>SIZE*</td>
<td>-0.008</td>
<td>0.066</td>
<td>0.078</td>
<td>0.009</td>
<td>-0.017</td>
</tr>
</tbody>
</table>
Appendix 4

Measure of Strategic Focus

To obtain a measure of strategic focus, we used the chi-square distribution of each bank's client product matrix. Though normally used to test hypothesized relationships among categories of data points, we used chi-square in this case as a measure to establish degree of strategic focusing. We first classified institutions' clients and products and developed "client-product" matrices. Therupon, two measures were developed.

A)

In the first measure, a comparison was made between the chi-square obtained for particular client-product matrices with respect to a client-product matrix of a totally unfocused institution (for practical purposes one with a large number of products in each cell of the client-product matrix). The procedure used was as follows:

Let

\[ N_{cp} = \text{number observed in (c,p)th cell of the client product matrix, and} \]

\[ e_{cp} = \text{number expected in the (c,p)th cell under the assumption of a totally unfocused institution with a large and equal number of products in each cell.} \]

for \( c = 1,2,3 \); and \( p = 1,2,3 \).

Let \( N_p = \sum_{p=1}^{3} N_{cp} \), and

\[ N_c = \sum_{c=1}^{3} N_{cp} \]

Then we calculated a chi square as follows:
\[ \chi^2 = \sum_{c=1}^{3} \sum_{p=1}^{3} \frac{(N_{cp} - e_{cp})^2}{e_{cp}} \]

Because we compare with a hypothetical, highly innovative and "unfocused", institution, the higher the value obtained the more "focused" (i.e. the more concentrated in certain segments and product categories) it is, and vice-versa: smaller values mean the institution is closer to the hypothetical bank we are setting up for comparison purposes and, therefore, more dispersed and covering a wider array of clients and product categories. Redundantly, a scale of self-assessed degree of focusing was obtained from informants through a questionnaire scale. This scale had four items that evaluated the degree of product variability, the number of market segments the company was attacking, geographic coverage, and the number of customers. An index was developed by linearly combining reported scores. This variable turned out to be, as we had expected, highly intercorrelated with the analytically determined measure.

B)

A second measure was developed to see how the bank itself changed with the inclusion of the new product in its portfolio. To do so we simply calculated the chi-square for the bank with and without the product in question (i.e., pension fund, credit card or debit card) and estimated the difference. This figure gave us a sense of how much the bank had "moved". A large value indicated that the new product was less related to the current product portfolio than small values. Analytically the procedure was as follows:

\[ \chi^2 = \chi^2_1 - \chi^2_0 = \sum_{c=1}^{3} \sum_{p=1}^{3} \frac{(N_{cp} - e_{cp})^2}{e_{cp}} - \sum_{c=1}^{3} \sum_{p=1}^{3} \frac{(M_{cp} - e_{cp})^2}{e_{cp}} \]

Where N indicates the “full” bank matrix and M the “reduced” bank matrix.
Chapter 2

Order of Market Entry and Competitive Strategy in Financial Services Innovations
This essay examines the relationship between order of market entry, competitive strategy, and performance in financial services. We attempt to answer one question: Are there variations in the relationship between order of market entry and long term market share and performance for financial service firms that exhibit different strategic behaviors? To do so, we first review extant literature on the subject. Thereupon, we formulate hypotheses and propose a model. The model is empirically tested and followed by a summary of results and a discussion. Our results reveal that the effects of early entry are stronger for strategic types which are typical early entrants.

**Introduction and Research Background**

As reviewed in chapter 1, first-movers have been shown to enjoy important long-term market share advantages. A negative relationship between order of market entry and market share has been found to be consistent across many and different product lines.

Aside from this relationship, two other generalizations are fairly well established (Kalyanaram et al., 1993). First, "...in the case of consumer packaged goods and prescription anti-ulcer drugs, the entrant's market share divided by the first entrant's share roughly equals one divided by the square root of order of market entry" (Kalyanaram et al., 1993:1). Second, "...the advantage of pioneers in mature markets slowly declines over time" (Kalyanaram et al., 1993:1).

In services Tufano (1989) found, for a sample of 58 financial innovations, that pioneering investment banks did gain larger market shares than later entrants. Tufano (1989) showed that pioneers capture shares which are "...almost 2.5 times as large as the
followers in those markets" (Tufano, 1989: 231). Such advantage seems to remain consistent in subsequent years of the life of the product. The same firm is shown to capture substantially less share with imitations than with innovations. Our empirical study in chapter 1 also suggests that pioneers of financial services innovations tend to capture larger market shares than later entrants. However, whether such proclivity to innovate is associated with particular strategies is not directly tested in these studies. Despite the remarkable consistency of the relationship between order of entry and market share, the question remains whether certain strategies are associated with better performance for a given timing of entry decision. Schnaars (1994) argues that later entrants can seize markets from pioneers through the management of adequate imitation strategies. Yet, other authors (for example Zahra, et al., 1995) support the opposing notion: that pioneering, if properly managed, can provide competitive advantage. In general, there is evidence that indicates that some firms might be good at pioneering while others probably perform better as imitators. Given that imitating a financial product is considerably less expensive than creating it,¹ it is plausible that some firms find it more profitable to become perennial imitators. Hence it becomes important to examine not only entry per se, but the alignment of firms' strategic intentions in regard to entries into new markets. Both variables in conjunction should provide us with a more complete view of factors that mediate the well-known relationship between order of market entry and market share.

We shall not repeat here the main findings of the literature on order of market entry, which have been reviewed in the previous chapter and elsewhere (Robinson et al., 1994, Szymanski et al., 1995; Kerin et al., 1992), but will concentrate on the much smaller subset that examines concepts that might somehow be related to competitive strategy and order of market entry.

¹Tufano (1988) indicates that imitating a financial product can cost only 25% to 50% of the cost involved in creating it.
Some studies have shown that pioneering doesn't necessarily result in larger market shares. Golder and Tellis (1993), using an historical approach, found that not all pioneering efforts end in success. In fact they report a 47% failure rate for pioneers. Such results are different from the findings of other authors, and the discrepancies may be attributed to differences in the operational definition of the pioneer. While some authors in the marketing area define pioneers as those which first achieve national distribution (Urban et al., 1986) or as "... the first business to develop such product or service" (Robinson and Fornell, 1992), Golder and Tellis define the pioneer as the first to enter a market. Golder and Tellis, however, do find that "early leaders", defined as firms which are the market share leaders during the early growth phase of the product life cycle, are very successful. Their findings indicate that these early leaders retain a large market share (28% on average) and have low failure rates. These "early leaders" are not necessarily the pioneers. Some enter the market several years after the pioneer, and Golder and Tellis (1993) speculate that they are successful because have developed particular traits and abilities which condition such success. In their words (Golder and Tellis, 1993:167):

Why are early leaders so successful? The reason may be their ability to spot a market opportunity and their willingness to commit large resources to develop the market. Indeed, in many of the categories we studied, the start of the growth phase in the product life cycle may well be attributed to the market-building efforts of these early leaders. Our finding is similar to Chandler's (1990) for industrial goods, where long-term survival and success were due more to the commitment of adequate resources to large-scale production than to entering first.

This indicates that firms may be conditioned by their strategies to reap different market shares for different times of entry. Pioneering, hence, may exert an important main effect upon market share, but interactions with other variables, particularly variables that
are associated with firms' skills, resources, and abilities to deploy such resources, is plausible.

Several authors have advocated the need to study these interactions and to specifically model the effect of pioneering on market share in combination with strategic variables (Kerin et al., 1992; Moore et al., 1991; Kalyanaram and Urban, 1992) and not only the main effect caused by pioneering. For instance, Robinson et al., (1992) explored whether entering a market at various times was coupled to different skill and resource profiles. They discussed "two conflicting patterns": on the one hand, if pioneering results in market share advantages, then all firms will want to enter markets first. It will only be those competitors with intrinsic strengths that will force themselves into the market, thus resulting in an "absolute pioneering advantage." On the other hand, the "comparative pioneering advantage hypothesis" would stress that "strategic windows" open during the course of market evolution for certain strategic types. As these authors indicate (Robinson et al., 1992:1-2), "...the market pioneer-type will realize greater performance if both it and the later entrant-type attempt to be market pioneers. The later entrant-type will realize greater performance if both it and the market pioneer-type attempt to be later entrants." Their findings indicate that market pioneers, early followers, and late entrants tend to have different skills and resource profiles, and "...the 'strategic window' for market entry tends to open at different times for different entrant types" (Robinson et al., 1992: 622). Szymanski et al. (1995: 30) also argue, utilizing data from several studies, that "...modeling order of entry as an interaction effect appears to capture best the relationship between order of entry and market share." Success, hence, doesn't immediately follow from pioneering, and this, in turn, might be a function of the way in which skills and resources are deployed by pioneering and follower firms. Lilien and Yoon (1990), for instance, model entry as a strategic decision (in this case defined as the choice between
being a pioneer or a follower) influenced by the competition of other entrants in R&D, product, market, and the like. These authors found that the likelihood of success for first and second entrants was lower than the likelihood of success for the third and fourth entrants in a sample of 112 new industrial products from 52 French firms. This could suggest that later entrants can overcome pioneer advantages through a more apt deployment of resources and skills. Along these lines, Moore et al. (1991) developed a model in which pioneering was considered to be endogenous, (that is, they assigned the advantage earned by first-movers to firm proficiency rather than solely to pioneering). The authors found that the relationship between market share gains and entry times is partially based on "...unobservable determinants of success such as management skills and resources" (Moore et al., 1991: 103). Murthi, Srinavan and Kalyanaram (1996) reexamine the relationship between pioneering and market share controlling for managerial skills. Their analysis shows that the strength of the relationship between order of market entry and market share is not diminished or altered in any important way when such controls are introduced. Perhaps such unobservable determinants should encompass managerial skills and a combination of additional organizational variables.

In all, this suggests that the relationship between order of market entry and market share should be treated in conjunction with environmental and organizational factors. Firms have different strategic inclinations in terms of innovation and entry order, and these different inclinations should be taken into account when studying pioneering advantages. Kerin et al. (1992), for instance, stress the need to link organizational and environmental variables to the research on pioneering advantages. Such link is needed because (Kerin, et al., 1992: 48):

...environmental change presents opportunities to all firms, but a particular firm must have certain competencies and capabilities, such as technological foresight, perceptive market research, skillful product and process development capabilities,
marketing acumen, and possibly luck to be a successful market pioneer. Indeed, depending on their unique strategic posture, some firms might benefit from early entry and others might benefit from following.

Studying the interaction between entry and different business strategies could help explain different patterns of performance for a given entry order and some of the mixed results that are observed in the literature about pioneering (Szymanski, et al., 1995). The relationship between pioneering and market share is consistent across studies but the possibility of a follower outperforming an early entrant exists, and it could correspond to the different strategies that firms follow. As Kerin et al. (1992:40) indicate,

Though environmental change provides an opportunity for a firm to be a first mover, the likelihood of a firm benefiting from being a first mover depends on several organizational factors, including the degree of fit between the (1) skills and resources necessary to capitalize on an environmental opportunity and the skills and resources possessed by the firm and (2) skills and resources necessary to capitalize on mechanisms for enhancing a first-mover advantage and skills and resources possessed by the firm to convert these mechanisms into a first-mover advantage.

Few studies have explicitly studied competitive strategy and order of market entry together. Lambkin (1988) considered strategy when investigating whether pioneers enjoyed long term advantages from entering first into new markets. She classified entrants into pioneers, early followers, and late entrants, and her results confirm that pioneers perform better than later entrants. For 2 subsamples of 129 start-up businesses (using data for their first four years of operation) and 187 adolescent businesses (data for their second four years of operation), Lambkin found that, generally speaking, pioneers attain an important market share advantage over later entrants (on average 23.96% for pioneers vs. 9.7% for late entrants in the start-up subsample and 32.56% vs. 12.95 in the

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2See for example Szymanski et al. (1995) for a meta-analysis.
adolescent subsample). In Lambkin's study, however, strategy is equated to order of market entry. As a result, the paper suggests the existence of different strategic typologies moderating the relationship between order of market entry and market share, but such moderating effects are not clearly explicated, particularly because it is assumed that certain strategic typologies are inextricably linked to certain entry categories.

DeCastro and Chrisman (1995), contrary to Lambkin, treat this relationship as an empirical question. These authors start with the premise that it is the combination of an entry strategy and a competitive strategy that gives firms an enduring performance advantage. Strategy is categorized as either low cost differentiation, utility and "stuck-in-the-middle". These categorizations of strategy are an extension of Porter's (1980) low-cost-differentiation dichotomy. In such vein, strategy is operationalized using 13 items such as inventory/sales, receivables/sales, and the like. These authors found that both order of market entry and competitive strategy have a significant effect upon performance. For example, the ROI of pioneers with utility strategies (61.54%) was significantly higher than the ROIs of pioneers with "stuck-in-the-middle" strategies (19.85%). The study does suggest that the relationship between OME and performance (in this case, financial performance measured by ROI) is influenced by the strategic characteristics of firms. The definition of competitive strategy is, however, somewhat unclear. Because strategy is defined ex post, based on observed values attained by firms in a number of aspects, the sample ends up containing a disproportionately small number of firms that follow a utility strategy. This notwithstanding, the study is valuable because it clearly establishes that viewing order of market entry in the light of firm strategies can render important insights, and particularly in regard to financial services.

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3Pioneers are, ex-post, automatically termed "r-generalists", and late entrants become "k-specialists" (following the terminology of population ecologists).
Order of Market Entry and Strategy

We can see from the above that although much literature looks at order of market entry by itself, strategy is inextricably linked to the outcomes of market entry. As Collis and Montgomery (1995: 120) indicate,

Competitive advantage, whatever its source, ultimately can be attributed to the ownership of a valuable resource that enables the company to perform activities better or more cheaply than competitors...Superior performance will therefore be based on developing a competitively distinct set of resources and deploying them in a well-conceived strategy.

Yet, having resources and deploying them in attractive industries is insufficient if adequate policies and consideration of the dynamics of entry are absent. Order of market entry will inevitably require careful assessment, regardless of the uniqueness, abundance, appropriability, or durability of the resources being deployed.

The effects of order of market entry can be analyzed from several perspectives. A first approximation is to treat average order of market entry as a proxy for firm strategy (Lambkin, 1988). Because firms posses unique resources and orientations (Collis and Montgomery, 1995), deployment of such resources might result in distinctive patterns of entry (i.e., firms could be, characteristically, pioneers, early entrants, late entrants, or laggards). Such first approximation has to be refined by incorporating other, very salient, dimensions of strategy. First, expectations about entry are different at the corporate, multi-business, and business level strategy. Definitions vary at these levels, and one must
be careful in identifying the aspects that characterize strategy in all cases. Second, a
definition of strategy may be more or less dynamic. Ex post definitions based on Porter’s
low cost and differentiation categories or modifications thereof, result in
conceptualizations that are essentially static. This contrasts ex ante definitions of strategy
which seek to understand institutions’ strategic behaviors as a series of actions taken
through time. These two dimensions, the level of analysis and the dynamism associated to
the firm’s strategy, interplay differently, rendering categories in which the relationship
between order of market entry and market share must by analyzed correspondingly. Such
analysis within each of the four categories must be examined in terms of the effects they
have upon positioning (where applicable), focus, and the fit of the products with the rest
of the product line. Where strategy is viewed as firms seeking to accommodate
themselves in an industry with predetermined characteristics, market share might be
conditioned primarily by competitive positioning rather than order of market entry. Here
the effect of order of market entry would be dwarfed by the effect of the competitive
positioning at the business level. The study by De Castro et al. (1995) might be
conceptualized as falling within this category. At the corporate level issues of entry are
important also, particularly across international markets (Mascarenas, 1992), but the
notions of focus and fit acquire different proportions. At the corporate level decisions of
focus and fit (or relatedness) are evaluated in terms of whole businesses. The decision to
participate in a market coupled to the extent to which businesses are going to be
interrelated determine the degree of focus (or diversification) of the corporation.
At the business level, scope will be determined in the amplitude of product offerings and focus in the degree of interrelatedness of subsequent product offerings with the rest. At this level, therefore, we can evaluate order of market entry and strategy directly, by studying how one particular entry fits with the rest of the product portfolio. In our previous chapter we devised a methodology for calculating product interrelatedness by categorizing products into client-product matrices and estimating a value for the dispersion of the data points. Subsequent product offerings will be of three kinds: a) entries that reduce the variability, b) entries that increase variability, or, plausibly, c) entries that do not affect variability. These entries can be conceptualized as strategic decisions related to business scope and focus, hence establishing a direct link between order of market entry and strategy. By establishing characteristic orders of market entry for certain players and, in particular, by establishing the relationship between order of market entry with the strategic effect in terms of greater or less focus or fit, we can then directly observe the effect of strategy on the relationship between order of market entry and market share.

In this study we seek to operationalize the strategy variable by characterizing institutions into prototypical categories using extant measures. One widely used classificatory scheme is Miles and Snow's strategic typology. This typology has originated a large amount of research interest and support (Conant, et al., 1990; Zahra, 1987; MacDaniel and Kolari, 1987). Miles and Snow (1978) proposed that firms develop patterns of behavior through a process that involves three multidimensional
collections of problems and solutions: an entrepreneurial problem set which focuses upon an organization's product and market scopes; an engineering problem that is centered around the choice of technologies and processes which will be used for production and distribution; and an administrative problem that has to do with the selection and development of processes and organizational structures. Miles, Snow et al., (1978) proposed a theoretical framework that classified behavioral patterns used by organizations to coalign with their environments. This framework defined three strategic types of organizations: Defenders, Analyzers, and Prospectors. A fourth type, the Reactors, is composed of firms that exhibit inconsistencies in their strategies, technologies, structures, and processes. The characteristics of these typologies are established along several dimensions associated with the entrepreneurial, administrative, and engineering problems. One important dimension that differentiates these strategic types is the rate of product innovation and the definition of product-market domains. Prospectors actively engage in continuous expansion into new markets with new products. Analyzers tend to carefully look for product-market opportunities and to embrace those which minimize risks and maximize profit opportunities. Defenders remain narrowly focused trying to create a stable set of products and customers. Reactors exhibit uneven and transient behavior with "...opportunistic thrusts and coping postures." (Conant, et al., 1990). For instance, McDaniel and Kolari (1987) found that the importance ascribed by executives to various marketing elements in a large sample of financial institutions was significantly different among strategic types. They found that the most significant differences were found
among Defenders and either Prospectors or Analyzers. These different manners of strategic coalignment appear to be stable over time. Given the different ways in which the entrepreneurial problem is solved, one should expect to see different results from pioneering for each of the typologies. Kerin et al. (1992) argue that:

It is significant that the Miles and Snow strategy typology does not explicitly advocate market pioneering as the normative strategic behavior conducive to superior performance for all organizations, nor does it impute insurmountable competitive advantages to the first mover. It suggests that though some organizations might be inclined to enter a market first (prospector firms) because of a distinct set of organizational competencies, others influenced by a different set of distinct organizational competencies may be more inclined to enter a market after its viability has been proven, and yet achieve performance levels comparable or superior to those of the pioneer.

Despite the abundance of research about this typology, systematic classificatory schemes are scarce. Zahra et al. (1990) review in detail several studies on the Miles-Snow typology and conclude that most of this research doesn't take into account many of the dimensions that comprise each of the typologies originally proposed by Miles and Snow (1978). Conant et al. (1990), in another study, reach similar conclusions, but they offer a multi-item scale which does take all the underlying dimensions into account and helps in the determination of pure strategic types. In this work we are using the scale provided by Conant et al. (1990) with slight adaptations. Moreover, Shortell and Zajac (1990) provided evidence that strongly support the validity of CEO assessment of the firm's strategic orientations. These authors found that the use of knowledgeable key informants within organizations was a valid approach for measuring strategy.
Another approach, and perhaps one of the most complete empirical analysis, is that of Venkatraman. Venkatraman (1989) argues that,

...in spite of several discussions on alternate approaches to operationalizing strategy (Ginsberg, 1984; Hambrick, 1980; Pitts and Hopkins 1982; Snow and Hambrick 1980), the linkage between theoretical definitions and their corresponding measures has been generally weak. Most existing measures for the strategy constructs are either nominal (and/or single-item) scales that have questionable measurement properties or multi-item scales whose measurement properties (such as reliability, and unidimensionality, convergent and discriminant validity as well as nomological validity) have not been systematically assessed.

More recently, several authors (Miller and Friesen, 1978 and 1984; Dess and Davis, 1984; and Venkatraman and Grant, 1986; and Venkatraman, 1989) have developed alternate measurement systems to unveil differences in strategies. These systems are comprised of several dimensions which together facilitate the development of a fairly detailed portrayal of firms' strategic inclinations. Venkatraman (1989) proposes a scale to measure strategic orientations of firms. The scale, denominated STROBE (Strategic Orientation of Business Enterprises), consists of six dimensions: Aggressiveness, Analysis, Defensiveness, Futurity, Proactiveness, and Riskiness. Venkatraman’s STROBE scale, although conceptualized at the business level, doesn’t establish a clear link between its dimensions and decisions of scope and focus of the business unit. Using our methodology, aggressiveness, for instance, could be conceptualized as radical departures from the firms’ average plot or, as another instance, defensiveness could be viewed in terms of entries which are consistently reducing the variability around the firms average client-product plot.

In this study, of course, we are not interested in advancing the development of such schemes for measuring strategy. Rather, we are interested in studying in more detail
the effects of order of market entry when observed under the light of the entrant's competitive strategy. Hence, to this end, we use already developed scales to measure the construct. We must underscore that these measures of strategy do not provide clear means for establishing the aforementioned effects through the client-product plots. Moreover, such measures encompass only a portion of the total phenomenon. They portray dynamic characteristics of business level strategy and, therefore, results cannot be extrapolated to the corporate level.

Our purpose here is only to investigate whether certain strategic types will enjoy advantages from pioneering, or, as Robinson et al. (1992: 622) indicate, whether "...strategic windows for market entry tend to open at different times for different entry types." There might exist firms with a built-in inclination for developing new products. These would be firms that are on the constant lookout for new developments and are interested in disrupting the market. Because of this, they might have developed skills for coping with related risks and uncertainties associated with the development and launching of new services. Other less aggressive firms may encounter themselves in a situation of being a pioneer or an early entrant, but, because of inexperience in dealing with the situation, fail. Conversely, they may have become adept at exploiting proven markets, hence they may achieve good performance despite entering relatively late.
Hypotheses

From the aforementioned we propose that:

HO: Firms that are characteristically early entrants will have a stronger effect of order of market entry on long term market share. Prospectors will exhibit larger long term-market shares than all other Miles and Snow strategic types. Firms which are characteristically late entrants (such as defenders) will achieve performance outcomes comparable to those of the pioneer.

H1: The relationship between order of market entry and market share will significantly change when controlling for business strategic orientations. In particular, firms that score high on the Aggressiveness dimension of Venkatraman's (1989) STROBE scale, will enjoy greater long term market shares than other firms

Aggressiveness is understood, following Venkatraman (1989), as "...referring to the posture adopted by a business in its allocation of resources for improving market positions at a relatively faster rate than the competitors in its chosen market." Thus, we would expect aggressive firms to improve market positions through the introduction of new products and through aggressive pricing. We should expect higher scores of this dimension to be found among firms which are typically pioneers and early entrants. Venkatraman's pilot findings indicate that firms which have aggressive postures did not fare well when performance was measured using financial indicators. Yet, these firms did have greater market shares despite weaker financial positions.

*See Table 2 for a summary of the six strategy dimensions contemplated by Venkatraman to conform the measuring scale.*
Methods

This study is based primarily on historical analysis. Product histories for several financial products have been reconstructed and assembled using archival records available in published sources of information (which include primarily newspapers, trade journals, and research papers) and from other sources such as regulatory institutions. The historic information was then validated with data from informants in pertinent institutions and other people who were familiar with the industry. For convenience of data gathering, the sample chosen is a set of three financial services launched in Costa Rica within the past 15 years. As in the preceding essay, we use a sample of 36 entries in three product lines (credit cards, debit cards, and pension funds). Our choice of sample encompasses products that were created recently. This permitted gathering a significant amount of information from public records and cross-validating it with people in the industry who had actually participated in the conceptualization and launching of the products.

In order to obtain information about strategic inclinations of firms, we used primarily two sources of information. First we interviewed bank executives. These interviews were semi-structured and were used to administer in-situ all scales used to measure strategy. We also gathered information from three industry experts. Information was then compared and contrasted. We requested clarification through the telephone. Care was taken to interview top level managers in the institutions under study. In some cases we performed interviews with several members of the top management team in each institution.
Model and Measures

The dependent variable of this study is total market share of the nth entrant at the time of the study. Order of market entry is used as an independent variable. Pioneers are operationalized as the first entrant. The institution's strategy is used as a control variable. The model to be tested can be summarized as follows:

$$MS_{nc} = E_{nc}^{\alpha_1} S_{nc}^{\alpha_2}$$

Where:

$MS_{nc} =$ market share of the nth product to enter category c, in percent. It is termed SHARE.

$E_{nc}^{\alpha_1} =$ Order of entry of nth product in category c. It is termed ENTRY.

$S_{nc}^{\alpha_2} =$ Strategy of the firm that launched the nth product in category c. It is named STRATEGY.

Two measuring schemes were used to characterize STRATEGY. Following our discussion earlier, the first measure involves the use of Miles and Snow's (1978) typology. In order to minimize the observations made by Zahra (1987) with respect to the correct categorization of industry participants into such categories, a systematic scheme was used to assign categories. The measuring device closely follows the one proposed by Conant et al. (1990).

The second measure utilizes Venkatraman's *Strategic Orientation of Business Enterprises* or STROBE scale. This scale is comprised of six dimensions of strategic orientation. These dimensions are: Aggressiveness, Analysis, Defensiveness, Futurity,
Proactiveness, and Riskiness. The meaning of each dimension is summarized in Table 2, and the items used to measure them are indicated in Appendix 2.

<table>
<thead>
<tr>
<th>Dimension of Strategic Orientation</th>
<th>Description</th>
</tr>
</thead>
</table>
| Aggressiveness                    | • Improving market positions at a relatively faster rate than the competitors, based on product innovations and/or market development or high investments to improve relative market share and competitive position.  
  • Improvement of market positions in the short run (explosion).  
  • Pursuit of market share as an important path towards achieving business unit profitability. |
| Analysis                          | • Tendency to search deeper for the roots of problems and to generate the best possible solution alternatives.  
  • Extent of internal consistency achieved in the overall resource allocation for the achievement of chosen objectives  
  • Use of appropriate management systems.  
  • Does not reflect the 'Analyzer' behavior of Miles and Snow. |
| Defensiveness                     | • Emphasis on cost reduction and efficiency seeking methods.  
  • Reflects view of organizations seeking to defend their core technology and the preservation of own products, markets and technologies. |
| Futurity                          | • Reflects temporal considerations.  
  • Relative emphasis of effectiveness (longer-term) considerations versus efficiency (shorter-term) considerations.  
  • Manifested through emphasis in areas such as forecasting sales and customer preferences and formal tracking of environmental trends. |
| Proactiveness                     | • Reflects proactive behavior to participate in emerging industries.  
  • Continuous search for market opportunities and experimentation  
  • Introduction of new products. |
| Riskiness                         | • Patterns of decision making and resource allocation in the choice of products and markets. |
Data Analysis and Results

In this section we first compare and contrast the two alternative ways that were utilized to measure the independent variable STRATEGY. Then, after an exploratory data analysis, we fit regression models in which SHARE is regressed against ENTRY and STRATEGY.

Measurement of the independent variable STRATEGY

Before conducting any data analysis, all items in Venkatraman's Strategic Orientation of Business Enterprises Scale (STROBE) were tested for reliability in terms of the Cronbach $\alpha$ coefficient. This index is commonly used for measuring the reliability of indicators. For pre-testing purposes, we administered our questionnaire to a group of MBA students with experience in the financial services sector and thereupon to a group of managers of financial institutions from several countries. We finally tested the instrument with a group of 23 financial institutions. These pre-tests indicated that some reversed items appeared to confuse respondents. By changing these items we were able to attain reliability indicators which ranged between 0.49 to 0.84, as shown in Table 3. The reliability of the Riskiness indicator is very close to the cutoff point of 0.5 proposed by Nunnally (1967) for preliminary research. After the first pre-test we tried to improve the reliability of this indicator by adding more items and primarily through improving the quality of the items. In the subsequent pre-test, an important improvement was observed. This item is also one of the two that exhibits the lowest internal consistency reliability indices (0.53) in Venkatraman's (1989) original work. We decided to utilize this indicator, noting, nonetheless, its potential drawbacks.
Table 3. Reliability Analysis of indicators of STROBE scale used to measure strategy.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of items</th>
<th>Cronbach’s alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggressiveness</td>
<td>3</td>
<td>0.57</td>
</tr>
<tr>
<td>Analysis</td>
<td>5</td>
<td>0.83</td>
</tr>
<tr>
<td>Defensiveness</td>
<td>3</td>
<td>0.69</td>
</tr>
<tr>
<td>Futurity</td>
<td>4</td>
<td>0.83</td>
</tr>
<tr>
<td>Proactiveness</td>
<td>4</td>
<td>0.84</td>
</tr>
<tr>
<td>Riskiness</td>
<td>3</td>
<td>0.49</td>
</tr>
</tbody>
</table>

Scatterplots of these indicators for our final pre-test show a fairly strong positive relationship between Analysis, Defensiveness, and Proactiveness. No evident curvilinearities appear to be present. Descriptive statistics for each of the items, shown in Table 4, reveal that the smallest means occur for Aggressiveness and Riskiness. Likewise, though certainly at least one institution scored the maximum score (7) in the variables Analysis, Defensiveness and Futurity; the maximum score observed in the variable Riskiness is 5.3. This might be due, according to the opinion of an industry expert, to the peculiar meaning that the word risk entails in banking. Risk in this industry is a multidimensional concept that must be actively managed, and bankers tend to be risk averse. Thus, in the banking industry managers deal with several types of risk, for example: credit risk (risk that loans will not be repaid), interest rate risk (risk that earnings will decline if interest rates change), liquidity risk (risk that funds will be tied up and cash will not be available when needed), insolvency risk (risk of liabilities becoming greater than assets), and currency risks. As a result the variable Riskiness in this industry has more connotations and implications than simply a reflection of businesses’ resource allocations.
Table 4. Descriptive statistics of the indicators in the STROBE scale.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggressiveness</td>
<td>3.6</td>
<td>1.3</td>
<td>2.0</td>
<td>6.3</td>
</tr>
<tr>
<td>Analysis</td>
<td>4.9</td>
<td>1.4</td>
<td>2.2</td>
<td>7.0</td>
</tr>
<tr>
<td>Defensiveness</td>
<td>4.5</td>
<td>1.4</td>
<td>2.7</td>
<td>7.0</td>
</tr>
<tr>
<td>Futurity</td>
<td>5.1</td>
<td>1.3</td>
<td>2.0</td>
<td>7.0</td>
</tr>
<tr>
<td>Proactiveness</td>
<td>4.0</td>
<td>1.5</td>
<td>1.8</td>
<td>6.3</td>
</tr>
<tr>
<td>Riskiness</td>
<td>3.8</td>
<td>1.1</td>
<td>1.0</td>
<td>5.3</td>
</tr>
</tbody>
</table>

The emerging relationships we observed in the scatterplots were confirmed through Spearman-rank correlation coefficients (Table 5) which showed a strong and positive relationship between Analysis and Defensiveness, Futurity and Proactiveness (in all cases $S-r \geq 0.59$, $p<0.001$). This suggests that, from a strategic standpoint, Analytical proclivity is not associated solely with passive strategic postures but also with more proactive stances even for firms operating in the same environment. Similarly, Proactiveness is positively correlated with Defensiveness ($S-r=0.74$, $p<0.001$) which suggests that one company may adopt a proactive stance towards defending its existing markets or that a firm may be proactive while defending certain market niches. No significant relationships are observed between the variables Aggressiveness and Riskiness, either between them or with other variables. This would suggest that an aggressive strategic posture is rather divorced from a more analytical long-term orientation.
### Table 5. Spearman-rank correlation coefficients for all indicators of the Strategic Orientation of Business Enterprises Scale.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggressiv.</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Analysis</td>
<td>0.08</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Defensiveness</td>
<td>0.25</td>
<td>0.77***</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Futurity</td>
<td>0.05</td>
<td>0.70***</td>
<td>0.72***</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Proactiveness</td>
<td>-0.07</td>
<td>0.72***</td>
<td>0.74***</td>
<td>0.59**</td>
<td>1.00</td>
</tr>
<tr>
<td>Riskiness</td>
<td>-0.14</td>
<td>0.03</td>
<td>-0.01</td>
<td>-0.15</td>
<td>0.07</td>
</tr>
</tbody>
</table>

***p<0.001, **p<0.01

The results shown in Table 5 are similar to those obtained by Venkatraman (1989: 955) in his pilot study where the variable Analysis is positively and significantly correlated with Defensiveness, Futurity and Proactiveness. Defensiveness is also positively and significantly correlated with Futurity and Proactiveness, and Futurity is correlated (positively and significantly) with Proactiveness. The only observed difference with Venkatraman's results is in the relationship between Aggressiveness and Riskiness. He found a positive correlation while here we observe no correlation. Such difference could arise from definitional problems we have already observed when exploring the data. In all, though, observed results do not depart significantly from the expected outcomes, particularly those mentioned in Venkatraman (1989) which were the only benchmark available. We were fairly comfortable that the STROBE scale was adequately portraying strategy for this sample of firms.

We then proceeded to classify the 23 firms into typologies, utilizing Conant et al.'s (1990) strategic types scale. According to this scale, 10 entries in our sample were made by institutions that were categorized as Prospectors, 9 were done by Analyzers, 8 by Defenders, and 7 by Reactors.

Although the measurements of STRATEGY that we were using were essentially different, we decided to check whether both scales were categorizing and classifying the
institutions object of the study in ways which were somewhat consistent. To do so, we first cross tabulated the results as shown in Figure 1. The figure shows that Prospectors score higher in the Analysis, Defensiveness, Futurity and Proactiveness variables of the STROBE scale.

![Graph showing strategy types]

Figure 1. Cross tabulation of Miles and Snow Strategic Types with Venkatraman's Strategic Orientation of Business Enterprises Scale.

Table 6 shows Wilcoxon Rank-Sum for differences in medians for each of the six strategy dimensions and the typology of Miles and Snow. Prospectors, as a class, are clearly significantly different from Defenders in 5 of the six categories but only significantly different from Analyzers in 3 of the six categories. Analyzers fall, as expected from the theory (Miles, et al., 1978), somewhere between Prospectors and Defenders. Entries in this typology are significantly different from Defenders and Prospectors in 3 of the six categories. Reactors appear to have an uneven behavior across categories.
Table 6. Wilcoxon Rank-Sum Test for difference in medians. Difference in medians found significant by strategic type and for each of the six strategy dimensions of the STROBE scale.

<table>
<thead>
<tr>
<th>Aggressiveness</th>
<th>Analysis</th>
<th>Defensiveness</th>
<th>Futurity</th>
<th>Proactiveness</th>
<th>Riskiness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-3*</td>
<td>1-2*</td>
<td>1-3−</td>
<td>1-2−</td>
<td>1-2−</td>
<td></td>
</tr>
<tr>
<td>1-4−</td>
<td>1-3*</td>
<td>3-4−a/</td>
<td>1-3−</td>
<td>1-3−a/</td>
<td></td>
</tr>
<tr>
<td>2-3−a/</td>
<td></td>
<td></td>
<td>1-4−a/</td>
<td>2-3*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2-3−a/</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2-4−a/</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*a* one-tailed
\[ p<0.1, *p<0.05 \]
1=Prospectors, 2=Analyzers, 3=Defenders, 4=Reactors.

Regression Analyses.

Once we had evaluated the scales used to measure our independent variable STRATEGY, we concentrated on fitting the proposed regression models to evaluate entry effects in conjunction with firm strategy. Our first step in the analysis was to devise scatterplots of SHARE against ENTRY and the items of STRATEGY. Inspection of the scatterplot of SHARE against ENTRY denoted the existence of curvilinearity. We therefore decided to transform the independent variable SHARE taking its natural logarithm. The transformed variable was thereupon termed SHARE*. Bi-variate scatterplots showed that such transformation apparently restored linearity to this relationship. A table of Spearman-rank correlation coefficients (Table 7) indicated the existence of a strong and negative correlation between SHARE* and ENTRY.
We observed a similar relationship among the items of the STROBE scale for institutions that had product entries to the one we observed when pre-testing with a larger sample of financial institutions. There are strong and positive bivariate correlations among Analysis, Defensiveness, Futurity, and Proactiveness. There is a weak positive relationship between ENTRY and Aggressiveness. This could indicate that aggressive firms do not necessarily tend to enter the market first with innovative products. Perhaps such firms are likely to enter the market later with an emphasis on price undercutting or heavy investments in promotion.

Following these analyses, we established one control predictor (ENTRY) and one question predictor (STRATEGY), represented in this case by the several items that comprise the STROBE scale. The relatively large correlations among the variables that comprise the STROBE scale, particularly the high correlations observed among Analysis, Defensiveness, Futurity, and Proactiveness, could eventually result in problems with multicollinearity. We, hence, built a sequence of nested models carefully observing the possible occurrence of multicollinearity. Three regression models were subsequently fitted and analyzed. In the first model we simultaneously introduced the variables Analysis, Defensiveness, Futurity and Proactiveness as question predictors, together with the question predictor ENTRY. The rationale behind such choice of predictors is that the
observed correlation of the analytical orientation of the businesses with the other key strategic dimensions suggests that firms scoring high on these items have developed a somewhat consistent manner and evaluation of strategic options. Here we follow Venkatraman (1989) who indicates that "...perhaps, those businesses with strong analytical orientations are neither too risky nor too aggressive in pursuing market share in general." Thus, here we would be facing institutions that tend to have a longer-term inclination toward the allocation of resources for operating the business. New product development is probably associated with such resource allocation tendencies.

The second model tested has Aggressiveness solely as a question predictor. The observed positive relationship between Aggressiveness and ENTRY would seem to suggest that aggressive behavior is not necessarily related to entering the market first. This is a bit counterintuitive, but, nevertheless, plausible, if firms that aggressively seek market share do so through means other than the disruption of markets by introducing entirely new products.

We finally fitted a model in which Riskiness was used singly as a question predictor and ENTRY is used as a control. Risky behavior should be associated with exploration of new markets where returns are not certain.

The results of these analyses are summarized in Table 8.

Table 8. A taxonomy of fitted regression models for the relationship between order of market entry, strategy and market share for a set of financial service innovations.

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-2.23***</td>
<td>-0.24***</td>
<td>0.13</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>62</td>
</tr>
<tr>
<td>2</td>
<td>-3.27***</td>
<td>-0.22***</td>
<td>-0.42</td>
<td>0.013</td>
<td>0.65*</td>
<td>0.002</td>
<td></td>
<td></td>
<td>69</td>
</tr>
<tr>
<td>3</td>
<td>-1.42~</td>
<td>-0.23***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.10</td>
<td></td>
<td>62</td>
</tr>
<tr>
<td>Base</td>
<td>-1.79***</td>
<td>-0.24***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>62</td>
</tr>
</tbody>
</table>

***p<0.001, *p<0.05, ~p<0.1
Table 8 shows that, contrary to what we expected, the variables Aggressiveness and Riskiness have little effect upon the fit. The addition of these variables (singly or jointly) do not render an appreciable change in the R2 statistic of the baseline model in which SHARE* is simply regressed against ENTRY. The addition of the variables Analysis, Defensiveness, Futurity, and Proactiveness, do appear to have an important impact on the fit. We observe that Futurity has a beta coefficient of 0.65 (p<0.05). Such occurrence warrants further exploration.

We introduced the aforementioned four variables (Analysis, Defensiveness, Futurity, and Proactiveness) into the model in various combinations. We found that only the Futurity variable showed an important effect upon the model. As can be seen in Table 9, introduction of this variable into the baseline model results in a difference in R-sq. of 0.0434. This difference is important (Fobserved = 4.486 >Fcritical=3.316).

We also tested the effects of interactions. None was appreciable. An inspection of the scatterplot of studentized residuals for this model did not show heteroscedasticity and permitted validating the assumptions about independence of errors. The assumption about normality of the residuals was validated through inspection of the normal probability plot. No evidence of multicollinearity was found when the model was tested through the tolerance statistic (Tol=1 which renders a Variance Inflation factor slightly greater than one which precludes collinearity even for small data sets).

<table>
<thead>
<tr>
<th>Model</th>
<th>Intercept</th>
<th>ENTRY</th>
<th>FUTURITY</th>
<th>R2</th>
<th>ΔR2</th>
<th>dfE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reduced</td>
<td>-1.792***</td>
<td>-0.236***</td>
<td>0</td>
<td>0.62</td>
<td></td>
<td>34</td>
</tr>
<tr>
<td>Full</td>
<td>-3.42***</td>
<td>-0.235***</td>
<td>0.314*</td>
<td>0.659</td>
<td>0.0434</td>
<td>31</td>
</tr>
</tbody>
</table>

***p<0.001, *p<0.05
Before interpreting the model, we performed sensitivity analyses to examine the potential impact of atypical data points upon the regression model. Influence statistics, Cook's D and Hat H, were then calculated to perform such assessment. Figure 3 shows a scatterplot of Hat vs. Cook's D statistics. No single point seems to stand out conspicuously from the rest. Nevertheless, regression analyses were performed to evaluate the impact of points labeled 4, 15, and 16 in Figure 3. The Beta coefficients of the regression model remained fairly stable with changes in the Beta coefficients that did not exceed 15%.

Figure 3: Plot of influence statistics (Cook's D vs. Hat H) to observe influence of atypical data points.

After performing these analyses our best and chosen model was one that regressed SHARE* against ENTRY and Futurity. The assumption about normality of the residuals was validated through inspection of the normal probability plot of the residuals. Inspection of plots of raw and studentized residuals served to validate the assumptions about independence of errors.
Thereupon, we fitted an additional regression model using the categorical measure of the variable STRATEGY. These categories were used as dummies, in which 1 indicated whether the entrant belonged to that particular category. We first did an exploratory data analysis. Given the categorical nature of our variable STRATEGY, the mean of such variables is interpreted only as the percentage of entries that are considered to be done by firms which belong to this strategic typology (in Table 10: Prospectors 29%, Reactors 21%, etc.). These numbers do not permit making any inference about relative frequency of entry by strategic type.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>s.d.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ENTRY</td>
<td>8.30</td>
<td>5.92</td>
<td>1</td>
<td>21</td>
</tr>
<tr>
<td>SHARE*</td>
<td>-3.75</td>
<td>1.78</td>
<td>-7.46</td>
<td>-0.39</td>
</tr>
<tr>
<td>Prospectors</td>
<td>0.29</td>
<td>0.46</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Analyzers</td>
<td>0.26</td>
<td>0.45</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Defenders</td>
<td>0.24</td>
<td>0.43</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Reactors</td>
<td>0.21</td>
<td>0.41</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Further related inquiry was performed by inspecting Spearman-rank correlation coefficients of all variables. Given that we use ranks to evaluate emerging correlations, a positive correlation between ENTRY and some strategic type should signal the tendency of such type to be composed primarily of late followers (and vice versa, a negative correlation should signal the tendency of the particular strategic type to be constituted principally by pioneers or early entrants). Such appears to be the case. Table 11 shows a negative correlation ($S-r = 0.33, p < 0.1$) between Prospectors and ENTRY. This indicates that entries done by Prospectors tended to occur early. In contrast, the positive correlation between ENTRY and Defenders indicates that entries done by Defenders
tended to happen late (relatively speaking). As a result, we observe a fairly strong and significant correlation between Prospectors and SHARE (S-r = 0.38, p<0.05). We can infer from this table that Prospectors tend to enter early and, possibly as a result, tend to reap higher market shares. This indicates that SHARE varies for different strategic types for a given order of market entry. These observations are of course not conclusive given the dichotomous characteristics of the variables at issue, but they do warrant further exploration.

Table 11: Spearman-rank correlation coefficients for ENTRY, SHARE, and variables that measure Miles and Snow strategic typologies.

<table>
<thead>
<tr>
<th></th>
<th>ENTRY</th>
<th>SHARE*</th>
</tr>
</thead>
<tbody>
<tr>
<td>ENTRY</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>SHARE*</td>
<td>-0.80***</td>
<td>1.00</td>
</tr>
<tr>
<td>Prospectors</td>
<td>-0.33~</td>
<td>0.38*</td>
</tr>
<tr>
<td>Analyzers</td>
<td>0.12</td>
<td>-0.25</td>
</tr>
<tr>
<td>Defenders</td>
<td>0.32~</td>
<td>-0.22</td>
</tr>
<tr>
<td>Reactors</td>
<td>-0.09</td>
<td>0.08</td>
</tr>
</tbody>
</table>

***p<0.001. **p<0.01, *p<0.05, ~ p<0.1

Following these analyses, and as suggested by the observation of the Spearman-rank correlation coefficients, we decided to use the strategic typologies as question predictors, using ENTRY as a control, and proceeded to fit a taxonomy of regression models. To do so, we built a model in which the question predictors were introduced simultaneously to the baseline model of SHARE* vs. ENTRY. Table 12 summarizes the results of this analysis.
Table 12.: **Taxonomy of regression models in which ENTRY is used as a control and Miles and Snow typologies are used as question predictors. The question predictors are introduced into the model simultaneously. The fourth typology becomes automatically defined when all other question predictors are zero.**

<table>
<thead>
<tr>
<th>Model</th>
<th>Intercept</th>
<th>ENTRY</th>
<th>Prospectors</th>
<th>Analyzers</th>
<th>Defenders</th>
<th>R2 (%)</th>
<th>ΔR2 (%)</th>
<th>df</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>-1.79***</td>
<td>-0.236***</td>
<td>0.32</td>
<td>-0.81</td>
<td>-0.26</td>
<td>61.59</td>
<td>66.54</td>
<td>4.95</td>
<td>29</td>
</tr>
<tr>
<td>M1</td>
<td>-1.76***</td>
<td>-0.219***</td>
<td>0.32</td>
<td>-0.81</td>
<td>-0.26</td>
<td>66.54</td>
<td>4.95</td>
<td>29</td>
<td></td>
</tr>
</tbody>
</table>

***p<0.001, **p<0.01, *p<0.05, ~ p<0.1

We have included only three of the four strategic dimensions. Given that they are dichotomous (0 or 1) the fourth dimension will become automatically specified when all others are set to zero. Assumptions about normality of the residuals were validated through inspection of the normal probability plot. Plots of raw and studentized residuals and serial correlations of residuals did not show evidence of infringement of the assumption about the independence of errors (see Figure 4). We chose this model as our basis for discussion and interpretation. Notice, however, how remarkably strong is the relationship between order of market entry and SHARE. Despite the introduction of additional variables, the difference in the R2 statistic is relatively small.
Summary and Discussion

We wanted to assess the effect of order of market entry upon market share, controlling for some "strategic effects." The goal was to determine whether innovation initiatives in the development of new financial services may result in better performance if launched during certain time frames by firms which follow particular strategies. We found that a baseline model in which SHARE* was regressed against order of market entry (ENTRY) explained over 60% of the variability in performance. Including variables that measured firm strategy only had a minor effect on our baseline model. The relationship between ENTRY and SHARE remained remarkably consistent, and in line with most other work that has been done in this area. The effects of strategic interactions are dwarfed by the magnitude of the main effect (ENTRY).

When we classified entrants into Miles and Snow's strategic typologies, we found that early entry had larger effects upon Prospectors. Figure 6 shows that, for a given entry, Prospectors gain, on average, higher market shares than all other strategic types.
This is in line with what we had hypothesized. The relatively small size of our sample made it very difficult to assess performance by entry type and entry decision. The graph, then, shows only the average result (that Prospectors tend to outperform other entry types for a given time of entry). The results, however, permit making some inferences as to when certain followers may turn out to outperform the pioneer. Such observations must be taken with caution. We can see that, for instance, other things being equal, a Defender that pioneers a new product will be outperformed by a fourth entrant which is a Prospector. Such occurrences could explain why in certain studies it has been found that followers are able to capture larger market shares than pioneers. Further research could assess whether these observed differences, and in general, whether observed differences in strategic types correspond to fundamental differences in available resources and capabilities.

Our results apply only to business level strategy, and we are not assessing the effect that each entry has upon the product portfolio of the company. It is suggestive, however, that our limited data indicated that certain strategic types have less focused product portfolios. Prospectors appear to have larger product arrays aimed at different markets. Although, given the limitations of our data, we cannot rigorously test these differences, it could be interesting if further research could look into the parallelism existing in the characteristics of product portfolios and strategic types. By assessing the effect of subsequent entries on the dispersion of the matrix, one could more easily understand the effects of strategy upon the relationship between order of market entry and market share.
These results are in rough consonance with our qualitative data. When we asked bank executives to determine how pioneering products had been developed and to rate their success, we observed that pioneering products were developed differently. Some (about 24% of the cases listed) were generated in an orderly and formalized manner with a somewhat structured process of market research and a subsequent development process aimed at satisfying certain market needs. Most products (43.5%) were adaptations of ideas that had been seen operating in other countries. A third large category of products (13%) stemmed from regulatory changes.⁵ Products that were developed or produced in response to some perceived market need seemed to be the most successful, as shown in Table 13. The performance measures here are clearly inadequate (executives' self ratings), but the results suggest that longer-term considerations do have an important impact upon performance, and, particularly, that formal processes of research and development may

⁵These products, according to executives, could be anticipated and developed in a somewhat automatic mode.
result in improved returns for a given entry decision in financial services innovations. These structural modes of product generation seem to conform to different strategic Miles and Snow types. Establishing such correspondence for financial services could be an interesting research path.

<table>
<thead>
<tr>
<th>Table 13. Sources of ideas for pioneering products developed within firms.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation of the idea</td>
</tr>
<tr>
<td>1. Perceived market need. Formal process of research,</td>
</tr>
<tr>
<td>development and launching of product to satisfy the need.</td>
</tr>
<tr>
<td>2. Realized product was successful in other countries and</td>
</tr>
<tr>
<td>decided to launch a similar product.</td>
</tr>
<tr>
<td>3. Spontaneous. The idea &quot;happened&quot; and all of the sudden</td>
</tr>
<tr>
<td>we were working on the product.</td>
</tr>
<tr>
<td>4. Regulatory changes allowed launching the product</td>
</tr>
<tr>
<td>locally.</td>
</tr>
<tr>
<td>5. It was just a small adaptation to something that already</td>
</tr>
<tr>
<td>existed in the market.</td>
</tr>
</tbody>
</table>

Our analysis showed that only one of the strategic dimension in the Venkatraman STROBE scale had a significant impact upon the baseline model. This was counterintuitive and opposed to our hypothesized relationship. We had presumed that Aggressive firms, and aggressiveness as a strategic trait, would magnify returns from pioneering efforts. This was not the case. A regression model in which the variable Aggressiveness was added to a baseline model (of SHARE* against ENTRY) did not show any significant increment in the R2 statistic. Figure 5 is a visual display of SHARE
against Futurity for different entry times. The results indicate a positive relationship between SHARE and Futurity. However, this relationship is significant only at the 0.05 level and, given the limitations of our data, we cannot make any normative conclusion based on this isolated outcome. Perhaps the apparently intended comprehensiveness of Venkatraman’s (1989) scale and the lack of orthogonality among the different items that comprise them tend to overwhelm and conceal the effect of more routinary strategic decisions. Not having enough discriminant power it becomes almost impossible to assess the characteristics of the firms that exhibit stronger entry effects.

This study has many limitations. One with which we were particularly concerned was the need to stratify the sample. Perhaps such stratification (into say early entrants, early followers, late entrants, and laggards) could then indicate different strategic types to be better than others for each subsample (hence for different timing of entry decisions).

Another limitation of this study is the presumption that strategies are persistent over time. Though it is apparent that strategic traits tend to remain stable over time (Miles, Snow, et al., 1978), perhaps to the point of inducing rigidity (Leonard-Barton, 1992; Christensen and Rosenbloom, 1995), it is perfectly plausible that strategies change over time particularly because of possible and important changes in institution personnel. Our data do not permit us to assess this fully. We measured strategy at one point in time and presumed that the same strategy had been maintained when products were launched. To explore this, we gathered data on top management tenure within each institution. We were able to collect data for 11 institutions in the sample which reported that the CEO had an average of 14.7 years of experience within the same institution (St. dev. = 5.6 years). We had no means to validate this information and we also had relatively young institutions that had entries in our sample.
In all, the study showed that it might be fruitful to consider organizational and environmental factors when analyzing the effects of order of market entry. Such considerations might reveal strategic traits that are better adapted to different timing of entry decisions. Though our results are only suggestive, further research could address the limitations of this pilot study in order to evaluate whether in fact entry decisions can be actively managed to maximize performance for a given set of skills and resources.
References


Appendix 1

Selected scatterplots.
Appendix 2


I. Aggressiveness Dimension. Seven-point scales for the following: 1) In our organization we sacrifice profitability to gain market share; 2) In our organization we often cut prices to increase market share; 3) In our organization we tend to set prices below competition; 4) In our organization we seek market share position at the expense of cash flow and profitability.

II. Analysis Dimension. Seven-point scales for the following: 1) We emphasize effective coordination among different functional areas; 2) Our information systems provide support for decision making; 3) When confronted with a major decision, we usually try to develop thorough analyses; 4) We normally use different planning techniques; 5) We use the outputs of management and control systems to make decisions; 6) Our organization does manpower planning and performance appraisal of senior managers.

III. Defensiveness Dimension. Seven-point scales for the following: 1) We often introduce significant modifications to our technological platform; 2) We use cost control systems for monitoring performance; 3) We use different techniques to improve productivity of systems and people.

IV. Futurity dimension. Seven-point scales for the following: 1) Our criteria for resource allocation generally reflect short-term considerations (rev); 2) We emphasize basic research to provide us with future competitive edge; 3) In this organization we are constantly forecasting key indicators of operations; 4) In this organization we formally track significant general trends; 5) When confronted with critical issues we perform scenario analyses.

V. Proactiveness Dimension. Seven-point scales for the following: 1) We are constantly seeking new opportunities related to the present operations; 2) We are usually the first ones to introduce new brands or products in the market; 3) We are constantly on the lookout for businesses that can be acquired; 4) Competitors usually precede us in the introduction of new products or practices (rev); 5) We eliminate operations which are in the later stages of their life cycle.

VI. Riskiness Dimension. Seven-point scales for the following: 1) Our operations can be generally characterized as high-risk; 2) We seem to adopt a rather conservative view when making major decisions (rev); 3) New projects are approved on a "stage-by-stage" basis rather than with "blanket" approval (rev); 4) We have the tendency to support projects where expected returns are certain (rev); 5) Our organization generally follows a "tried and true" paths (rev).

Strategic Types scale. Adapted from Conant, Mokwa, and Varadarajan (1990).

1. **Entrepreneurial: product-market domain.** In comparison to other banks, the services which we provide are best characterized as: a) Services which are more innovative, continually changing and broader in nature throughout the organization and marketplace (P); b) Services which are fairly stable in certain units/departments and markets while innovative in other units/departments and markets (A); C) Services which are well focused, relatively stable and consistently defined throughout the organization and marketplace (D); d) Services which are in a state of transition, and largely based on responding to opportunities or threats from the marketplace or environment (R).

---

6 Reverse scored.
2. **Entrepreneurial: success posture.** In contrast to other banks, my organization has an image in the marketplace as a bank which: a) Offers fewer, selective services which are high in quality (D); B) Adopts new ideas and innovations, but only after careful analysis (A), c) Reacts to opportunities or threats in the marketplace to maintain or enhance our position (R); d) Has a reputation for being innovative and creative (P).

3. **Entrepreneurial: surveillance.** The amount of time my bank spends on monitoring changes and trends in the marketplace can best be described as: a) Lengthy: We are continuously monitoring the marketplace (P); b) Minimal: We really don't spend much time monitoring the marketplace (D); c) Average: We spend a reasonable amount of time monitoring the marketplace (A); d) Sporadic: We sometimes spend a great deal of time and at other times spend little time monitoring the marketplace (R).

4. **Entrepreneurial: growth.** In comparison to other banks, the increase or losses in demand which we have experienced are due most probably to: a) Our practice of concentrating on more fully developing those markets which we currently serve (D); b) Our practice of responding to the pressures of the marketplace by taking few risks (R); c) Our practice of aggressively entering into new markets with new types of service offerings and programs (P); d) Our practice of aggressively penetrating more deeply into markets we currently serve, while adopting new services only after a very careful review of their potential (A).

5. **Engineering: technological goal.** One of the most important goals in this bank, in comparison to other banks, is our dedication and commitment to a) Keep costs under control (D); b) Analyze our costs and revenues carefully, to keep costs under control and to selectively generate new services or enter new markets (A); c) Insure that the people, resources and equipment required to develop new services and new markets are available and accessible (P); d) Make sure that we guard against critical threats by taking whatever action is necessary (R).

6. **Engineering: technological breadth.** In contrast to other banks, the competencies (skills) which our managerial employees possess can best be characterized as: a) Analytical: their skills enable them to both identify trends and then develop new service offerings or markets (A); b) Specialized: their skills are concentrated into one, or a few, specific areas (D); c) Broad and entrepreneurial: their skills are diverse, flexible, and enable change to be created (P); d) Fluid: their skills are related to the near-term demands of the market place (R).

7. **Engineering: technological buffers.** The one thing that protects my organization from other banks is that we: a) Are able to carefully analyze emerging trends and adopt only those which have proven potential (A); b) Are able to do a limited number of things exceptionally well (D); c) Are able to respond to trends even though they may possess only moderate potential as they arise (R); d) Are able to consistently develop new services and new markets (P)

8. **Administrative: dominant coalition.** More so than many other banks, our management staff tends to concentrate on: a) Maintaining a secure financial position through cost and quality control measures (D); b) Analyzing opportunities in the marketplace and selecting only those opportunities with proven potential, while protecting a secure financial position (A); c) Activities or business functions which most need attention given the opportunities or problems we currently confront (R); d) Developing new services and expanding into new markets or market segments (P).

9. **Administrative: planning.** In contrast to many other banks, my organization prepares for the future by: a) Identifying the best possible solutions to those problems or challenges which require immediate attention (R); b) Identifying trends and opportunities in the marketplace which can result in the creation of service offerings or programs which are new to the banking industry or which reach new markets (P); c) Identifying those problems which, if solved, will maintain and
then improve our current service offerings and market position (D); d) Identifying those trends in
the industry which other banks have proven possess long-term potential while also solving
problems related to our current service offerings and our current customers’ needs (A).
10. Administrative: structure. In comparison to other banks, the structure of my organization is:
a) Functional in nature (i.e. organized by departments like marketing, accounting, personnel, etc.)
(D); b) Service or market oriented (i.e. departments like corporate or retail banking have
marketing or accounting responsibilities (P); c) Primarily functional (departmental) in nature;
however, a service or market oriented structure does exist in newer or larger service offering areas
(A); d) continually changing to enable us to meet opportunities and solve problems as they arise
(R).
11. Administrative: control. Unlike many other banks, the procedures my organization uses to
evaluate our performance are best described as: a) Decentralized and participatory encouraging
many organizational members to be involved (P); b) Heavily oriented toward those reporting
requirements which demand immediate attention (R), c) Highly centralized and primarily the
responsibility of senior management (D); d) Centralized in more established service areas and
more participatory in newer service areas (A).
Chapter 3

Effects of Organization on Financial Innovation
This essay explores the interaction between organizational structure and innovation in financial services. The essay addresses one research question: Are there differences in the characteristics of the organizational structures for innovators and non-innovators? The paper is organized into three sections. First, we review pertinent literature and develop a conceptual framework. Then, hypotheses and the research design are introduced. This is followed by a discussion of results. The essay is based on the presumption that certain aspects of a firm's structure affect the manner and extent to which financial service firms innovate. The organizational structure of the firm - its flexibility and its research capabilities - are hypothesized to determine the organization's ability to recognize and exploit opportunities for innovation. Our findings indicate that firms with formalized procedures and product development orientation appear to have larger product arrays aimed at different markets. We cannot, however, make any normative assertion based on the data available because error in our model is high. This notwithstanding, our results are useful in associating certain measures of organizational structure to product development in financial services.

**Research Background**

**Organizational structure**

Sustained competitiveness, long-term profitability, and long-term growth require organizations to adjust to their environments (Lawrence and Dyer, 1983). The very notion of strategic management implies the possibility of adaptation (Chakravarty, 1982). Contingency theorists suggest that there is not one best way to organize, and that organizations change their structures to adapt to their environments, resulting in
formalized responses to uncertainty and complexity (Lawrence and Lorsch, 1967a and 1967b; Galbraith, 1973). Lawrence and Lorsch (1967b: 4) suggest that organizations develop specialized functional appendages to deal with environmental vicissitudes. This ends in a "... state of segmentation of the organizational system into subsystems, each of which tends to develop particular attributes in relation to the requirements posed by its relevant external environment." For these authors, firms adapt to the environment by matching sub-unit differentiation and inter-unit coordination.

Other authors place a stronger emphasis on transmutations into more informal or "organic" systems as the environment becomes turbulent. Burns and Stalker (1961) showed that organic firms were more successful in industries with rapidly changing markets and technology. In stable markets, success was associated with "mechanistic" organizations. These "organic" structures are decentralized, informal, loosely controlled, and imprinted with flexibility. Individual tasks are constantly adjusted and re-defined, and, as a result, organizations with such structures adapt more easily. This type of institution is characterized by "...a network structure of control, authority, and communication" (Burns and Stalker, 1961:121). Communications are lateral and open, and they contain information rather than instructions. In contrast, in "mechanistic" structures tasks are specialized, and "...functionaries tend to pursue the technical improvement of means, rather than the accomplishment of the ends" (Burns and Stalker, 1961: 120). Communications, control, and authority are hierarchically structured. Information flows vertically and contains precise unambiguous instructions rather than equivocal ideas and unclear chatter. As a result, this type of mechanistic organization is formal, tightly controlled, and rigid.

Decision-making in the organic type is non-programmed: "...problems cannot be broken down and distributed among specialist roles within a clearly defined hierarchy"
(Burns and Stalker, 1961:121). In mechanistic organizations, choices are "...to some extent a foregone conclusion... because of the existence of an institutional framework around the individual" (Burns and Stalker, 1961: 115).

Mechanistic structures function better under stable conditions because procedures and communications can be abridged, and roles and duties are easier to define (Galbraith, 1973; Starbuck and Dutton, 1973). Organic structures deal better with innovation and changing conditions. Open communications, flat hierarchical structures, and close interaction between people are traits of archetypal innovative organizations (Bentley, 1990; Hull and Hage, 1982; Kanter, 1985). As environmental uncertainty increases (for example in markets characterized by rapid new product introduction), product development processes should become more organic and decentralized (Shrivastava and Souder, 1987). In summary, different structural forms are necessary for long-term success, as the environment impinges upon existing arrangements, and "...firms purposefully adopt structures to encourage learning" (Dodgson, 1993:387). Thus, innovation, according to this literature, seems to be fostered by flexibility (more open forms of communication and less formality): what Burns and Stalker (1961) called organic forms.

**Innovation = Invention + Exploitation** (Roberts, 1988).

Along with these structural adjustments, organizations teeter between the pursuit of the unknown and the development of the known. They have to allocate wisely limited resources to exploration and exploitation, because "...an organization that engages exclusively in exploration will ordinarily suffer from the fact that it never gains the returns
of its knowledge, (and) ...an organization that engages exclusively in exploitation will ordinarily suffer from obsolescence" (Levinthal and March, 1993: 105).

Engaging in new businesses too aggressively can result in failure. Rumelt (1974) found that firms prone to diversify into uncharted territories failed more often; their current capabilities ill-equipped them to withstand alien environments. Similarly, Meyer and Roberts (1986) found that new businesses had a higher likelihood of failure when entering unfamiliar markets through new market applications.

Yet firms that concentrate on improving their existing capabilities and neglect searching for new opportunities can also fail. The institutionalization of routinized capabilities leads to inertia, and firms become unable to react when confronting environmental changes (Haveman, 1992). Tushman and Anderson (1986) show that technological discontinuities herald the demise of many organizations, as their core competencies are obliterated. This paradoxical predicament places firms between a rock and a hard place: to innovate and not to innovate both increase the likelihood of failure:

The farther a company seeks to innovate, the greater the likelihood its innovation effort will fail. But the less it seeks to innovate, the greater the likelihood the corporation will fail (Roberts, 1994).

Such dilemma is conspicuously present in new product development. Technological change causes environmental upheaval, and firms try to ride the furious waves of the circumstances on top of new products and services. Technological discontinuities are ephemeral bridges that close the gap between the known and the unknown. However, firms often lock onto established routines that carry them away from the bridges, along "...trajectories that can ultimately prove fatal" (Christensen and Rosenbloom, 1993:17).
There is, then, an apparently inevitable trade-off between aggressive exploration and exploitation. Too much innovation allows little benefiting from the old, and firms that become entrenched in established routines fail to recognize and take advantage of the new. The work of Meyer and Roberts (1986, 1988) is particularly illustrative. They found that small high-technology firms performed best when they had a well-focused strategy. Firms that went too far away from their core technologies and markets in successive innovations were the worst performers. Hence, a balance between exploration and exploitation seemed to be necessary.

Thus, certain structural characteristics of organizations are apparently more conducive to innovation than others, but innovation is in itself a delicate balance between exploring the new and exploiting the old. Organizations can be structured so that "...exploration is strengthened while exploitation is undermined" (Levinthal and March, 1993) or vice versa. Some structures can restrain process routinization while others can force behavior into habit.

Given that organizations can vary in their structural arrangements and in their innovation habits, the interaction of these two variables will render different routine modes. In highly organic firms exploration will be continuous. Structural arrangements are organic, communications are lateral, decision-making is not "...broken down and distributed among specialist roles within a clearly defined hierarchy" (Burns and Stalker, 1961:5), and knowledge is distributed. There is a network structure of power and control, but it is constantly changing. Communications are lateral and unpredictable. "Decision-making is a garbage can process, where solutions, participants, loosely coupled problems and choice opportunities with different half-lives flow into the organization at different rates and connect whenever they meet in time and space" (Cohen, et al., 1972). The structure has no checks for continuous exploration and no incentives for exploitation. At
the other extreme, highly mechanistic firms will routinize what's seemingly unroutinizable, and they will create hierarchies that methodically explore. These firms will devote much attention to developing differentiated capabilities to create products: problems, broken down into sub-tasks, will be assigned to different people in the hierarchy; communications will be vertical and will carry instructions and outcomes rather than raw information or suggestions; power and control will be localized; and knowledge is going to be at the top. Products, then, will emerge through such differentiated capabilities and through tight controls.

**Hypothesis**

In the aforementioned literature, we see that different patterns of innovation occur as a function of the structural characteristics the organization and, also, the extent to which they have developed an orientation toward product development (in, among other things, the degree of organizational differentiation that exists for creating new products). We propose that this observation also applies to financial service firms:

H0: Controlling for product development orientation, financial service firms which are either highly rigid or highly flexible (i.e., highly organic or highly mechanistic) will exhibit the highest degree of innovation.

We propose that there will be a curvilinear concave relationship between innovation and structure. Institutions that are highly organic will have flexible structures and ad-hoc methodologies for developing new services. In the extreme, product development activities may resemble garbage-can processes of organizational choice.
(Cohen et al., 1972), and they will generate a large number of ideas very frequently. Ideas will generate in disparate places and take shape informally, casually, and randomly. Ideas for new products may often, for instance, be brought into firms by executives who see them working elsewhere and think they might be adapted locally. After some informal evaluation projects may be carried on by provisional committees or other emergent quasi-structures. Thus, decision-making may even become an "organized anarchy" (Cohen, et al., 1972). Ideas can start flashing spontaneously throughout the organization "...as collections of choices looking for problems, issues and feelings looking for decision situations in which they might be aired, solutions looking for issues to which they might be an answer, and decision-makers looking for work." (Cohen et al., 1972: 1) As a result there may be a high degree of new idea generation and innovation.

On the other extreme, highly mechanistic institutions will create specific hierarchical sub-units to generate new products and will tend to have formalized procedures to create them. Processes for carefully documenting ideas may exist, and each product will have to be approved through established channels. By incorporating these structures, exploration becomes routinized, and the respective sub-units develop and generate streams of new products. As a result, these organizations may create and launch products methodically, thus resulting in a high degree of product proliferation.

Therefore, these different interactions between organizational structural characteristics and innovation will render a curvilinear, concave, relationship between organizational characteristics and degree of innovation, as shown in Figure 1.
As suggested in Figure 1, we will focus on two organizational design choices. First, we will determine the effects of organizational flexibility upon innovative activity. Second, we will determine whether "product development orientation", i.e., the degree to which the organizations have developed norms, routines, procedures, or functions for the creation of new products mediates the effect of structure upon innovation.

The model to be tested is:

\[ I_n = k + C_n + F_n + \varepsilon \]

Where \( I_n = \) Degree of innovation as measured through the number of products the institution has aimed at various markets (as explained later).

\( C_n = \) The degree to which the firm has developed an orientation for identifying opportunities for innovation and for new product creation.
\[ F_n = \text{The firm's flexibility, i.e., the degree to which an organization has structural schemes at the firm level for dealing with innovation opportunities.} \]

\[ k = \text{constant.} \]

Specifics of these measures are explained in what follows:

**Methods**

**Measures**

**Predictor variables**

We used measures of organizational formality as surrogates for the degree to which organizations are either mechanic or organic. According to this, we presume that rigid organizations have also a high degree of formalization, defined as the degree to which norms, rules and procedures are explicitly formulated. The rationale for this approximation stems directly from extant organization theory. Social structure is one of the basic elements of organizations (Leavitt, 1965). Social structure is defined as “the patterned or regularized aspects of the relationships existing among participants in an organization” (Scott, 1992: 16), and it “...varies in the extent to which it is formalized.” (Scott, 1992: 18). Thus,
A formal social structure is one in which the social positions and the relationships among them have been explicitly specified and are defined independently of the personal characteristics of the participants occupying these positions. By contrast, in an informal social structure, it is impossible to distinguish between the characteristics of the positions and the characteristics of the participants. In an informal structure, when specific participants leave or enter the system, their roles and relationships develop and change as a function of their personal characteristics and the interactions that occur among them.

Thus, through formalization behavior becomes predictable. The attributes of formal social structures are similar to the attributes of “mechanistic” organizations as defined by Burns and Stalker. As these authors indicate (Burns and Stalker, 1961: 5):

In mechanistic organizations the technical methods, duties, and powers attached to each functional role are precisely defined. Each individual pursues his task as something distinct from the real tasks of the concern as a whole, as if it were the subject of a sub-contract.

In contrast, organic firms do not have an unambiguously defined structure, both in terms of the relationships among the participants and the characteristics of the tasks they perform. In that type of organization (Burns and Stalker, 1961: 6):

Individuals have to perform their special tasks in the light of their knowledge of the tasks of the firm as a whole. Jobs lose much of their formal definition in terms of methods, duties, and powers, which have to be redefined continually by interaction with others participating in a task.

Thus, the extent to which social structures are formalized are also an indication of the extend to which they are more mechanistic. A useful approximation can be obtained with scales that have traditionally used for measuring formalization. These scales measure the construct by determining the amount or norms and rules which are present in the
organization in written form. Oldham and Hackman (1981: 71), for instance, define formalization as "the extent to which rules, procedures, instructions, and communications are written." Thus, using commonly accepted measures of formality, it is possible to obtain good approximations of the extent to which organizations are either mechanic or organic. As shown in Table 1, two scales were used to measure the degree of formalization. One was adapted from Inkson, et al. (1970), and it measures the degree of formalization by determining the extent to which rules and procedures are written. The second one is based on a seven-point Likert scale adapted from Oldham and Hackman (1981), and it also measures formalization in terms of the extent to which rules, procedures and instructions are written. Both measures were expected to be positively intercorrelated. They were designated with the acronyms FORM1 and FORM2. The explanation of these items is included in Appendix 1.

Product Development Orientation indicates the degree to which firms have created specialized abilities through the development of norms, routines, procedures, or functions for the creation of new products. We were interested in several facets that comprise Product Development Orientation. Part of such orientation is related to the extent to which an organization has created differentiated organizational functions to confront particular external demands (Lawrence and Lorsch, 1967). Hence, we assessed the existence of a specialized appendage to perform research and to develop new products in a manner equivalent to that of the traditional R&D function found in many goods-producing industries. In addition, we evaluated whether companies formally developed
business plans to launch products and had performance indicators to monitor product performance. The existence of such procedures would be indicative of a product development orientation (Cooper et al., 1994; Thwaites, 1992; Iwamura et al., 1991). A 5-item scale, adapted from Thwaites (1991, 1992) and Iwamura et al. (1991), was used to measure this (as presented in Appendix 1). The variable was designated PDO.

<table>
<thead>
<tr>
<th>Variable (NAME)</th>
<th>Measure</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Formalization (FORM)</td>
<td>Degree to which norms, rules and procedures are explicitly formulated. Two redundant measures.</td>
<td>Inkson, Pugh, and Hickson (1970), Oldham and Hackman (1981)</td>
</tr>
<tr>
<td>Product Development Orientation (PDO)</td>
<td>Extent to which an organization has created specialized abilities through the development of norms, routines, procedures, or functions for the creation of new products.</td>
<td>Thwaites (1991, 1992), Iwamura et al. (1991)</td>
</tr>
</tbody>
</table>

**Outcome variable**

To assess the degree of innovation it was necessary to account for the tension between invention and exploitation (Roberts, 1988, 1991), or March's (1991: 71) "...exploration of new possibilities and exploitation of old certainties." Exploration produces a variety of experiences. It is associated with "...experimentation, variation, diversity, search, risk taking, play, flexibility, discovery and innovation...Exploitation, on the other hand, produces reliability in experiences and it is associated with refinement, choice, production, efficiency, selection, implementation, execution, consistency, unity,
and convergence" (March, 1991: 71). Levinthal and March (1993: 105) suggest that firm survival requires striking a fine balance between the two processes "...by engaging in enough exploitation to insure the organization's current viability, and to engage in enough exploration to ensure its future viability." The challenge of measuring this tension is indeed not trivial because the construct has multiple determinants, and it may not necessarily translate into discernible behavioral outcomes at the firm level.

March (1991) has proposed a theoretical model in which learning, understood as (exploration + exploitation), is operationalized into a turnover variable which, arguably, introduces the exploration ingredient into organizations, while exploitation is operationalized as the speed at which people learn an organizational extant code or way of doing things (March, 1991). Measuring this may be difficult. It is very complicated to determine what "the code" is for a particular organization and also to establish a useful base line for comparison purposes. Moreover, the introduction of new people or practices might be a result and not a cause of exploration and doesn't necessarily mean that exploration will be encouraged.

In this study we are using what is perhaps a less refined but much simpler and direct approach. If exploration "...is associated with experimentation, variation, diversity, search, risk taking, play, flexibility, discovery and innovation... and.... exploitation, on the other hand, produces reliability in experiences and it is associated with refinement, choice, production, efficiency, selection, implementation, execution, consistency, unity, and convergence..." (March, 1991:71); it is not unreasonable to assume that such tendencies will be reflected in companies' outputs. In particular, if a firm's products have often been produced for very different markets or using different technologies, we observe that exploratory tendencies appear to be important or at least present in that firm. If, on the
contrary, a firm exhibits little variability in its product offerings, exploratory tendencies seem slight and exploitation appears to be the dominant innovation mode.

In order to evaluate the firm's position along these dimensions, we use a variation of Roberts' (1991) methodology for evaluating strategic focus. Roberts (1991) and Meyer and Roberts (1986) tracked institutions' new products over time and assessed their newness in terms of technological characteristics and target markets. They obtained various "focus" measures which were then correlated with performance. In their studies, a "highly focused" strategy indicated that the associated company remained adept at a relatively narrow range of products and markets and therefore leaned towards the exploitation side of the innovation equation (and vice versa).

Following these authors, a similar approach is used here. Two dimensions, clients and products, are employed to define the market for financial services. Financial products have a very broad range of possible combinations even when choices are reduced to these two dimensions. Different client-product combinations should yield different strategic and competitive profiles and the degree of variability would render a surrogate for our variable innovation. When confined to these two dimensions, each company's choices can be represented in the form of a matrix composed of several product and client categories. Each cell requires a particular knowledge base, both in the form of knowledge of certain fundamental operations at the level of the firm and also in the form of public-policy and regulatory considerations. Hence, we presume that the dispersion of the cloud of points in this matrix provides a measure of innovation (Meyer and Roberts, 1988; Meyer and Roberts, 1986; Roberts, 1991).

In order to simplify the analysis, the client dimension was divided into major client groups. Traditionally, banks have divided this dimension into corporate and retail banking. We found such categorization adequate, but added a third segment to include:
a) the government, which encompasses all products related to the nation's state and other products not particularly aimed at corporate or individual clients; b) corporate customers, which includes all non financial companies in any industry; and c) individuals, which includes products aimed at individual clients of varied net worth. These three "client" categories can be broken down into smaller segments, but we found this to be rather cumbersome and unnecessary for the purposes of this study.

A wide range of financial services can be supplied to each of the client groups, but, for simplicity, the product dimension was broken down into three possibilities. The first category is composed of traditional financial intermediation, in the second category we included financial processes, and in the third category we included financial strategies. There is an increasing degree of complexity in each successive product category. As Alic (1994) indicates, newer financial products are based upon the intensive application of systems, knowledge, or both. Transactional applications (Alic, 1994) are developed based on the ability to transfer, manage, and manipulate large volumes of data. Additionally, analytical tools provide new services through the use of solutions to previously difficult mathematical problems and with a very thick component of creativity. These products differ substantially from traditional banking intermediation and "...open up strategic opportunities for supplying new service products and for delivering existing services in new ways." (Alic, 1994: 7). As a result, "...in the U. S. retail banking, the half-dozen standard products of two decades ago have given way to more than a hundred" (Alic, 1994: 8).

The classification into these three categories is also in line with extant literature on processes of service innovation. Barras (1986) and Buzzacchi et al. (1995) argue that many service industries have evolved through a series of distinctive stages. Buzzacchi et
al. (1995), for instance, posit a transition in the Italian banking industry that moves banks from a technological regime of "mass automation" to one of "smart automation". The first regime is characterized by a strong drive to attain efficiency and is primarily driven by traditional banking services. The latter regime is based upon bringing new products to an increasingly sophisticated clientele that requires more complex solutions to their needs.

Thwaites (1995) also posits a multi-stage historical evolution of financial services (exemplified with the Building Society Industry in the UK). The first era, termed "the mass production era", is characterized by undifferentiated product development, price competition, and little innovation. This is also associated with traditional financial services. The second phase, named the "mass marketing era", is characterized by the provision of differentiated products which are heavily pushed through marketing campaigns and, finally, the "post industrial era" is distinguished by a more complicated and changing environment that requires a greater degree of innovation and the creation of sophisticated new services. The mass marketing era is roughly equivalent to Alic's (1995) "transactional applications" and the post-industrial era corresponds to his "analytical applications". This literature then suggests that the proposed classification represents a progressively increasing level of complexity and adequately encompasses not only the array of products a financial institution may have, but also its ability to explore and pursue progressively more sophisticated products and markets.

Thus, we determined an index by tabulating the banks' products over time along these dimensions, and this measure of dispersion served as a surrogate for the degree of
innovation that characterized the firm. The measure has, evidently, many shortcomings. To be entirely accurate, one should include all products ever developed by the firm regardless of whether they were ever launched (successfully or not). Because records of such activities are rarely kept, such measures would have to be pursued based entirely on recollections from executives, thus resulting in an extremely complex data-gathering process and, possibly, in poor reliability. Creating histories of products launched is more feasible, and it is likely to capture firms' innovative proclivities. Thus, to develop these indices we followed the work of Roberts (1991) closely.

Because of the characteristics of the products studied, Meyer and Roberts (1986) were able to depict very accurate sequential histories of products developed by several firms. In financial institutions, like the ones under analysis in this work, we found it extremely difficult to replicate exactly the methodology. Banks were typically instituted with a minimum package of products, before they moved to other cells of their client-product matrices, thus making it difficult to establish a consistent and comparable baseline. Therefore, we employed an alternative approach using the chi-square distribution.

Though normally used to test hypothesized relationships among categories of data points, in this case we used chi-square as a measure to establish degree of firm innovation. A comparison was made between the chi-square obtained for each bank's client-product matrix and a client-product matrix for a totally unfocused bank (for practical purposes a bank with a large number of products in each cell of the client-product matrix). The procedure used was as follows:
Let,

\[ N_{cp} = \text{number observed in (c,p)th cell of the client product matrix, and} \]

\[ e_{cp} = \text{number expected in the (c,p)th cell under the assumption of a totally} \]

unfocused bank with a large and equal number of products in each cell.

for \( c = 1,2,3 \); and \( p = 1,2,3 \).

Let \( N_p = \sum_{p=1}^{3} N_{cp} \), and

\[ N_c = \sum_{c=1}^{3} N_{cp} \]

Then we calculate a chi square statistic as follows:

\[ \chi^2 = \sum_{c=1}^{3} \sum_{p=1}^{3} \frac{(N_{cp} - e_{cp})^2}{e_{cp}} \]

Because we were comparing with a hypothetical highly innovative (or
"unfocused") bank, the higher the value obtained the more "focused" (i.e. the more
concentrated in certain segments and product categories) the institution was and vice-versa: smaller values meant the institution was closer to the hypothetical bank we were
setting up for comparison purposes and, therefore, it was more dispersed and covering a
wider array of clients and product categories. We designated this variable as INNOV.

Appendix 2 illustrates the dispersion calculation using two matrices of very different
banks. Our choice of comparing to a "highly unfocused" bank was one of convenience.
Conceptually it is perhaps more adequate and rigorous to define the reference point as the
average of all banks. This would render a measure of differentiation with respect to a
prototypical average bank and not a hypothetical bank. Moreover, choosing the average bank does not have the potential problem of confounding the choice of an arbitrary point of comparison with any sort of implicit normative statement about optimal dispersion of client product matrices. However, although conceptually clearer, it is also a bit more cumbersome to evaluate and interpret, particularly because of the existence of negative values and the dynamic nature of the overall average. From a numerical standpoint results are not altered by choosing any other reference point, and, hence, we chose as such, arbitrarily, a hypothetical bank with 30 products per cell.

Redundantly, for validation purposes, we incorporated a scale for executives to self-assess firm innovativeness. This four-item scale evaluated degree of product variability, number of market segments the company was attacking, geographic coverage, and number of customers. An index was developed by linearly combining reported scores. The variable was designated INN_SLF.

Sample

Our hypothesis was tested in a group of 23 commercial banks in Costa Rica. This sample of firms was chosen for several reasons: a) We wanted to study organizations working in a relatively confined environment. By using institutions within the same country we were seeking to control effectively for regulatory and macroeconomic effects. b) We wanted to choose organizations that were experiencing a discernible environmental change (primarily because of changes in regulations). c) We wanted to analyze not necessarily a large sample but all institutions within a given environment (i.e. the "population"). We were particularly concerned with the possibility of excluding
institutions that were influencing a given market in an important manner. d) We wanted to obtain relevant information from archival sources and first-hand data from industry participants, and therefore wanted to deal with relatively young institutions.

Semi-structured interviews with executives complemented with archival studies were chosen as the most appropriate data-gathering techniques. Archival data were used for corroborating questionnaire and interview data. A questionnaire was prepared and pre-tested twice. Length, confusing wording, and other errors were corrected during the pre-testing phase of our research. The final product was used fundamentally as an instrument to guide semi-structured interviews. A database of top management teams of all institutions included in the sample was prepared, and this served as the basis for arranging appointments and conducting interviews.

After designing and pre-testing our questionnaire, we reviewed secondary sources. We checked local available trade journals (in finance, economics and business) and the country's main newspapers. The search narrowed down to four sources which were checked one by one between 1975 and 1995. Preliminary product histories by institution were developed based on these references. Once these preliminary product histories were developed, products were classified into client-product matrices by institution. We sought help from industry experts to code products into these matrices.

We then carried on detailed interviews with bank executives. During the interviews we jointly determined with the interviewee the accuracy of the client-process matrices that had been developed from secondary sources, and assessed the accuracy of the classification made in the different categories of these matrices. Questionnaires were administered during these interviews, and, in most cases, were filled out in the presence of the researcher. This was intended to provide immediate clarification and assistance and also to allow for additional questioning and expansion on some topics. Usually, questions
were read aloud, and the respondent would offer explanations aside from simply filling out the form. Notes were taken throughout by the researcher and many interviews were recorded. Clarification was sought afterwards, when necessary, via telephone. Care was taken to interview top level managers with several years of experience in the same institution. We gathered additional data through conversations with bank employees and industry experts.

**Data Analysis**

Before conducting any statistical analyses, we carried on a psychometric evaluation of our measuring instruments. As mentioned before, we performed two pre-tests. In the first instance we administered a preliminary questionnaire to a group of MBA students who had experience in the financial arena. A second pre-test, which was performed with a much improved questionnaire, was conducted with high-level bank managers from several countries. Chronbach's alpha was used to measure the reliability of the research instrument. Nunnally (1967) advocates a Cronbach's alpha greater than 0.5 for exploratory research. Using this as a guide we improved the quality of our indicators until acceptable results were obtained. Our final instrument rendered a Chronbach's alpha coefficient of 0.93 for FORM and 0.85 for PDO. In both cases the value of alpha did not undergo any important variation when any single item was omitted. Individual items presented in both cases high and significant correlations with the other items that comprised the scale. These analyses showed that the scales used to measure these variables were internally consistent. To assess construct validity we included some
redundant measures in our instrument. A second scale was introduced to measure formality. Figure 2 is a bivariate scatterplot of the two variables that measured formality.

![Scatter plot of two redundant measures of formality, FORM1 and FORM2.](image)

Figure 2. Scatter plot of two redundant measures of formality, FORM1 and FORM2.

The Pearson correlation coefficient for the bivariate relationship shown in Figure 2 was 0.86 at the 1% significance level (Spearman rank correlation coefficient of 0.76, p< 0.001). The correlation of the redundant measure with our variable FORM is strong and positive, hence both scales were apparently measuring the same underlying construct. Similarly, for our variable INNOV, we introduced a self assessment of the degree of innovativeness exhibited by each institution. A bivariate plot (Figure 3) for these two measures of innovation (i.e., the index calculated through the Roberts-Meyer methodology and the self evaluation of the executives) also exhibits a strong and positive relationship. The Pearson correlation coefficient for this bi-variate relationship is equal to 0.84
(p<0.001) and the Spearman-rank correlation coefficient is equal to 0.82 (p<0.001). Both measures are measuring the same underlying construct.

![Figure 3. Scatterplot of two redundant measures of innovation.](image)

Once comfortable with our measures, univariate statistics were determined to gain a preliminary understanding of the different dimensions of information at our disposal. Table 2 shows a summary of descriptive statistics for all variables of interest. In this table we have included measures of organizational size (number of employees, total assets, # of branches) to obtain better insights into emergent relationships and organizational patterns.

Table 2. Descriptive statistics for all variables in the dataset of organizational factors and innovation in financial services.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>s.d.</th>
<th>min.</th>
<th>max.</th>
<th>Normality*</th>
</tr>
</thead>
<tbody>
<tr>
<td>N_EMPLOY</td>
<td>536.4</td>
<td>975.1</td>
<td>35</td>
<td>3200</td>
<td>No</td>
</tr>
<tr>
<td>TOT_ASSET</td>
<td>39.7</td>
<td>77.9</td>
<td>0.64</td>
<td>306.8</td>
<td>No</td>
</tr>
<tr>
<td>#BRANCH</td>
<td>14.98</td>
<td>34.1</td>
<td>0</td>
<td>125</td>
<td>No</td>
</tr>
<tr>
<td>FORM</td>
<td>4.94</td>
<td>1.73</td>
<td>1.80</td>
<td>7</td>
<td>Yes</td>
</tr>
<tr>
<td>PDO</td>
<td>4.81</td>
<td>1.39</td>
<td>1.71</td>
<td>6.6</td>
<td>Yes</td>
</tr>
<tr>
<td>INNOV</td>
<td>224.7</td>
<td>12.4</td>
<td>199.8</td>
<td>242.5</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*Normality is assessed through Kolmogorov-Smirnov tests, p-value<0.05
Numbers for TOTASSET are in millions of monetary units.
Table 2 presents a large range of values for all variables related to size (NEMPLOY, TOTASSET, #BRANCH), with a few institutions which are notably larger than the rest. The wide variability in the #BRANCH variable suggests that some institutions have wider geographical coverage than others. Presuming that size implies more systems and formal procedures, the presence of large institutions suggests a few institutions that notably depart from the rest in the variable FORM. This is, however, not the case. Inspection of frequency plots for this variable reveals the presence of a slightly bimodal distribution with a larger count of observations in the protuberance associated with larger values of FORM (see Figure 4). This suggests that some small institutions have developed and have systems and procedures in place that are similar to those of larger institutions.

![Figure 4. Histogram of FORM.](image)

The distribution observed in Figure 4 also suggests the presence of a fairly large number of institutions that either score high or low on FORM. This could signal that firms are clustered into distinct categories. Moreover, this distribution signals the possible
presence of non-linearity, hence requiring carefulness when applying any statistical tests that assume linearity.

The measure of innovation in Table 2, INNOV, reveals a fairly large variance. This suggests that firms in the sample apparently have different arrays of products, that is, some firms are very focused and dedicated to particular market segments with a reduced set of products, and others attack several market segments with a more extended assortment of products.

Before conducting any further analysis, all variables were plotted against each other to detect any emergent relationship and to check for linearity. Inspection of the scatterplots revealed the presence of non-linearity in several bi-variate relationships. This was particularly true for all variables involving size, denoting the presence of some scale effects. The bi-variate relationships between INNOV and all measures of organizational characteristics do exhibit curvilineairties (see for example Figure 5).

![Scatter plot of INNOV* versus FORM.](image)

Figure 5. Scatter plot of INNOV* versus FORM.
To further examine the nature of these emergent relationships, a correlation matrix was computed. Because of the detected curvilinearities, and the non-normalities (in the case of the size measures) we noted in the descriptive statistics section, Spearman-rank correlation coefficients were used to construct the correlation matrix. Table 3 presents the Spearman-rank correlations for the variables under study. Our measure INNOV exhibits a negative correlation because the chi-square value computed becomes smaller for firms with larger arrays of products. To avoid confusion we included the accessory variable INNOV* (= 1/INNOV).

Inspection of the correlation matrix suggests that all variables that are being used to measure size are intercorrelated. This is not true for the measure of total assets and number of branches, suggesting that there are institutions which are large but operate in a limited geographic area or vice versa. This, in turn, suggest different strategic approaches to conducting the business. Notice that measures of formality do not present very high correlations with measures of size. This indicates that some small institutions may have a high degree of formality.

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>2</td>
<td>0.79***</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.79**</td>
<td>0.32</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
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<td>0.26</td>
<td>0.58*</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.12</td>
<td>0.15</td>
<td>-0.03</td>
<td>0.18</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>-0.74***</td>
<td>-0.80***</td>
<td>-0.67*</td>
<td>-0.48*</td>
<td>-0.21</td>
<td>1.00</td>
</tr>
<tr>
<td>7</td>
<td>0.74***</td>
<td>0.80***</td>
<td>0.67*</td>
<td>0.48*</td>
<td>0.21</td>
<td>-1.00</td>
</tr>
</tbody>
</table>

*** = p<0.001, ** = p<0.01, * = p<0.05, ~ = p<0.1
1=NEMPLOY, 2=TASSET, 3=#BRANCH, 4=FORM, 5=PDO, 6=INNC, 7=INNOV*
Inspection of the scatterplot of INNOV* against FORM, as depicted in Figure 5, reveals a curvilinear relationship between the variables. The polynomial line fitted to the data shows the presence of a non-linear, non-monotonic relationship between INNOV* and FORM. To confirm this apparent non-linearity, we performed recursive linear fits. Starting with the first quartile and performing one-step increments in the number of observations, we calculated least-squares trend lines for all partial data-sets. In Figure 6 we have plotted the results for three of these fits and included a least-squares trend line to observe the evolution of the slope of the resulting curve.

![Figure 6. Linear fits for first 6 observations, first 8 observations, and complete data set.](image)

It can be seen that the slope of the curve appears to be negative for the first 6 observations. It remains negative through part of the range of the independent variable and then it becomes positive as more observations are added. In Figure 7 we have overlaid all one-step incremental fits and plotted least-squares trend lines. This figure clearly shows that the slope of the linear fits change sign, going from negative to positive, thus indicating the presence of a concave non-linearity.
Figure 7. Recursive linear fits for sub data sets with one-step increments.

A Durbin-Watson Value of 1.39, calculated through a bivariate linear regression of INNOV* against FORM did not permit us to reject the possibility of residuals being autocorrelated (at the 5% level, lower limit for rejecting the possibility of autocorrelation is 1.257 and the upper limit for accepting such occurrence is 1.437). Though the DW test is used only to detect autocorrelation, such occurrence could also indicate non-linearity. Therefore, to further look into this apparent curvilinearity, we performed a non-linear regression in an attempt to develop a model to describe the observed relationship, and thus check whether such non-linearity had an important impact. We fitted a polynomial of the second degree with the form:

\[ Y = A + BX + CX^2 + \varepsilon \]

Table 4 presents summary results of parameter estimates and pseudo-R-squared statistics for the non-linear model. The polynomial model seems to perform a better job in describing the relationship at hand than a simpler linear model. The small values of the parameter associated with the quadratic portion of the model suggest that by introducing this term a correction is made with the linear portion of the model thus improving the R-
square statistic (from 0.16 to 0.22). Hence, we thought it necessary to transform the independent variable FORM in order to restore linearity to this relationship.

<table>
<thead>
<tr>
<th>Model</th>
<th>Dep. var.</th>
<th>Parameter</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>R²(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Estimate</td>
<td>S. E.^</td>
<td>Estimate</td>
<td>S. E.^</td>
<td>Estimate</td>
</tr>
<tr>
<td>1</td>
<td>INNOV*</td>
<td>4.81</td>
<td>2.54</td>
<td>-1.08</td>
<td>1.27</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* PSEUDO-R-SQ. ^Asymptotic standard error

Using Tukey's ladder of transformations we presumed that power functions of the independent variable FORM would be adequate for this case. We, nevertheless, tried several possibilities, but it was apparent that power functions of the independent variable were the most adequate transformations to induce linearity in the relationship. By fitting nonlinear regression models we observed that the quadratic term of the fitted second degree polynomial would tend to zero (thus leaving a linear form) when FORM was raised to approximately the 3.75 power. This was confirmed through visual inspection. In Figure 8 we have re-plotted INNOV* against the transformed version of FORM (hereupon named FORM*). A least-squares trend line and a polynomial fit of the second degree are superimposed on the model. It can be seen that both lines are practically indistinguishable, thus indicating that, for our purposes, a satisfactory transformation had been attained.
Figure 8. Scatter plot of transformed version of FORM (FORM*) versus the dependent variable INNOV.

Once comfortable with the independent variable FORM*, we performed a similar analysis with the independent variable PDO. Figure 9 is a scatterplot of this variable against the dependent variable INNOV* with a least-squares trend line and a polynomial line of the second degree overlaid on it. We performed a partial regression of INNOV* against PDO and obtained a Durbin-Watson statistic of 1.63, indicating that the residuals were not autocorrelated (critical value at the 5% significance level = 1.437). To check this result we fitted a non-linear quadratic function to this relationship. Although the Beta coefficient of the quadratic term was small, we noticed an important relative increment in the fit through the addition of the quadratic term. The pseudo R-square statistic for the non-linear fit was equal to 4.00% while its value for a simple linear function was 3.34%. The addition of the quadratic term improves the R-square by 0.66%, which is not negligible if compared to the original value (i.e., improves the R-squared value by 19.7%).
We again found, using Tukey's ladder of transformations that power functions adequately restored linearity to this relationship. To find the optimum point we graphically estimated the point at which the value of the Beta coefficient of the quadratic term became zero (thus leaving a linear functional form). Such estimation can be observed in Figure 10. This figure shows that at around 1.87 the coefficient of the quadratic goes to zero and then changes sign (i.e. becomes convex), rendering a good approximation of the power transformation that was required.
As a result of these analyses we decided to utilize a transformed version of our original independent variable PDO. The transformed version of this variable was termed PDO*. Figure 11 is a plot of PDO* versus the independent variable INNOV. We can see, through the overlaid trend and polynomial lines (which are indistinguishable from each other), that linearity has been attained through this transformation.

![Scatterplot of PDO* (the transformed version of PDO) and INNOV*](image)

**Figure 11. Scatterplot of PDO* (the transformed version of PDO) and INNOV*.**

Finally, we noticed an interaction between our two independent variables, manifested through a convex curvilinear relationship. As Figure 12 shows, firms with differentiated capabilities for developing new products tend to attain intermediate scores on the variable FORM. The observed relationship urged us to include this interaction into our model, given that the main effects may not be manifesting themselves entirely through their additive terms.
We therefore created an interaction term PDO_FORM by multiplying the variables FORM* and PDO*. In multiplying these two variables very large numbers are obtained, and, therefore, very small Beta coefficients are likely to happen. We quickly checked for linearity (using a similar methodology to the one we used for the independent variables PDO and FORM). Figure 13 is a scatterplot of the interaction term against the independent variable INNOV*. We can see that both the polynomial fit and the linear fit are straight lines. The coefficient of the quadratic term in the polynomial line is negative and very small (hence the curve is slightly convex), but we found, using a variety of tests, that no functional transformation appeared to be necessary.
Figure 13. Scatterplot of PDO_FORM vs. INNOV*.

Once we were comfortable with the variables to analyze, we estimated Pearson correlation coefficients to examine emergent bi-variate relationships. Table 5 shows that FORM* is positively correlated to INNOV*, possibly indicating that larger arrays of product offerings aimed at different markets are found among institutions which are highly formal. As expected from studying the bivariate scatterplots, PDO* presents positive correlation coefficients with respect to INNOV*, though not significant. This could indicate that the existence of differentiated intrafirm functions to develop new products is not correlated with innovation. The interaction term, however, is positively correlated to both independent variables and to the dependent variable INNOV*, thus indicating that the main effect of PDO* is not specified through its additive term but through an interaction with the other independent variable.
Table 5. Pearson correlation coefficients for variables of interest.

<table>
<thead>
<tr>
<th></th>
<th>INNOV*</th>
<th>FORM*</th>
<th>PDO*</th>
</tr>
</thead>
<tbody>
<tr>
<td>INNOV*</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FORM*</td>
<td>0.48*</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>PDO*</td>
<td>0.19</td>
<td>0.13</td>
<td>1.00</td>
</tr>
<tr>
<td>PDO_FORM</td>
<td>0.45***</td>
<td>0.73***</td>
<td>0.66***</td>
</tr>
</tbody>
</table>

***p<0.001, *p<0.05

Following these analyses we decided to use PDO* as our question predictor and FORM* as a control. We built a sequence of nested models, starting with our baseline (INNOV* regressed against PDO*) and subsequently adding the control and interaction variables (FORM* and PDO_FORM). Table 6 summarizes these results. Notice that the Beta coefficients are small. We had anticipated such small numbers would occur as a result of the large magnitudes of the independent variables after transformation.

Table 6. Results of regression analyses.

<table>
<thead>
<tr>
<th>Model</th>
<th>Intercept</th>
<th>PDO*</th>
<th>FORM*</th>
<th>PDO_FORM*</th>
<th>R-sq (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.39***</td>
<td>4.84E-3</td>
<td></td>
<td></td>
<td>3.8</td>
</tr>
<tr>
<td>2</td>
<td>4.26***</td>
<td>3.34E-3</td>
<td>2.21E-4*</td>
<td></td>
<td>24.8</td>
</tr>
<tr>
<td>3</td>
<td>4.29***</td>
<td>1.57E-3</td>
<td>1.82E-4</td>
<td>2.71E-6</td>
<td>25.0</td>
</tr>
</tbody>
</table>

***p<0.001, *p<0.05

We then inspected influence statistics to uncover possible perturbations caused by atypical data points. Figure 14 is a scatter plot of influence statistics Hat diagonal and Cook's D. We notice that observation number 23 appears to have an unduly large effect on our final fit.
Figure 14. **Plot of influence statistics, Hat Diagonal vs. Cook’s D.**

We reran the model without this observation and did observe an important change in the magnitudes of the Beta coefficients. We therefore decided to leave this observation out and chose the model shown in Table 7.

<table>
<thead>
<tr>
<th>Model</th>
<th>Intercept</th>
<th>PDO*</th>
<th>FORM*</th>
<th>PDO<em>_FORM</em></th>
<th>R-sq (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Final</td>
<td>4.29***</td>
<td>9.07E-4</td>
<td>1.26E-4</td>
<td>5.58E-6</td>
<td>25.1</td>
</tr>
</tbody>
</table>

***p<0.001, *p<0.05

The model was "untransformed" to facilitate interpretation. The model, after substitution of the corresponding untransformed variables, is as follows:

\[
\text{INNOV} = I + \beta_1 \text{PDO}^{1.87} + \beta_2 \text{FORM}^{3.75} + \beta_3 \text{PDO}^{1.87} \text{FORM}^{3.75} + \varepsilon
\]

where \(I\) denotes the intercept and the \(\beta\)s are the beta coefficients indicated in Table 7. This model was chosen as the basis for our discussion. Assumptions about normality of
the residuals were revised through the normal probability plot. We found some evidence of heteroscedasticity when inspecting diverse plots of residuals versus our independent variables. The plot of residuals versus the predicted values shows that variance is not homogeneous throughout. The normal probability plot confirms this by showing a departure from normality at the lower end of the residual distribution (see Figure 15). Although slight departures from the normality assumption may not appreciably alter our inferences, we were concerned with such departures because of the small size of our data set, and thus we prefer to treat our results cautiously. We tested for the presence of autocorrelated disturbances using the Durbin-Watson statistic and found no evidence of such occurrence. Multicollinearity (determined using tolerance statistics) did not appear to be a problem. In all we found that more robust estimations were difficult to achieve because of the small size of our data set. However, we must note that the observations included in the set represented 82% of all banks operating in this economy.

Figure 15. Normal Probability Plot and plot of residuals versus predicted for final model.
Summary and Discussion

We wanted to assess the effect of some organizational factors on innovation in financial services. Hence, we established a baseline model in which INNOV, the degree to which firms in the sample innovated, was regressed on PDO (the degree to which these firms had developed an orientation for developing new products) and firm flexibility, using as a proxy a formality measure (FORM). The goal was to establish whether different organizational arrangements were more or less conducive to innovative activities. We found that the baseline model explained little of the variability observed in our dependent variable INNOV. However, when the variable FORM was introduced into the model and, particularly, when the interaction between FORM and PDO was introduced, we obtained a model which explained approximately 25% of the observed variability in the dependent variable.

Figure 16. INNOV vs. FORM for various levels of PDO.
Figure 16 is a visual display of the final model in which our dependent variable INNOV is plotted against FORM for different levels of PDO. Although our findings appear to indicate that formal firms with a product development orientation seem to have larger product arrays aimed at different markets, we cannot make any normative assertion to this respect. We had expected that very flexible firms would also exhibit a high degree of innovativeness, perhaps in spite of not having well-defined product development orientation. Such was not the case. We also thought that having an orientation toward product development would, per se, result in higher degrees of innovativeness. This was not the case either. Such effects appear to reveal themselves more strongly through the interaction with our formality measure. We can only claim, with the data at hand, that there appears to be some variability, which makes us believe that in fact some organizational characteristics do have an effect upon innovation. Results, however, are not entirely compelling for the following reasons:

1) The theoretical frameworks do not seem to provide an adequate backdrop to understand what goes on in these banks. Although these frameworks have been widely used in describing organizational characteristics associated with innovation and management in many areas\(^1\), the predictive power of the framework appears to be weak in our setting. The framework is adequate in perhaps explaining arrangements at the

\(^1\) For instance the management of information resources (Nosek, 1989); the understanding of strategic management of small firms in different environments (Covin and Slevin, 1989); public accounting firms (Zanzi, 1987); R&D efficiency (Link and Zmud, 1986); the management of end-user computing (Brown and Bostrom, 1994); the effects of downsizing (Finne, 1991); the relationship between strategy formation patterns and sales growth rates (Slevin and Covin, 1997); etc.
organizational level associated with products that require few variations and
customization, but probably fails when explaining tailor-made products. Our simplistic
measures at the organizational level might be suitable for explaining differences observed
in, for instance, retail products; but they may not be so useful when applied to, for
instance, corporate products, simply because the latter case could require a more direct
customer connection. Our data do not permit to draw such distinctions.

2) Although helpful at the level of the organization, our study seems to point to
the need of evaluating product development practices at a functional level. Use of
alternative frameworks, like proximity to the customer, the importance of lead users (von
Hippel, 1988), the sources of innovations (von Hippel, 1988), and the variations that
occur in the functional sources of innovation and associated structural arrangements for
each of the cells in the client-product matrix might render better insights and would be an
interesting path to follow in further research. Such alternative theoretical schemes could
perhaps be more tightly related to performance, controlling for type of product.

3) Our results have a high error. There are many other variables that might be
affecting the hypothesized relationship. Many of these intervening variables cannot be
controlled for with the data at hand. In particular, we are not measuring resources
available. Organizational structure should mediate the relationship between resources
deployed and innovation. Firms’ resource allocation levels will clearly be correlated with
productivity, and such relationship will be mediated by the organizational arrangements
chosen by firms to develop new products. Should we be able to determine data on
resource allocation, normative conclusions could be drawn with respect to which organizational arrangements seem to work better, not only in terms of products developed, but in terms of products developed for given levels of resources. Such path is clearly an interesting one to follow in further research.

4) Our results are statistically weak. Excluding from consideration the obvious weakness of having such small number of data points, we can clearly see that constructs, despite being fairly common and relatively simple, did not provide enough granularity for more detailed and enlightening analyses. We need to refine and develop more precise constructs for studying the effects of organization on innovation in financial services. Further research could use an inductive approach. Case studies are the needed vehicle for developing such constructs with a grounded theory approach.

In all, the results are useful in bringing concepts forward to the study of structural arrangements associated with financial innovations. Such results are in line with a few studies that report similar findings. Reidenbach et al. (1986), for instance, explored new product development practices in retail banks and found that the existence of a formalized development process was positively correlated with bank performance. Average and below-average performing banks tended to have less structured new product development processes. Iwamura and Jog (1991), for a sample of 86 investment houses, found that the degrees of centralization and formalization were significantly higher for firms categorized as innovators than for non-innovators. In our study we found some variance that points to
similar outcomes, but our results are hard to confirm due to the drawbacks of extant theory, measures chosen, and availability of data.

A more detailed look is needed of product development activities themselves, particularly the activities that precede the development of a product (such as emergence of ideas, roles needed for bringing ideas forward, and the prominence such roles acquire at different points in time). Aside from understanding organizational level effects upon innovation, we should also take a more detailed look into product development processes at the functional level and to identify the most important variables that them within financial service firms. An ample literature on the management of innovation is available to theoretically ground such effort. The studies of Marquis (1969), Roberts and Frohman (1978), Roberts (1988), and others refined and developed exact definitions of many product development mechanisms, which could provide a useful starting point for the understanding of the emergent R&D function within financial services firms.

As corollaries, differential effects of alternative organizational forms can be conceptualized as influencing innovation and performance in terms of their effect upon the strategy of the firm (Burgelman, 1983). Lacking strategic intent may render innovation efforts useless. For instance, a firm's subunit may generate a multitude of new products, but such products may not have any inter relation among themselves in the context of the company's strategic pursuits². Quinn (1986) and Maidique and Hayes (1984) have shown

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²Easingwood and Storey (1993) for instance, analyzed 78 financial products in the UK and found that Internal Synergy, defined as the degree to which new products extended or complemented the firms product line and fitted with the delivery system of the organization accounted for over 25% of the observed variability in product performance.
that strategic planning and thinking are important ingredients of the innovative firm in ways which move further into actively managing the alternative periods of chaos versus continuity that innovation implies (Roberts, 1988). If R&D works in isolation, firms may not take full advantage of possible synergy that may emerge from its association with business activities and strategic objectives (Spencer and Triant, 1989). Strategy can serve to integrate several aspects of the organization in order to gain advantage from innovation (Shrivastava and Souder, 1987). Here, further research could add to our overall framework by exploring the interaction of organization and strategy on innovation. Such an investigation should include the effects of managerial profiles and marketing and technological inputs upon innovation activities.

Finally, an interesting ramification would be to look at the possibility of both organic and mechanistic types coexisting within firms and, although processes might be initiated in a typical organic fashion, they are implemented in a mechanistic way (Spender and Kessler, 1995).

Our observed results and the above suggestions need further and more thorough assessment with larger samples of data over longer periods of time.
References


Appendix 1

Scale 1 for FORM1.
Seven point scales for the following items: 1) The organization has a large number of rules and written procedures; 2) In my organization there are manuals that specify procedures; 3) There are written job descriptions for most positions in the organization; 4) There are written performance indicators for the people who work in this company; 5) There is a formal orientation program for individuals who are new to the organization.

Scale 2 (redundant measure of formality) for FORM2:
Five-point scales for the following items in answer to: In my organization the following documents exist, are formally written and are well-known by employees: 1) Formal job contracts; 2) Information brochures for employees; 3) Organizational chart; 4) Written operating instructions; 5) Formal job descriptions; 6) Manuals of procedures; 7) Policy manuals; 8) Research reports.

Scale 3 (to measure degree of product development orientation) for PDO.
Seven-point scale for the following items: 1) The organization has assigned somebody the task of investigating, evaluating and developing new products; 2) When a new product is developed, the company develops a formal design and a business plan; 3) New product performance is formally evaluated; 4) We have performance indicators that permit determining how new products are doing; 5) The person assigned to develop new products is a top level manager.
Appendix 2

Calculation of the indices is as follows:

We compare with a hypothetical, highly unfocused, bank with many products in each cell of the matrix. In this case we set this number, arbitrarily, to 30. In general if we labeled matrices as shown in Figure Ap2-1, we would have:

![Client-Product matrices for given bank and for hypothetical comparison base.]

We calculate Chi-square as follows

\[ \chi^2 = \sum_{c=1}^{3} \sum_{p=1}^{3} \frac{(Ncp - ecp)^2}{ecp} \]

Hence,

\[ \chi^2 = \frac{(a_{11} - e_{11})^2}{e_{11}} + \frac{(a_{12} - e_{12})^2}{e_{12}} + \ldots + \frac{(a_{33} - e_{33})^2}{e_{33}} \]

An example of these matrices is shown in Figures Ap2-2 and Ap2-3. Figure Ap2-2 depicts the client product matrix of a small bank which is apparently concentrated in the corporate segment, and Figure Ap2-2 shows a matrix of a bank which provides more services to all three market segments in the c-p matrix.
Following the above formulae we obtain a Chi-sq. of 242.5 for the c-p matrix of Figure Ap2-2 and a Chi-sq. equal to 211.97 for the c-p matrix in Figure Ap2-3.

Given that we had longitudinal data (i.e., bank product histories over time), we compared rates of change in the observed chi-squared values at different times. These rates of change were highly correlated to the value of the most recent c-p matrix, hence we used this value as our measure.
Chapter 4

Modeling the Diffusion of Financial Innovations
The purpose of this chapter is to study patterns of diffusion of financial innovations. In particular, we are concerned with developing a model to explain and predict the adoption of a financial innovation by producers and users within one country. Such a model could be a useful tool for financial product developers to determine sales volumes that could be expected over time, and to estimate the number of competitors likely to enter markets for new products. In order to assess such diffusion patterns, we utilize and extend diffusion models and the diffusion modeling methodology proposed by Mansfield (1961), Bass (1969), especially Mahajan and Schoeman (1977), and others.

Although diffusion models have been widely used for industrial and consumer products, they have been seldom used for financial services. Molyneux and Shamroukh (1996: 505) point out that the strategic aspects of innovation adoption by banks need to be included into our general understanding of financial innovation because "...the decision to adopt a new financial product by one bank and the timing of adoption are likely to have an impact on other banks' adoption decisions."

Moreover, these models are largely based on the existence within populations of potential adopters of "innovators" and "imitators" which, in the first case, acquire products influenced by external sources of information and, in the second instance, adopt products influenced by previous adopters. Thus, fundamentally, the dynamics of most diffusion models are driven by the intrinsic characteristics of individuals within given populations of potential adopters. The effects of user adoption dynamics upon producer adoption dynamics are rarely considered. Clark and Staunton (1989: 125) indicate that such linkage must be established more clearly in diffusion modeling because one should expect that profit expectations, as seen through the lens of demand growth or decay, are the key motives for producers to adopt a given practice:
Particular attention needs to be given to examining the variability of the supply side and to the consequences for the diffusion process. For example, the case study of the fast-food sector indicated that McDonald's undertook much of the development of the innovations in technology and organization within the firm, and that example poses the issue of the relations between users and suppliers. Economists have emphasized the significance to the supply side of future expectations of profits and of the role of profits in creating "corridors" down which innovations are likely to flow (Metcalf, 1981). Moreover, the supply side takes widely-varying forms. One particular form which is briefly noted is the tendency for the supplier to benefit from the learning experiences of the users.

Freeman (1995: 481), in a recent and comprehensive review of the literature on technological innovation, addresses the same issue and criticizes diffusion theory for overlooking user-producer interactions:

One of the major problems in diffusion research is to take into account the supply side as well as the demand side. As Gibbons and Metcalfe (1986) particularly show, the interaction between supply and demand results in the evolution both of new and improved products and of new design configurations. Although empirical research has amply demonstrated the role of suppliers in improving the product, diversifying new models, enlarging the market, promoting applications research, training potential users, and coping with institutional barriers, much diffusion research (despite the good advice of Metcalfe, 1988 and other researchers) continues to neglect the supply side and treat diffusion as a demand phenomenon.

Many diffusion theorists have recognized this weakness also. Mahajan et al. (1990) stress the need to incorporate explicitly product growth rates into models of diffusion among producers. In a recent review of diffusion modeling in marketing these authors make reference to the Bass' (1969) model (which is one of the most frequently cited diffusion models in the marketing literature) and posit questions as suggestions for further research (Mahajan et al., 1990: 21):

How do the number of competitors and the rivalry among them influence the growth of a product category? Does the growth affect the entry/exit patterns of
competitors? Answers to these questions are within the domain of the diffusion modeling framework and provide a linkage with the strategic planning literature. Theoretical and empirical work on these questions will enhance the utility of diffusion models.

In financial services it is extremely important to establish such user-producer interrelationships because products are very easy to imitate. Thus, transient monopolies are not allowed to innovators by virtue of product complexity or legal protection, but by pioneering advantages. It is possible that a bandwagon of producers, uninhibited by cost or complexity considerations (as would if imitating industrial products), will enter the market when demand starts rising. Various factors affect rates of adoption. First, many innovations require changes in laws and regulation to take place. These changes in regulation relax constraints and allow firms to enter new markets. Second, technical complexity and firm level capability required to bring about many innovations are often small. Thus, imitation by producers is easy. Third, the decision to adopt by a user often imposes little or no burden upon the customer, and, as a result, attributes associated with many financial innovations suggest rapid diffusion rates and an almost unimpaired reciprocal transfer of information between producers and users. These factors result in small barriers to entry and imply that diffusion curves would exhibit high imitation rates both among users and among producers, and that there should be system interdependencies much more readily observable. therefore, it doesn’t seem realistic just to look either at suppliers or users in financial innovation. It is, apparently, more sensible to attempt developing models that relate users and producers directly.

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1 The five attributes of innovations that regulate diffusion rates are (Rogers, 1971): 1) The relative advantage of the product with respect to extant practice, 2) Compatibility, 3) Complexity, 4) Trialability, and 5) Observability. In many financial innovations many of these attributes tend to favor a rapid diffusion rate. In addition, many decisions to adopt are individual, influenced through mass media, and promoted, directly or indirectly, by regulatory changes.
To shed some light into these issues, in what follows we first review pertinent literature and develop a mathematical model. The model is tested in a subsequent section where we find that it has good descriptive capabilities and also provides reasonable parameters to estimate a user diffusion curve. At the end we summarize and conclude.

**Literature review and model development.**

Diffusion models are generally based upon the premise that an innovation is a piece of information that spreads within social groups. Such phenomenon can be represented using mathematical functions (like, for instance, the logistic growth curve (Griliches, 1957)). Mansfield (1961) proposed a method to explain such diffusion patterns in terms of a deterministic model where the equation for the cumulative proportion of total adopters has the form:

\[
(*) \quad F(t) = \frac{\exp[bt + c_0]}{b + \exp[bt + c_0]}
\]

This model presumes that diffusion will be primarily an imitation phenomenon, and that the rate of imitation is governed by only one parameter (parameter b in equation *). This model has shown good descriptive capabilities when tested with data from industrial and administrative innovations (Mansfield, 1961; Teece, 1980).

Later, Bass (1967) introduced a model which explains diffusion not only in terms of the rate of imitation among adopters but also innovation. That is, an innovation will be initially adopted by entities (within a given social group) which are influenced by external signals and, subsequently, by adopters who imitate other adopters. Bass' model subsumes Mansfield's one. It contains two parameters in which one, a in equation **, governs the
rate of "innovation", and the other, b in the same equation, governs the rate of imitation (in a manner analogous to Mansfield's model).

\[
F(t) = \frac{\overline{F}(1 - \exp[-(a+k)t])}{1 + \frac{k}{a} \exp[-(a+k)t]} \quad \text{where } b = \frac{k}{\overline{F}}
\]

\(k\) is a constant.

Mahajan and Schoeman (1977) have suggested a fundamental diffusion model to represent time patterns of diffusion processes. In their model the rate of diffusion is directly proportional to the proportion of potential adopters available at that time. Or (Mahajan and Schoeman, 1977:13), "...in other words, as the cumulative proportion of adopters approaches its ceiling, say \(\overline{F}\), the rate of diffusion decreases proportionately.". The authors express such situation as follows.

\[
f(t) = \frac{dF(t)}{dt} \propto (\overline{F} - F(t))
\]

Where:

\(F(t)\) = cumulative proportion of adopters at time \(t\),
\(\overline{F}\) = ceiling on the cumulative proportion of adopters,
\(f(t)\) = proportion of adopters at time \(t\).\(^2\)

\(^2\)Notice that \(F(t)\) is the cumulative sum of entrants at time \(t\), i.e.,

\[F(t) = \sum f(t)\]

hence,

\[f(t) = \frac{dF(t)}{dt}\]
in other words, the rate of change of the cumulative proportion of adopters with respect to time is proportional to the remaining potential adopters. Thus, the constant of proportionality provides us with an equality. Such "constant" is a function of time:

\[
\frac{dF(t)}{dt} = g(t) \left( \bar{F} - F(t) \right)
\]

Different authors provide different specifications for this diffusion coefficient \(g(t)\). As Mahajan and Peterson (1978) indicate, some specify it as a function of time (Dobb, 1956) but most authors represent \(g(t)\) as a function of the number of previous adopters (e.g. Fourt et al., 1960; Mahajan and Haynes, 1977). This means that \(g(t)\) is a function (usually linear for parsimony) of \(I'(t)\):

\[
g(t) = a + b \cdot I'(t)
\]

where \(a\) and \(b\) are positive constants. From here it is possible to obtain a basic formula to represent diffusion patterns as generally portrayed in many diffusion studies. This formula is given by Mahajan and Schoeman (1977) as:

\[
\frac{dF(t)}{dt} = \left( a + bF(t) \right) \cdot \left( \bar{F} - F(t) \right)
\]

From this expression we get an equation for the cumulative proportion of adopters at time \(t\) (Mahajan and Schoeman, 1977):
\[
F(t) = \frac{\bar{F} - \frac{a(\bar{F} - F_0)}{(a + bF_0)} \exp\left[-(a + b\bar{F})(t - t_0)\right]}{1 + \frac{b(\bar{F} - F_0)}{(a + b\bar{F}_0)} \exp\left[-(a + b\bar{F})(t - t_0)\right]}
\]

(5)

Using different sets of assumptions it is now possible to derive a variety of models commonly used in the diffusion literature like Mansfield's imitation model and Bass' model (Mahajan and Schoeman, 1977). For example, Mansfield's model is derived by setting \(a = 0\), that is basing diffusion solely on imitation\(^3\) to obtain:

\[
F(t) = \frac{\exp\left[bt + c_0\right]}{b + \exp\left[bt + c_0\right]}
\]

(6)

which is the equation used by Mansfield (1961).

**Proposed model**

The above models are based on the premise that the "constant" of proportionality is a function of the number of previous adopters (producers or users, but not both). For instance, banks that adopt a particular practice, say credit cards, would do so either as innovators (pioneers) or imitating other banks which have entered the market, but not responding to changes in the number of credit card users. In contrast, in order to start exploring the interrelationships of producer adoption with user adoption, we will assume here that \(g(t)\) is a function of the number of users, and, thus, the rate of adoption among

---

\(^3\)Mansfield (1961) explored the rate of imitation in technical change.
producers will be influenced not only by imitation and innovation but by the rate to which the product is adopted downstream by its users. Thus, if we let \( H(t) \) be the cumulative proportion of users adopting the product at time \( t \), our basic equation becomes:

\[
\frac{dF(t)}{dt} = (a + bH(t)) \cdot \left[ F - F(t) \right]
\]  

As we mentioned before, Mahajan and Schoeman have derived a generalized form for \( H(t) \). Hence, \( H(t) \) is (Mahajan and Schoeman, 1977):

\[
H(t) = \frac{-c(H - H_0)}{H - \frac{c}{c + dH_0}} \exp\left[-(c + dH)(t - t_0)\right]
\]  

Where

\( H_0 = H(t = t_0) \)

\( c = \text{index of uninfluenced user adoption} \)

\( d = \text{index of influenced user adoption} \).

Using this generalized form for \( H(t) \) we will assume that the number of producers who enter the market is influenced by the number of users who adopt the product over
time. The number of adoptions by users, however, is not influenced by the number of producers\textsuperscript{4}, but by the rate of user innovation and imitation.

Thus we obtain:

\[
\frac{dF(t)}{dt} = \left\{ \begin{array}{l}
a + b \\
\frac{\frac{\bar{H} - H}{0} - \frac{c + d H}{0}}{1} \exp\left[ -\frac{c + d H}{0}(t - t_0) \right]
\end{array} \right\} \left( F - F(t) \right)
\]

From here we use elementary integration to derive an expression for \( F(t) \) (See Appendix 1 for details):

\[
F(t) = \bar{F} - 1 \cdot \exp\left\{ \begin{array}{l}
\frac{b + \bar{H}}{c + d H} \ln\left\{ \exp\left[ -\frac{c + d H}{0}(t - t_0) \right] + \frac{d}{0} \left( H - H_0 \right) \right\}
\end{array} \right\} - \\
\frac{bc}{d(c + d H)} \ln\left\{ 1 + \frac{d}{0} \left( H - H_0 \right) \exp\left[ -\frac{c + d H}{0}(t - t_0) \right] \right\} - \\
\frac{b}{d} \ln\left\{ 1 + \frac{d}{0} \left( H - H_0 \right) \right\} - \ln(F - F_0)
\]

\textsuperscript{4}Jain et al. (1991) developed a generalized model with supply restrictions. Their model, however, introduces supply restrictions by splitting the user diffusion curve into two stages. Thus, in the first stage products "diffuse" into a pool of waiting applicants and, in a second stage, become adopters. With this time delay forced by the inventory of waiting applicants, the authors are able to depict user diffusion curves under supply restrictions quite accurately.
This expression can be simplified. In doing so, however, we also want to reexpress it in terms of absolute cumulative number of adopters and not in terms of proportions of adopters (as it currently stands). Thus, if we define for the producers:

\[ P(t) = \text{Cumulative number of adopters as a function of time} \]
\[ M = \text{Total potential number of adopters and,} \]
\[ \overline{P} = \text{Ceiling on the number of producers adopting the product or process.} \]
\[ P_0 = P(t = t_0) \]

Then,

\[ F(t) = \frac{P(t)}{M}, \quad \overline{F} = \frac{\overline{P}}{M}, \quad F_0 = \frac{P_0}{M} \]

In words, the cumulative proportion of adopters at time \( t \) is going to be equal to the total number of adopters at time \( t \) divided by the total potential number of adopters. The ceiling on the proportion of adopters (i.e., the expected proportion of all potential adopters to adopt) will be equal to the ceiling on the total number of adopters divided by the total potential number of adopters.

Similarly, for the users of the product (produced by the producers), we define

\[ U(t) = \text{Cumulative number of users adopting the product at time } t \]
\[ N = \text{Total number of potential users} \]
\[ \overline{H} = \text{Ceiling on the number of users.} \]
\[ H_0 = H(t = t_0) \]

Then,
\[ H(t) = \frac{U(t)}{N}, \quad \bar{H} = \frac{\bar{U}}{N}, \quad F_0 = \frac{U_0}{N} \]

Substituting these expressions into (10) we get:

\[
\left\{
\begin{aligned}
& a \left( t - t_0 \right) + \frac{b \bar{U}}{N \left( c + d \frac{\bar{U}}{N} \right)} \ln \left[ \exp \left[ \left( c + d \frac{\bar{U}}{N} \right) \left( t - t_0 \right) \right] + \frac{d \bar{U}}{N \left( c + d \frac{\bar{U}}{N} \right)} \right] \\
& \quad + \frac{U_0}{N} \left( c + d \frac{U_0}{N} \right) ^{t-t_0} 
\end{aligned}
\right.
\]

(11) \quad \frac{P(t)}{M} = \frac{P}{M} - 1 \cdot \exp \left\{ \frac{b \bar{U}}{d \left( cN + dU_0 \right)} \ln \left[ 1 + \frac{d \left( \bar{U} - U_0 \right)}{cN + dU_0} \exp \left[ \left( cN + d\bar{U} \right) \left( t - t_0 \right) \right] \right] \right\} - \\
\quad \frac{b}{d} \ln \frac{1 + \frac{d \left( \bar{U} - U_0 \right)}{cN + dU_0}}{1 + \frac{d \left( \bar{U} - U_0 \right)}{cN + dU_0}} \ln \frac{P}{M} - \frac{P_0}{M}
\]

This is the general expression for \( P(t) \). If we assume that the total potential number of users of the product equals the ceiling on the number of users (i.e., that the ceiling on the number of adopters is equal to the total number of potential adopters), and that there are no adoptions by producers or consumers at time equal to zero, then

\[ U_0 = P_0 = 0 \]

\[ \bar{U} = N \]

and letting, for simplicity, \( T = (t - t_0) \), we obtain (details in Appendix 2):
\[
P(t) = P \cdot \left\{ 1 - \frac{(c + d)^{\frac{b}{d}} \exp\left[ \frac{bc - ad}{d} \cdot T \right]}{\left[ d + c \cdot \exp(c + d)^{\frac{b}{d}} \right]} \right\}
\]

In this expression, \(a\) can be interpreted as an index of uninfluenced adoption by producers (i.e., adoption by innovators), \(b\) can be interpreted as an index of influenced adoption by producers (i.e., producers who adopt imitating other producers); \(c\) is an index of uninfluenced adoption by users and \(d\) is an index of influenced adoption by users. Hence, we can see in the expression that the total number of producers adopting at time \(t\) is going to be a fraction of the total number of potential adopters. As time passes this fraction increases influenced by a combination of \(a\), \(b\), \(c\), and \(d\). Moreover, we could expect parameters \(c\) and \(d\) to behave well when used in a model to describe the time pattern of diffusion of the innovation among the users via the fundamental model (or its variations) of equation (8). Notice that, with the above assumptions, the model has four parameters and one term, the expected ceiling on the number of adopters, which has to be provided by the analyst or which, alternatively, could also be treated as a parameter in a regression analysis. Notice that the link with the user diffusion curve is given via two parameters (\(c\) and \(d\)). Thus, the model can be used with externally estimated parameters or it could be used to estimate such parameters for characterization of a plausible demand curve. Figure 1 illustrates the effects of variations in each parameter on the diffusion curve when other parameters are held constant. In Appendix 3 we characterize the equation and compare it to the standard model of Equation 5.
Figure 1. Incremental effect of parameters on diffusion curves.

Parameter $a$ varies from 0.1 to 1 to 10. Parameters $b$, $c$, and $d$ are all set to 1.

Parameter $b$ varies from 1 to 5 to 10. Parameters $a=0.1$, $c=0.1$ and $d=1$.

Parameter $c$ varies from 0.1 to 1 to 10. Parameters $a=0.1$, $b=1$, $d=1$.

Parameter $d$ varies from 0.1 to 1 to 10. Parameters $a=0.1$, $b=1$, $c=0.1$.

A pilot study

Mutual Funds

We used this model to study the diffusion of mutual funds in Costa Rica. Data for number of producers and number of users were gathered from the country's regulatory commission. All funds must first obtain permission to operate from this commission and have to report fairly detailed data about their operation on a regular basis. Given the data
available, we measured producer diffusion using the number of funds in the market and user diffusion using number of investors. Our data did not permit us to assess repeated purchases (i.e., same customer holding more than one account) hence we assumed all investors were different.

Figure 2 displays the total number of shareholder accounts over time. The data show an initial small peak before the curve starts shooting upward. This corresponds to a producer (the pioneer) which entered the market and then progressively abandoned it. The number of customers in the market again increases after a second producer enters the market. Figure 3 displays total number of producers.

![Cumulative number of users (000)](image)

Figure 2. Total number of shareholder accounts for mutual funds in Costa Rica.

We provided an estimate on the ceiling of the number of producers. To do so, we asked 6 industry experts to provide an estimate of number of funds in the long run. All provided numbers that ranged between one hundred and two hundred different funds with accounts per fund that ranged from 250 to 1000. The rationale was in most cases that practically all banks would eventually have to enter this market and, in fact, many had already been registered but were not operating at the time of this study.
Figure 3. Total number of funds in Costa Rica

We also used comparative U. S. data to estimate a likely number of funds. In the U. S., the number of shareholder accounts per fund has averaged 21,157 (standard deviation 1,084)\(^5\). Using these data and normalizing to total population we estimated a peak of 163 funds in the country and, given the exploratory characteristics of this pilot study, used this number to estimate parameters\(^6\). Notice, however, that the average accounts per fund in Costa Rica at the time of the study was only 235\(^7\).

The parameters of the model for the mutual fund data were estimated using a non-linear least squares procedure with a Levenberg-Marquardt algorithm. We rescaled the time axis to avoid overflowing (due to too large exponents). The parameter estimates \(a\), \(c\), and \(d\) are quite well estimated with relatively small standard errors. Parameter \(b\) shows a relatively high standard error. Considering the small number of data points and also the particularities of the data set (particularly the producer who leaves the market early after

---

\(^5\)In 1995 there were 5,761 funds operating in the U. S. The average is computed using available data from years 1980, 1985, 1989-95.

\(^6\)Parameters appear to be fairly stable to variations in the ceiling of total Producers.

\(^7\)Using the ceiling as a parameter in a non-linear regression we did not attain convergence after 1000 iterations, however the ceiling (with a very large standard error) appear to stabilize around 148.
entry, creating a somewhat bimodal curve, the result seems to be plausible although not entirely satisfactory. The estimates (standard error) are: \(a = 0.01898 \pm 0.00226\); \(b = 6.6098 \pm 9.5\); \(c = 0.00003187 \pm 0.0000156\); \(d = 11.748 \pm 1.66\); and the R-squared statistic is 0.976. The parameter estimates are positive (as expected). Imitation effects, as represented by parameters \(b\) and \(d\) seem to exert the greatest influence upon this fit. Figure 4 shows that with these parameters the model appears to closely fit the data. This close correspondence indicates that the model is successful in, at least, providing a good descriptive functional form of innovation diffusion among producers.

![Figure 4. Actual number of producers and predicted number of producers for data on mutual funds.](image)

**Comparison to simpler model**

We compared the fit obtained with the proposed model with an alternative model, namely the one described by the generalized standard model of diffusion (equation (8)). Parameter estimates for this model were obtained using also a non-linear least squares
procedure with a Levenberg-Marquardt algorithm. Two parameters were estimated, parameter $a$, which indicates innovation by producers and parameter $b$ which indicates imitation. The ceiling provided was again the estimated figure of 163. Figure 5 depicts the fitted model against the real data. The model also shows a close correspondence to the data.

![Graph showing cumulative number of producers over time]

Figure 5. Predicted producers versus real producers. Mutual funds.

Parameter estimates (standard errors) for this model were $a=0.000396$ (9.6e-5) and $b=8.28$ (0.293). Convergence was attained more easily and the fit was good although, at least using the R-squared statistic as a comparison measure, not as good as the proposed model (R-squared = 0.955 for the more parsimonious model vs. 0.976 for the proposed model). The disadvantage of this model is that it doesn't provide at least an approximate parameter to estimate a user diffusion curve.
Forecasting of demand

We then used the parameter estimates obtained for the proposed model as inputs for the generalized model (equation 8) in order to generate, with data from producer diffusion, a demand curve. The demand curve thus generated was compared to the actual data. Notice that for such exercise we needed to provide a ceiling in the number of adopters. Figure 6 is a plot for different ceilings. We can see that the data appear to fit a curve whose ceiling is given by 30,000 users using the parameter estimates of the proposed model (i.e., $c = 0.00003187$ and $d = 11.748$). These results would point to about 127 funds in the long run with the present average of 235 customers per fund.

![Figure 6](image)

Figure 6. Comparison of real data on number of mutual fund users with predicted models for different ceilings on the number of users.

We then compared parameter estimates with the estimates generated using a parsimonious model solely based on imitation and innovation among users (Equation 8).
Using similar statistical methodologies we fitted equation 8 to our data and obtained parameter estimates for the user diffusion curve.

Table 1. Parameter estimates of user diffusion curve using the parsimonious model of Equation (8) for various ceilings.

<table>
<thead>
<tr>
<th>Ceiling</th>
<th>c</th>
<th>d</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>40000</td>
<td>6.631857e-5</td>
<td>10.32675</td>
<td>76.17%</td>
</tr>
<tr>
<td>30000</td>
<td>6.338549e-5</td>
<td>10.84625</td>
<td>75.97%</td>
</tr>
<tr>
<td>20000</td>
<td>5.0570957e-5</td>
<td>11.58276</td>
<td>75.55%</td>
</tr>
<tr>
<td>10000</td>
<td>1.937082e-5</td>
<td>13.99623</td>
<td>73.78%</td>
</tr>
</tbody>
</table>

These parameters are shown in Table 1 for different ceilings. We can see that our estimation of $b = 11.75$ is not too far off the mark and provides the basis for a useful forecasting of the demand curve based only on the producer diffusion curve. In fact, as shown in figure 7, both estimates provide very similar user diffusion curves, although the parameters obtained with the proposed model tend to overestimate the dependent variable.²

²Where the fraction of the ceiling of adopters is given by the final equation

$$\exp(11.748)r - 1$$

$$\exp(11.748)r + (11748 / 3187e - 5)$$
Figure 7. Estimates of user diffusion curve using parameters from proposed model (dotted curve) and from model based on Equation (8) for mutual funds.

Credit Cards

Further empirical testing was carried on using data about credit card diffusion in Costa Rica. Data were gathered from informants, industry experts, and archival data. Archival data was obtained from periodicals, books, papers and monographs. We assembled a database which provided a fairly accurate longitudinal history of this product line. We measured producer diffusion using the number of credit card operators in the market and user diffusion using number of customers. Our data did not enable us to assess repeated purchases.

Figure 8 displays the total number (in thousands) of credit cards in circulation over time. The data show that the industry starts booming several years after the first company entered the market, roughly at the time of entry of the second producer. We used as our
estimate of the ceiling of producers the total number of commercial banks in the country (28 at the time of the study).

Figure 8. Total number of credit cards in circulation.

The parameters of the model for the credit card data were estimated using also a non-linear least squares procedure with a Levenberg-Marquardt algorithm. We had to rescale the time axis to avoid overflowing (due to large exponents). In fact, this appeared to be a serious drawback of this model. Too few data points or inadequate starting values made convergence very difficult. We had monthly data for the number of producers (that is we could pinpoint the month and year of entry with accuracy) but only yearly data for the user side. Difficulties experienced in fitting the regression model with yearly data made us approximate the user data month by month. The parameter estimates were then quite well estimated with relatively small standard errors. The estimates (standard errors) for the model were: $a = 0.05$ (0.00548); $b = 4.23$ (1.25); $c = 0.00170$ (0.000324); $d = 3.37$ (0.31). Figure 9 shows that these parameters render a predicted producer diffusion curve that appears to have close correspondence with the actual data.
Figure 9. Actual number of producers and predicted number of producers for credit cards.

Comparison to simpler model

For comparison purposes we also fitted the generalized standard model (equation 8) to our credit card data using similar non-linear regression procedures. Parameter estimates (standard errors) for a ceiling of 28 producers were: $a = 7.73e-3 (5.95e-4)$; $b = 2.809 (0.0475)$. Again we found that this model permitted a much easier application of our non-linear regression procedure. The model, as can be observed in figure 10, provides a very good approximation to the real data on credit card producer diffusion.
Forecasting of demand.

The parameter estimates generated with the proposed model were therupon utilized as inputs for the generalized model. With this we were trying to generate a user diffusion curve based on parameters generated with producer data. In this exercise we again needed to provide a ceiling on the number of users. We, hence, calculated fits for different ceilings and visually determined the approximate one predicted by the model. Figure 11
depicts actual user data with different forecasted curves for various ceilings on the number of adopters.

![Cumulative number of users (thousands) vs. Time](image)

**Figure 11. Comparison of real data on number of credit card users with predicted models for different ceilings on the number of users.**

We can see that the data appear to render a very close correspondence to a curve whose ceiling is in the vicinity of 600,000 users. The parameter estimates obtained with producer data only are not very much different from parameter estimates obtained using a more parsimonious model based only on imitation and innovation among users (Equation 8). Table 2 shows parameter estimates for user diffusion curves generated with this simpler model.
Table 2. Parameter estimates of user diffusion curve using the parsimonious model of Equation (8) for various ceilings. Credit Cards.

<table>
<thead>
<tr>
<th>Ceiling</th>
<th>c</th>
<th>d</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,000,000</td>
<td>9.89e-4</td>
<td>3.15</td>
</tr>
<tr>
<td>750,000</td>
<td>9.07e-4</td>
<td>3.42</td>
</tr>
<tr>
<td>600,000</td>
<td>7.22e-4</td>
<td>3.73</td>
</tr>
<tr>
<td>550,000</td>
<td>6.23e-4</td>
<td>3.89</td>
</tr>
<tr>
<td>450,000</td>
<td>3.66e-4</td>
<td>4.38</td>
</tr>
<tr>
<td>350,000</td>
<td>1.07e-4</td>
<td>5.35</td>
</tr>
</tbody>
</table>

We again see that our estimation of \( a = 1.70e-3 \) and \( b = 3.37 \) gives a very good approximation and provides the basis for a useful forecasting of the demand curve based only on the producer diffusion curve. In Figure 12 we can observe that the proposed model exhibits a very close similarity to a diffusion curved derived using the generalized model for a customer ceiling of 550,000 cards.

![Cumulative number of users vs. time](image)

**Figure 12.** Estimates of user diffusion curve using parameters from proposed model (dotted curve) and from model based on Equation (8) for credit cards.
Pension funds

We sought to repeat the empirical exercise by fitting data on pension funds. We had a longitudinal data set with yearly data for the number of users and producers. Only 9 companies had entered the market at the time of the study. We purposefully then limited the number of points to a total of 8 (years from 1988 to 1996). When using such a discrete time scale, the model started exhibiting serious drawbacks. The lack of "degrees of freedom" made convergence impossible despite attempting fits using several different starting values. Though such behavior was predictable (given that we had so few datapoints per parameter to be estimated), the issue illustrated the limitations of this model and, perhaps, the limitations of diffusion modeling in general. Such limitation stems from the fact that for the model to work we need a large amount of datapoints, and when enough points become available the forecasting exercise is not useful anymore. As Mahajan et al. (1990:9) indicate "by the time sufficient observations have developed for reliable estimation, it is too late to use the estimates for forecasting purposes."

Ex ante, however, we did not expect the model to work very well in this case. Adoption decisions by users are, in the case of pension funds, much different from the adoption decisions faced by users of credit cards or mutual funds. In these two products the decision to launch by a producer soon results in a unilateral decision to adopt (or not) by an individual user. Our model does seem to respond to more automatic, simple decisions to adopt by users; decisions which are not mediated by many institutional considerations. In the case of pension funds, however, such might not be the case. There is an institutional framework at the nation's level. State-owned funds, however inefficient, still require compulsory contributions which result in automatic deductions from people's paychecks. Moreover, banks or financial organizations that wish to engage in such
dealings require a long term financial and institutional commitment. Furthermore, pension funds are not primarily marketed to the individual, but to employers. Hence, although we have data in terms of total individual users, such data do not necessarily accurately reflect adoption decisions by users, who might have gotten enrolled as part of a corporate decision and not as a result of their own individual will.

We must note, however, that a simpler model (equation 8) with this small dataset did converge, and it rendered parameter estimates that adequately described user and producer diffusion curves. This indicates that the diffusion model here proposed, and in general all diffusion models, should be chosen according to the circumstances. Parker (1994) shows that different models behave better under different circumstances (i.e., pre-launch, post-launch when few data are available, post-launch with many data available). This hints at the possibility of our proposed model being useful within a somewhat narrow arrangement of circumstances, particularly in post-launch situations with a moderate amount of data, or in pre-launch situations where many data about similar products are available.

CONCLUSION

We developed a model to represent patterns of financial innovation diffusion. The model is derived from prior work in the theory of technological diffusion. A generalized formula derived by Mahajan and Schoeman (1977) is extended to take into account both demand and supply considerations. The resultant model provides good descriptive properties and fits well with available empirical data for two financial innovations. Parameter estimates
are used to estimate plausible demand curves using the generalized formula proposed by Mahajan and Schoeman (1977). The estimated curves reproduce, based on data about number of producers and without any information about users, diffusion curves that closely match curves generated using data on number of users with other usually accepted model of diffusion. One of the principal uses of this model could be to provide reasonable parameters to estimate a demand curve based on the rate of producer adoption of the product at issue or other similar products.

The model and approach taken here are more exploratory than normative. Because financial products are relatively easy and inexpensive to imitate, it is apparent that adoption diffusion curves by producers will not be driven by the relative cost of imitation but by the success and the rate of diffusion of the product among users. Hence, a model that somehow relates both user and producer diffusion dynamics is both more realistic and could be useful.

Though our main interest here is in financial innovations, the model could also be applied to other types of products. Perhaps such applications with larger data sets could unveil limitations of this model. We tried to establish whether parameters remained stable for different starting values of the nonlinear algorithm, and they did so. Our data however, are clearly representative of an emerging market within one country. Such data only provided few data points turning our empirical test into a forecasting exercise. The use of the model requires judicious determination of likely ceilings in the number of adopters. An evident weakness of this model is that an overestimation of total number of producers likely to enter the market will render an overestimation of the demand curve. Another evident weakness of this model is its instability when only few datapoints are available. Testing model properties retrospectively, with larger sets of data is necessary to evaluate more conclusively the applicability and soundness of this model.
References


Appendix 1

Mahajan and Schoeman have derived a generalized form for $H(t)$ (Mahajan et al., 1977):

$$H(t) = \frac{-c(H - H_0)}{1 + \frac{d(H - H_0)}{(c + dH_0)}} \exp\left[-\frac{(c + dH)(t - t_0)}{c + dH_0}\right]$$

Where

$H_0 = H(t = t_0)$

and, $c = \text{index of uninfluenced user adoption}$ and $d = \text{index of influenced user adoption}$.

Thus we obtain.

$$\frac{dF(t)}{dt} = \left\{\begin{array}{l}
a + b \\
\frac{-c(H - H_0)}{1 + \frac{d(H - H_0)}{(c + dH_0)}} \exp\left[-\frac{(c + dH)(t - t_0)}{c + dH_0}\right]
\end{array}\right\} \cdot \left(F - F(t)\right)$$

Integrating both sides of the above equation,

$$-\ln\left(F - F(t)\right) + c_0 = \int a \cdot dt + b \left(\begin{array}{l}
\frac{-c(H - H_0)}{1 + \frac{d(H - H_0)}{(c + dH_0)}} \exp\left[-\frac{(c + dH)(t - t_0)}{c + dH_0}\right]
\end{array}\right) dt$$

We use partial fractions to integrate the second term on the right-hand side of the equation:

This term can be expanded as
\[ b \int \frac{-H \, dt}{1 + \frac{d(H - H_0)}{(c + d\bar{H})} \exp \left[ -\left( c + d\bar{H} \right)(t - t_0) \right]} = \frac{bc(H - H_0)}{(c + d\bar{H})} \ln \left[ \frac{\exp \left[ -\left( c + d\bar{H} \right)(t - t_0) \right]}{(c + d\bar{H})} \right] + c_0 \]

Let's deal first with the first term of the above equation. We multiply and divide by \( \exp \left[ (c + d\bar{H})(t - t_0) \right] \)

and obtain, using substitution, the following expression for the first integral:

\[ b \int \frac{-H \, dt}{1 + \frac{d(H - H_0)}{(c + d\bar{H})} \exp \left[ -\left( c + d\bar{H} \right)(t - t_0) \right]} = \frac{bcH}{(c + d\bar{H})} \ln \left[ \exp \left[ (c + d\bar{H})(t - t_0) \right] + \frac{d(H - H_0)}{(c + d\bar{H})} \right] + c_0 \]

For the second term of expression we use substitution,

\[ v = 1 + \frac{d(H - H_0)}{(c + d\bar{H})} \exp \left[ -\left( c + d\bar{H} \right)(t - t_0) \right] \]

\[ dv = \frac{d(H - H_0)}{(c + d\bar{H})} \exp \left[ -\left( c + d\bar{H} \right)(t - t_0) \right] \left[ -\left( c + d\bar{H} \right) \right] \, dt \]

and the integral becomes

\[ \frac{bc(H - H_0)}{(c + d\bar{H})} \int \left( c + d\bar{H} \right) \frac{dv}{d(H - H_0)(c + d\bar{H})} \] v

which is equal to,
\[
\frac{bc}{d(c + dH)} \ln \left\{ 1 + \frac{d(H - H_0)}{(c + dH_0)} \exp \left[ -\frac{(c + dH)(t - t_0)}{(c + dH_0)} \right] \right\} + c_0
\]

We thus obtain the following expression,

\[
- \ln (F - F(t)) + c_0 = at + \frac{bH}{c + dH} \ln \left\{ \exp \left[ (c + dH)(t - t_0) \right] + \frac{d(H - H_0)}{(c + dH_0)} \right\} +
\]

\[
\frac{bc}{d(c + dH)} \ln \left\{ 1 + \frac{d(H - H_0)}{(c + dH_0)} \exp \left[ -(c + dH)(t - t_0) \right] \right\}
\]

We can now determine the constant of integration by assuming that

\[
F(t = t_0) = F_0
\]

then,

\[
c_0 = at_0 + \frac{bH}{(c + dH)} \ln \left\{ 1 + \frac{d(H - H_0)}{(c + dH_0)} \right\} + \frac{bc}{d(c + dH)} \ln \left\{ 1 + \frac{d(H - H_0)}{(c + dH_0)} \right\} +
\]

\[
\ln (F - F_0)
\]

\[
c_0 = at_0 + \left[ \frac{bH}{(c + dH)} + \frac{bc}{d(c + dH)} \right] \ln \left\{ 1 + \frac{d(H - H_0)}{(c + dH_0)} \right\} + \ln (F - F_0)
\]

\[
c_0 = at_0 + \frac{b}{d} \ln \left\{ 1 + \frac{d(H - H_0)}{(c + dH_0)} \right\} + \ln (F - F_0)
\]
Substituting into equation we obtain an expression for $F(t)$:

$$F(t) = F - 1 \exp\left\{ \frac{b}{d} \ln\left( 1 + \frac{d}{c + dH_0} \exp\left[ -\left( c + dH_0 \right) \left( t - t_0 \right) \right] \right) \right\} - \ln\left( F - F_0 \right)$$
Substituting into equation we obtain an expression for $F(t)$:

$$F(t) = F - 1 + \frac{bc}{d(c + dH)} \ln \left[ \frac{d(H - H_0)}{c + dH_0} \right]$$

$$- \frac{b}{d} \ln \left[ 1 + \frac{d(H - H_0)}{c + dH_0} \right] - \ln \left( F - F_0 \right)$$
So we get,

\[
P(t) = \frac{1}{\exp(a^T)} \cdot \left( e^{\frac{a^T}{d}} \cdot \frac{(c + d)^T}{d} \cdot \frac{bc}{d(c + d)} \cdot \exp\left(\frac{c + d}{d} \cdot (c + d)\right) \cdot \frac{bc}{d(c + d)} \right)
\]

and,

\[
P(t) = \frac{1}{\exp(a^T)} \cdot \left( e^{\frac{a^T}{d}} \cdot \frac{(c + d)^T}{d} \cdot \exp\left(\frac{hc^T}{d}\right) \right)
\]

\[
P(t) = \frac{1}{\exp(a^T)} \cdot \left( e^{\frac{a^T}{d}} \cdot \frac{(c + d)^T}{d} \cdot \exp\left(\frac{bc - ad}{d} \cdot (c + d)\right) \cdot \frac{bc}{d(c + d)} \right)
\]
Appendix 3

To better understand the difference between the proposed model (Equation 12) and the more standard model based solely on imitation and innovation amongst producers (Equation 5), we characterized Equation 12 utilizing the parameters obtained from the mutual funds data. The expressions for the first and second derivative of the cumulative proportion of adopters are graphed and displayed in Figure App3-1. We observe, as expected that the noncumulative proportion of adopters peaks once at a point in time that corresponds to the inflection point of the diffusion sigmoid. Differences with the standard model can be also observed in Figure App3-2, using the parameters obtained for each of them with our mutual fund data. We can see that both models do not exhibit any apparent relevant difference during early stages of the diffusion process. There is an initial short period of time in which the difference between the standard and the proposed model is positive (indicating a slightly faster rate of producer entry according to the standard model), but the rate of adoption by producers appears to increase faster than in the standard model thereafter, presumably because of the combined influence (in the case of our proposed model) of adoption rates by users and also producers. The proposed model peaks a bit earlier than the other model. Soon after reaching its ceiling the difference between the standard and the proposed model is positive (indicating less entries being predicted at this stage by the latter than by the former). In all, the effect of user adoptions appears to exert an influence in the rate of adoption by producers. Such influence is reflected in the form of a faster rate of entry up to the inflection point, and a slower rate of entry thereafter.
Figure App3-1 Analytical properties of the proposed model.

Cumulative proportion of adopters, $F(t)$

Noncumulative proportion of adopters, $f(t)$, 

Rate of change in the noncumulative proportion of adopters, 

\[
\frac{df(t)}{dt}
\]
Figure 4PP3.2: Difference between the proposed model and the standard model.
\[
\left\{ \frac{\int_{1}^{q} \left( \frac{p}{p + \omega} \right) \exp \omega \left( p + \omega \right) \, dp}{\left( \frac{p}{p + \omega} - 1 \right) \exp \omega (q + \omega) \omega} \right\} \int_{q}^{p} \left( \frac{p}{p - \omega} \right) \exp \omega \, dp = \frac{ip}{(1 + ip)} \frac{1}{(1 + i)^{2}} \\
\text{First derivative:}\\

\frac{p}{q} \left[ \int_{q}^{p} \left( \frac{p + \omega}{p - \omega} \right) \exp \omega \left( p + \omega \right) \, dp \right] - 1 = (1 + i)A\\
\text{Model (expressed in terms of proportions):}
\[
\left[ t \left( \frac{p}{pq - cq} \right) \exp \left( pq - cq \right) - t \left( \frac{p}{t \left( p + p' + pq - cq \right)} \right) \exp \left( q + v \right) \right] \left( 1 + \frac{p}{q} \right) \left( f \left( p + c \right) \exp c \right) (p + c) c
\]

\[
- \left\{ f \left( p + c \right) \exp c + p \left[ t \left( \frac{p}{pq - cq} \right) \exp \left( pq - cq \right) - \left( \frac{p}{t \left( p + p' + pq - cq \right)} \right) \exp \left[ \frac{p}{t q \left( p + p' + pq - cq \right)} \right] \left( q + v \right) c \right] \right\} f \left( p + c \right)
\]

\[
= \frac{fp}{t} \left\{ f \left( p + c \right) \exp c + p \right\}
\]

Second derivative:
\[
\left\{ \frac{(\lambda(q + v) - \sigma)dx \cdot \frac{\sigma}{p} + 1}{(\lambda(q + v) - \lambda)dx \cdot \frac{\sigma}{p} - 1} \right\} \cdot \left\{ \frac{(\lambda(p + c) - \sigma)dx \cdot \frac{\sigma}{p} + 1}{(\lambda(p + c) - \lambda)dx \cdot \frac{\sigma}{p} - 1} \right\}^{q}
\]

\[(a_iftime - 1) (a_iftime - (a_jftime)) = ((a_iftime - (a_jftime)) \cdot (a_jftime + a_jftime)) - (a_iftime - (a_jftime)) \cdot (a_jftime + a_jftime))\]

Difference with standard model given by:
Summary and Conclusions
The goal of this research was to establish a foundation for the exploration of the management of innovation in financial services. Our goal was twofold. On the one hand we wanted to extend the research in the management of innovation and new product development to focus on services and products based on information. On the other hand, we wanted to develop a starting base for the study of innovation in financial services and, therefore, we attempted to build a framework for examining and understanding several facets related to innovation in that field. The framework that served as an overall guide for this research is shown again in Figure 1. As the Figure illustrates, we examined financial innovation as an outcome of organizational arrangements and established links between innovations, their success, and the degree to which they diffuse within an economy. We explored the framework in four self-contained essays.

Figure 1. Framework for this study.
In our first essay we focused on financial products. Institutions need carefully to protect their innovation efforts. We argued that many of the options available to industrial innovators to protect their innovations are not available to financial innovators. Because technical and institutional requirements to create some financial products are often relatively small, and because appropriability is practically nonexistent, financial innovators are left with pioneering to attain and retain transient monopolies and to generate rents. Hence, we looked into the pioneering literature and extended some of those insights to financial services by studying the relationship between order of market entry and long term market share for a set of financial products. In doing so, our methodology and choice of sample also permitted us to minimize many problematic aspects often found in the literature on pioneering. We used historical analysis to take into account the characteristics of firms that launched new products and operationalized the pioneer as the first entrant. After controlling for numerous variables our analyses indicate a negative relationship between order of market entry and long term market share for three financial services innovations (credit cards, pension funds, debit cards). The available data indicate that a second entrant is likely to capture approximately 78% of the pioneer's eventual market share. A tenth entrant would only capture 11% on average, and so forth. The results are strongly similar to findings in various other industries.

In our second essay we refined the previous study by establishing a connection between pioneering tendencies and firm strategy. We examined whether there were variations in the relationship between long term market share and performance for financial service firms that exhibited different strategic behaviors. We found that the relationship between order of market entry and long term market share remained remarkably consistent, and in line with most other research work that has been done in the pioneering area. Although the effects of strategic interactions were small compared to the
magnitude of the main effect (order of market entry), some suggestive results were obtained. When we classified entrants into Miles and Snow's strategic typologies, we found that certain strategic types appeared to gain larger share advantages from pioneering financial innovations. The study showed that it might be fruitful to consider organizational and environmental factors when analyzing the effects of order of market entry. Such considerations might reveal strategic traits that are better adapted to different timing of entry decisions.

In the third essay we explored the interaction between organizational structure and innovation in financial services and tried to determine whether there were differences in the characteristics of the organizational structures for innovators and non-innovators. This essay was based on the presumption that certain aspects of a firm's structure affect the manner and extent to which financial service firms innovate. The organizational structure of the firm (its flexibility and its research capabilities) would then determine the organization's ability to recognize and exploit opportunities for innovation. Extant theory led us to hypothesize that firms which are either highly organic or highly mechanistic would exhibit innovative behavior, thus rendering a curvilinear, concave, relationship between organizational characteristics and degree of innovation. Along these lines we focused on two organizational design choices. First, we determined whether the degree to which organizations had a product development orientation, as reflected in several organizational traits, was related to innovation. Second, we probed the effects of organizational flexibility upon innovative activity. Our analysis showed that certain organizational arrangements appeared to be associated with innovative behavior. Our findings, although very tentative, indicate that financial firms with formalized procedures and a differentiated intrafirm organization designed to develop new financial products appear to have larger product arrays aimed at different markets.
Finally, we turned our attention to the diffusion of financial innovations. We wanted to incorporate into our framework an instrument that would permit managers to roughly approximate times of market saturation and rates of product diffusion. We argued that in financial products there could be very strong system interdependencies from the adopter side, and therefore it was necessary to examine diffusion patterns taking into account user and producer dynamics simultaneously. In order to assess such diffusion patterns, we utilized and extended diffusion models and the diffusion modeling methodology proposed by several authors. The resultant model appeared to have good descriptive properties and fitted well with available empirical data for two financial innovations. Despite limitations in the number of data points, the estimated curves reproduced, based on data about number of producers and without any information about users, diffusion curves that closely matched curves generated using data on number of users with other usually accepted models of diffusion.

This research has several managerial implications. The study supports the notion that financial services innovation can be consciously managed and should not occur randomly, casually, accidentally, haphazardly, or fortuitously. If financial innovation can be managed, it can become a competitive weapon. Findings appear to indicate that part of this management should focus on establishing certain organizational arrangements and carefully timing market entry. The model developed in the second essay provides managers with a rule of thumb to estimate approximate returns of their innovation efforts. The diffusion model permits developing a rough idea of the interrelationships that might develop between users and producers of a financial innovation.

The research hints at some implications for further research. We observed that although firms with similar strategies tended, on average, to enter the market at similar time frames, it wasn't always the same firms that entered earlier, at least in the product
lines we examined. For instance, the pioneer in the pension fund industry embraced other product lines much later in relative terms. In the case of credit cards we do observe a clearly downward sloping curve when we compare innovation (using the first essay's measures) and order of market entry, but such a relationship is not apparent in the other product lines. Such observations deserve further study with broader samples and over longer periods of time. Should we believe that there is such a thing as an innovative organization, then it might be useful to determine in much more detail the characteristics of such prototypical organizations in financial services by, for instance, studying the reasons why some firms appear to enter first in certain markets and not in others. We can speculate that the nature of financial products varies as to the influences that must be overcome at the national, industry, firm, organization, and even individual level for development to take place. More research is needed to assess details of the financial product development process at these levels and, particularly, the organizational level, and on how different product platforms evolve in different firms, both in terms of their customer profiles as well as their risk profiles as financial institutions. The evolution of these product platforms, and the co-evolution of organizational forms and technological platforms also deserves much closer scrutiny. Likewise, it might be fruitful to explore possible relationships between strategy and both organizational arrangements and the rate of product diffusion. These connections are indicated in Figure 1 with dashed lines. Such additional research could add completeness to the incipient framework we have sketched here.

Our study has many limitations. Some of these weaknesses have been indicated in each of the individual chapters. One general limitation is the idiosyncratic data we utilized. Although our choice of studying innovation in a small country permitted us to control for possible differences in environmental conditions experienced by the
organizations, particularly regulatory conditions, it also resulted in data which might not be representative of what might happen in other countries. The institutions we studied were undergoing a process of liberalization, and fairly dramatic changes in regulatory and competitive conditions were taking place in this environment. In other countries such might not be the case. Comparative country data are needed to establish the external validity of the findings reported here.

This work suggests that research in the management of innovation in financial services can be fruitfully explored using ideas that have been derived from, and applied to, the study of industrial innovation. The reverse might be also true: that the frameworks we have so far used to study industrial innovation can be enriched by studying the phenomenon in financial services.