

ENTREPRENEURIAL DISCOVERY AND INFORMATION COMPLEXITY IN  
KNOWLEDGE-INTENSIVE INDUSTRIES

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A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the Kenan-Flagler Business School (Strategy & Entrepreneurship Department).

Chapel Hill  
2011

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## **ABSTRACT**

Amol Madhukar Joshi

### **ENTREPRENEURIAL DISCOVERY AND INFORMATION COMPLEXITY IN KNOWLEDGE-INTENSIVE INDUSTRIES**

(Under the direction of Atul Nerkar)

Why are some firms better able than others to exploit new opportunities? I posit that differences in the type and level of complexity of the information obtained through the entrepreneurial discovery process may be a meaningful indicator of the likelihood that a firm is able to exploit a new opportunity. Specifically, I investigate knowledge reproduction processes for product replication (internal copying) and imitation (external copying) as a means of exploiting opportunities and building competitive advantage. Integrating concepts from information theory and the knowledge-based view of the firm, I introduce a generalized model and quantitative methods for estimating the inherent complexity of any unit of knowledge, such as a strategy, technology, product, or service, as long as the unit is represented in algorithm form. Modeling organizations as information processing systems, I develop measures of the information complexity of an algorithm representing a unit of knowledge in terms of the minimum amount of data (algorithmic complexity) and the minimum number of instructions (computational complexity) required to fully describe and execute the algorithm. I apply this methodology to construct and analyze a

unique historical dataset of 91 firms (diversifying and *de novo* entrants) and 853 new product introductions (1974-2009), in a knowledge-intensive industry, digital signal processing. I find that: (1) information complexity is negatively and significantly related to product replication and imitation; (2) replicators have the greatest advantage over imitators at moderate levels of information complexity; (3) intellectual property regimes strengthening the patentability of algorithms significantly increase product replication, without significantly decreasing imitation; (4) outbound licensing of patented technologies decreases product replication and increases imitation; (5) products introduced by *de novo* entrants are less likely to be replicated and more likely to be imitated than products introduced by diversifying entrants; and (6) diversifying entrants have the greatest advantage over *de novo* entrants at high and low levels of information complexity; neither type of entrant has a significant advantage at moderate levels of complexity. These empirical findings support and extend predictions from earlier simulation studies. The model is applicable to other aspects of organizational strategy and has important implications for researchers, managers, and policymakers.

**Keywords:** complexity, entrepreneurship, discovery, replication, imitation, algorithm

*In loving memory of my parents, Madhukar and Sulabha Joshi.*

## **ACKNOWLEDGEMENTS**

I am honored and grateful to have the assistance of many people in completing this research. First and foremost, I would like to thank my wife, Alpa Joshi, my brother, Abhijeet Joshi, and my mother-in-law, Usha Kotecha, for their ongoing support and encouragement throughout the entire research process.

I am indebted to my dissertation chair and advisor, Atul Nerkar, and my Ph.D. program advisor, Rich Bettis, for sharing with me their limited time and their unlimited enthusiasm for actively pursuing this research idea from the initial proposal stage to the final defense. I am especially thankful for and appreciative of the scholarly direction and guidance provided by dissertation committee members Howard Aldrich, Christopher Bingham, and Dean Shepherd. I would also like to thank my dear colleague and fellow “entrepreneur-turned-academic,” Ted Zoller, for inspiring me to join UNC’s Ph.D. program and my old friend and classmate, Fernando Chaddad for keeping me focused on completing it.

This research is funded in part by a Dissertation Fellowship grant from the Ewing Marion Kauffman Foundation. (The contents of this publication are solely the responsibility of Amol Madhukar Joshi.) Undertaking and completing this research would simply not have been possible without the generous support of the Kauffman Foundation. I express my deepest thanks to the leadership and staff of the Kauffman Foundation for making financial resources and intellectual capital available to scholars to conduct entrepreneurship-related research.

The development of this research benefited enormously from numerous formal and informal discussions and interactions with colleagues around the world. I would like to thank the faculty and staff of the following institutions for giving me the opportunity to formally present my work during Fall 2010:

- Escuela Superior de Administración y Dirección de Empresas (ESADE), Business School, Barcelona, SPAIN
- Instituto de Empresa (IE) University, IE Business School, Madrid, SPAIN
- Nanyang Technological University, Nanyang Business School, SINGAPORE
- National University of Singapore, NUS Business School, SINGAPORE
- Università Commerciale Luigi Bocconi, Milan, ITALY
- University of Hawaii at Manoa, Shidler College of Business, Honolulu, HI
- University of Maryland, Smith School of Business, College Park, MD
- University of Texas at Austin, McCombs School of Business, Austin, TX
- Vanderbilt University, Owen Graduate School of Management, Nashville, TN

I would specifically like to thank the following people (listed alphabetically) who provided extremely thoughtful and insightful feedback on this research as part of invited presentations at their respective universities, sessions at research conferences, doctoral workshops, or impromptu discussions: Rajshree Agarwal, Phil Anderson, Dharm Bhawuk, Max Boisot, Alfonso Gambardella, Martin Ganco, Brent Goldfarb, Robert Grant, Ben Hallen, Andy Henderson, Kiyohiko Ito, Daniel Malter, Ishtiaq Mahmood, Matt Marx, Nandini Lahiri, Mike Lawless, Ivan Png, Rhonda Reger, Dimo Ringov, Juan Santolo, M.B. Sarkar, and Giovanni Valentini.

I thank Ashish Arora for encouraging me to conduct a historical analysis of the evolution and commercialization of signal processing (see Appendix) as part of my course project in his doctoral seminar on the Economics of Innovation. I

would like to extend a special thanks to the array of industry experts whose vast knowledge of the history, products, firms, and technologies related to digital signal processing (DSP) were an extremely valuable resource for conducting this research. In particular, I would like to thank Will Strauss, CEO, of Forward Concepts and Robert Cravotta, former Technical Editor of *Electronic Design News*, for their assistance with obtaining extensive archival data and background materials on the DSP industry. I also thank Paul Allison of the University of Pennsylvania and the wonderful staff of the Odum Institute at UNC for their help in setting up some of the preliminary statistical analyses used in this research.

I thank the judges, fellow finalists, and three anonymous reviewers from the 2010 INFORMS Organization Science Dissertation Proposal Competition for their constructive criticism of the original dissertation proposal upon which this research is based. I also thank session participants at the following events held in 2010 for their comments and suggestions for improving earlier versions of this research: the Consortium for Competitiveness & Cooperation (CCC) Colloquium, the Strategic Management Society (SMS) Conference, the Atlanta Competitive Advantage Conference (ACAC), the Business History Conference (BHC) Annual Meeting, and the Industry Studies Association (ISA) Conference.



## **PREFACE**

*From time immemorial, man has desired to comprehend the complexity of nature in terms of as few elementary concepts as possible.*

Abdus Salam, 1979 Nobel Laureate in Physics

## TABLE OF CONTENTS

LIST OF TABLES.....	xiii
LIST OF FIGURES .....	xv
LIST OF ABBREVIATIONS AND SYMBOLS.....	xvi
Chapter	
I. INTRODUCTION.....	1
Research Focus and Goal .....	2
What is an Algorithm?.....	3
Why are Algorithms Important? .....	3
Knowledge Replication and Imitation.....	4
II. THEORY AND MODEL.....	10
Information Complexity .....	10
Algorithmic Complexity and Computational Complexity .....	10
Organizations as Information Processing Systems .....	12
A Generalized Model of Information Complexity.....	14
Model Assumptions and Definitions .....	14
Model Derivation .....	16
Properties of the Model .....	24
Model Summary .....	27
III. HYPOTHESES .....	28
Hypotheses for Effects of Differences in Information Complexity .....	28
Algorithmic Complexity and the Likelihood of Replication and Imitation.....	28

Computational Complexity and the Likelihood of Replication and Imitation	29
Level of Information Complexity and the Likelihood of Replication and Imitation.....	31
Hypotheses for Effects of Differences in Intellectual Property (IP) Regime .....	33
Change in Strength of IP Regime and the Likelihood of Replication and Imitation.....	33
Technology Licensing and the Likelihood of Replication and Imitation.....	35
Hypotheses for Effects of Differences in Type of Entrant .....	38
IV. METHODS AND DATA .....	41
Empirical Setting: The Signal Processing Industry .....	41
Data Sample and Data Collection Procedures .....	43
Statistical Technique.....	50
Variables and Measurement.....	50
Dependent Variables.....	51
Independent Variables .....	53
Control Variables.....	55
V. RESULTS .....	57
Descriptive Statistics and Correlations .....	57
Binary Logit Models for Replication .....	58
Binary Logit Models for Imitation .....	65
Sub-Sample Analyses for Different Levels of Complexity.....	68
Multinomial Logit Models for Product Outcomes .....	70
Analyses for Different Types of Entrants .....	71
VI. DISCUSSION AND CONCLUSION .....	80
Contributions .....	81

Implications.....	82
Limitations and Future Directions for Research.....	89
APPENDIX: INDUSTRY SETTING AND HISTORICAL CONTEXT .....	95
The Science of Signal Processing .....	95
The Early Origins of Signal Processing, c. 2500 B.C.....	98
The “Palermo Stone” and Nilometers .....	98
Innovation in Primitive DSP System and Modern DSP Chips.....	102
Modern Signal Processing as a Formalized Field of Research, 1948-1973 ..	103
Information Theory in 1948: The Mathematical Logic for Designing DSPs	104
Transistors in 1948: The Physical Materials for Building DSPs .....	106
Stored-Program Computing in 1948: The System Architecture for Implementing DSPs.....	108
Timeline and Milestones in Modern Signal Processing, 1948-1974 .....	110
The Role of Computational Complexity in Driving Technological Adoption	115
The Role of Key Inventors in Generating More than One Type of Innovation.....	119
DSP as a Global High-Technology Industry, 1974-2008 .....	120
Initial Generation of Commercial DSP .....	121
1st Generation of Commercial DSP .....	122
2nd Generation of Commercial DSP .....	122
Subsequent Generations of Commercial DSP .....	123
Moore’s Second Law and Gene’s Law: Addressing What Moore’s Law Left Out .....	125
Discussion and Summary of Historical Analysis .....	129
REFERENCES .....	133

## LIST OF TABLES

Table 1. Summary of the Generalized Model of Information Complexity .....	27
Table 2. Established U.S. Legal Precedents on the Patentability of Algorithms .	34
Table 3. Total Number of Product Introductions by Top 20 DSP Firms .....	47
Table 4. New Production Introductions by Each Generation of DSP Technology .....	49
Table 5. Descriptive Statistics and Correlation Matrix.....	60
Table 6. Binary Logit Models of Likelihood that a Product is Replicated.....	61
Table 7. Binary Logit Models of Likelihood that a Product is Imitated .....	62
Table 8. Estimating the “Paradox of Replication” .....	63
Table 9. Multinomial Logit Models of Likelihood of Product Outcomes.....	64
Table 10. Contingency Tables and Odds Ratios.....	73
Table 11. Estimating the “Paradox of Replication” for Diversifying vs. <i>De Novo</i> Entrants .....	74
Table 12. Multinomial Logit Model of Likelihood of Product Outcomes for Diversifying vs. <i>De Novo</i> Entrants .....	75
Table 13. Summary of Results for Hypothesized Differences in Products, Levels of Complexity, and Entrants .....	76
Table 14. “Rules of Thumb” for Estimating Replication and Imitation .....	88
Table 15. Type of Innovation in Primitive DSP System and Modern DSP Chips.....	101
Table 16. Functional Specifications of the Small-Scale Experimental Machine (SSEM).....	108
Table 17. Timeline of Events in the Field of Signal Processing, 1948-1949 .....	111
Table 18. Timeline of Events in the Field of Signal Processing, 1950-1959 .....	112
Table 19. Timeline of Events in the Field of Signal Processing, 1960-1969 .....	113

Table 20. Timeline of Events in the Field of Signal Processing, 1970-1974 .....	114
Table 21. Discovery and Rediscovery of Computationally Efficient Alternatives to the DFT .....	118
Table 22. Generations of DSP Technology and Market Drivers .....	124

## LIST OF FIGURES

Figure 1. Conceptual “Wedge” between Ease of Replication and Difficulty of Imitation .....	31
Figure 2. Knowledge Production and Key Milestones in Signal Processing, 1963-2008.....	46
Figure 3. Feasible Complexity and Average Values of AC and CC for Each Generation of DSP Technology .....	48
Figure 4. Photograph of a Large Fragment of the “Palermo Stone” .....	99
Figure 5. Illustration of the Nilometer on the Isle of Rhoda, Cairo.....	100
Figure 6. Photograph of a Modern DSP Chip Manufactured by Texas Instruments, 1988 .....	100
Figure 7. Photograph of a Replica of the SSEM, The World’s First Stored-Program Computer .....	109
Figure 8. The Computational Complexity of Fast Fourier Transform (FFT) in Comparison to the Discrete Fourier Transform (DFT).....	116

## LIST OF ABBREVIATIONS AND SYMBOLS

A	Algorithm
AC	Algorithmic Complexity
AD	Analog Devices
BDTI	Berkeley Design Technologies, Inc.
C	Code or Description Method for Encoding Data or Instructions
CC	Computational Complexity
CCPA	Court of Customs and Patent Appeals
D	Data Sequence
E	Expected Number of Errors
$\epsilon$	Error Rate (in number of errors per bit)
DFT	Discrete Fourier Transform
DSP	Digital Signal Processing
DSPs	Digital Signal Processors
EDN	Electronic Design News
FC	Forward Concepts
FFT	Fast Fourier Transform
H	Candidate Model or Hypothesis for Compressing Data
IEEE	Institute of Electrical and Electronics Engineers
I	Instruction Sequence
IP	Intellectual Property
L	Length of a Data Sequence (in bits)
M	Candidate Model or Hypothesis for Compressing Instructions



MDL	Minimum Description Length
N	Set of all Natural Numbers
P	Complexity Class of Problems Solvable in Polynomial Time
R	Length of an Instruction Sequence (in bits)
SCOTUS	Supreme Court of the United States
SSEM	Small-Scale Experimental Machine
TI	Texas Instruments
USPTO	United States Patent and Trademark Office
$\Omega$	Language Used to Describe Data and Instructions

## I. INTRODUCTION

*The beginning of knowledge is the discovery of something we do not understand.*

Frank Herbert

*Entrepreneurial discovery* is a dynamic competitive process through which market participants obtain *information* about *new opportunities* (Fiet 1996; Kirzner 1997; Shane 2000). Entrepreneurial discovery is the initial spark which catalyzes the creation of new industries, fuels the formation of new firms, and ignites the introduction of new products. As prospective market participants, *de novo entrants* (startup and spinoffs) and *diversifying entrants* (established firms) alike may exploit entrepreneurial opportunities (Companys and McMullen 2007; Ganco and Agarawal 2009) by “carrying out new combinations” of technical or managerial innovations (Schumpeter 1934).

*Ex ante* validation of entrepreneurial opportunities is challenging for firms because “the only reliable confirmation that a previously unseen or unknown valuable opportunity does in fact exist occurs when a market has been created for the new item” (Eckhardt and Shane 2003). Thus, market participation in the form of a new product introduction by a firm may indicate the successful exploitation of the information obtained through the process of entrepreneurial discovery. Previous research suggests that there are two main sets of factors which are likely to impact the ability of entrepreneurs to discover new

opportunities: “(1) the possession of the prior information necessary to identify an opportunity and (2) cognitive properties necessary to value it” (Shane and Venkataraman 2000). A key implication of this research is that a firm’s ability to engage in entrepreneurial discovery and exploit new opportunities is essentially a function of the *availability of prior information* and the *capacity to process this information* (Galbraith 1977; Hayek 1945).

### **Research Focus and Goal**

But what if the prior information that is available to firms is extremely complex, as is the case in many knowledge-intensive industries? Then does the *inherent complexity* of the available information in some way affect the ability of the firm to handle and use it in identifying and pursuing new opportunities? These questions stem from a more fundamental question which asks: “*Why are some firms better able than others to exploit new opportunities?*” This core issue in strategic management and entrepreneurship research has potentially significant implications for theory, practice, and policy, and is the primary focus of this study. My main goal is to answer this question in the context of how firms build competitive advantage in knowledge-intensive industries (Grant 1996a). In particular, I aim to extend earlier research (Rivkin 2000, 2001) by developing a methodology and testing a general model which explains how the complexity of the information (Boisot and Canals 2004) obtained through the process of entrepreneurial discovery affects the ability of firms to exploit new opportunities.

The general term *complexity* has a broad definition which is commonly used to describe the extent to which an entity exhibits the characteristics of

intricacy, interdependency, complicatedness, multiplicity, etc. (Anderson 1999; Gell-Mann 1995; Simon 1962). In this study, the term complexity specifically refers to the concept of *information complexity* (Boisot and Child 1999; Boisot et al. 2007; Sorenson 2005), which is based on information theory (Blum 1967; Kolmogorov 1968; Shannon 1948) and describes the properties of *algorithms*.

### **What is an Algorithm?**

Simply put, an algorithm is a set of instructions, a code. Though a seemingly basic concept, it is what made the modern world possible, for without the algorithm, there would be no computer. (Berlinski 2001)

An *algorithm* is defined as a collection or set of simple instructions for carrying out a task and may also be called a procedure or recipe (Sipser 1997). Patent law more precisely defines an algorithm as “a finite series of steps (or sequence of actions) for making a numerical or other mathematical calculation, terminating with provision of the result of the calculation” (Stem 1991).

### **Why are Algorithms Important?**

Algorithms sound scary, of interest only to dome-headed mathematicians. In fact they have become the instruction manuals for a host of routine consumer transactions. Browse for a book on Amazon.com and algorithms generate recommendations for other titles to buy. Buy a copy and they help a logistics firm decide on the best delivery route. Ring to check your order's progress and more algorithms spring into action to determine the quickest connection to and through a call-centre. From analysing credit card transactions to deciding how to stack supermarket shelves, algorithms now underpin a large amount of everyday life.

Source: “Algorithms - Business by numbers,” The Economist, Sept. 13, 2007

Beyond the consumer examples described above, within the knowledge-intensive sector of the economy, there are a number of emerging, high-growth industries which are based primarily on scientific and engineering advances in

fundamental algorithms. In addition to digital signal processing (DSP) (Widrow and Stearns 1985), which is the empirical context for this study, these *algorithm-based industries* include the following: Internet search engines (Brin and Page 1998), the semantic web (Hendler and Berners-Lee 2010), bioinformatics and computational genomics (Sanger 2004), cryptography (Diffie and Hellman 1976), encryption (Goldwasser and Micali 1984), networking (Karmarkar 1984), telecommunications (Shannon 1948), fraud detection (Bolton and Hand 2002), and actuarial sciences (Jonker and Volgenant 1987). These examples reflect the diversity of segments of the knowledge-based economy where firms purposefully pursue innovation in algorithms in order to build competitive advantage.

### **Knowledge Replication and Imitation**

In the previously described examples of algorithm-based industries, firms intentionally and systematically use algorithms to represent a unit of knowledge (Boulding 1966) such as a strategy, a product, a service, or a technology. Competitive advantage may arise from differences in the ability of firms to *replicate* and *imitate* (Grant 1996a, b) the algorithms representing these units of knowledge. *Replication* is the internal copying of a unit of knowledge (Nelson and Winter 1982) by the firm that originally produced it (Winter and Szulanski 2001), while *imitation* is the external copying of a unit of knowledge by the competitor(s) of the firm that originally produced it (Hill 1992). In other words, “imitation is simply replication performed by a competitor” (Teece and Pisano 1994).

In the context of the process of entrepreneurial discovery, knowledge replication and imitation activities may be strategic drivers of firm success or

failure. Prior research suggests that “knowledge-based resources (applicable to discovery and exploitation of opportunities) are positively related to firm performance” (Wiklund and Shepherd 2003). The ability to replicate and imitate knowledge may also be an important determinant of the lead time (Bayus 1997; Cohen et al. 1996) required for introducing a new product and may affect the market share (Datar et al. 1997) and market value of the firm (Hendricks and Singhal 1997). A new product’s lead time “acts as an enhancing moderator in entrepreneurs’ exploitation decision policies” (Choi and Shepherd 2004). Furthermore, imitation in particular may be an underexplored factor (Mansfield 1961) in entrepreneurial discovery and related processes.

As Aldrich and Martinez (2007) explain “Overestimating the innovating capacity and personal traits of entrepreneurs has hidden the major role of imitation in entrepreneurial processes. Evolutionary theory calls our attention to the numerically dominant role of reproducers, rather than innovators.” Whether a firm is primarily an originator of new innovations, or simply an imitator of existing innovations may have a profound influence on its chances of survival and growth (Aldrich and Kenworthy 1999; Lieberman 2006). However, originating an innovation is no guarantee of commercial success (Lieberman and Montgomery 1998; Srinivasan et al. 2004), and the “paradox of replication” (Kogut and Zander 1992) implies that originators and imitators face similar challenges in copying knowledge from internal and external sources (Cassiman and Veugelers 2006).

The “paradox of replication” embodies the concept that “efforts by a firm to grow by the replication of its technology enhances the potential for imitation”

(Kogut and Zander 1992). For example, products based on technologies that are easy for a firm to replicate may also be easy for the firm's competitors to imitate, while products based on technologies that are difficult for a firm to replicate may also be correspondingly difficult for its competitors to imitate (Rivkin 2000). Thus, in terms of assessing competitive advantage, it is critical to understand the relative difference in the ease of replication versus the ease of imitation associated with the reproduction of a unit of knowledge (Grant 1996a). The magnitude of the difference between the ease of replication and imitation may be influenced by the strength of the prevailing intellectual property (IP) regime (Lerner 2002), which may be a "formidable imitation barrier" (Teece et al. 1997) for firms in many knowledge-intensive industries including semiconductors, (Ziedonis 2004), software (Bessen and Maskin 2009), telecommunications (Hill 1997), biotechnology (Gallini 2002), pharmaceuticals (Thomke and Kuemmerle 2002), and chemicals (Arora 1997).

In addition to legal barriers to imitation such as strong IP regimes, firms in knowledge-intensive industries may also encounter organizational barriers to imitation. Management theorists posit that causally ambiguous competencies create barriers to imitation and may increase the sustainability of competitive advantage (Barney 1991; Dierickx and Cool 1989). Causal ambiguity arises from three intrinsic characteristics of competencies (Reed and DeFillippi 1990): tacitness, specificity, and complexity. While previous conceptual work (Bharadwaj et al. 1993; Ganco and Agarwal 2009; Mosakowski 1997; Powell et al. 2006; Reed and DeFillippi 1990; Rivkin 2000, 2001) generates testable

propositions for the individual and combined effects of these characteristics on knowledge replication and imitation processes in firms, there are relatively few empirical studies that validate and refine these propositions (King and Zeithaml 2001; Lippman and Rumelt 1982; Zander and Kogut 1995).

In particular, there is a dearth of empirical testing of the direct relationship between the complexity of a unit of knowledge and the subsequent replication and imitation of this knowledge. *Investigating this relationship is critical for unlocking how firms in knowledge-intensive industries successfully exploit the information obtained through the process of entrepreneurial discovery.* While prior research on complexity and knowledge replication and imitation is highly insightful, the bulk of this work is almost exclusively conceptual in nature and relies extensively on simulation studies (Ethiraj and Levinthal 2004; Ethiraj et al. 2008; Rivkin 2000, 2001) to test the propositions generated. Furthermore, the few existing empirical studies in this area (Sorenson 2005; Sorenson et al. 2006; Yayavaram and Ahuja 2008) all utilize some variation of the NK model (Kauffman and Levin 1987; Kauffman and Weinberger 1989; Lenox et al. 2006; Levinthal 1997; Siggelkow and Levinthal 2003) for capturing the relational complexity or interdependence among the modules of a complex system (Baldwin and Clark 2000; MacCormack et al. 2006; Sanchez and Mahoney 1996; Schilling 2000).

However, there are a number of situations in knowledge-intensive industries where the values of  $N$  (the number of nodes in a complex system) and  $K$  (the number of interconnections among these nodes) do not vary across units of knowledge. For example, two similar products that incorporate the same



product architecture (Ulrich 1995) may not necessarily differ in terms of their values of  $N$  and  $K$  — measures which only capture the relational complexity of a product as a complex system (Frenken 2000, 2006). These two architecturally similar products may in fact differ greatly in *other dimensions of complexity* such as the *inherent complexity of the information* associated with each product (Boisot et al. 2007; Solow et al. 1999; Sorenson 2005; Wilson and Latombe 1994). It is precisely this gap in the current research on complexity and knowledge reproduction processes that this study seeks to address both theoretically and empirically. *I posit that under certain conditions that are prevalent in many knowledge-intensive industries, information complexity may serve as meaningful predictor of the likelihood that a newly introduced product is subsequently replicated, imitated, or both.*

To evaluate this idea, I organize the study into five major steps described as follows. First, I outline the relevant theory related to information complexity. I integrate aspects of information theory and the knowledge-based view (KBV) of the firm to develop a generalized model of information complexity, replication, and imitation. Second, using this theoretical framework and generalized model, I formulate hypotheses which may be applied to any unit of knowledge such as a product, as long as the unit is representable in the form of an algorithm. Third, I explain the methodology including the data sample and collection methods, and specify the dependent, independent, and control variables in the model. Fourth, I test the model using a unique longitudinal dataset of new product introductions in a knowledge-intensive industry, digital signal processing (see Appendix for an in-

depth analysis of the history and evolution of this industry). I quantify the previously described “paradox of replication” and present in detail the results of the analyses and summarize the key findings. Fifth and finally, I conclude with a discussion of the overall contributions, implications, limitations, and future directions of this research.

As a brief preview, this study provides empirical support for the following findings: (1) information complexity is negatively and significantly related to product replication and imitation; (2) in general, replicators have the greatest advantage over imitators at moderate levels of information complexity; (3) an IP regime change which strengthens the patentability of algorithms increases product replication, but does not significantly decrease imitation; (4) outbound licensing decreases product replication and increases imitation; (5) products introduced by *de novo* entrants are less likely to be replicated and more likely to be imitated than products introduced by diversifying entrants; and (6) diversifying entrants have the greatest advantage over *de novo* entrants at high and low levels of information complexity; neither type of entrant has a significant advantage over the other at moderate levels of complexity.

The background theory and derived model presented in the next chapter frames and guides the overall development of the study in subsequent chapters.

## II. THEORY AND MODEL

In this chapter, I outline a theoretical framework and generalized model of information complexity. I define the two main types of information complexity and conceptualize organizations as information processing systems with memory. I then develop a model for capturing the relationship between information complexity and knowledge reproduction via replication and imitation. Built on information-theoretic principles, the model is extensible to any information processing system, including organizations, and to any unit of knowledge that is represented as an algorithm.

### **Information Complexity**

As introduced earlier, an *algorithm* is defined as a collection or set of simple instructions for carrying out a task and may also be called a procedure or recipe (Sipser 1997). If a unit of knowledge such as a strategy, a product, a service, or a technology can be *fully specified as a finite and complete set of data and instructions*, then it is representable in the form of an algorithm and the information complexity of the algorithm may be estimated (MacKay 2003). Based on the computational resources required, Gell-Mann (1995) describes two types of *information complexity* — *algorithmic* and *computational*.

### *Algorithmic Complexity and Computational Complexity*

As a simple analogy, if one characterizes a unit of knowledge as a “recipe” (Nelson and Winter 1982), then the algorithmic complexity of this recipe

corresponds to the *number of words* required to fully represent the entire recipe, while its computational complexity corresponds to the *number of steps* required to fully complete the recipe. As a general statistical theory for the estimation of the limits and efficiency of information processing, information theory (Shannon 1948) is ideally suited to the measurement and analysis of such recipes.

More formally defined in information-theoretic terms, *algorithmic complexity* measures the *Minimum Description Length (MDL)* (Barron et al. 1998) of the information required to represent an algorithm, while *computational complexity* measures the *minimum amount of information processing capacity* required to execute the algorithm (Blum 1967). Algorithmic complexity is based on the construct of space complexity, which measures the program size or memory required to completely encode and store an algorithm (Blum 1967). Algorithmic complexity is also referred to as the descriptive complexity (Chaitin 1997) of an algorithm or as its Kolmogorov (1968) complexity, or stochastic complexity (Rissanen 1986).

Computational complexity is based on the construct of time complexity, which is the *number of instructions* that it takes to solve “an instance of the problem as a function of the size of the input using the most efficient algorithm” (Blum 1967). Computational complexity is also referred to as the Blum (1967) complexity of an algorithm or as its communication complexity (Yao 1979), circuit complexity (Wegener 1987), or decision tree complexity (Buhrman and de Wolf 2002). Both types of information complexity, algorithmic and computational, embody a fundamental degree of irreducibility (Boisot 2000; Chaitin 2007). The

two measures of complexity, algorithmic and computational, can be used to represent the availability of prior information and the capacity to process this information — two factors that are essential to the ability of a firm to exploit new opportunities. Now, specifically defined in terms of the process of entrepreneurial discovery, a firm's ability to exploit new opportunities is a function of the algorithmic and computational complexity of the algorithm(s) representing the firm's prior information.

### *Organizations as Information Processing Systems*

A key assumption of this study is that organizations are information-processing systems with *memory* (Tushman and Nadler 1978). Organizational memory enables firms to *encode*, *store*, and *retrieve* information (Walsh and Ungson 1991). In this study, I define a firm's *product architecture* as a simplified subset of its organizational memory and a firm's *new product introductions* as the *output* of this organizational memory.

*Product architecture is an over-arching methodology for organizing how a firm manages its innovation capabilities* (Henderson and Clark 1990; Sanchez and Mahoney 1996). "Product architecture consists of three elements: a set of functions, a map of functions to modules, and interface specifications that explain how modules relate to one another" (Brown and Eisenhardt 1995). Within an organization, product architecture serves as a store of the modular information components or units of knowledge associated with a product or set of products (Frenken 2000; Hobday 1998; Hobday et al. 2000; Rosenkopf and Nerkar 1999, 2001). Product architecture is a form of organizational memory, which may be

situated in standard operating procedures (March et al. 1958), routines (Nelson and Winter 1982), individuals (Loftus and Loftus 1976), dominant logics (Prahalad and Bettis 1986), dominant coalitions (Hambrick and Mason 1984), roles (Simon 1976), and culture (Smircich 1983).

*New product introductions are viewed as the output of the firm's prior information stored in the organizational memory represented by product architecture* and thereby indicate the earlier discovery and evaluation of an entrepreneurial opportunity (Eckhardt and Shane 2003). If one conceptualizes organizations as information processing systems (Tushman and Nadler 1978) and units of knowledge such as products as the input and output of these systems, the principle of irreducibility (Chaitin 2007) implies that the inherent complexity (Wilson and Latombe 1994) of the prior information used to generate a new product cannot be less than the inherent complexity of the product itself. Thus, by first observing the new product introductions made by firms in an industry, then representing these products in algorithm form, and finally measuring the algorithmic and computational complexity of these algorithms, the lower bound (Rissanen 1996) of the inherent complexity of each firm's prior information can be estimated. Following this approach, in the next section, I develop a generalized model for estimating information complexity.

## A Generalized Model of Information Complexity

First, I state core assumptions and define key concepts used in the formal construction of the generalized model of information complexity. Second, I derive the model using principles from information theory and the KBV of the firm. Third, I examine the basic properties of the model to generate insights for developing testable hypotheses. Fourth and finally, I summarize the generalized model of information complexity in relation to the replication and imitation of knowledge.

### Model Assumptions and Definitions

The generalized model of information complexity is based on the explicit assumptions and definitions delineated below. Note that these fundamental information-theoretic concepts apply to *any* information processing system, including *organizations*. My approach directly follows the earlier work of Homer and Selman (2001).<sup>1</sup> For consistency, I use identical notation as the authors.

1. “A finite set  $\Sigma = \{a_1, a_2, a_3, \dots, a_k\}$  of symbols is called a finite *alphabet*. A *word* is a finite sequence of symbols. The *length* of a word  $w$ , denoted  $|w|$ , is the number of symbols composing it. The *empty* word is a unique word of length 0 and is denoted as  $\lambda$ . Note that  $\lambda$  is *not* a symbol in the alphabet” (Homer and Selman, 2001, p. 1).<sup>2</sup>
2. “ $\Sigma^*$  denotes the *set of all words* over the alphabet  $\Sigma$ . A *language* is a set of words.” Thus,  $\Omega$  is a language if and only if  $\Omega \subseteq \Sigma^*$ . This means that every

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<sup>1</sup> See “Chapter 1 – Preliminaries” of Homer and Selman (2001) (“Section 1.1 Words and Languages” and “Section 1.2 K-adic Representation” on pages 1-3) for a comprehensive set of assumptions, definitions, and functions.

<sup>2</sup> Note that any set is, by default, a subset of itself. Also, the empty set,  $\{\}$ , (sometimes called the null set) is a subset of any set. Further note that the empty word,  $\lambda$ , is *not* a set and has no relation to the empty set,  $\{\}$ . (Homer and Selman, 2001, p.1)

element contained in set  $\Sigma^*$  is also contained in set  $\Omega$  (Homer and Selman, 2001, p. 2).

3. A *prefix* is a substring that begins the word, while a *suffix* is a substring that ends the word (Homer and Selman, 2001, p. 2).
4. “The *concatenation* of two words,  $x$  and  $y$ , is the word  $xy$ . For any word  $w$ ,  $\lambda w = w\lambda = w$ . If  $x = uvw$ , then  $v$  is a *subword* of  $x$ . If  $u$  and  $w$  are not both  $\lambda$ , then  $v$  is a *proper* subword. ... The *lexicographic* ordering of  $\Sigma^*$  is defined by  $w < w'$ , if  $|w| < |w'|$ , or if  $|w| = |w'|$  and  $w$  comes before  $w'$  in ordinary dictionary ordering” (Homer and Selman, 2001, p. 2).
5. “Let  $N$  denote the set of all natural numbers, i.e.,  $N = \{0, 1, 2, 3, \dots\}$ . ... Let  $\Sigma$  be a finite alphabet with  $k$  symbols. Call the symbols  $1, \dots, k$ . Every word over  $\Sigma$  will denote a unique natural number” (Homer and Selman, 2001, p. 2-3).<sup>3</sup>
6. Let  $x = \sigma_n \cdot \dots \cdot \sigma_1 \sigma_0$  be a word in  $\Sigma^*$ . Defined as a *polynomial* expression of finite length constructed from variables and constants,  $N_k(x)$  is the natural number that word  $x$  represents (Homer and Selman, 2001, p. 3):

$$N_k(\lambda) = 0, \quad (\text{Eq. 1})$$

$$N_k(x) = N_k(\sigma_n \cdot \dots \cdot \sigma_1 \sigma_0) \quad (\text{Eq. 2})$$

$$= \sigma_n * k^n + \dots + \sigma_1 * k^1 + \sigma_0 \quad (\text{Eq. 3})$$

7. Defined *recursively*<sup>4</sup>,

$$N_k(ax) = k * N_k(x) + a \quad (\text{Eq. 4})$$

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<sup>3</sup> In order to represent the natural numbers as words over a finite alphabet, I use  $k$ -adic notation, which provides a one-to-one correspondence between  $\Sigma^*$  and  $N$  (Homer and Selman, 2001, p.3).

<sup>4</sup> To compute  $N_k(ax)$ , first find  $a_0$  and then iterate until all values are known. For a formal mathematical proof showing that  $N_k$  maps  $\Sigma^*$  onto the natural numbers, see page 3 of Homer and Selman (2001).



## Model Derivation

The *minimum description length (MDL) principle* is “based on the idea that the more we are able to *compress* (describe in a compact manner) a set of data, the more regularities we have found in it and therefore, the more we have *learned* from the data” (Grünwald 2007). A *regularity* in the data is a discernable pattern which can be used to compress the data, i.e., “describe it using fewer symbols than the number of symbols needed to describe the data literally” (Grünwald 2007). Utilizing the MDL principle, I derive the generalized model of information complexity in the series of steps enumerated below. My derivation closely follows the earlier work of Grünwald (2007) and uses similar notation and naming conventions throughout.<sup>5</sup>

1. Let  $A$  be an *algorithm* representing a unit of knowledge  $U$ . The complete information content of algorithm  $A$  consists of a finite sequence of *data* and *instructions* expressed in language  $\Omega$ .
2. Let *data*  $D$  be the finite sequence of words  $X = \{x_1, x_2, x_3, \dots, x_j\}$  which fully describes  $D$  and is associated with algorithm  $A$ . The natural number  $N_k(x_j)$  represents the  $j^{\text{th}}$  word,  $x_j$  (Homer and Selman, 2001).
3. Let  $C$  be a *code* or *description method* which *encodes* or maps  $D$  to  $D'$ . Under the MDL principle, all such description methods,  $C$ , satisfy the *unique*

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<sup>5</sup> For a basic introduction to the MDL principle, see Chapter 1 “Learning, Regularity, and Compression,” on pages 1-40 of Grünwald (2007). For additional background material on the fundamental mathematical concepts associated with algorithmic complexity, see (Barron et al. 1998; Chaitin 1975; 1997; Kolmogorov 1968; Li and Vitányi 2008; Rissanen 1986; 1996). For concepts related to computational complexity, see (Arora and Barak 2009; Cobham 1965; Goldreich 2008; Knuth 1968; MacKay 2003; Papadimitriou 1994). For a historical overview of the development of these concepts, see (Berlinski 2001; Chabert and Barbin 1999; Fortnow 2003) and the Appendix.

*decodability property*: given a description  $D'$ , one can fully reconstruct the original sequence  $D$  (Grünwald, 2007, p.7).

4. The *maximum value or upper bound of the total description length of  $D$*  is the summation of the length of all of the words  $x$ , represented as natural numbers  $N_k(x_j)$ , in the sequence  $X$ , such that

$$L_{max} = |x_1| + |x_2| + |x_3| + \dots + |x_j| \quad (\text{Eq. 5})$$

Note that the value of  $L_{max}$  is literally the full length of the entire word sequence  $X$  representing data  $D$  and includes all of the words, subwords, prefixes, and suffixes in  $X$  (Homer and Selman, 2001).

5. If the sequence of words  $X$  is not purely random, then there exists a code  $C$  which results in a length value,  $L$  that is a minimum value or lower bound of the total description length of  $D$  (Grünwald, 2007, p.14-15). The value of  $L$  is strictly less than  $L_{max}$  and satisfies the unique decodability property described earlier. *The value of  $L$  is the minimum description length or MDL of the data sequence  $D$  associated with algorithm  $A$*  and is defined in steps 6-8 below.
6. To select the best code,  $C$ , for encoding data sequence  $D$  into  $D'$ , let  $\mathcal{H}_1, \mathcal{H}_2, \mathcal{H}_3, \dots$  be a list of candidate models (e.g.  $\mathcal{H}_g$  is the set of  $g^{\text{th}}$  degree polynomials), each containing a set of point hypotheses (e.g., individual polynomials) (Grünwald, 2007, p.14).<sup>6</sup>
7. The best point hypothesis  $H \in \mathcal{H} = \mathcal{H}_1 \cup \mathcal{H}_2 \cup \mathcal{H}_3 \dots$  for code  $C$  to represent the data  $D$  is the one which minimizes the sum  $L(H) + L(D | H)$ , where

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<sup>6</sup> For a detailed proof that such a code,  $C$ , always exists, see Chapter 5 of Grünwald (2007). As described in the section entitled "From Crude to Refined MDL" (Grünwald 2007, p. 15), "A *model* refers to a set of probability distributions or functions ... A *hypothesis* refers to an *arbitrary* set of probability distributions or functions ... A *point hypothesis* is a *single* probability distribution and ... may also be viewed as an *instantiation* of a model."

$L(H)$  = the length in bits, of the description of the hypothesis,  $H$ ; and

$L(D | H)$  = the length, in bits, of the description of the data when encoded using the hypothesis,  $H$  (Grünwald, 2007, p.14).

8. Thus, the MDL, which is the minimum length of data sequence,  $D$ , may be formally expressed as (Grünwald, 2007, p.16):

$$L(D) = \min_H \{L(D | H) + L(H)\} \text{ (in bits)} \quad (\text{Eq. 6})$$

and may serve as an estimate of the *algorithmic complexity* of algorithm  $A$ .

9. Using the number of errors per bit,  $\epsilon$ , for the expected error rate when copying data sequence  $D$  either through replication or imitation, results in the following estimates of the *expected number of errors*,  $E(D)$ :

$$E_{\text{replication}}(D) = (\epsilon_{\text{replication}}) \cdot L(D) \quad (\text{Eq. 7})$$

is the expected number of replication errors; and

$$E_{\text{imitation}}(D) = (\epsilon_{\text{imitation}}) \cdot L(D) \quad (\text{Eq. 8})$$

is the expected number of imitation errors. Note that  $L(D)$  is a function of  $N_k(x_i)$  expressed in polynomial form (Homer and Selman, 2001).

10. *Instructions* are the specific procedures or steps that algorithm  $A$  must properly execute to complete a defined task. In the most general sense, instructions are simply another form of data and as such are representable using an alphabet, symbols, words, languages and numbers as defined earlier (Homer and Selman, 2001). Let  $C$  be a code or description method which encodes or maps  $I$  to  $I'$  (Grünwald, 2007, p.7).
11. Let  $P$  be the *complexity class* of computational problems that are solvable in polynomial time (Cobham 1965). For any decision problem that can be

expressed as an algorithm  $A$  in complexity class  $P$ , it is feasible to execute the algorithm and compute a solution to the problem (Homer and Selman, 1992). This implies that the amount of computational resources or information processing capacity required to execute all of the instructions contained in algorithm  $A$  that is in class  $P$  has a maximum value or upper bound,  $R_{max}$ , that may be expressed in polynomial form (Goldreich 2008).

12. Let  $I$  be the finite sequence of instructions  $I = \{i_1, i_2, i_3, \dots, i_j\}$  which fully describes the execution of algorithm  $A$  that is in class  $P$  and uses data sequence  $D$ . The natural number  $N_k(i_j)$  represents the  $j^{th}$  instruction,  $i_j$ , in polynomial form (Homer and Selman, 2001).<sup>7</sup>

13. *The maximum value or upper bound of the total instruction length of  $I$  is the summation of the length of all of the instructions  $i$ , represented as natural numbers  $N_k(i_n)$ , in the sequence  $I$ , such that*

$$R_{max} = |i_1| + |i_2| + |i_3| + \dots + |i_j| \quad (\text{Eq. 9})$$

Note that the value of  $R_{max}$  is literally the full length of the entire instruction sequence  $I$  associated with algorithm  $A$  and includes all of the words, subwords, prefixes, and suffixes in  $I$  (Homer and Selman, 2001).

14. If the sequence of instructions  $I$  is not purely random, then there exists a code  $C$  which results in a length value,  $R$  that is a minimum value or lower bound of the total instruction length of  $I$  (Grünwald, 2007, p.14-15).

15. The value of  $R$  is strictly less than  $R_{max}$  and satisfies the unique decodability property described earlier (Grünwald, 2007, p.7). *The value of  $R$  corresponds to the minimum amount of information processing capacity required to fully*

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<sup>7</sup> Note that the values of  $j$  for  $I$  and  $D$  do not have to be equal and can be any finite integer.

execute the instruction sequence  $I$  associated with algorithm  $A$ . The value of  $R$  is more explicitly defined in steps 16 through 18 below.

16. To select the best code,  $C$ , for encoding instruction sequence  $I$  into  $I'$ , let  $\mathcal{M}_1, \mathcal{M}_2, \mathcal{M}_3, \dots$  be a list of candidate models (e.g.  $\mathcal{M}_n$  is the set of  $n^{\text{th}}$  degree polynomials), each containing a set of point hypotheses (e.g., individual polynomials) (Grünwald, 2007, p.14).

17. The best point hypothesis  $M \in \mathcal{M} = \mathcal{M}_1 \cup \mathcal{M}_2 \cup \mathcal{M}_3 \dots$  for code  $C$  to represent the instructions  $I$  is the one which minimizes the sum  $R(M) + R(I | M)$ , where  $R(M)$  = the length in bits, of the description of the hypothesis,  $M$ ; and  $R(I | M)$  = the length, in bits, of the description of the instructions when encoded using the hypothesis,  $M$  (Grünwald, 2007, p.14).

18. Thus, the minimum amount of information processing capacity required,  $R$ , may be expressed as (Grünwald, 2007, p.16):

$$R(I) = \min_M \{R(I | M) + R(M)\} \text{ (in bits)} \quad (\text{Eq. 10})$$

19. Using the number of errors per bit,  $\epsilon$ , for the error rate when copying instruction sequence  $I$  either through replication or imitation, results in the following estimates of the *expected number of errors*,  $E(I)$ :

$$E_{\text{replication}}(I) = (\epsilon_{\text{replication}}) \cdot R(I) \quad (\text{Eq. 11})$$

is the expected number of replication errors; and

$$E_{\text{imitation}}(I) = (\epsilon_{\text{imitation}}) \cdot R(I) \quad (\text{Eq. 12})$$

is the expected number of imitation errors. Note that  $R(I)$  above is a function of  $N_k(i_j)$  expressed in polynomial form (Homer and Selman, 2001). Specifically,  $R(I)$  is also a function of the  $n^{\text{th}}$  degree or highest order point

hypothesis  $M_n \in M_n$  included in code  $C$  which minimizes the sum  $R(M) + R(I | M)$ .

20. Let  $T_C(s)$  be the *time* or *total number of steps* (Papadimitriou 1994) required to execute algorithm  $A$  using code  $C$  for a given size input  $s$  into algorithm  $A$ . Since the code  $C$  includes  $n^{th}$  degree or highest order point hypothesis  $M_n$ , the total number of steps required to execute algorithm  $A$ , must be a function of and proportional to the size of input  $s$  to the  $n^{th}$  degree, as shown below:

$$T_C(n) = f(s^n) \propto s^n \quad (\text{Eq. 13})$$

21. Let  $O(z)$  be a function<sup>8</sup> which returns the highest order polynomial contained in the polynomial expression  $z$  (Knuth 1997, 2000). If  $z = R(I)$ , then

$$O(R(I)) = n, \text{ and} \quad (\text{Eq. 14})$$

$$O(T_C(s)) = O(f(s^n)) = n, \text{ since } T_C(s) = f(s^n) \propto s^n \quad (\text{Eq. 15})$$

22. Substituting  $O(R(I))$  for  $n$ , results in the following

$$O(T_C(s)) = O(R(I)) = n \quad (\text{Eq. 16})$$

Since the value of  $R$  is strictly less than  $R_{max}$ , it follows that the value of  $O(R)$  must be less than or equal to  $O(R_{max})$ . Therefore the value of  $n$  is the lower bound of the amount of polynomial time required to compute a solution to the decision problem represented by algorithm  $A$  in complexity class  $P$ . Since  $n$  is also the degree of highest order polynomial included in code  $C$ , which minimizes the encoding of instruction sequence  $I$  into  $I'$ , then computing  $O(R(I))$  yields *exactly the same value* as computing  $O(T_C(s))$ . Thus,  $O(R(I))$  may serve as an estimate of the *computational complexity* of algorithm  $A$ .

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<sup>8</sup> This is commonly referred to as “big oh” or “big Omicron” notation (Knuth 2000) and is widely used in the analysis of algorithms. For a detailed explanation and proof of this function see (Knuth 1997; Sipser 1997).

23. Based on the results obtained in steps 1-22, I now formally define the expressions for the *algorithmic complexity* and *computational complexity* of algorithm  $A$ . The algorithmic complexity corresponds to the *space complexity* or *program size* associated with algorithm  $A$ , and it is denoted as  $AC$ . The computational complexity corresponds to the *time complexity* or *number of steps* associated with algorithm  $A$ , and it is denoted as  $CC$ . The formal expressions for estimating  $AC$  and  $CC$  are shown below.

$$\text{Algorithmic Complexity: } AC = L(D) = \min_H \{L(D | H) + L(H)\} \quad (\text{Eq. 17})$$

$$\text{Computational Complexity: } CC = O(T_C(n)) = O(R(I)) = n \quad (\text{Eq. 18})$$

24. Based on the preceding steps, I formally define the probability that a unit of knowledge  $U$  represented by algorithm  $A$  is successfully copied via replication or imitation as shown below.

$$Pr(U_{\text{replication}}) = f(AC, CC, \epsilon_{\text{replication}}) \quad (\text{Eq. 19})$$

$$Pr(U_{\text{imitation}}) = f(AC, CC, \epsilon_{\text{imitation}}) \quad (\text{Eq. 20})$$

The probability of successfully replicating a unit of knowledge  $U$  is a function of the  $AC$ ,  $CC$ , and the replication error rate,  $\epsilon_{\text{replication}}$ , for copying the data  $D$  and instructions  $I$  associated with algorithm  $A$ . Similarly, the probability of successfully imitating a unit of knowledge  $U$  is a function of the  $AC$ ,  $CC$ , and the imitation error rate,  $\epsilon_{\text{imitation}}$ , for copying the data  $D$  and instructions  $I$  associated with algorithm  $A$ .

25. If the occurrence of copying is modeled as a binary event (a unit of knowledge  $U$  either *is* copied or it *is not* copied), then the logistic function can be used to model the outcome (Allison 2003; Hosmer and Lemeshow 2008).

Since replication and imitation are both forms of copying and the only difference is in the actor that is doing the copying, the general model shown below applies to both. For  $k$  explanatory variables and the  $i^{th}$  unit of knowledge  $U_i$  the model (Allison 2003) is specified as follows:

$$\ln \left[ \frac{p_i}{1-p_i} \right] = \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} \cdots + \beta_k x_{ik} \quad (\text{Eq. 21})$$

$$p_i = \frac{1}{1 + e^{-\alpha - \beta_1 x_{i1} - \beta_2 x_{i2} - \beta_3 x_{i3} \cdots - \beta_k x_{ik}}} \quad (\text{Eq. 22})$$

26. Let  $k=3$  and let  $AC$ ,  $CC$ , and the error rate,  $\varepsilon$ , be the three explanatory variables in the model as shown below:

$$x_{i1} = AC = L(D_i) \quad (\text{Eq. 23})$$

$$x_{i2} = CC = n_i \quad (\text{Eq. 24})$$

$$x_{i3} = \varepsilon = \varepsilon_{\text{replication}} \text{ for replication and } \varepsilon = \varepsilon_{\text{imitation}} \text{ for imitation} \quad (\text{Eq. 25})$$

27. Substituting Eq. 23-25 into Eq.22, results in the following generalized model of information complexity, which may be used to estimate the probability  $p_i$  that  $y_i = 1$  for the replication and imitation of unit of knowledge  $U$  represented by algorithm  $A$ .

$$p_i = \frac{1}{1 + e^{-\alpha - \beta_1 AC - \beta_2 CC - \beta_3 \varepsilon}} \quad (\text{Eq. 26})$$

28. For replication, the general model is

$$p_i(\text{replicated}) = \frac{1}{1 + e^{-\alpha - \beta_1 AC - \beta_2 CC - \beta_3 \varepsilon_{\text{replication}}}} \quad (\text{Eq. 27})$$

29. Similarly, for imitation, the general model is

$$p_i(\text{imitated}) = \frac{1}{1 + e^{-\alpha - \beta_1 AC - \beta_2 CC - \beta_3 \varepsilon_{\text{imitation}}}} \quad (\text{Eq. 28})$$



### Properties of the Model

I examine some basic mathematical properties of the previously derived generalized model of information complexity. The purpose of this “thought experiment” (Davis et al. 2007) is to generate insights for developing testable hypotheses. A summary of the thought experiment is outlined below:

1. Assume that the value of the coefficient  $\beta_1$  in the general model (Eq. 26) is negative, then *ceteris paribus*, an *increase* in the algorithmic complexity AC will *decrease* the probability  $p_i$  of successfully copying a unit of knowledge  $U$  represented by algorithm  $A$ .
2. Assume that the value of the coefficient  $\beta_2$  in the general model (Eq. 26) is negative, then *ceteris paribus*, an *increase* in the computational complexity CC will *decrease* the probability  $p_i$  of successfully copying  $U$ .
3. Assume that the value of the coefficient  $\beta_3$  in the general model (Eq. 26) is negative, then *ceteris paribus*, an *increase* in the error rate  $\epsilon$  will *decrease* the probability  $p_i$  of successfully copying  $U$ .
4. If  $\epsilon_{\text{replication}} < \epsilon_{\text{imitation}}$ , implying that replicators have an advantage over imitators in terms of the error rate  $\epsilon$  for copying a unit of knowledge  $U$ , then *ceteris paribus*,  $p_i(\text{replicated}) > p_i(\text{imitated})$ .
5. As  $\epsilon_{\text{imitation}}$  approaches the value of  $\epsilon_{\text{replication}}$ , the value of  $p_i(\text{replicated})$  approaches  $p_i(\text{imitated})$ . If  $\epsilon_{\text{replication}} = \epsilon_{\text{imitation}}$ , implying that replicators do not have an advantage over imitators in terms of the error rate for copying a unit of knowledge  $U$ , then *ceteris paribus*,  $p_i(\text{replicated}) = p_i(\text{imitated})$ .

6. If the values of the coefficients  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$  in the general model (Eq. 26) are all negative and the values of AC and CC both approach zero, then *ceteris paribus*, the probability  $p_i$  of successfully copying  $U$  may be represented as

$$p_i \approx \frac{1}{1 + e^{-\alpha - \beta_3 \varepsilon}} \quad (\text{Eq. 29})$$

In other words, at low levels of algorithmic complexity AC and computational complexity CC, the probability  $p_i$  of successfully copying  $U$  is primarily a function of the error rate  $\varepsilon$ . As  $\varepsilon$  approaches zero in Eq. 29,  $p_i$  approaches 1. In this case, if replicators have only a slight advantage over imitators such that the replication error rate is approximately equal to the imitation error rate,  $\varepsilon_{\text{replication}} \approx \varepsilon_{\text{imitation}}$ , then *ceteris paribus*,  $p_i(\text{replicated}) \approx p_i(\text{imitated})$ .

7. If the values of the coefficients  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$ , in the general model (Eq. 26) are all negative and the values of AC and CC both approach infinity, then *ceteris paribus*, the probability  $p_i$  of successfully copying  $U$  may be represented as

$$p_i \approx \frac{1}{1 + e^{-\alpha - \beta_1 AC - \beta_2 CC}} \quad (\text{Eq. 30})$$

In other words, at high levels of algorithmic complexity AC and computational complexity CC, the probability  $p_i$  of successfully copying  $U$  is primarily a function of AC and CC as shown in Eq. 30. In this case, regardless of the possible size of the copying advantage of replicators versus imitators (reflected in the relative magnitude of the respective values of  $\varepsilon_{\text{replication}}$  and  $\varepsilon_{\text{imitation}}$ ), the probability  $p_i$  is driven by the values of AC and CC. Thus, at large values of both AC and CC, *ceteris paribus*,  $p_i(\text{replicated}) \approx p_i(\text{imitated})$ .

8. If the values of the coefficients  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$ , in the general model (Eq. 26) are all negative and the value of  $AC$  approaches infinity while the value of  $CC$  approaches zero, then *ceteris paribus*, the probability  $p_i$  of successfully copying  $U$  is primarily a function of  $AC$ .
9. Similarly, If the values of the coefficients  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$ , in the general model (Eq. 26) are all negative and the value of  $AC$  approaches zero while the value of  $CC$  approaches infinity, then *ceteris paribus*, the probability  $p_i$  of successfully copying  $U$  is primarily a function of  $CC$ .
10. If the value of the coefficient  $\beta_1$ , is negative in the model for replication, but positive in the model for imitation, then *ceteris paribus*, an increase in  $AC$  increases the difference between  $p_i(\text{replicated})$  and  $p_i(\text{imitated})$ . In this case, an increase in  $AC$  increases the relative advantage of replicators over imitators.
11. If the value of the coefficient  $\beta_2$ , is negative in the model for replication, but positive in the model for imitation, then *ceteris paribus*, an increase in  $CC$  increases the difference between  $p_i(\text{replicated})$  and  $p_i(\text{imitated})$ . In this case, an increase in  $CC$  increases the relative advantage of replicators over imitators.

### Model Summary

The generalized model of information complexity developed in this chapter is summarized in Table 1 below.

Table 1. Summary of the Generalized Model of Information Complexity

Variable or Function of Interest	Definition or Description
$AC = L(D) = \min_H \{L(D   H) + L(H)\}$	<b>Algorithmic Complexity</b> – the minimum description length (MDL) of the algorithm $A$ used to represent a unit of knowledge $U$ , corresponds to the number of words in a “recipe”
$CC = O(T_C(n)) = O(R(I)) = n$	<b>Computational Complexity</b> – the minimum number of instructions required to execute algorithm $A$ used to represent a unit of knowledge $U$ , corresponds to the number of steps in a “recipe”
$\varepsilon_{replication}$	<b>Replication Error Rate</b> – a constant representing the number of errors/bit when replicating an algorithm $A$
$\varepsilon_{imitation}$	<b>Imitation Error Rate</b> – a constant representing the number of errors/bit when imitating an algorithm $A$
$p_i = \frac{1}{1 + e^{-\alpha - \beta_1 AC - \beta_2 CC - \beta_3 \varepsilon}}$	<b>Probability</b> $p_i$ that $y_i = 1$ for the replication and imitation of by algorithm $A$ . The error rate $\varepsilon = \varepsilon_{replication}$ or $\varepsilon_{imitation}$

### III. HYPOTHESES

Based on the theoretical framework and generalized model presented in the previous chapter, I present hypotheses for the effects on replication and imitation of differences in (1) the type and level of information complexity of a product; (2) the IP regimes under which a product is introduced; and (3) the type of entrants introducing the product.

#### **Hypotheses for Effects of Differences in Information Complexity**

##### *Algorithmic Complexity and the Likelihood of Replication and Imitation*

In this study, algorithmic complexity corresponds to the *minimum description length* (MDL as defined earlier) or the *minimum amount of information* required to fully represent a unit of knowledge in the form of an algorithm (Chaitin 1975). In terms of organizational information processing activities, which may be subject to chunking limits (Gobet and Simon 1998; Miller 1956; Simon 1974), the greater the amount of information associated with a product, the smaller the number of information chunks and the larger the size of each chunk required to fully represent the product (Baddeley 1994; Shannon 1948). In other words, the longer the MDL required for representing a unit of knowledge such as a product, the greater the potential number of errors in copying the information associated with the product (Grünwald 2007).

If the expected error rate of copying information is constant for a firm, then as the algorithmic complexity of a firm's products increases, the total number of

errors made in the replication of the firm's own products should also increase. The total number of errors made in the imitation of the firm's products by competitors should also increase, since the inherent complexity of the product is the same for the firm and its competitors and is independent of possible differences in the respective error rates of copying information for firms and their competitors (Cowan et al. 1999). In addition, an increasing number of errors in copying previously introduced products may result in a decreasing number of new product introductions, once the cumulative number of copying errors reaches a threshold which impacts the proper functioning of the product (Rivkin 2000), which suggests Hypotheses H1a and H1b shown below:

**Hypothesis H1a.** The *greater* the algorithmic complexity of a product, the *lower* the likelihood that the product is subsequently replicated by the firm that first introduced it.

**Hypothesis H1b.** The *greater* the algorithmic complexity of a product, the *lower* the likelihood that the product is subsequently imitated by competing firms.

#### Computational Complexity and the Likelihood of Replication and Imitation

In this study, computational complexity corresponds to the *minimum amount of information processing capacity* required to fully execute an algorithm (Goldreich 2008). In terms of organizational information processing activities, instructions are simply another form of information associated with a unit of knowledge such as a product, and as such are also subject to chunking limits

(Baddeley 1994; Miller 1956; Shannon 1948). Independent of the number of information chunks and size of each chunk, the number of instructions and the size of each instruction associated in the product also impacts the number of errors in copying the information content of the product (Grünwald 2007).

Just as a larger data length increases potential errors in copying information, a larger instruction set increases potential errors in copying instructions. At constant expected error rates of copying information, if the computational complexity of a firm's products increases, then the total number of errors that a firm makes in replicating its own products should also increase. Because the inherent complexity of the product is the same for the firm and its competitors and is independent of the respective error rates of copying information (Cowan et al. 1999), then the total number of errors made in the imitation of the firm's products by competitors should also increase. Furthermore, if the cumulative number of copying errors exceeds a level which impairs the intended operation of the product (Rivkin 2000), then for both replicators and imitators, the likelihood of new product introductions should decrease. This suggests Hypotheses H2a and H2b presented below:

**Hypothesis H2a.** The *greater* the computational complexity of a product, the *lower* the likelihood that the product is subsequently replicated by the firm that first introduced it.

**Hypothesis H2b.** The *greater* the computational complexity of a product, the *lower* the likelihood that the product is subsequently imitated by competing firms.

### Level of Information Complexity and the Likelihood of Replication and Imitation

Although increased complexity generally favors firms that are replicators versus imitators in knowledge reproduction activities, there are organizational limits on the ability to handle increasing levels of complexity (March and Sutton 1997; Reed and DeFillippi 1990; Rivkin 2000) that apply to both replicators and imitators. In reproducing knowledge, replicators appear to have the greatest relative advantage or “wedge” versus imitators (see Figure 1) when faced with decision problems of *intermediate* complexity (Cohen and Levinthal 1990; Knudsen and Levinthal 2007; Rivkin 2001). This is because replicators are more likely than imitators to have preferential access to “superior yet imperfect information about good solutions to complex problems,” which results in a larger “wedge” between the ease of replication and ease of imitation (Rivkin 2001).

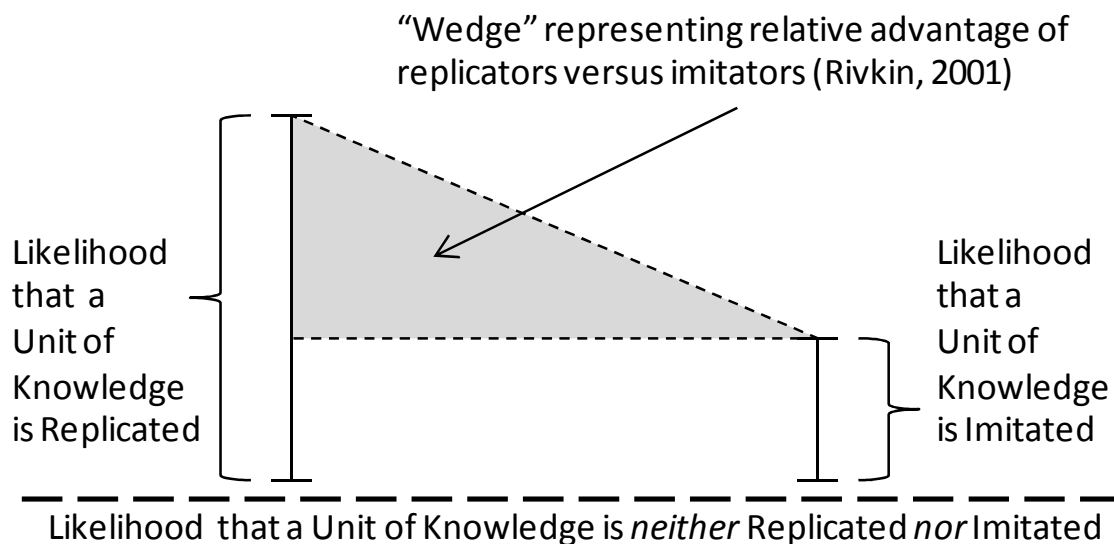


Figure 1. Conceptual “Wedge” between Ease of Replication and Difficulty of Imitation



In contrast, when faced with decision problems of low complexity and correspondingly low causal ambiguity (Lippman and Rumelt 1982), both replicators and imitators appear to be able to effectively engage in the incremental search for solutions. Thus, at low levels of complexity, the informational advantage of replicators is short-lived and “easy imitation implies the rapid dissipation of rents” (Teece and Pisano 1994). When faced with decision problems of high complexity and correspondingly high causal ambiguity (King and Zeithaml 2001), both replicators and imitators appear to be similar in their ineffectiveness in conducting incremental searches for solutions. Because systems of greater complexity are sensitive to errors (Anderson 1999) in copying data *and* instructions, “the replicator's slightly imperfect knowledge then has little more value than the imitator's highly imperfect knowledge” and the “wedge” size is small (Rivkin 2001). Based on this logic, I propose Hypotheses H3a and H3b:

**Hypothesis H3a.** The relative difference between the likelihood that a product is replicated and the likelihood that it is imitated will be *higher* at moderate levels of information complexity, in comparison to low levels of information complexity.

**Hypothesis H3b.** The relative difference between the likelihood that a product is replicated and the likelihood that it is imitated will be *higher* at moderate levels of information complexity, in comparison to high levels of information complexity.

## **Hypotheses for Effects of Differences in Intellectual Property (IP) Regime**

The hypotheses presented thus far examine the direct relationship between the types and levels of information complexity and the likelihood that a product is subsequently replicated and imitated. As introduced earlier, in addition to organizational barriers to imitation, a legal barrier to imitation is the strength of the IP regime. In this section, I propose two sets of hypotheses related to IP regimes. The first set of hypotheses (H4a and H4b) concerns the establishment of a legal precedent strengthening the patentability of algorithms.<sup>9</sup> The second set of hypotheses (H5a and H5b) concerns IP regimes that foster the formation of markets for technology which enable firms to make their patents available to other firms via licensing arrangements.

### *Change in Strength of IP Regime and the Likelihood of Replication and Imitation*

If products are representable in algorithm form, and IP regimes confer patents to the firms that invent these algorithms, inventor firms may have clear economic incentives which encourage product replication and discourage product imitation (Klemens 2006; Oddi 1993). A prime example of an IP regime strengthening the patentability of algorithms occurred in 1988 when the United States Patent and Trademark Office (USPTO) granted AT&T a patent (U.S. Patent 4,744,028) for Narendra Karmarkar's (1984) linear programming algorithm used to optimize the routing of calls over telecommunications networks. This

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<sup>9</sup> Given the overall technological and economic importance of algorithms, there are remarkably few empirical studies of the innovation consequences of granting patents for algorithms (Bessen 2008; Bessen and Maskin 2009; Graham and Mowrey 2004; Hall and MacGarvie 2010). For a comprehensive analysis of aggregate trends in patenting and research, including software patents for algorithms, see Kortum and Lerner (1998). For a literature review of theoretical and empirical research on major patent policy shifts, see Jaffe (2000).

landmark grant by the USPTO established, for the first time, that specific applications of algorithms are patentable as long as they meet the criteria of being novel, useful, and non-obvious (Stem 1991). The established U.S. legal precedents on the patentability of algorithms (Chisum 1985; Oddi 1993; Stem 1991) are summarized in Table 2 below.

Table 2. Established U.S. Legal Precedents on the Patentability of Algorithms

Year	Case(s)	Institution	Impact on Patent Policy
1972	Gottschalk v. Benson	Supreme Court of the U.S. (SCOTUS)	<ul style="list-style-type: none"> <li>Defined for the first time what legally constitutes an algorithm</li> <li><b>Weakened</b> the patentability of algorithms by specifically ruling that mathematical algorithms are <i>not</i> patentable</li> </ul>
1978	Parker v. Flook	SCOTUS	<ul style="list-style-type: none"> <li>Rejected the idea of a defined field of use for algorithms</li> <li>Ruled that not just the algorithm, but also its implementation had to be novel and non-obvious</li> <li><b>Weakened</b> the patentability of algorithms</li> </ul>
1980	Diamond v. Diehr	SCOTUS	<ul style="list-style-type: none"> <li>Purged the concept of treating an inventor's mathematical discoveries as known prior art</li> <li>Ruled that an algorithm-related patent should be allowed when the implementation of the algorithm is novel and the system as a whole is non-obvious</li> <li><b>Weakened</b> the patentability of algorithms</li> </ul>
1982	Taner, Abele, Pardo, and Meyer cases	Court of Customs and Patent Appeals (CCPA) <sup>10</sup>	<ul style="list-style-type: none"> <li>Largely reaffirmed earlier SCOTUS decisions</li> <li><b>Weakened</b> the patentability of algorithms</li> </ul>
1988	Granting of patent to AT&T for Karmarkar's algorithm	U.S. Patent and Trademark Office (USPTO)	<ul style="list-style-type: none"> <li>Contradicted earlier SCOTUS and CCPA decisions</li> <li><b>Strengthened</b> the patentability of algorithms by ruling for the first time that specific applications or uses of algorithms <i>are</i> patentable as long as they are new, useful, and non-obvious</li> </ul>

<sup>10</sup> As of October 1, 1982 the appellate jurisdiction of the Court of Customs and Patent Appeals was officially abolished. Since then, all appeals by patent applicants regarding claims rejected by the United States Patent and Trademark Office are handled by the Court of Appeals for the Federal Circuit. This appellate court adopted all of the earlier precedents for the patentability of algorithms from its predecessor (Chisum, 1985).

Legal precedents strengthening the patentability of algorithms may enable replicators of algorithm-based products to capture greater economic rents (Amit and Schoemaker 1993; Teece and Pisano 1994) from these products, while simultaneously increasing the costs for competitors to engage in imitation or “reverse engineering” (Chang 1995; Klemens 2006; Markman et al. 2004; Samuelson and Scotchmer 2002). The preceding logic suggests Hypotheses H4a and H4b shown below:

**Hypothesis H4a.** After a legal precedent *strengthening* the patentability of algorithms is established, the likelihood that new products are subsequently replicated by the firms that first introduced them is *greater* in comparison to products introduced before the precedent.

**Hypothesis H4b.** After a legal precedent *strengthening* the patentability of algorithms is established, the likelihood that new products are subsequently imitated by competing firms is *lower* in comparison to products introduced before the precedent.

#### *Technology Licensing and the Likelihood of Replication and Imitation*

*Markets for technology* are arrangements in which IP representing intermediate technological inputs may be commercially exchanged among market participants via licensing transactions (Arora et al. 2001). Stronger IP rights frequently enable high degrees of specialization among firms within markets for technology (Arora et al. 2001) in knowledge-intensive industries (Hall and Ziedonis 2001; Linden and Somaya 2003). For example, in the

semiconductor industry in the 1980s, the “strengthening of U.S. patent rights spawned ‘patent portfolio races’ among capital-intensive firms, but it also facilitated entry by specialized design firms” (Hall and Ziedonis 2001).

By facilitating trade in IP assets such as patents, markets for technology enable participating firms to harness the productivity gains that come from the division of labor into specialized activities by each firm (Arora and Merges 2004). As Adam Smith states in the opening line of *The Wealth of Nations* (1776), “the greatest improvement in the productive powers of labour, and the greater part of the skill, dexterity, and judgment with which it is anywhere directed, or applied, seem to have been the effects of the division of labour.” Smith (1776) further explains that the division of labor is determined by the extent of the market. Limited markets will exhibit limited specialization, while larger markets will provide firms with greater opportunities for specialization (Stigler, 1951).

In a market for technology fostered by the existence and enforcement of strong IP rights, a firm’s *strategy space* includes three main options for trading or commercializing units of knowledge that are protected by patents (Arora et al. 2001). A firm may choose to (1) setup *inbound licensing* for technology from external suppliers instead of pursuing internal development (Porter 1985); (2) offer *outbound licensing* of its own proprietary technology to other firms (Chesbrough and Crowther 2006); or (3) produce an *integrated product* by itself (Arora and Fosfuri 2003). Accordingly, a firm may be classified as an *Inbound Licensee*, an *Outbound Licensor*, or an *Integrated Producer*, based on its dominant mode of interaction with the market for technology. The strategic

rationale for a Licensee to externally source IP is framed from a transaction cost minimization perspective as the classic “make vs. buy” decision (Teece 1986; Walker and Weber 1984). Similarly, the managerial logic for a firm to act as a Licensor or an Integrated Producer is framed in terms of determining whether the “revenue effect” outweighs the “rent dissipation effect” when licensing out (Arora and Fosfuri 2003).

Firms that find this trade-off unattractive will choose to take actions to enhance revenue (through higher unit pricing) and reduce rent dissipation (via exclusivity in licensing uses) or produce the integrated product themselves (Motohashi, 2008). Thus, a firm that makes its patented technologies available to other firms via outbound licensing does so with the explicit understanding that such licensing arrangements disclose knowledge (Arrow 1962; Dasgupta and David 1985) that may make its protected technologies easier to imitate. At the same time, the firm’s economic incentives to replicate the technologies that are being licensed out are also reduced (Arora and Ceccagnoli 2006; Fosfuri 2006; Walker and Weber 1986). Based on the potential for increased ease of imitation and decreased incentives for replication associated with the intentional and strategic choice to license out patented technologies, I propose Hypotheses H5a and H5b below:

**Hypothesis H5a.** For products available through outbound licensing, the likelihood that the product is replicated is *lower* than that of products that are not available through licensing.

**Hypothesis H5b.** For products available through outbound licensing, the likelihood that the product is imitated is *higher* than that of products that are not available through licensing.

### **Hypotheses for Effects of Differences in Type of Entrant**

As stated out the outset of this study, startups and spinoffs (Klepper and Sleeper 2005) are nascent firms that are *de novo* entrants into a new market, while established firms are classified as diversifying entrants (Ganco and Agarawal 2009; Helfat and Lieberman 2002). Consistent with the taxonomy proposed by Helfat and Lieberman (2002), in this study, a *de novo* entrant is a *separate* legal entity from an established firm, while a diversifying entrant is the *same* legal entity as an established firm. As noted earlier, markets for technology expand the feasible strategy space for all firms (*de novo* entrants and diversifying entrants alike) by making it possible to trade and commercialize IP assets such as patents by engaging in inbound licensing, outbound licensing, or the integrated production of final products. Although the strategic options created by the formation of a market for technology are possible for all firms to pursue, different types of market entrants may find some options substantially more attractive than others.

For example, *de novo* entrants participating in a market for technology may have fewer resources available (Heirman 2005) than diversifying entrants and a greater strategic incentive to engage in *outbound licensing*. If a *de novo* entrant is an originator of innovations (Aldrich and Martinez 2007) then it may be able to effectively pre-empt the research and development (R&D) activities

(Gallini 1984) of potential competitors by licensing out its patented technologies to these other prospective market participants. Doing so may be a less costly and more profitable technology commercialization path for *de novo* entrants to pursue (Hall and Ziedonis 2001; Kim and Vonortas 2006; Lichtenthaler and Ernst 2009; Motohashi 2008), especially in knowledge-intensive industries which require substantial investments in R&D.<sup>11</sup>

In contrast, diversifying entrants participating in a market for technology may have more resources available (Bayus and Agarwal 2007) than *de novo* entrants and a greater strategic incentive to engage in *integrated production*. If a diversifying entrant is an originator of innovations (Grindley and Teece 1997), then it may be able to maximize its potential profits by replicating its own patented technologies to produce final products rather than sell intermediate technological inputs via outbound licensing (Hall and Ziedonis 2001; Linden 2003; Ziedonis 2004). Note that although diversifying entrants are typically larger than *de novo* entrants, “large size per se does not impart the advantage in R&D. Rather, it results from the limited character of firm growth and the nature of appropriability mechanisms that confine firms to exploiting their innovations chiefly through their own output” (Cohen and Klepper 1996). In other words, the pursuit of replication is advantageous to firms that have the technologies, resources, and organizational capabilities to “make” rather than “buy” (Walker

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<sup>11</sup> For *de novo* entrants, outbound licensing may be considerably more attractive in knowledge-intensive industries such as semiconductors, where “Rising fixed costs give rise to Moore’s Second Law: as the cost of transistors comes down, the cost of fabs goes up, albeit not at quite the same rate.” Source: “The Semiconductor Industry: Under New Management,” *The Economist*, April 2, 2009. For these same reasons, integrated production may be considerably more attractive for diversifying entrants than *de novo* entrants in these types of industries.



and Weber 1984; 1986). In many knowledge-intensive industries, diversifying entrants may be better equipped than *de novo* entrants to engage in integrated production (Malerba 2010; Yoon and Malerba 2009).

As an intentional strategic choice, outbound licensing increases the likelihood that a product is imitated (see Hypothesis H5b), while integrated production increases the likelihood that a product is replicated (see Hypothesis H5a). Since *de novo* entrants have stronger incentives to engage in outbound licensing, while diversifying entrants have stronger incentives to engage in integrated production, I propose Hypotheses H6a and H6b below, which are consistent with the IP regime hypotheses (H4a, H4b, H5a, and H5b) presented earlier.

**Hypothesis H6a.** The likelihood that a product is replicated is *lower* for products introduced by *de novo* entrants in comparison to products introduced by diversifying entrants.

**Hypothesis H6b.** The likelihood that a product is imitated is *higher* for products introduced by *de novo* entrants in comparison to products introduced by diversifying entrants.

In the next chapter, I describe in detail the methods and data used to systematically test all of the hypotheses developed in this chapter.

#### **IV. METHODS AND DATA**

First, I describe the signal processing industry<sup>12</sup> and the special characteristics which it shares with other algorithm-based industries and which facilitate the proposed analysis. Next, I discuss the data sample and data collection procedures. Finally, I outline the statistical technique and specify the key dependent, independent, and control variables.

##### **Empirical Setting: The Signal Processing Industry**

The KBV of the firm (Grant 1996b) suggests that “knowledge generation, accumulation, and application may be the source of superior performance” for firms (Decarolis and Deeds 1999). My choice of the signal processing industry is driven by the core premise of the study — that the inherent complexity of any product that is represented in algorithm form may be estimated by measuring its information complexity, and that the level of information complexity affects the likelihood that the product is subsequently replicated and imitated. Previous research has examined knowledge-intensive industries and studied firm performance and its association with attributes of knowledge such as its tacitness or codifiability (Cowan et al. 2000; Galunic and Simon 1998; Johnson et al. 2002; Kogut and Zander 1993). In contrast, this study examines the information complexity of newly introduced products and I would like to rule out alternative explanations.

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<sup>12</sup> See Appendix for a detailed examination of the pre-history of signal processing as a scientific field and its technological evolution.

The empirical setting of this study is formally referred to as the Digital Signal Processing (DSP) industry. *Digital Signal Processors (DSPs)* are physical devices or semiconductor “chips” that are used to digitally convert, transform and analyze audio, voice, image, video and other sensory signals from one form to another (Smith 1997). DSPs are essential components (Eyre and Bier 1998; Frantz 2000) used in a variety of consumer applications (cell phones, DVD players, stereos) and industrial solutions (telecommunications network switches, satellite transmission, global positioning). In 2007, worldwide DSP revenues were \$27.2 billion, representing about 10% of the total semiconductor industry revenue (Strauss 2007). The DSP industry and other algorithm-based industries exhibit a unique characteristic — their product introductions can be mapped to a finite set of algorithms of known or computable complexity (Deka 1995), which makes the proposed type of information-theoretic analysis possible.

Also, the algorithms underlying these product introductions are public knowledge and extensively codified. In fact, many of the algorithms first appeared in published academic research years, if not decades, before their actual implementation in the form of DSP products (Nebeker 1998a, b, c). Thus, there is a substantial common, codified, and cumulative base of knowledge available in the public domain to all firms that are current and prospective industry participants. Figure 2 shows historical knowledge production in the underlying scientific and engineering field of signal processing, measured in terms of the total annual number of patents granted and research papers published in academic journals.

The generally low levels of tacitness of product knowledge for all firms in the DSP industry means that the process of “reverse engineering” of competitors’ DSP products is not only feasible, it is a prevalent practice in the industry (Nelson and Winter 1982). The choice of the DSP industry<sup>13</sup> effectively enables me to control for and minimize the potential for tacitness as a major source of competitive advantage and causal ambiguity (Reed and DeFillippi 1990) and focus on the inherent complexity of the products themselves as the primary simultaneous source of advantage and ambiguity.

### **Data Sample and Data Collection Procedures**

In this study, I hand-assembled a comprehensive historical dataset of firm-level and product-level market entry data and technical specifications for DSP chips from 1973 to 2009 (from industry inception to the most recent full year in which new product introduction data is available). I obtained the data from seven independent sources including: Berkeley Design Technology, Inc. (BDTI), Electronic Design News (EDN), Forward Concepts (FC), the Institute of Electrical and Electronics Engineers (IEEE) Signal Processing Society, the Smithsonian Institution’s Chip Collection as well as information provided by the most active firms such as Analog Devices (AD) and Texas Instruments (TI).

I collected the firm-level and product-level data in the following manner. First, I contacted representatives from BDTI, EDN, FC, the IEEE, the Smithsonian, AD and TI to obtain access to each organization’s archives on the DSP industry. Next, I gathered and verified the firm-level and product-level data

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<sup>13</sup> The first DSP product was introduced in 1973 (Strauss 2007), the year after the *Gottschalk v. Benson* case was decided by the SCOTUS (see Table 2). This also makes the DSP industry ideal for the study of the IP regime hypotheses H4a, H4b, H5a, and H5b presented earlier.

in each of the seven main datasets and then compared them to each other to generate a combined list of unique firms and products. Using this extensive archival data, I then validated the year that each product was introduced, the key technical characteristics of each product (architecture, generation of technology, performance specifications, etc.), and assigned each product to the firm that introduced it. In this combined list, firm and product names were normalized, duplicate firms and products were removed, and successor firms formed through mergers, acquisitions and spinoffs were identified and accounted for consistently.

After completing this data consolidation effort, the combined sample was found to have 91 unique firms and a total of 853 new product introductions over a 37-year period. Each firm has at least one product introduction, and each product is assigned to only one firm. There are no jointly produced products in the sample. For firms with greater than 10 product introductions, the number of products and the approximate percentage of the sample that these products represent are shown in Table 3. The top 20 firms introduced 589 or 69.1% of the 853 products in the sample. The top 2 firms, AD and TI, accounted for 16.8% and 15.0%, respectively, of all products introduced since industry inception.

The new product introductions span 8 generations (designated 0 through 7) of DSP technology as shown in Figure 3. Each successive generation of DSP technology incorporates architectural improvements which facilitate increasing levels of feasible complexity for DSPs. The value of the feasible complexity for each generation of technology is largely driven by Moore's Law, which states that the number of transistors which can be placed on an integrated circuit doubles

every 18 to 24 months (Mollick 2006; Moore 1995). In this study, Moore's Law is used to extrapolate the theoretical upper bound of the overall level of complexity that is possible for all semiconductor products, including DSPs. Note that in Figure 3, the values of algorithmic and computational complexity as well as the value of the feasible complexity are base 10 logarithms of the actual values. Thus, a one unit increase on the Y-axis corresponds to a 10X or one order of magnitude increase in algorithmic, computational, or feasible complexity. Each shift in the generation of DSP technology reflects one to two orders of magnitude or a 10X to 100X increase in the feasible complexity of DSP products. This indicates that dramatic increases in the level of algorithmic and computational complexity of DSP products are technologically possible for firms in this industry.

Table 4 summarizes the average levels of algorithmic and computational complexity and the maximum feasible complexity that is theoretically possible in each generation of technology. Nearly 51% or 434 products in the sample were introduced in the 6<sup>th</sup> generation of DSP technology and about 25% or 209 products in the sample were introduced in the 7<sup>th</sup> and most recent generation. In the 6<sup>th</sup> generation of DSP technology, 134 (or 31%) out of the 434 products introduced were made available through licensing. The 134 licensable products introduced in the 6<sup>th</sup> generation of technology represent just over 71% of all of the licensable products introduced in the entire industry from inception to 2009. In the 7<sup>th</sup> generation, 31 (or 15%) out of the 209 products introduced were made available through licensing.

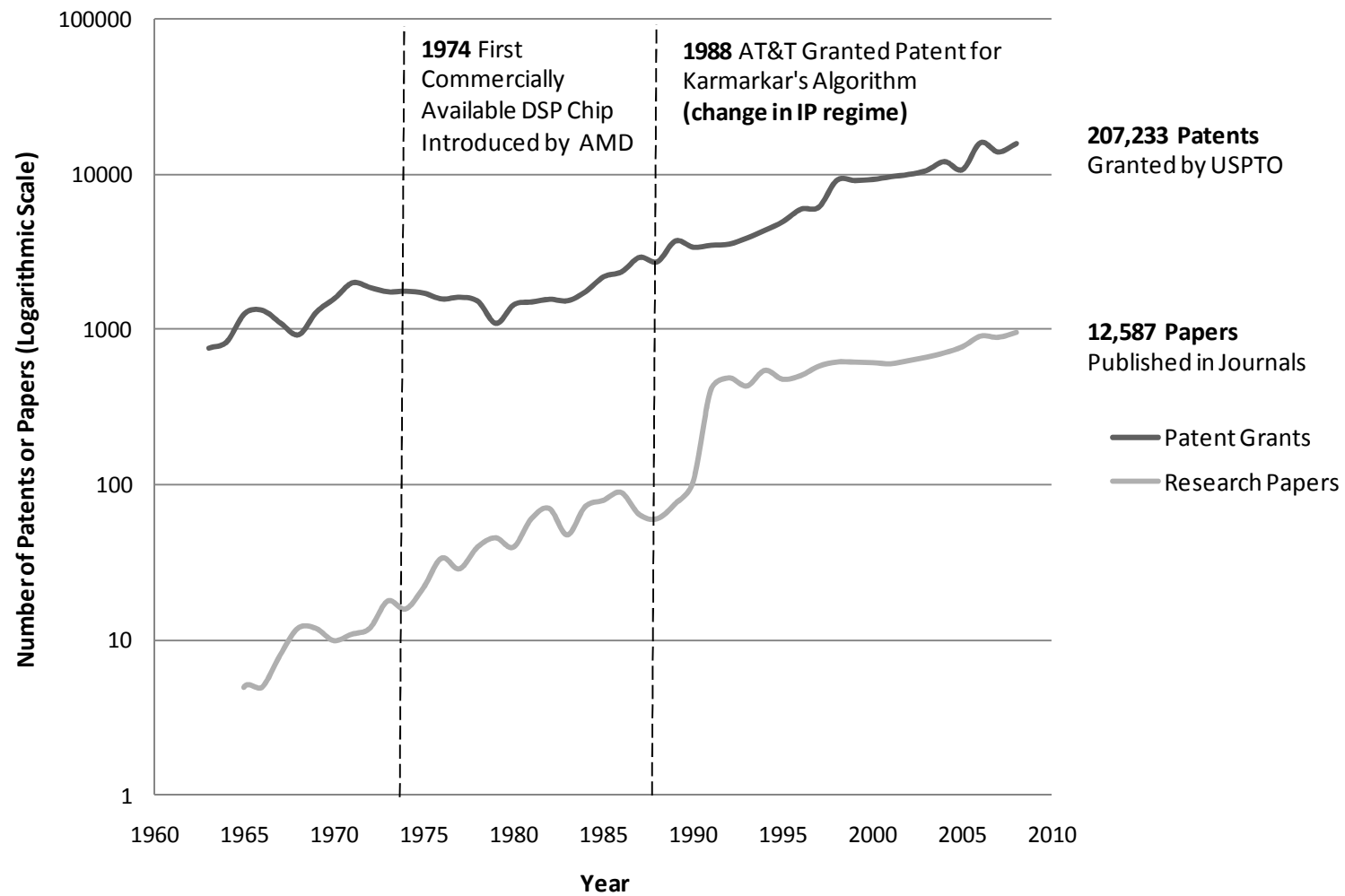


Figure 2. Knowledge Production and Key Milestones in Signal Processing, 1963-2008

Table 3. Total Number of Product Introductions by Top 20 DSP Firms

Rank	Firm Name	Year of First DSP Product Introduction	Total Number of DSP Products Introduced by Firm, 1973-2009	% of Total
1	ANALOG DEVICES	1986	143	16.8%
2	TEXAS INSTRUMENTS	1982	128	15.0%
3	MOTOROLA	1987	31	3.6%
4	RENESAS	2002	30	3.5%
5	CEVA	2002	24	2.8%
6	LSI LOGIC	1999	21	2.5%
7	FREESCALE	2003	20	2.3%
8	ALTERA	2004	18	2.1%
9	HITACHI	1982	18	2.1%
10	NEC ELECTRONICS	1980	18	2.1%
11	ARC	2001	16	1.9%
12	ARM	1998	16	1.9%
13	AT&T MICROELECTRONICS	1984	16	1.9%
14	MICROCHIP TECHNOLOGY	1988	15	1.8%
15	NXP SEMICONDUCTORS	2006	15	1.8%
16	DSP GROUP	1993	13	1.5%
17	VERISILICON	2005	13	1.5%
18	INFINEON TECHNOLOGIES	1999	12	1.4%
19	CIRRUS LOGIC	2001	11	1.3%
20	PHILIPS	1987	11	1.3%
Subtotal for the Top 20 DSP Firms in Sample			589	69.1%
Subtotal for the other 71 DSP Firms in Sample			264	30.9%
TOTAL			853	100.0%



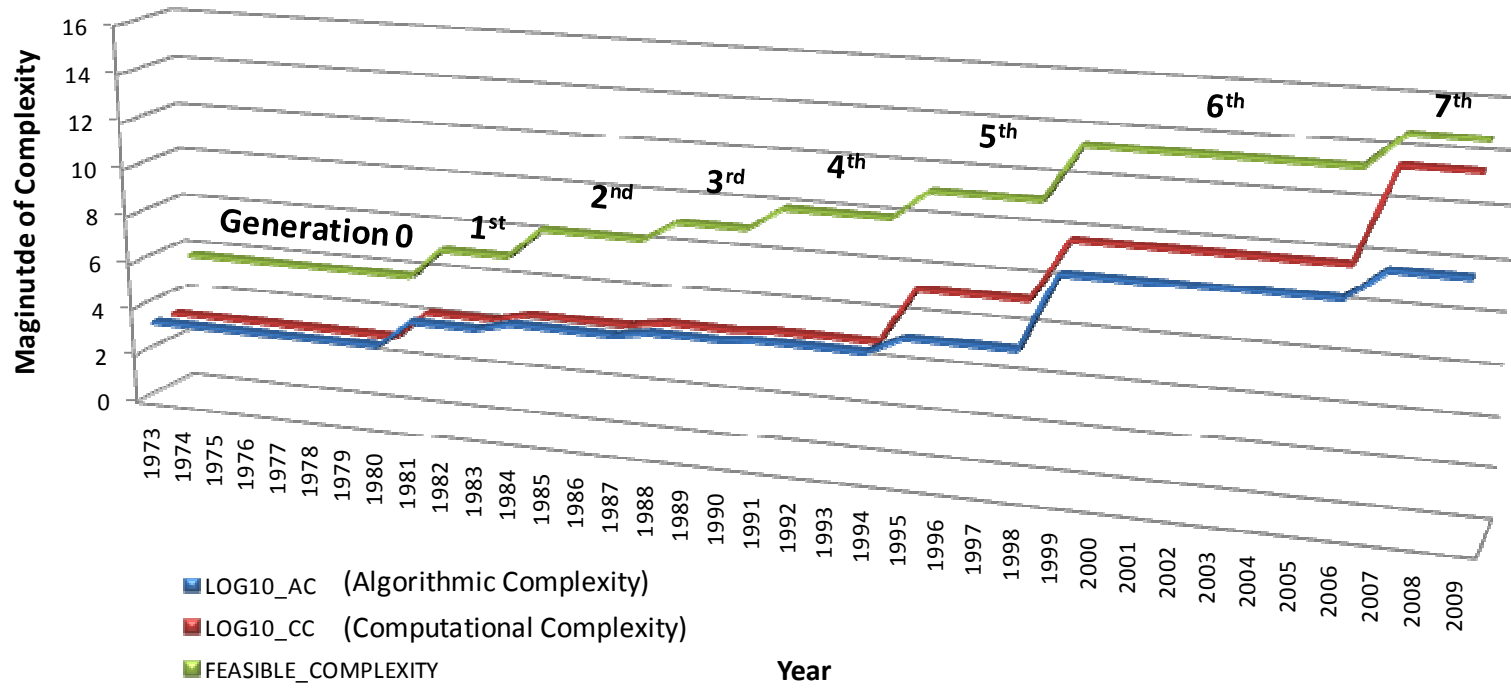


Figure 3. Feasible Complexity and Average Values of AC and CC for Each Generation of DSP Technology

Table 4. New Production Introductions by Each Generation of DSP Technology

GENERATION OF TECHNOLOGY	NUMBER OF NEW PRODUCTS INTRODUCED	% OF TOTAL INTRODUCED	NUMBER OF NEW PRODUCTS AVAILABLE AS LICENSABLE CORES	% OF TOTAL LICENSABLE	% OF GENERATION	AVERAGE LOG10_AC	AVERAGE LOG10_CC	FEASIBLE COMPLEXITY
0	5	1%	0	0%	0%	3.37	3.37	5.61
1	8	1%	0	0%	0%	4.52	4.52	6.85
2	40	5%	0	0%	0%	4.85	4.85	8.09
3	59	7%	1	1%	2%	5.08	5.08	8.88
4	41	5%	2	1%	5%	5.20	5.20	9.82
5	57	7%	20	11%	35%	5.89	7.44	10.99
6	434	51%	134	71%	31%	8.98	9.92	13.21
7	209	25%	31	16%	15%	10.19	13.68	14.55
<b>ALL GENERATIONS</b>	<b>853</b>	<b>100%</b>	<b>188</b>	<b>100%</b>		<b>8.39</b>	<b>9.82</b>	<b>12.58</b>

*For a summary of the specific technological changes and key market drivers associated with each generation of DSP technology listed above, see Table 22 in the Appendix.*

## **Statistical Technique**

As described earlier, the research sample in this study consists of 853 products introduced by 91 firms over a 37-year period. Because my primary interest is in establishing the effect of the theoretical variables (algorithmic and computational complexity) at the product-level on the dependent variables, i.e., the likelihood of a product being replicated and imitated, across all of the products in the sample, I decided to use the generalized estimating equations (GEE) method (Nerkar 2003; Zeger and Liang 1986) to estimate the logistic regression model. The GEE framework is appropriate in this context for two main reasons: 1) the objective of the study is to estimate the average effect across the population as opposed to attributing heterogeneity to the clustering level, in this case the firm, as is typical in most firm-strategy research, 2) the sample of products is drawn from multiple firms and introduced over a large time window. The GEE logit framework estimates the same model as the standard logistic regression. The GEE logistic estimation differs from maximum-likelihood based logistic regression in that it allows for dependence within clusters, such as in longitudinal data (Diggle and Kenward 1994) and gives consistent estimates of the parameters and the standard errors by using a robust ‘sandwich’ estimator (Allison 2003; Hosmer and Lemeshow 2008).

## **Variables and Measurement**

In this study, the dependent variables are the subsequent occurrences of replication or imitation of newly introduced products. The independent variables are information complexity measures (algorithmic and computational) and the

change in IP regime. Note that an alternative to algorithmic and computational complexity is the use of an analytical technique called the design structure matrix (DSM), which captures the degree of modularity of a design (MacCormack et al. 2006). Measurement of inherent complexity using a DSM is not necessarily a meaningful predictor of replication and imitation for the DSP products in this study, because the degree of modularity does not vary much across architecturally similar products from the same generation of technology.

In addition to dummy variables for capturing firm fixed effects, the control variables include the geographic region in which the firm introducing the focal product is headquartered and the availability of the product through licensing. Lagged dependent variables (O'Brien 2003) control for possible unobserved heterogeneity at the product-level (Heckman et al. 1979) by taking into account the number of times a product has been previously replicated and imitated. I also control for the number of firms that have previously entered the market.

### Dependent Variables

1. REPLICATED: This binary outcome variable indicates whether or not the focal product is subsequently replicated (copied by the same firm) within the same generation of technology. All 853 products are classified based on their technical features into one of eight mutually exclusive and collectively exhaustive categories representing each generation of DSP technology (Strauss 2007). If, for example, after its first product introduction, a firm later introduces a new product that is an extension of the original product (part of the same product line or product family) within the same generation of

technology, then this is classified as the occurrence of a replication of the original product by the firm (REPLICATED=1). Note that later product introductions within the same product line or product family but not within the same generation of technology are not classified as the occurrence of a replication, because of the substantial technological differences between the products. I adopted this classification approach after extensive discussions with several DSP industry experts. For consistency and to ensure an independent and objective classification of the products grounded in industry practices, I followed the exact product categorizations standardized by EDN in their annual DSP industry directories and BDTI in their annual DSP chip benchmarking studies.

2. IMITATED: This binary outcome variable indicates whether or not the focal product is subsequently imitated (copied by competing firm(s)) within the same generation of technology. Similar to the approach described above for determining the subsequent occurrence of a replication, I followed a standardized process for determining the subsequent occurrence of an imitation. Based on the advice of my group of DSP industry experts, I relied solely on the available independent benchmarking studies from the archival sources described earlier. These annual studies compared the technical performance of a firm's newly introduced DSP chips with chips from its competitors and with previously introduced chips from all firms. If, for example, after the introduction of the focal product, a competitor later introduces a new product that closely matches the independently-

benchmarked key technical features of the original product within the same generation of technology, then this is classified as the occurrence of a imitation of the original product by the competitor (IMITATED=1).

3. OUTCOME: The dependent variables REPLICATED and IMITATED are used in the initial set of binary logit regression analyses described in the Results section. As a further refinement of these analyses, an additional set of multinomial logit regression analyses are conducted by constructing a new categorical dependent variable, OUTCOME, directly from the variables REPLICATED and IMITATED. For each product in the sample, the variable OUTCOME is assigned a value of 0, if the product is *neither* replicated *nor* imitated within the same generation of technology. A value of 1 is assigned if the product is replicated, *but not* imitated. A value of 2 is assigned if the product is imitated, *but not* replicated. Finally, a value of 3 is assigned if the product is replicated *and* imitated.

#### Independent Variables

1. LOG10\_AC: This is the base 10 logarithm of the algorithmic complexity of the focal product. The value of the algorithmic complexity is estimated using the data width (in bits) of the product. For example, a data width of 16 bits equals a value of  $2^{16} = 65,536$  which is equivalent to a value of  $\text{LOG10\_AC} = 4.816$ . The rationale for using the data width of a DSP chip as an approximation for its algorithmic complexity is that the data width completely describes the maximum size of the data space for the operation of the DSP chip (Lee 1988). A larger data space requires a larger MDL for representing a product

(MacKay 2003). Therefore, the value of the data width is proportional to the MDL of the product and may be suitable as a measure of algorithmic complexity (Grünwald 2007).

2. LOG10\_CC: This is the base 10 logarithm of the computational complexity of the focal product. The value of the computational complexity is estimated using the instruction width (in bits) of the product. For example, an instruction width of 8 bits equals  $2^8 = 256$  bits which is equivalent to a value of  $\text{LOG10\_CC} = 2.408$ . Similar to the logic for using the data width as an approximation of a DSP chip's algorithmic complexity, I use the instruction width as an approximation of its computational complexity. This is because the instruction width completely describes the maximum size of the instruction space for the operation of the DSP chip (Lyons 1997). A larger instruction space means that a larger set of instructions are required to represent a product (MacKay 2003; Zhao et al. 2002). Therefore, the value of the instruction width is proportional to the size of the instruction set of the product and may be useful as a measure of computational complexity (Goldreich 2008).
3. IP\_REGIME: This binary variable is assigned a value of 1 only if the focal product was first introduced after the change in IP regime in 1988, the year the Karmarkar patent was granted by the USPTO (Stem 1991). Including this policy variable enables the analysis of a natural experiment of the effect of strengthening the patentability of algorithms on the likelihood of subsequent replication and imitation of algorithm-based products such as DSP chips.

### Control Variables

1. GEO\_REGION: This categorical variable corresponds to the geographic region where the headquarters of the firm that produced the focal product is located. A value of 0 = Asia-Pacific (Japan, China, Taiwan). A value of 1 = Europe (Austria, Belgium, France, Germany, Netherlands, Poland, Russia, Switzerland, United Kingdom) and a value of 2 = North America (Canada, United States). The speed and cost of innovation and the propensity to use technology replicated internally versus technology imitated from external sources may differ for firms headquartered in different geographic regions because of fundamental differences in managerial practices (Mansfield 1988).
2. LICENSABLE\_CORE: This variable is assigned a value of 1 if the product is available as a licensable core, or = 0 otherwise. DSPs available as licensable cores may be more likely to be imitated and less likely to be replicated than DSPs only available as chips (Grindley and Teece 1997).
3. DIVERSIFYING\_ENTRANT: This variable is assigned a value of 1 if the firm that introduced the product is a diversifying entrant, or a value of 0 if it is a *de novo* entrant. Different types of entrants may have different strategies and incentives for engaging in outbound licensing (Motohashi 2008) versus integrated production (Arora and Fosfuri 2003). Products introduced by diversifying entrants may be more likely to be replicated and less likely to be imitated than products introduced by diversifying entrants (Gallini 1984).<sup>14</sup>

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<sup>14</sup> To avoid potential problems of multi-collinearity, DIVERSIFYING\_ENTRANT is used in place of LICENSABLE\_CORE in testing Hypotheses H6a and H6b. The tests for all of the other hypotheses in this study use LICENSABLE\_CORE.



4. NREPLICATED\_LAG1: This variable is a running count of the number of times a focal product has been previously replicated. Products that are in high demand may be frequently replicated (Winter and Szulanski 2001).
5. NIMITATED\_LAG1: This variable is a running count of the number of times a focal product has been previously imitated. Products that are in high demand may be frequently imitated (Saviotti 2001).
6. NFIRMS\_LAG1: This variable counts the total number of firms that entered the market in the previous year. Firm entry may indicate shifts in aggregate demand or technology and changes in barriers to imitation (Makadok 1998).

## V. RESULTS

### Descriptive Statistics and Correlations

Table 5 presents descriptive statistics and a correlation matrix of the variables used in the analyses. REPLICATED and IMITATED are the dependent variables for the two separate sets of binary logit analyses for estimating the likelihood that a newly introduced product is subsequently replicated or imitated within the then current generation of technology. OUTCOME is the dependent variable used in the follow-on set of multinomial logit analyses. Of the 853 products introduced by DSP firms from 1974-2009, about 77% were replicated by the originating firm and about 45% were imitated by competitors. Thus, some products were both replicated and imitated. More precisely, as summarized in the bottom of Table 9, a mutually exclusive and collectively exhaustive breakdown of the possible product outcomes indicates the following. About 4% of products introduced by DSP firms are *neither* replicated *nor* imitated, 51% are replicated *but not* imitated, 19% are imitated *but not* replicated, and the remaining 26% are replicated *and* imitated.

The mean values of algorithmic complexity (LOG10\_AC) and computational complexity (LOG10\_CC) for the 853 products in the sample are about 8.35 and 9.79, respectively, which correspond to bit values of approximately 27.7 bits and 32.5 bits, respectively. About 94% of all of the products in the sample were introduced after the change in IP regime

(IP\_REGIME=1) marked by the Karmarkar patent grant in 1988. In terms of the categorical control variable GEO\_REGION, about 12% of the products are introduced by firms headquartered in the Asia-Pacific region, another 13% by firms based in Europe, and the remaining 75% by firms in North America. Over 22% of the products are available as licensable cores, as indicated by the control variable LICENSABLE\_CORE. Diversifying entrants introduced 59% of the products. On average, about 4 DSP firms enter the market for the first time in the year preceding each new product introduction. The control variables for the running count of the number of times a product has been previously replicated or imitated, represented by lagged dependent variables NREPLICATED\_LAG1 and NIMITATED\_LAG1, respectively, are only used in separate sets of analyses, so the correlation of  $r = 0.281$  is not a concern. The highest correlation between any two independent variables is  $r = -0.242$  ( $p < 0.05$ ) between LOG10\_CC and GEO\_REGION. This level of correlation indicates that there is little likelihood of multi-collinearity influencing the internal and external validity of the results.<sup>15</sup>

### **Binary Logit Models for Replication**

Table 6 reports the results of the models examining how the values of algorithmic and computational complexity affect the likelihood that a newly introduced product is *replicated* within the then current generation of technology (Hypotheses H1a and H2a). Specifically, Model 1 represents a baseline specification comprised of all of the control variables. Models 2, 3, and 4 extend

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<sup>15</sup> The correlation between DIVERSIFYING\_ENTRANT and LICENSABLE\_CORE is  $r = -0.438$  ( $p < 0.05$ ). To avoid potential problems associated with multi-collinearity, I use the variable LICENSABLE\_CORE in testing all of the hypotheses, except for H6a and H6b. Because only H6a and H6b make predictions based on the type of entrant, I replace LICENSABLE\_CORE with DIVERSIFYING\_ENTRANT in the tests of these hypotheses.

this baseline model by separately adding the direct effects of algorithmic complexity, computational complexity, and the change in IP regime. Model 5 is the full model with all of the independent variables and controls included. All of the Models 1-5 include firm fixed effects. Across Models 1-5, all of the control variables are significant and are in the expected direction. All of the models are significant and the relative improvement in quasi likelihood associated with each model in comparison to the baseline model is shown at the bottom of Table 6. This comparison indicates that Model 5 is the best fit model for estimating the likelihood that a product is replicated.

The coefficient of the independent variable LOG10\_AC is *negative* and *significant* in both Model 2 ( $\beta = -0.0188$ ,  $p < 0.1$ ) and in Model 5 ( $\beta = -0.0233$ ,  $p < 0.05$ ), which is the full model. This supports Hypothesis H1a, which predicts that the greater the algorithmic complexity of a newly introduced product, the lower the likelihood that it is subsequently replicated. The coefficient of the independent variable LOG10\_CC is slightly positive *but not significant* in either Model 3 or Model 5. This does not support Hypothesis H2a, which predicts that the greater the computational complexity of a newly introduced product, the lower the likelihood that it is subsequently replicated. The coefficient of the independent variable IP\_REGIME is *positive* and *significant* in both Model 4 ( $\beta = 0.9605$ ,  $p < 0.01$ ) and in Model 5 ( $\beta = 0.9729$ ,  $p < 0.01$ ). This supports Hypothesis H4a, which predicts that after a legal precedent strengthening the patentability of algorithms, the likelihood that a product is subsequently replicated is higher in comparison to products introduced before the precedent.

Table 5. Descriptive Statistics and Correlation Matrix

Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12
1 REPLICATED	.77	.42	1											
2 IMITATED	.45	.50	-.408**	1										
3 OUTCOME	1.67	.91	.014	.907**	1									
4 LOG10_AC	8.35	7.30	-.009	-.005	-.009	1								
5 LOG10_CC	9.79	14.33	.041	-.105**	-.096**	.110**	1							
6 IP_REGIME	.94	.24	.173**	-.060	.014	.130**	.092**	1						
7 GEO_REGION	1.62	.70	.162**	-.095**	-.030	-.025	-.242**	.104**	1					
8 LICENSABLE_CORE	.22	.41	-.110**	.178**	.145**	.168**	-.022	.137**	-.137**	1				
9 DIVERSIFYING_ENTRANT	.59	.49	.106**	-.124**	-.087*	-.252**	-.121**	-.165**	.327**	-.438**	1			
10 NFIRMS_LAG1	4.28	2.55	.193**	-.019	.068*	.148**	.032	.196**	.061	.061	-.117**	1		
11 NREPLICATED_LAG1	5.39	10.80	.130**	-.107**	-.057	-.001	.023	.112**	.192**	-.129**	.255**	.000	1	
12 NIMITATED_LAG1	17.17	27.29	.010	.056	.066	-.154**	-.135**	.082*	.116**	.078*	-.037	.049	.281**	1

\*\* . Correlation is significant at the 0.01 level (2-tailed).

\* . Correlation is significant at the 0.05 level (2-tailed).

Table 6. Binary Logit Models of Likelihood that a Product is Replicated

Variable		Model 1	Model 2	Model 3	Model 4	Model 5
Intercept		0.8467 (0.3138) ***	0.9576 (0.3391) ***	0.7879 (0.3472) **	0.0018 (0.4709)	0.0711 (0.4829)
LOG10_AC	Algorithmic Complexity		-0.0188 (0.0098) *			-0.0233 (0.0098) **
LOG10_CC	Computational Complexity			0.01 (0.0106)		0.0078 (0.0102)
IP_REGIME					0.9605 (0.3426) ***	0.9729 (0.3395) ***
GEO_REGION	Asia-Pacific	-1.0008 (0.3716) ***	-0.9859 (0.3642) ***	-1.0778 (0.3574) ***	-0.9251 (0.3760) **	-0.9799 (0.3590) ***
GEO_REGION	Europe	-0.9776 (0.3886) **	-0.9894 (0.3953) **	-0.9664 (0.3899) **	-0.9021 (0.3716) **	-0.9052 (0.3790) **
GEO_REGION	North America	0	0	0	0	0
Reference Category						
LICENSABLE_CORE		-0.9401 (0.3724) **	-0.9014 (0.3623) **	-0.9153 (0.3703) **	-1.0304 (0.3806) ***	-0.9596 (0.3685) ***
NREPLICATED_LAG1		0.0202 (0.0098) **	0.0207 (0.0097) **	0.0196 (0.0099) **	0.0181 (0.0099) *	0.0181 (0.0099) *
NFIRMS_LAG1		0.2435 (0.0704) ***	0.2513 (0.0717) ***	0.2407 (0.0690) ***	0.2297 (0.0675) ***	0.2366 (0.0674) ***
Fixed Firm Effects		Included	Included	Included	Included	Included
Quasi Likelihood Improvement		13322.16	13298.59 23.57	13346.07 -23.91	13233.59 88.57	13218.54 103.62
Comparison Model			1	1	1	1

Values in parentheses represent robust standard errors clustered on firms.

All tests are two-tailed, \*\*\* p<0.01, \*\* p<0.05, \* p<0.10

Table 7. Binary Logit Models of Likelihood that a Product is Imitated

Variable		Model 6	Model 7	Model 8	Model 9	Model 10
Intercept		-0.6792 (0.2109) ***	-0.6676 (0.2607) **	-0.3569 (0.2213)	-0.2436 (0.2422)	-0.1375 (0.2518)
LOG10_AC	Algorithmic Complexity		-0.0017 (0.0142)			0.0074 (0.0150)
LOG10_CC	Computational Complexity			-0.04 (0.0100) ***		-0.0364 (0.0114) ***
IP_REGIME					-0.4739 (0.2905)	-0.2928 (0.2915)
GEO_REGION	Asia-Pacific	0.8235 (0.3407) **	0.8248 (0.3392) **	1.0818 (0.2519)	0.7827 (0.3350) **	1.0491 (0.2417)
GEO_REGION	Europe	0.9173 (0.3776) **	0.9158 (0.3811) **	0.8339 (0.3700) **	0.8731 (0.3538) **	0.8122 (0.3554) **
GEO_REGION	North America	0	0	0	0	0
Reference Category						
LICENSABLE_CORE		0.8899 (0.2808) ***	0.8944 (0.2594) ***	0.8301 (0.2819) ***	0.9205 (0.2880) ***	0.8293 (0.2712) ***
NIMITATED_LAG1		0.0067 (0.0053)	0.0066 (0.0057)	0.0046 (0.0052)	0.0068 (0.0053)	0.0049 (0.0054)
NFIRMS_LAG1		-0.0423 (0.0446)	-0.0419 (0.0469)	-0.0322 (0.0446)	-0.0375 (0.0447)	-0.0308 (0.0452)
Fixed Firm Effects		Included	Included	Included	Included	Included
Quasi Likelihood Improvement		20451.88	20504.07 -52.19	20205.84 246.04	20425.79 26.09	20239.29 212.59
Comparison Model			6	6	6	6

Values in parentheses represent robust standard errors clustered on firms.

All tests are two-tailed, \*\*\* p<0.01, \*\* p<0.05, \* p<0.10

Table 8. Estimating the “Paradox of Replication”

	Estimated Odds Ratios		Estimated Odds Ratios at Different Levels of Overall Complexity									
			LOW		MODERATE		MODERATE		MODERATE		HIGH	
CASE	FOR ALL CASES		CASE 1		CASE 2		CASE 3		CASE 2 and CASE 3		CASE 4	
Value of AC	All Values of AC		LOW, AC < 4.8165		LOW, AC < 4.8165		HIGH, AC >= 4.8165		ALL VALUES IN CASE 2 and CASE 3		HIGH, AC >= 4.8165	
Value of CC	All Values of CC		LOW, CC < 7.2247		HIGH, CC >= 7.2247		LOW, CC < 7.2247				HIGH, CC >= 7.2247	
Likelihood a Product is	REPLICATED	IMITATED	REPLICATED	IMITATED	REPLICATED	IMITATED	REPLICATED	IMITATED	REPLICATED	IMITATED	REPLICATED	IMITATED
LOG10_AC	<b>0.977</b>	-	<b>1.684</b>	-	-	-	-	<b>1.107</b>	-	<b>1.074</b>	<b>0.975</b>	-
LOG10_CC	-	<b>0.964</b>	-	-	<b>1.26</b>	<b>0.892</b>	-	<b>2.277</b>	<b>1.164</b>	-	-	<b>0.973</b>
IP_REGIME	2.646	-	2.227	-	-	-	-	-	-	-	-	-
GEO_REGION Asia-Pacific vs. North America	0.375	-	0.524	2.592	-	-	0.066	7.182	0.175	4.631	0.33	2.363
GEO_REGION Europe vs. North America	0.404	2.253	0.313	3.038	0.301	-	-	0.405	-	-	0.429	6.547
LICENSABLE_CORE	0.383	2.292	0.355	2.437	0.031	2.321	0.113	-	0.091	2.24	-	1.839
NREPLICATED_LAG1	1.018	-	1.065	-	0.963	-	-	-	0.971	-	1.05	-
NIMITATED_LAG1	-	-	-	0.996	-	1.047	-	1.25	-	1.076	-	1.009
NFIRMS_LAG1	1.267	-	1.078	-	1.643	0.911	1.81	1.699	1.751	0.876	1.205	1.065
Percent Concordant	77.4	65.9	76.2	63.1	88.1	74.3	86.2	81	87.5	73	72.6	67
Somers' D	0.553	0.329	0.533	0.295	0.777	0.511	0.75	0.672	0.762	0.479	0.459	0.36
Number of Products	853		332		125		128		253		268	
Mean Value of AC	8.35		4.74		4.68		10.07		7.41		13.71	
Mean Value of CC	9.79		4.94		15.00		5.33		10.11		15.50	
Estimated Size of the "Wedge" Between Replication and Imitation	-2.3%	-3.6%	68.4%	-	26.0%	-10.8%	-	127.7%	16.4%	7.4%	-2.5%	-2.7%
	<b>1.3%</b>				<b>36.8%</b>				<b>9.0%</b>		<b>0.2%</b>	

Note: Only the estimated Odds Ratios associated with parameters that are significant at the p<0.10 level or better in each model are shown



Table 9. Multinomial Logit Models of Likelihood of Product Outcomes

Variable	Estimated Odds Ratios for Comparisons of Outcomes					
	1 vs. 0	2 vs. 0	3 vs. 0	2 vs. 1	3 vs. 1	3 vs. 2
LOG10_AC	0.963	-	0.971	1.019	-	-
LOG10_CC	-	0.939	0.915	0.975	0.958	-
IP_REGIME	2.848	-	3.341	0.364	-	3.064
GEO_REGION Asia-Pacific vs. North America	0.432	1.804	-	3.583	2.225	0.529
GEO_REGION Europe vs. North America	-	1.884	-	3.199	1.521	0.42
LICENSABLE_CORE	0.454	-	-	3.717	1.81	0.496
NREPLICATED_LAG1	-	0.981	-	0.972	-	1.025
NFIRMS_LAG1	1.452	1.225	1.451	0.816	-	1.234

Note: Only the estimated Odds Ratios associated with parameters that are significant at the  $p < 0.10$  level or better in each model are shown

**Coding of Possible Outcomes:**

	% of Outcomes
0 = Product is Not Replicated and is Not Imitated within the current generation of technology	4.0%
1 = Product is Replicated, but is Not Imitated within the current generation of technology	51.0%
2 = Product is Imitated, but is Not Replicated within the current generation of technology	18.8%
3 = Product is Replicated and is Imitated within the current generation of technology	26.3%
<b>TOTAL</b>	<b>100.0%</b>

## Binary Logit Models for Imitation

Table 7 reports the results of the models examining how the values of algorithmic and computational complexity affect the likelihood that a newly introduced product is *imitated* within the then current generation of technology (Hypotheses H1b and H2b). Specifically, Model 6 represents a baseline specification comprised of all of the control variables. Models 7, 8, and 9 augment this baseline model by separately adding the direct effects of algorithmic complexity, computational complexity, and the change in IP regime. Model 10 is the full model with all of the independent variables and controls included. Consistent with the previously described Models 1-5 for examining the likelihood of replication, Models 6-10 for examining imitation include firm fixed effects. Across Models 6-10, all of the control variables are in the expected direction, but only the coefficients of the variables for GEO\_REGION and LICENSABLE\_CORE are significant. All of the models are significant and the relative improvement in quasi likelihood associated with each model in comparison to the baseline model is shown at the bottom of Table 7. This comparison indicates that Model 8 is the best fit for estimating the likelihood that a product is imitated.

The coefficient of the independent variable LOG10\_AC is *not significant* in either Model 7 or in Model 10, which is the full model. This does not support Hypothesis H1b, which predicts that the greater the algorithmic complexity of a newly introduced product, the lower the likelihood that it is subsequently imitated. The coefficient of LOG10\_CC is *negative* and *significant* in Model 8 ( $\beta = -0.04$ ,

$p < 0.01$ ) and Model 10 ( $\beta = -0.0364$ ,  $p < 0.01$ ). This supports Hypothesis H2b, which predicts that the greater the computational complexity of a newly introduced product, the lower the likelihood that it is subsequently imitated. The coefficient of IP\_REGIME is *negative* (its expected direction), but not significant in either Model 9 or in Model 10. This does not support Hypothesis H4b, which predicts that after a legal precedent strengthening the patentability of algorithms, the likelihood that a product is subsequently imitated is lower in comparison to products introduced before the precedent.

As a next step, I compute the odds ratios associated with the coefficients that are significant in the full models for replication (Model 5) and imitation (Model 10). These values are shown in Table 8 in the column labeled “Estimated Odds Ratios - For All Cases”. Since the values I used for the algorithmic and computational complexity are base 10 logarithms, a unit increase in LOG10\_AC or LOG10\_CC corresponds to a 10X increase in the measure.

Note that it is entirely possible for a 10X increase in the algorithmic and computational complexity of DSPs to occur in only a few years’ time, since Moore’s Law implies that the overall feasible complexity of such chips doubles every 18 to 24 months (Mollick 2006). A 10X increase in the algorithmic complexity of a newly introduced product reduces the odds that the product is replicated by -2.3%. Similarly, a 10X increase in the computational complexity of a newly introduced product reduces the odds that the product is imitated by -3.6%. In terms of estimating the size of the “wedge” between ease of replication and difficulty of imitation (Rivkin 2001), the net difference between the odds of

replication and the odds of imitation is 1.3% for all 853 DSP products in the sample.

In addition, the change in IP regime appears to have a significant effect on the likelihood that a product is replicated, but no significant effect on the likelihood that a product is imitated. For products introduced *after* the change in IP regime, the odds of subsequently being replicated are 2.65 times *higher* than for products introduced *before* the change in IP regime. Note that the coefficient of the control variable LICENSABLE\_CORE is in the *expected direction* and *significant* ( $p < 0.01$ ) in all of the Models 1-10 for replication and imitation shown in Table 6 and Table 7. In Model 5, the full model for replication, the coefficient of LICENSABLE\_CORE is *negative* ( $\beta = -0.9596$ ,  $p < 0.01$ ). In Model 10, the full model for imitation, the coefficient of LICENSABLE\_CORE is *positive* ( $\beta = 0.8293$ ,  $p < 0.01$ ). This supports Hypotheses H5a and H5b, which predict that making a product available through outbound technology licensing *decreases* the likelihood of replication and *increases* the likelihood of imitation.

For DSPs available as licensable cores, the odds of subsequently being replicated are 62% *lower*, while the odds of subsequently being imitated are 129% *higher* than for DSPs that are not available via licensing. A one product increase in the number of times that a product is previously replicated (NREPLICATED\_LAG1) increases the odds of subsequent replication by 1.8%. In contrast, a one product increase in the number of times that a product is previously imitated (NIMITATED\_LAG1) does not appear to have a significant effect on the odds of subsequent imitation.

### **Sub-Sample Analyses for Different Levels of Complexity**

As a refinement of the previously described analyses, I repeat the binary logistic regressions for replication (Model 5) and imitation (Model 10) on 4 distinct sub-samples of the 853 DSP products in the total sample. Each sub-sample corresponds to a separate case which represents a different level of information complexity. Classification in the appropriate sub-sample is determined by computing the median values of LOG10\_AC (4.8165) and LOG10\_CC (7.2247) respectively. Case 1 represents low overall information complexity and the 332 products in this sub-sample all have a value of LOG10\_AC and LOG10\_CC *below* their respective median values. Case 2 represents one of two possible scenarios for moderate overall complexity, while Case 3 represents the other. In Case 2, all of the 125 products in this sub-sample have a value of LOG10\_AC that is *below* the median and a value of LOG10\_CC that is *above* the median. Case 3 is exactly the opposite of Case 2. In Case 3, all of the 128 products in this sub-sample have a value of LOG10\_AC that is *above* the median and a value of LOG10\_CC that is *below* the median. Case 4 represents high overall information complexity and the 268 products in this sub-sample all have a value of LOG10\_AC and LOG10\_CC *above* their respective median values.

For comparison purposes, an additional case, which combines Case 2 and Case 3 is also shown. At moderate levels of overall information complexity (Case 2 and Case 3 combined), a 10X increase in algorithmic complexity *increases* the odds that a product will be replicated by 16.4%, while a 10X increase in computational complexity *increases* the odds that a product will be

imitated by 7.4%. In terms of estimating the size of the “wedge” between ease of replication and difficulty of imitation (Rivkin 2001), the net difference between the odds of replication and the odds of imitation is 9.0% for the 253 DSP products in the combined sub-sample for moderate levels of overall information complexity.

Decomposing the moderate complexity case further, the size of the “wedge” appears to be largest for the 125 products in Case 2, where algorithmic complexity is below its median value and computational complexity is above its median value. For Case 2, a 10X increase in computational complexity *increases* the odds that a product will be replicated by 26.0% and simultaneously *decreases* the odds that a product will be imitated by -10.8%. The net difference of 36.8% between the odds of replication and the odds of imitation for Case 2 is the largest of any of the 4 cases. In comparison, for Case 4, the net difference between the odds of replication and the odds of imitation is only 0.2%.

A meaningful direct comparison to Case 1 is not possible because neither algorithmic nor computational complexity appear to have a significant effect on imitation in Case 1. For the products in Case 1, geographic region and the availability of a product as a licensable core appear to have a significant effect on the likelihood that a product is imitated. For each of the cases shown, the closer that the percent of observations concordant with predictions are to 100% and the higher that the values of Somer’s D are above 0.5, the better the models fit with the observed data (Hosmer and Lemeshow 2008). Note that the proposed models have the largest percent concordance and highest values of Somer’s D for Case 2 and Case 3, which represent moderate complexity. Based on these

results, Hypothesis H3a is not supported, but Hypothesis H3b is supported. The difference between the likelihood that a product is replicated and the likelihood that it is imitated appears to be *greater* at moderate levels of complexity, in comparison to high levels of complexity.

### **Multinomial Logit Models for Product Outcomes**

As the next step in my analyses, I reformulate the model as a multinomial logit model which incorporates the four possible product outcomes as shown in Table 9. The comparison shown in the column labeled “3 vs. 0” shows the odds of the outcome that a product is replicated *and* imitated (OUTCOME=3) versus the outcome that a product is neither replicated *nor* imitated (OUTCOME=0). A 10X increase in algorithmic complexity reduces the odds of the outcome that a product is replicated and imitated by -2.9%, in comparison to the outcome that the product is neither replicated *nor* imitated. A 10X increase in computational complexity reduces the odds of the outcome that a product is replicated and imitated by -8.5%, in comparison to the outcome that the product is neither replicated *nor* imitated. The comparison shown in the column labeled “3 vs. 1” shows the odds of the outcome that a product is replicated *and* imitated (OUTCOME=3) versus the outcome that a product is replicated *but not* imitated (OUTCOME=1). A 10X increase in computational complexity reduces the odds of the outcome that a product is replicated and imitated by -4.2%, in comparison to the outcome that the product is replicated but not imitated. Thus far, Hypotheses H1a, H2b, H3b, H4a, H5a and H5b are supported. In the next section I test the remaining hypotheses, H6a and H6b.

## Analyses for Different Types of Entrants

Hypothesis H6a predicts that the likelihood that a newly introduced product is replicated is lower for *de novo* entrants than for diversifying entrants. Hypothesis H6b predicts that the likelihood that a newly introduced product is imitated is higher for *de novo* entrants than for diversifying entrants. To evaluate hypotheses H6a and H6b, I replace the variable LICENSABLE\_CORE with DIVERSIFYING\_ENTRANT and conduct additional analyses as described below.

First, I construct the series of contingency tables shown in Table 10. I compute the odds ratios (all are significant at the  $p < 0.01$  level) for each set of contingency tables and observe the following:

1. The odds that a product is replicated are 39.7% *lower* for *de novo* entrants than diversifying entrants.
2. The odds that a product is imitated are 66.2% *higher* for *de novo* entrants than diversifying entrants.
3. The odds that a product is replicated are 44.3% *lower* for products that are available as licensable cores than for products not available via licensing.
4. The odds that a product is imitated are 139% *higher* for products that are available as licensable cores than for products not available via licensing.
5. The odds that a product is available as a licensable core are 10.46 times *greater* for *de novo* entrants than for diversifying entrants.

The baseline observations listed above suggest that *de novo* entrants in the DSP industry have a greater propensity to make their newly introduced products available as licensable cores and, as a consequence, these products



are more likely to be imitated than products introduced by diversifying entrants. This supports Hypothesis H6a and H6b but further support is needed using models which include the full set of explanatory variables, beyond the 2 x 2 contingency tables and computed odds ratios shown in Table 10.

Next, I repeat the sub-sample analyses for different levels of complexity following the same steps as before (see page 68), except that I now replace the variable LICENSABLE\_CORE with DIVERSIFYING\_ENTRANT.<sup>16</sup> I control for all of the same factors as before. The results of these sub-sample analyses are shown in Table 11 (see the column labeled “Estimated Odds Ratios - For All Cases”). Overall, the odds that a newly introduced product is replicated are 99.5% higher for diversifying entrants than for *de novo* entrants. Also, overall, the odds that a product is imitated are 36.2% lower for a diversifying entrant than for a *de novo* entrant. These results are consistent with the observations obtained earlier from computing the odds ratios from the contingency tables in Table 10 and lend additional support to Hypothesis H6a and H6b.

Note that a 10X increase in algorithmic complexity *decreases* the odds that a product is replicated by 2.2%, but appears to have no significant effect on the odds that a product is imitated. A 10X increase in computational complexity, *increases* the odds that a product is replicated by 1.4% and *decreases* the odds that it is imitated by -3.9%. Thus, as a function of computational complexity, the size of the “wedge “ in terms of the relative difference between ease of replication and ease of imitation is 5.3% for all products.

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<sup>16</sup> Including both variables, LICENSABLE\_CORE and DIVERSIFYING\_ENTRANT could increase the potential for problems associated with multi-collinearity. The odds ratios computed for the observations listed on the previous page provide support for making this variable substitution.

Table 10. Contingency Tables and Odds Ratios

**CONTINGENCY TABLE FOR ENTRANT TYPE - NUMBER OF PRODUCTS IN EACH CATEGORY ARE SHOWN**

ENTRANT TYPE	OUTCOMES			TOTALS	OUTCOMES			% OF TOTAL
	REPLICATED	NOT REPLICATED			IMITATED	NOT IMITATED	TOTALS	
<i>DE NOVO</i>	251	98		<b>349</b>	183	166	<b>349</b>	41%
<i>DIVERSIFYING</i>	408	96		<b>504</b>	201	303	<b>504</b>	59%
<b>TOTALS</b>	<b>659</b>	<b>194</b>		<b>853</b>	<b>384</b>	<b>469</b>	<b>853</b>	100%
<b>% OF TOTAL</b>	77%	23%		100%	45%	55%	100%	
	Odds Ratio = 0.603				Odds Ratio = 1.662			

**CONTINGENCY TABLE FOR TECHNOLOGY LICENSING - NUMBER OF PRODUCTS IN EACH CATEGORY ARE SHOWN**

LICENSABLE CORE	OUTCOMES			TOTALS	OUTCOMES			% OF TOTAL
	REPLICATED	NOT REPLICATED			IMITATED	NOT IMITATED	TOTALS	
<i>YES</i>	129	59		<b>188</b>	116	72	<b>188</b>	22%
<i>NO</i>	530	135		<b>665</b>	268	397	<b>665</b>	78%
<b>TOTALS</b>	<b>659</b>	<b>194</b>		<b>853</b>	<b>384</b>	<b>469</b>	<b>853</b>	100%
<b>% OF TOTAL</b>	77%	23%		100%	45%	55%	100%	
	Odds Ratio = 0.557				Odds Ratio = 2.387			

**CONTINGENCY TABLE FOR ENTRANT TYPE AND TECHNOLOGY LICENSING - NUMBER OF PRODUCTS IN EACH CATEGORY ARE SHOWN**

ENTRANT TYPE	LICENSABLE CORE		TOTALS	% OF TOTAL
	YES	NO		
<i>DE NOVO</i>	153	196	<b>349</b>	41%
<i>DIVERSIFYING</i>	35	469	<b>504</b>	59%
<b>TOTALS</b>	<b>188</b>	<b>665</b>	<b>853</b>	100%
<b>% OF TOTAL</b>	22%	78%	100%	
	Odds Ratio = 10.460			

The computed Odds Ratios shown in all of the tables above are significant (p<0.01)

Table 11. Estimating the “Paradox of Replication” for Diversifying vs. *De Novo* Entrants

CASE	Estimated Odds Ratios		Estimated Odds Ratios at Different Levels of Overall Complexity									
			LOW		MODERATE		MODERATE		MODERATE		HIGH	
	FOR ALL CASES		CASE 1		CASE 2		CASE 3		CASE 2 and CASE 3		CASE 4	
Value of AC	All Values of AC		LOW, AC < 4.8165		LOW, AC < 4.8165		HIGH, AC >= 4.8165		ALL VALUES IN CASE 2 and CASE 3		HIGH, AC >= 4.8165	
Value of CC	All Values of CC		LOW, CC < 7.2247		HIGH, CC >= 7.2247		LOW, CC < 7.2247				HIGH, CC >= 7.2247	
Likelihood a Product is	REPLICATED	IMITATED	REPLICATED	IMITATED	REPLICATED	IMITATED	REPLICATED	IMITATED	REPLICATED	IMITATED	REPLICATED	IMITATED
LOG10_AC	0.978	-	1.907	-	-	-	-	1.14	-	1.076	0.981	-
LOG10_CC	1.014	0.961	-	1.93	1.195	0.894	0.485	2.392	1.138	-	1.012	0.966
IP_REGIME	2.491	-	2.049	-	-	-	-	-	-	-	-	-
GEO_REGION Asia-Pacific vs. North America	0.373	-	-	2.685	0.251	4.414	0.088	5.675	0.094	6.075	0.479	2.073
GEO_REGION Europe vs. North America	0.466	2.066	0.314	2.971	0.473	-	3.534	0.311	-	-	0.455	5.821
DIVERSIFYING_ENTRANT	1.995	0.638	2.042	-	-	-	-	-	-	-	2.372	0.48
NREPLICATED_LAG1	1.018	-	1.066	-	0.974	-	-	-	0.98	-	1.043	-
NIMITATED_LAG1	-	-	-	0.996	-	1.05	-	1.224	-	1.077	-	1.009
NFIRMS_LAG1	1.281	-	1.094	-	1.641	0.904	1.476	1.661	1.701	0.871	1.222	1.061
Percent Concordant	76.1	65.5	75.4	63.8	84.9	73.7	84.7	80.3	85.3	72.7	74	68.2
Somers' D	0.529	0.322	0.519	0.304	0.713	0.496	0.712	0.656	0.715	0.473	0.488	0.385
Number of Products	853		332		125		128		253		268	
Mean Value of AC	8.35		4.74		4.68		10.07		7.41		13.71	
Mean Value of CC	9.79		4.94		15.00		5.33		10.11		15.50	
Estimated Size of the "Wedge" Between Replication and Imitation	1.4%	-3.9%	90.7%	93.0%	19.5%	-10.6%	-51.5%	139.2%	13.8%	7.6%	1.2%	-3.4%
	5.3%		-2.3%		30.1%		-190.7%		6.2%		4.6%	

Note: Only the estimated Odds Ratios associated with parameters that are significant at the  $p < 0.10$  level or better in each model are shown

Table 12. Multinomial Logit Model of Likelihood of Product Outcomes for Diversifying vs. *De Novo* Entrants

Estimated Odds Ratios for Comparisons of Outcomes						
Variable	1 vs. 0	2 vs. 0	3 vs. 0	2 vs. 1	3 vs. 1	3 vs. 2
LOG10_AC	0.959	-	0.969	1.021	-	-
LOG10_CC	-	0.953	0.917	0.969	0.956	-
IP_REGIME	2.303	-	3.047	0.395	-	3.16
GEO_REGION Asia-Pacific vs. North America	0.288	-	-	3.576	2.768	0.598
GEO_REGION Europe vs. North America	-	2.718	-	2.578	1.436	0.414
DIVERSIFYING_ENTRANT	-	0.398	-	0.464	-	2.448
NREPLICATED_LAG1	-	1.048	-	0.971	-	1.021
NFIRMS_LAG1	1.467	1.114	1.451	0.807	-	1.247

Note: Only the estimated Odds Ratios associated with parameters that are significant at the  $p < 0.10$  level or better in each model are shown

Coding of Possible Outcomes:	% of Outcomes
0 = Product is Not Replicated and is Not Imitated within the current generation of technology	4.0%
1 = Product is Replicated, but is Not Imitated within the current generation of technology	51.0%
2 = Product is Imitated, but is Not Replicated within the current generation of technology	18.8%
3 = Product is Replicated and is Imitated within the current generation of technology	26.3%
TOTAL	100.0%

Table 13. Summary of Results for Hypothesized Differences in Products, Levels of Complexity, and Entrants

Hypothesis	Variable(s) of Interest	Model(s)	Results
<b>H1a</b>	Algorithmic Complexity, REPLICATED	Binary Logit for Replication	<b>SUPPORTED</b> , coefficient of LOG10_AC is <i>negative</i> and <i>significant</i> ( $p < 0.05$ )
<b>H1b</b>	Algorithmic Complexity, IMITATED	Binary Logit for Imitation	NOT SUPPORTED, coefficient of LOG10_AC is <i>not</i> significant
<b>H2a</b>	Computational Complexity, REPLICATED	Binary Logit for Replication	NOT SUPPORTED, coefficient of LOG10_CC is <i>not</i> significant
<b>H2b</b>	Computational Complexity, IMITATED	Binary Logit for Imitation	<b>SUPPORTED</b> , coefficient of LOG10_CC is <i>negative</i> and <i>significant</i> ( $p < 0.05$ )
<b>H3a</b>	Moderate vs. Low Levels of Information Complexity, REPLICATED, IMITATED	Sub-Sample Analyses	NOT SUPPORTED, coefficient values in low complexity case are <i>not</i> significant, does not allow a meaningful comparison to moderate complexity case
<b>H3b</b>	Moderate vs. High Levels of Information Complexity, REPLICATED, IMITATED	Sub-Sample Analyses	<b>SUPPORTED</b> , size of the “wedge” is the greatest at moderate levels of complexity (9.0%) in comparison to high levels of complexity (0.2%) <sup>17</sup>
<b>H4a</b>	IP Regime Change, REPLICATED	Binary Logit for Replication	<b>SUPPORTED</b> , coefficient of IP_REGIME is <i>positive</i> and <i>significant</i> ( $p < 0.01$ )
<b>H4b</b>	IP Regime Change, IMITATED	Binary Logit for Imitation	NOT SUPPORTED, coefficient of IP_REGIME is <i>negative</i> (its expected direction) but <i>not significant</i>
<b>H5a</b>	Technology Licensing, REPLICATED	Binary Logit for Replication	<b>SUPPORTED</b> , coefficient of LICENSABLE_CORE is <i>negative</i> and <i>significant</i> ( $p < 0.01$ )
<b>H5b</b>	Technology Licensing, IMITATED	Binary Logit for Imitation	<b>SUPPORTED</b> , coefficient of LICENSABLE_CORE is <i>positive</i> and <i>significant</i> ( $p < 0.01$ )
<b>H6a</b>	Diversifying Entrants vs. De Novo Entrants, REPLICATED	Contingency Tables	<b>SUPPORTED</b> , odds of replication -39.7% for <i>de novo</i> entrants ( $p < 0.01$ )
		Sub-Sample Analyses	<b>SUPPORTED</b> , odds of replication +99.5% for diversifying entrants ( $p < 0.1$ )
		Multinomial Logit for Product Outcomes	<b>SUPPORTED</b> , odds of outcome “3 vs. 2” +245% for diversifying entrants ( $p < 0.1$ )
<b>H6b</b>	Diversifying Entrants vs. De Novo Entrants, IMITATED	Contingency Tables	<b>SUPPORTED</b> , odds of imitation +66.2% for <i>de novo</i> entrants ( $p < 0.01$ )
		Sub-Sample Analyses	<b>SUPPORTED</b> , odds of imitation -36.2% for diversifying entrants ( $p < 0.1$ )
		Multinomial Logit for Product Outcomes	<b>SUPPORTED</b> , odds of outcome “2 vs. 1” -53.6% for diversifying entrants ( $p < 0.1$ )

<sup>17</sup> When the variable LICENSABLE\_CORE is replaced with DIVERSIFYING\_ENTRANT, this result holds and the size of the “wedge” at moderate complexity is 6.2% in comparison to 4.6% at high levels of complexity.

At low levels of information complexity (Case 1), the odds that a product is replicated are 104% higher for diversifying entrants than for *de novo* entrants. However, at these low levels of information complexity, the type of entrant does not appear to have a significant effect on the odds that a product is imitated. At moderate levels of information complexity (Case 2, Case 3, and Case 2 and 3 combined), the type of entrant does not appear to have any significant effect on the odds that a product is replicated or on the odds that it is imitated. In contrast, at high levels of information complexity (Case 4), the type of entrant does appear to have a significant effect on the odds that a product is replicated and on the odds that it is imitated. At these high levels of information complexity, the odds that a product is replicated are 137% higher for diversifying entrants than for *de novo* entrants. The odds that a product is imitated are 52% lower for diversifying entrants than for *de novo* entrants.

As a final step in the analyses of the effect of the type of entrant on the likelihood of replication and imitation, I repeat the multinomial logit analyses following the same steps as before (see page 70). As explained in the previous set of sub-sample analyses, I again replace the variable LICENSABLE\_CORE with DIVERSIFYING\_ENTRANT and I control for all of the same factors as before. The results are shown in Table 12.

The comparison shown in the column labeled “2 vs. 0” shows the odds of the outcome that a product is imitated *but not* replicated (OUTCOME=2) versus the outcome that a product is replicated *nor* imitated (OUTCOME=0). These results indicate that the odds of outcome “2 vs. 0” occurring are 61.2% lower for

diversifying entrants than for *de novo* entrants, which suggests that products introduced by diversifying entrants are less likely to be imitated. This lends further support to Hypothesis H6b.

The comparison shown in the column labeled “2 vs. 1” shows the odds of the outcome that a product is imitated *but not* replicated (OUTCOME=2) versus the outcome that a product is replicated *but not* imitated (OUTCOME=1). These results indicate that the odds of outcome “2 vs. 1” occurring are 53.6% lower for diversifying entrants than for *de novo* entrants, which also suggests that products introduced by diversifying entrants are less likely to be imitated. Again, this lends further support to Hypothesis H6b.

The comparison shown in the column labeled “3 vs. 2” shows the odds of the outcome that a product is replicated *and* imitated (OUTCOME=3) versus the odds of the outcome that a product is imitated *but not* replicated (OUTCOME=2). These results indicate that the odds of outcome “3 vs. 2” occurring are 245% higher for diversifying entrants than for *de novo* entrants, which suggests that products introduced by diversifying entrants are more likely to be replicated. This lends further support to Hypothesis H6a.

Evaluated separately and collectively, the preceding analyses of contingency tables, sub-samples at different levels of complexity, and the multinomial logit model all consistently support Hypotheses H6a and H6b. Overall, for the 853 products introduced by the 91 firms in the sample, the likelihood that a product is replicated is lower for *de novo* entrants than for diversifying entrants, which supports Hypothesis H6a. Also for all of these

products and firms, the likelihood that a product is imitated is higher for *de novo* entrants than for diversifying entrants, which supports Hypothesis H6b. The “wedge” between ease of replication and ease of imitation appears to be greatest for diversifying entrants at high levels of information complexity. However, at moderate levels of information complexity, there does not appear to be a significant size “wedge” difference between diversifying and *de novo* entrants.

Overall, eight out of the twelve proposed hypotheses are supported (Hypotheses H1a, H2b, H3b, H4a, H5a, H5b, H6a and H6b). A summary of the results is presented in Table 13. The contributions, implications, limitations and future research directions related to all of the findings presented in this chapter are discussed in detail in the next chapter.



## VI. DISCUSSION AND CONCLUSION

Based on the preceding results, for the 91 DSP firms and 853 products in the sample, information complexity appears to be a meaningful predictor of the likelihood that a newly introduced product is replicated, imitated, or both. In general, increases in algorithmic complexity appear to *decrease* the likelihood that a product is replicated, while increases in computational complexity appear to *decrease* the likelihood that a product is imitated. However, the direction and significance of the effects of algorithmic and computational complexity appear to vary at different levels of overall information complexity and in the presence of the full set of control variables. Consistent with predictions of past simulation studies reported in the literature, there appears to be a “wedge” between the ease of replication and the difficulty of imitation, and the size of this “wedge” seems to be the greatest at moderate levels of complexity. At high levels of overall information complexity, in particular, the size of the wedge is comparatively smaller than at moderate levels of complexity.

In addition, an IP regime change which strengthens the patentability of algorithms appears to significantly increase the likelihood that a newly introduced product is subsequently replicated but does not significantly decrease the likelihood that the product is imitated. In contrast, under IP regimes which facilitate the formation of a market for technology, outbound licensing of a newly introduced product appears to significantly decrease the likelihood that the

product is replicated, while significantly increasing the likelihood that the product is imitated. Products introduced by *de novo* entrants are less likely to be replicated and more likely to be imitated than products introduced by diversifying entrants. Diversifying entrants appear to have the greatest advantage over *de novo* entrants at high and low levels of information complexity. Neither diversifying entrants nor *de novo* entrants appear to have a significant relative advantage over the other at moderate levels of complexity.

## **Contributions**

In terms of theory, this study contributes to the broader strategy and entrepreneurship literature by introducing a model and methods for estimating the inherent complexity of any product, when the product is represented in the form of an algorithm. I integrate research streams from information theory with research streams on the KBV of the firm to formulate a methodology for evaluating the relationship between information complexity and firm-level product replication and imitation processes. I extend earlier work on relational complexity and strategy based on NK models in a new direction by developing measures for information complexity based on the underlying information-theoretic concepts of algorithmic and computational complexity.

I also develop and test a method for mapping new product introductions to a finite set of algorithms of known or computable complexity. I apply this method to empirically test a generalized model of information complexity in the context of the process of entrepreneurial discovery in knowledge-intensive industries. I not only demonstrate “proof of concept” that the method works, I also obtain

empirical evidence to support largely untested predictions from prior simulation-based studies on knowledge replication and imitation processes. Specifically, I introduce an information-theoretic approach to quantifying the extent to which the “paradox of replication” (Kogut and Zander 1992) or the “wedge” between the ease of replication and the difficulty of imitation (Rivkin 2001) affects the reproduction of newly introduced products as units of knowledge.

The generalized model of information complexity may be applied to the analysis of a broad range of knowledge-intensive industries that are growing in their economic and technological importance, and where products may be represented in the form of an algorithm. This empirically testable model may be especially useful in industry contexts where the values of  $N$  and  $K$  or the degree of modularity does not vary substantially across products and relational complexity is therefore not a meaningful predictor of product replication or imitation (Solow et al. 1999). For researchers, managers, and policymakers involved in analyzing or making decisions related to R&D, product management, and technology strategy, this study outlines a practical tool for estimating how much the inherent complexity (Wilson and Latombe 1994) of a product affects a firm’s ability to replicate the product and its competitors’ abilities to imitate the product.

## **Implications**

My methodology for examining information complexity, replication, and imitation suggests several important theoretical, managerial, and policy implications, as described below. For strategy and entrepreneurship scholars

who seek to understand the antecedents and consequences of knowledge reproduction processes within firms, this methodology offers a means to analyze not only products, but any unit of knowledge that can be represented as an algorithm. For example, codifiable organizational routines may be represented in algorithmic form as a complete and finite set of information and instructions for completing a specified task (Dosi 2000; Grant 1996b; Lillrank 2003; Nelson and Winter 1982; Winter and Szulanski 2001). Codified organizational processes, procedures, mindsets, dominant logics, and strategic logics that undergird the rules and heuristics for making decisions (Bettis and Prahalad 1995; Bingham et al. 2007; Pentland and Feldman 2005; Pentland and Rueter 1994; Tollin 2008) may be analyzed in terms of their algorithmic and computational complexity in a similar manner to the analyses conducted in this study.<sup>18</sup>

Because the concepts of algorithmic and computational complexity are grounded in the fundamental principles of information theory, any algorithmic representation of the information associated with a unit of knowledge can be analyzed quantitatively. However, producing algorithmically and computationally complex products may not necessarily require that a firm's strategies, routines, and processes of firms also be algorithmically and computationally complex (Baldwin and Clark 2000; Beinhocker 2006; Davis et al. 2009). In fact, as Eisenhardt and Sull (2001) explain, "When the business landscape was simple, companies could afford to have complex strategies. But now that business is so

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<sup>18</sup> "Organizational routines can be conceptualized as generative systems with internal structures and dynamics ... For some questions, routines can be taken as a unit of analysis without considering their internal structure, but there are many research questions for which it is useful to consider the parts of routines either separately or as they interact" (Pentland and Feldman 2005).

complex, they need to simplify. Smart companies have done just that with a new approach: a few straightforward, hard-and-fast rules that define direction without confining it” (Eisenhardt and Sull 2001).

A further implication of this study may be the need to broaden complexity-related research in strategic management and entrepreneurship beyond the concept of relational complexity or interdependence implicit in the use of NK models. In particular, this study demonstrates the potential value of developing new, empirically testable models and measures for other dimensions of complexity such as information (Boisot 2000; Boisot and Canals 2004; Boisot et al. 2007; Sorenson 2005). While this study focused on the effects of differences in products, IP regimes, and the type of entrant on knowledge replication and imitation, this study also highlights the need for further research at multiple levels of analysis. For example, conceptual and experimental research on managerial cognition may help uncover the possible relationship between information complexity and the individual and collective decision-making processes of managers and management teams (Simon 1959).

For managers in knowledge-intensive industries who seek to build competitive advantage for their firms, different types of information complexity may have a different direction and magnitude of effect on the likelihood that a product is replicated or imitated. For example, in the DSP industry setting of this study, at moderate levels of overall information complexity, simultaneously increasing algorithmic and computational complexity results in the greatest size “wedge” between the likelihood of replication and imitation. However, in the same

industry setting, but at high levels of overall information complexity, simultaneously increasing algorithmic and computational complexity results in a much smaller “wedge” between the likelihood of replication and imitation. These empirical findings support and extend the propositions and predictions of previous conceptual work (Bharadwaj et al. 1993; Reed and DeFillippi 1990) and simulation studies (Rivkin 2000, 2001). These results suggest that the type of information complexity (algorithmic or computational), and the level of overall information complexity (low, moderate, or high), may matter a great deal in terms of the relative ease or difficulty of replication and imitation. Maximizing the size of the “wedge” at any given level of overall information complexity requires managers to understand how high-level product design choices (Hobday 1998; Hobday et al. 2000; Novak and Eppinger 2001; Sanchez and Mahoney 1996) and development paths (Baldwin and Clark 2000; Clark and Fujimoto 1991; Millson et al. 1992; Rothaermel and Deeds 2004) drive the different types of information complexity, and in turn how information complexity drives replication and imitation processes.

In addition, when operating at the same overall level of information complexity and when subject to the same IP regime, managers of different types of entrants (diversifying and *de novo*), may make different optimal decisions for their respective firms regarding outbound licensing and product strategy. Based on the empirical results obtained from the DSP industry, diversifying entrants have the greatest competitive advantage over *de novo* entrants at low and at high levels of complexity but no significant advantage at moderate levels of

complexity. Thus, when faced with a large number of *de novo* entrants as potential competitors, diversifying entrants should focus on introducing products of either low or high information complexity. In contrast, when faced with a large number of diversifying entrants as potential competitors, *de novo* entrants should focus on introducing products of moderate information complexity. Furthermore, to maximize its competitive advantage at moderate levels of complexity, a *de novo* entrant should, whenever possible, pursue a replicator strategy and opt to be an *Integrated Producer* rather than an *Outbound Licensor* of its products.

For policymakers in regulatory agencies and positions of authority who seek to encourage innovation in knowledge-intensive industries in a pro-competitive manner, providing institutional frameworks and legal precedents which reinforce the patentability of algorithms may be a vital policy tool. This study indicates that products introduced by DSP firms headquartered in the Asia-Pacific and European regions are substantially less likely to be replicated and substantially more likely to be imitated than products introduced by firms headquartered in North America. A change in IP regime in the U.S. which strengthens the patentability of algorithms appears to enhance the incentives for firms headquartered in North America to focus on replicating their own products. With stronger government assurances that their intellectual property rights for algorithms will be protected, North American firms may expect greater economic rents from replication (Hall and Ziedonis 2001; Jaffe 2000; Kortum and Lerner 1998; Schoemaker 1990). As a potential policy tool, supporting the patentability of algorithms may promote product replication, but may not necessarily deter

imitation. This is because imitation deterrence is often driven by the expected costs and benefits of future patent litigation (Lanjouw and Schankerman 2001; Somaya 2003) rather than the existence of past legal precedents.

IP regime changes which facilitate the formation of markets for technology may dramatically alter the competitive landscape by shifting the strategic incentives for firms to engage in outbound licensing or integrated production. If IP regime changes allow and approve of knowledge-sharing arrangements such as cross-licensing agreements (Grindley and Teece 1997; Hall and Ziedonis 2001; Shapiro 2000), patent pools (Gilbert 2004; Joshi and Nerkar 2011; Lerner 2002; Merges 2001) and R&D consortia (Branstetter and Sakakibara 2002; Grossman and Shapiro 1986; Sakakibara 2002), then these arrangements may also shift the incentives for firms to pursue a replicator or an imitator strategy. Beyond the information complexity of products themselves, the structural complexity of the IP regime (Alter and Meunier 2009; Coriat and Orsi 2002; Helfer 2009; Jaffe 2000; Malerba and Orsenigo 1993) under which these products are introduced may be a critical factor in determining the likelihood of replication and imitation.

Using the empirical results obtained from my analyses of the DSP industry, I compiled a list of questions and answers for researchers, managers, and policymakers to use when estimating the likelihood of replication and imitation of products introduced by different firms. This list is intended to serve as a set of “rules of thumb” for making “optimally imperfect decisions” (Baumol and Quandt 1964) based on whether a product is more or less likely to be replicated or imitated (see Table 14).



Table 14. “Rules of Thumb” for Estimating Replication and Imitation<sup>19</sup>

Main Question	Follow-up Question	Answers Based on This Study
Which product, A or B, is more likely to be replicated?	What is the algorithmic complexity of each product?	The product with the <i>greater</i> algorithmic complexity is <i>less</i> likely to be <i>replicated</i> . If the algorithmic complexity is the <i>same</i> for both products, then the products are <i>equally</i> likely to be replicated.
Which product, A or B, is more likely to be imitated?	What is the computational complexity of each product?	The product with the greater computational complexity is <i>less</i> likely to be <i>imitated</i> . If the computational complexity is the <i>same</i> for both products, then the products are equally likely to be <i>imitated</i> .
Should the respective firms that introduced product A and product B, pursue a replicator or an imitator strategy?	What is the overall level of information complexity of each product? LOW, MODERATE, or HIGH	At <i>moderate</i> levels of information complexity, replicators have the <i>greatest</i> advantage over imitators. Therefore, the firm introducing the product should pursue a <i>replicator</i> strategy. At <i>low</i> and <i>high</i> levels of information complexity, replicators have the <i>smallest</i> advantage over imitators. Therefore, the firm introducing the product should pursue <i>either</i> strategy without significantly affecting how likely the product is to be replicated or imitated.
How does a change in IP regime affect whether a product more or less likely to be replicated or imitated?	Does the new IP regime support the patentability of algorithms? YES or NO	If the IP regime supports the patentability of algorithms, then the product is <i>more</i> likely to be <i>replicated</i> but <i>not necessarily less</i> likely to be <i>imitated</i> .
How does technology licensing affect whether a product more or less likely to be replicated or imitated?	Is the product available via outbound licensing? YES or NO	If the product is available via outbound licensing, then the product is <i>less</i> likely to be <i>replicated</i> and <i>more</i> likely to be <i>imitated</i> .
How does the type of firm affect whether a product more or less likely to be replicated or imitated?	Is the firm that introduced the product a diversifying entrant (established firm) or a <i>de novo</i> entrant (startup or spinoff)?	At <i>low</i> and <i>high</i> levels of information complexity, a product introduced by a diversifying entrant is <i>more</i> likely to be <i>replicated</i> and <i>less</i> likely to be <i>imitated</i> than a product introduced by a <i>de novo</i> entrant. At <i>moderate</i> levels of information complexity, there is <i>no significant difference</i> between diversifying and <i>de novo</i> entrants in terms of how likely a product is to be <i>replicated</i> or <i>imitated</i> .

<sup>19</sup> Baumol and Quandt (1964) define a rule of thumb to be a set of rules describing a decision procedure with the following characteristics:

- (a) The variables which are employed in the decision criteria are objectively measurable;
- (b) The decision criteria are objectively communicable, and decisions do not depend on the judgment of individual decision-makers;
- (c) As a corollary to (b), every logically possible configuration of variables corresponds to a (usually unique) determinate decision;
- (d) The calculation of the appropriate decision is simple, inexpensive, and well suited for frequent repetition and for spot checking by management in higher echelons.

A decision process with these characteristics seems to be designed as the instrument par excellence of optimally imperfect decision-making for routine and recurrent problems.

## **Limitations and Future Directions for Research**

While this study contributes to the existing strategy and entrepreneurship literature and offers important implications for theory, practice, and policy, there are some limitations that future extensions could address. First and foremost, the fundamental assumption that makes my methodology analytically tractable and empirically testable — that units of knowledge such as products can be represented as algorithms — may not apply to a number of knowledge-based products such as creative, cultural or entertainment goods (Caves 2000; Cunningham 2002; Hirsch 1972). That said, as described earlier, there are a number of industries in which products may be represented as algorithms. This study focuses on one industry in particular, DSP, and the findings in terms of the direction and magnitude of the effects of algorithmic and computational complexity on the likelihood of replication and imitation may differ across industries.

One of the limitations of this single-industry study is that it is not possible to completely discern the extent to which technological, financial, and temporal constraints determine the feasible set of design choices which firms face prior to making decisions to replicate or imitate earlier products (Gonzalez-Zugasti et al. 2000; Pate-Cornell and Dillon 1998; 2001). These high-level design choices may directly drive the level and type of complexity associated with a newly introduced product and the related information processing activities of the organization introducing the product (Novak and Eppinger 2001; Sosa et al. 2004). Furthermore, these choices may change dramatically during generational shifts

in technology (Bass and Christensen 2002). For example, a generational shift in technology such as a new system architecture may reduce or even remove some critical technical, economic, and timing constraints for all firms while increasing or adding new constraints (Malerba and Orsenigo 1993). Changes in any of these constraints may enable the formation of new firms and the exploitation of new markets through replication and/or imitation (Shane 2001).

I speculate that one of the possible reasons why Hypotheses H1b, H2a, H3a, and H4b are not supported by the results of this study is because of the nature and duration of the eight distinct generational shifts in DSP technology which occurred from 1973 to 2009.<sup>20</sup> For example, in the initial stages and early generations of DSP technology, increases in algorithmic complexity may have been far more feasible than increases in computational complexity. Therefore, early on, copying data may have been easier than copying instructions, which makes replication somewhat easier and imitation slightly more difficult (this supports H1a, but not H1b). In contrast, in the mid-to-later generations of DSP technology, increases in computational complexity may have been much more feasible than increases in algorithmic complexity.<sup>21</sup> Therefore, later on, copying data may have been harder than copying instructions, which makes replication somewhat more difficult and imitation slightly easier (this supports H2b, but not H2a). Because the earlier generations of DSP technology are on average shorter

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<sup>20</sup> The recombination and rediscovery of mathematical, architectural, and material innovations may have had a profound effect on the technological evolution of the DSP industry. These factors are analyzed and discussed in detail from a historical perspective in the Appendix. Mathematical innovations in particular may have had a greater impact on the feasible level of computational complexity than on the feasible level of algorithmic complexity.

<sup>21</sup> See Figure 3 for a graph of the feasible complexity for each generation of DSP technology.

in duration with fewer products introduced than in the later generations, a meaningful comparison between moderate and low levels of complexity is not possible (this supports H3b, but not H3a).<sup>22</sup> In the case of a change in IP regime which strengthens the patentability of algorithms, this study found a positive and significant effect on the likelihood of replication and a negative but not significant effect on the likelihood of imitation (this supports H4a, but not H4b). The existence of a substantial common, codified, and cumulative base of knowledge available in the public domain may help explain why firms appear to be able to invent around (Samuelson and Scotchmer 2002) patented algorithms and imitate these algorithms without infringing on the IP rights of the original inventors, even when those rights are strengthened by an IP regime change.

Further empirical work is needed to refine and validate the model and findings presented here. Future work could expand the methodology to the analysis of the replication and imitation of new products in a diverse array of industries that are based on fundamental innovations in algorithms (Berlinski 2001). A multi-industry study comparing product introductions across a range of knowledge-intensive industries, or a single-industry study comparing product introductions based on different technologies may shed light on the extent to which the likelihood of replication and imitation varies as a function of industry and technology characteristics including technological, financial, and temporal constraints.

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<sup>22</sup> Recall from Figure 3 and Table 4 that only a small number of low complexity products were introduced in the earlier stages of the DSP industry. In fact, about 71% of all of the product introductions occurred in the last two generations of DSP technology. These products had, on average, higher levels of algorithmic and computational complexity than the products introduced in the preceding generations of DSP technology.

In this study, I control for firm effects by using robust standard errors that are clustered at the firm-level and this approach accounts for firm-level heterogeneity. If correlations exist between the complexity measures I examined and the unobserved attributes of products, the coefficients obtained will be overstated (Allison 2003; Hosmer and Lemeshow 2008). Research that controls for additional firm-level heterogeneity can improve the precision of the estimates of the effect of algorithmic and computational complexity on the likelihood that a newly introduced product is replicated or imitated. Despite these limitations, this research provides strong evidence that the likelihood of a product being replicated or imitated is associated with measurable dimensions of information complexity. In addition, there may be factors in the competitive environment that influence the likelihood that a product is subsequently replicated or imitated. Although I have attempted to control for these factors in my models, there may be some unobserved factors that are not fully captured in these models.

Future research could build on the model, methods, and results presented here in a number of potentially promising areas. One important area for future research may be the development of more precise measures for algorithmic and computational complexity. In this study, I use the data width and instruction width of a DSP product as proportional approximations of the algorithmic and computational complexity of the product (Goldreich 2008; Grünwald 2007). This approach may result in extremely conservative estimates which are only rough approximations of the respective quantities of interest. More advanced information-theoretic models and techniques may enable much more precise

measurement of information complexity in a variety of settings (Li and Vitányi 2008; MacKay 2003).

Another important area for future work may be investigating the error rates of replication and imitation associated with the processing of complex information. For tractability, this study assumed that error rates of replication and imitation were constant for each firm. However, these error rates may themselves be algorithmically and computationally complex functions of a wide range of explanatory variables (Anderson 1999)<sup>23</sup> including parameters associated with the breadth and depth of firm search patterns (Gavetti and Levinthal 2000; Siggelkow and Rivkin 2005), the level of pre-entry experience (Ganco and Agarawal 2009; Ganco and Hoetker 2009), and the degree of knowledge simplification implied by the use of managerial heuristics (Baumol and Quandt 1964; Davis et al. 2009). Furthermore, if errors occasionally generate beneficial mutations (Axelrod and Cohen 1999; McKelvey 1999; Mitleton-Kelly 2003) when copying knowledge, then under certain conditions, higher error rates may actually increase the chances of successfully exploiting the information obtained through entrepreneurial discovery processes.

Yet another important area for future research may be examining how firms produce complex products by cooperating with other firms including current and prospective competitors in innovation networks within industries and across industries. A firm's structural position as well as its degree of embeddedness in an innovation network (Granovetter 1985; Gulati et al. 2000; Henderson and

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<sup>23</sup> As Anderson (1999) points out, "It is usually impossible to forecast the exact value of a chaotic system in nature, because small measurement errors between two apparently identical values at time  $t$  can lead to large differences at time  $t + 1$ ."

Clark 1990) may enable it to absorb and handle differing amounts of information complexity. In addition, the underlying deep structure (Ackerman et al. 2008; Barley 1986; DeSanctis and Poole 1994; Orlikowski 1992) of the information obtained via participation in an innovation network may vary in ways not fully captured by the measurement of algorithmic and computational complexity.

Although the methodology developed in this study is primarily used to examine the replication and imitation of products as a unit of knowledge, other aspects of organizations may also be represented as algorithms. Quoting Winter (1986), Grant (1996b) defines an organizational routine as a “relatively complex pattern of behavior ... triggered by a relatively small number of initiating signals or choices and functioning as a recognizable unit in a relatively automatic fashion.” This definition of an organizational routine is congruent with the conceptualization of algorithms upon which this entire study is based. Embracing the methodology presented here may open up intriguing new possibilities for research on the quantitative measurement of information complexity and the replication and imitation of units of knowledge such as organizational routines, processes, procedures, decision-making rules and heuristics. Beyond entrepreneurial discovery in knowledge-intensive industries, information complexity may be a useful concept for understanding how the inherent structure of units of knowledge affects strategic decisions at the firm-level. In sum, I believe that extending this methodology to other aspects of organizational strategy as well as overcoming the previously described limitations of this study offer promising new directions for future research.

## APPENDIX: INDUSTRY SETTING AND HISTORICAL CONTEXT

### **Mixed Signals: How the Recombination and Rediscovery of Mathematical, Material, and Architectural Innovations Shaped the Signal Processing Industry, 1948-2008<sup>24</sup>**

#### **The Science of Signal Processing**

Signal processing is the science of identifying, analyzing, manipulating, and extracting physical signals such as audio, video, images and sensory data in real-time. Digital Signal Processors (DSPs) are semiconductor chips which are the core engines of a diverse array of products including cell phones, digital cameras, high-definition televisions, network equipment, global-positioning systems, and communications satellites. DSPs account for \$27 billion or 10% of global semiconductor revenues (Strauss 2008). Although DSPs are technologically and economically significant, the evolution of innovation in the signal processing industry is relatively unexplored.

In this appendix, I trace the commercialization of signal processing since its inception in 1948, when the following three breakthrough innovations occurred. Information theory, a *mathematical* innovation, introduced a conceptual foundation for designing DSPs. Transistors, a *material* innovation, provided the

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<sup>24</sup> A an earlier version of the material contained in this appendix was summarized and presented at the Business History Conference (BHC) Annual Meeting on the “The Business History of Everything” held March 25-27, 2010 in Athens, GA and was nominated for the K. Austin Kerr Prize for Best Ph.D. Student Paper. Parts of this appendix were also presented in a talk entitled “An Analysis of the Evolution of the Digital Signal Processing Industry as a Global Market for Technology, 1986-2008,” at the Industry Studies Association (ISA) Conference, held at the University of Illinois-Chicago, May 6, 2010.



physical building blocks for creating DSPs. Stored-program computing, an *architectural* innovation, offered an integrated framework for recombining mathematical and material innovations to produce functional DSPs. An analysis of sixty years of subsequent innovation in DSPs reveals that: (1) some fundamental mathematical innovations are actually rediscoveries of earlier inventions; (2) architectural innovations often lag mathematical innovations by decades due to the technological constraints of material innovations; and (3) architectural innovations frequently reconfigure industry alliances and open new markets. The unintentional loss and rediscovery of mathematical innovations, the unanticipated lag between architectural and mathematical innovations, and the unexpected rearrangement of firm alliances are all possible sources of surprising new entrepreneurial opportunities to be discovered and exploited by firms in the signal processing industry.

Within the domain of science, the discipline of signal processing has been described as a remarkable success story that has resulted in the tangible creation of a multitude of useful “products that have changed the way we live” (Chiariglione 1997). From a cell phone in a caller’s hand to a communications satellite in Earth’s orbit, and from local wireless networks for Internet connectivity to global positioning systems (GPS) for vehicle navigation — and nearly everything digital in between — signal processing is a fundamental, enabling technology which makes all of these products possible. Although most people are aware of the many end products resulting from signal processing research

and development, few people are aware of the existence of the underlying scientific field of signal processing itself.

As Leah H. Jamieson<sup>25</sup>, 2007 President and CEO of the Institute of Electrical and Electronics Engineers (IEEE)<sup>26</sup> observed regarding signal processing's lack of visibility as an engineering endeavor, "it often seems that only the people who actually work in signal processing think about who we are and what we do" (Nebeker 1998a).

The purpose of this appendix is to broaden and deepen our understanding of the origins, historical evolution, technological importance, and economic significance of the "numerous innovations in theory, algorithms, and implementation" (Hu 1997) in signal processing from 1948 to 2008. From a Schumpeterian perspective, the most essential aspect of innovation is "carrying out new combinations" to generate inventions which may include "discovery scientifically new and can also exist in a new way of handling a commodity commercially" (Schumpeter 1934). I examine how the *recombination* and *rediscovery* of three types of innovations — *mathematical*, *material*, and *architectural* — generated surprises and impacted the commercialization of signal processing.

This appendix is organized in the following manner. First, I briefly describe the *early origins of signal processing* and discuss the earliest known digital

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<sup>25</sup> August 2009. Biosketch of Leah H. Jamieson.

<sup>26</sup> The IEEE is the world's largest technical society. By 2008, IEEE had 375,000 members in 160 countries, with 43% outside of the United States, where it was founded in 1884 as the American Institute of Electrical Engineers (AIEE). IEEE includes 38 societies in various specialties and serves its members with 130 journals, transactions and magazines; more 300 conferences annually; and 900 active standards. See A Brief History of the IEEE.

representation of a signal. I also define the basic terminology used throughout the study. Next, I outline the growth of *modern signal processing as a formalized field of research* from its birth in 1948, to the introduction of the first digital signal processor chip in 1974; I highlight relevant and inter-related innovations in information theory, transistors, and computing. Then, I analyze the emergence and structure of *digital signal processing as a global high-technology industry* from 1974 to 2008, with an emphasis on exploring the role of innovation in reshaping inter-firm alliances and driving new opportunities. Finally, I summarize the main findings of this historical analysis and assess their potential implications for innovation in other knowledge-intensive industries. Based on these findings and implications, I evaluate recent speculation on the future of signal processing.

### **The Early Origins of Signal Processing, c. 2500 B.C.**

#### *The “Palermo Stone” and Nilometers*

Possibly the first known application of signal processing may be traced back to approximately 2500 B.C., when the ancient Egyptians used the “Palermo Stone” (St. John 2003; Wilkinson 2000) and a series of measuring stations called “nilometers” (Ardagh 1889; Manoug 1889) along the banks of the Nile River to measure seasonal water levels in an attempt to predict future flooding (Eltahir and Wang 1999; Jarvis 1964). In this c. 2500 B.C. example, the signal, or physical quantity sampled, was the water level of the Nile, and the processing, or codification of the signal, was the regular and periodic inscription of the corresponding hieroglyphs into stone by human hands (Prandoni and Vetterli 2008).



Figure 4. Photograph of a Large Fragment of the “Palermo Stone”

(On display in the Regional Archeological Museum in Palermo, Italy. Source: Wikimedia Commons)



Figure 5. Illustration of the Nilometer on the Isle of Rhoda, Cairo

David Roberts (1796-1864).  
Source: Wikimedia Commons



Figure 6. Photograph of a Modern DSP Chip Manufactured by Texas Instruments, 1988

Source: Wikimedia Commons

Table 15. Type of Innovation in Primitive DSP System and Modern DSP Chips

Type of Innovation	Primitive DSP System	Modern DSP Chips	Potential Impact on Field	Relevant Previous Findings
<b><i>Mathematical</i></b>	Egyptian calendar, writing system, & numerals (Gardiner and Gauthier-Laurent 1927)	Information theory & numerical analysis	The “formalization” and “axiomization” of a mathematical theory will facilitate its wider use (Glas 1999).	Both “thought experiments” and “numerical experiments” contribute to knowledge and are essential to the process of conceptual reform and mathematical innovation (Stoltzner 2003).
<b><i>Material</i></b>	Stones and the tools for carving & transport (Lucas and Harris 1962)	Transistors and the tools for design & manufacture	Technical benchmarks (such as Moore’s Law <sup>27</sup> ) are a self-fulfilling prophecy; technologies will evolve in ways not predicted by and even contradictory to established benchmarks (Tuomi 2002).	The entry of global competitors and the adoption of industry standards increase the diversity and rate of material innovation, thereby enabling organizations to overcome the performance barriers implicit in technical benchmarks (Mollick 2006).
<b><i>Architectural</i></b>	Construction of nilometers (Clarke and Engelbach 1990)	Construction of stored-program computer	Architectural innovation will be “initiated by new entrants and will lead to the failure of incumbents in a product class” (Tushman and Nelson 1990). <sup>28</sup>	Architectural innovation leads to “the failure of incumbents and the rise of new organizations; this process recurs over successive generations of architectural innovations” (Tushman and Nelson 1990).

<sup>27</sup> Moore’s Law characterizes an empirically observed relationship indicating that the number of transistors on an integrated circuit has doubled approximately every 18-24 months, over the history of computing. The Law is named in honor of Intel Co-Founder Gordon Moore. For Moore’s original article, see (Moore 1998). For Moore’s own updated perspective, see (Moore 1995).

<sup>28</sup>Quote is from page 3 of (Tushman and Nelson 1990) The referenced quote summarizes the original longitudinal study by Henderson and Clark of the photolithography industry from 1962 to 1986 appearing in the same issue. See (Henderson and Clark 1990). See also (Christensen 1992) For related work on recombinant innovation see (Galunic and Eisenhardt 2001).

Restated in more specific, 21<sup>st</sup> century A.D. technical terms, *signals* are analog or digital electrical representations of time-varying or spatial-varying physical quantities (Oppenheim and Schaffer 1975). *Signal processing* is the science of identifying, analyzing, manipulating, and extracting signals in real-time (Lyons 1997). *Digital Signal Processing (DSP)* “is the mathematics, the algorithms, and the techniques used to manipulate these signals after they have been converted into a digital form” (Smith 1997). *Digital Signal Processors (DSPs)*<sup>29</sup> are physical devices or semiconductor chips that are used to digitally convert, transform and analyze audio, voice, image, video and other sensory signals from one form to another (Eyre and Bier 1998; Eyre 2000).

Thus, now expressed in modern parlance, the “Palermo Stone”, “nilometers”, and human stone carvers can be regarded as the essential components of a primitive DSP system which was used to capture the measurement of Nile’s water level as a discrete-time digitally-sampled physical signal and manually convert it into the form of pictorial images (St. John 2003).

#### *Innovation in Primitive DSP System and Modern DSP Chips*

Because its hieroglyphically-encoded digital data is still used in contemporary hydrological (Atiya et al. 1999) and statistical (St. John 2003) research, the Palermo Stone is “arguably the first recorded digital signal which is still of relevance today” (Prandoni and Vetterli 2008). In the preceding example, the creation of a primitive stone-based DSP system was made possible by the

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<sup>29</sup> Within the industry and academia, the term “DSP” is commonly used to mean both “Digital Signal Processing” and “Digital Signal Processor,” the singular form of “Digital Signal Processors.” To avoid confusion, in this study, the term “DSP” is used specifically to refer to the science, while the terms “DSP chips” and “DSPs” are used to refer specifically to the chips.

earlier mathematical, material, and architectural innovations summarized in Table 15. As will be discussed in the next section, the development of modern silicon-based DSP chips was also made possible by significant advances within each type of innovation. The potential impact and relevant previous findings for each of these types of innovation are also shown in Table 15.

### **Modern Signal Processing as a Formalized Field of Research, 1948-1973**

The story of modern signal processing begins in 1948 and continues to the present day. *Three major research breakthroughs appeared in 1948: the introduction of information theory, the invention of the transistor, and the demonstration of the first stored-program computer* (Nebeker 1998c). Understanding the emergence of these three distinct, yet highly complementary research areas is critical for analyzing the evolution of signal processing as a general purpose technology (GPT). General purpose technologies (GPTs) are defined as *enabling technologies*, which “open up new opportunities, rather than offering complete, final solutions” (Bresnahan and Trajtenberg 1995).

A GPT is a type of “drastic innovation” which has “the potential for pervasive use in a wider range of sectors in ways that drastically change their modes of operation” (Helpman 1998). GPTs have four essential features: “(1) much scope for improvement initially, (2) many varied uses, (3) applicability across large parts of the economy, and (4) strong complementarities with other technologies” (Lipsey et al. 2005). Although prior studies have examined the evolution of related GPTs such as the electric dynamo and the personal computer (David 1990), as well as microprocessors (Grindley and Teece 1997;



Hall and Ziedonis 2001; Linden 2003), the current study is perhaps among the first to analyze the evolution of signal processing as a GPT from the perspective of economic history and Schumpeterian innovation (Nebeker 1998a, b, c).

*Information Theory in 1948: The Mathematical Logic for Designing DSPs*

The year 1948 is generally considered to be the starting point for signal processing as a formalized field of research. The seminal event which launched the field was the publication of Claude Elwood Shannon's (1948) paper entitled "A mathematical theory of communication" in which he laid out the foundations of information theory. According to Shannon (1948), "the fundamental problem of communication is that of reproducing at one point, either exactly or approximately, a message selected at another point." Shannon first introduced and defined the smallest unit of information to be a *bit*, which is a simple binary representation of a 0 or 1 value (Waldrop 2001). Shannon published his work in the *Bell System Technical Journal* and the core ideas in his paper were heavily influenced by the earlier work of Bell Labs researchers including Harry Nyquist and Ralph Hartley. While at Bell Labs, Shannon also briefly worked with Alan Turing as part of a joint cryptographic research project (Aspray 1985) with the British military during World War II and with John von Neumann and Norbert Wiener at Princeton's Institute for Advanced Study (Kahn 1967).

Earlier, in 1924, Nyquist published "Certain factors affecting telegraph speed" in the *Bell System Technical Journal*, in which he formulated a theory describing bandwidth requirements for accurate and reliable information transmission (Maliniak 2005). In 1928, Hartley published "Transmission of

information,” in the same journal and for the first time introduced “a quantitative measure by which the capacities of various systems to transmit information may be compared” (Hartley 1970). Hartley’s work was published shortly after the first successful transatlantic transmission of a television program (Burns et al. 1998) from London to Hartsdale, New York and he discussed “its application to systems of telegraphy, telephony, picture transmission and television over both wire and radio paths” (Hartley 1970). Nyquist’s and Hartley’s research can be further traced back to the even more fundamental physics concepts of energy and entropy and the principles of thermodynamics and statistical mechanics first proposed by Ludwig Boltzmann in 1877 and later refined in 1901 by Willard Gibbs and Max Planck (Gibbs et al. 1906; Planck 1901).

It is important to note that Shannon, Nyquist, and Hartley all developed their ideas while employed at Bell Labs (or its precursor research center at the Western Electric Company) and they all published their findings in the *Bell System Technical Journal*. Thus, if the birth of modern signal processing can be traced back to a single organization, it is Bell Labs. Another significant contribution which Shannon made in 1948 in collaboration with colleagues at Bell Labs was the enhancement of Pulse Code Modulation (PCM) which was originally invented independently by Paul Rainey in 1926 and Alan Reeves in 1937 (Nebeker 1998c). Shannon along with Bernard Oliver and John Pierce described the underlying theory of a new method for digitally converting and quantizing signals into an efficient binary format that is the basis for audio and video coding schemes widely used in digital telephone and multimedia systems

even to this day (Verdu 1998). In 1948, Shannon's fellow Bell Labs scientist and research collaborator, Richard Hamming developed an error-correction code for binary transmission which greatly improved the reliability of signal processing and today bears his name as "the Hamming code" (MacKay 2003). Also in 1948, the work of British statistician Maurice Bartlett on time-series analysis advanced mathematical techniques for spectrum estimation (Nebeker 1998c) which is critical for signal processing applications.

Why did so many important information-theoretic breakthroughs related to signal processing emerge around 1948? Norbert Wiener, generally regarded as the "father of cybernetics" speculated that "Largely because of the impetus gained during the World War II, communication and control engineering have reached a very high level of development today. Many perhaps do not realize that the present age is ready for a significant turn in the development toward far greater heights than we have ever anticipated" (Wiener 1949). Military investment in research and development for applications such as communications, cryptography, and radar appears to be the primary catalyst for early advances in signal processing (Walker 2003) and Claude Shannon, Norbert Wiener, Warren McCulloch, Walter Pitts, Alan Turing, and John Von Neumann emerged as the scientific leaders of the post-war research program to build a unified information theory from multi-disciplinary fields (Aspray 1985).

#### *Transistors in 1948: The Physical Materials for Building DSPs*

In 1948, another critical event which contributed to the birth of modern signal processing was the announcement of the invention of the transistor by Bell

Labs researchers John Bardeen, Walter Brattain, and William Shockley (Riordan and Hoddeson 1998). The original design of the transistor was actually begun by Bardeen and Brattain in 1947 and subsequently improved by William Shockley in 1948, who prototyped earlier field effect transistor designs (Clements 2007) that were patented by Julius Lilienfeld in Canada in 1927 and 1928 and by Oskar Heil in Germany in 1934 (Hutcheson 2005; Kleint and Lilienfeld 1998). The trio of Bardeen, Brattain, and Shockley was awarded the Nobel Prize in Physics in 1956 and a description of their invention is included below.

The transistor is a three terminal, solid state electronic device. In a three terminal device we can control electric current or voltage between two of the terminals by applying an electric current or voltage to the third terminal. This three terminal character of the transistor is what allows us to make an amplifier for electrical signals, like the one in our radio. With the three-terminal transistor we can also make an electric switch, which can be controlled by another electrical switch. By cascading these switches (switches that control switches that control switches, etc.) we can build up very complicated logic circuits.<sup>30</sup>

The invention of the transistor revolutionized the electronics industry. Expensive and energy-consuming vacuum tubes could be replaced with cheaper, lower-power and more reliable transistors which could perform the same amplification and switching functions essential for signal processing with much more efficiency (Riordan and Hoddeson 1998). It is interesting to note that the name “transistor” was actually coined by John Pierce, who was one of Claude Shannon’s original collaborators along with Bernard Oliver on PCM. Pierce supervised Bardeen, Brattain, and Shockley’s series of experiments on the development of the transistor. Bell Labs served as the intellectual nexus for the information theorists and transistor physicists whose collective work in

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<sup>30</sup> Description of the Transistor. Source: <http://www.nobelprize.org>

establishing a formal and axiomatic foundation for signal processing would soon radically shape its evolution.

*Stored-Program Computing in 1948: The System Architecture for Implementing DSPs*

In addition to the multiple breakthroughs in information theory and the invention of the transistor which occurred at Bell Labs in 1948, the third major area of innovation which catalyzed the formation of signal processing as a field of research was the demonstration of the first stored-program computer by Frederick Williams and Tom Kilburn at the University of Manchester in England (Nebeker 1998a). As first published in *Nature* (Lavington 1993), the Small-Scale Experimental Machine (SSEM), nicknamed the "Baby", was designed and built at the University of Manchester, and made its first successful run of a program on June 21, 1948 (Williams and Kilburn 1948). The SSEM was the first computer that could store not only data but any user program in electronic memory and process it at electronic speed (Williams and Kilburn 1949).

Table 16. Functional Specifications of the Small-Scale Experimental Machine (SSEM)

SSEM Functionality
32-bit word length
Serial binary arithmetic using 2's complement integers
A single address format order code
A random access main store of 32 words, extendable up to 8192 words
A computing speed of around 1.2 milliseconds per instruction

The SSEM functioned according to the specifications shown in Table 16. Although these specifications would appear to be extremely primitive and

painfully slow by modern computing standards, they were unprecedented at the time. A replica of the SSEM was built in 1998 in commemoration of the 50<sup>th</sup> anniversary of its invention and a picture is shown in Figure 7.

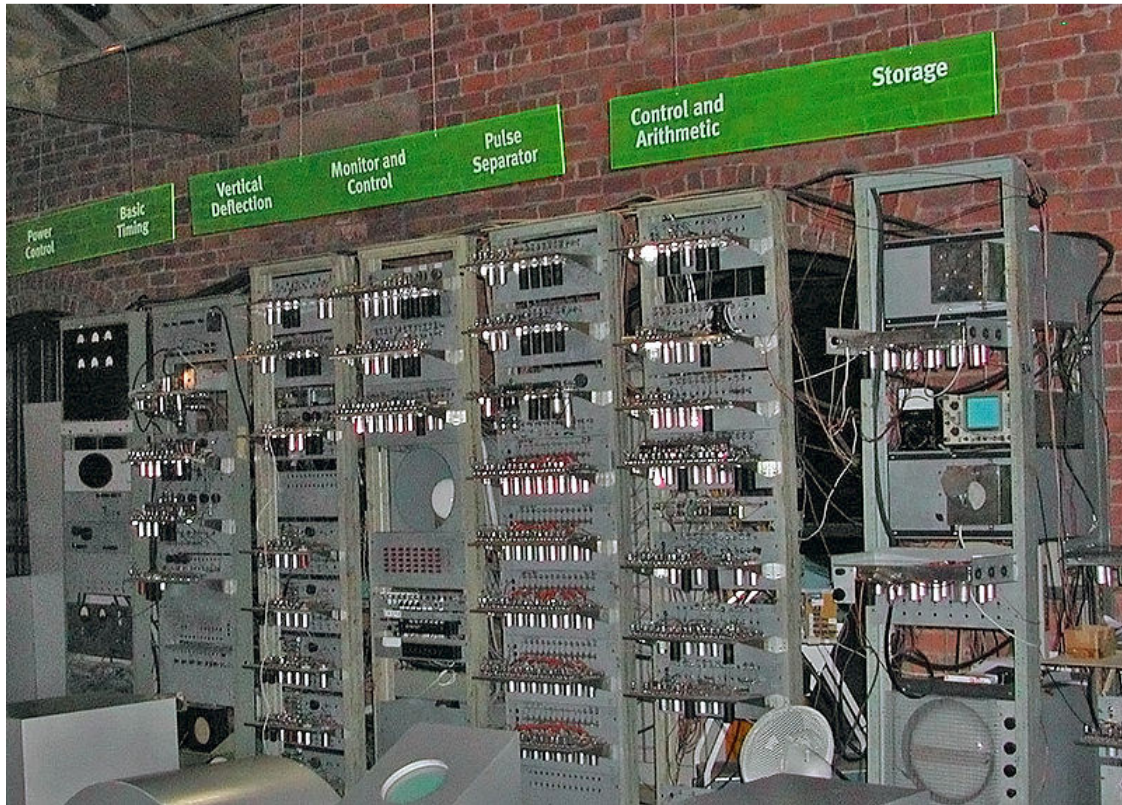


Figure 7. Photograph of a Replica of the SSEM, The World's First Stored-Program Computer  
(On Display at the Museum of Science and Industry in Manchester, England)  
Source: Wikimedia Commons

Williams and Kilburn along with other colleagues at the University of Manchester were later instrumental in producing the world's first transistor computer in 1953. This transistor computer was built using 200 contact point transistors and performed arithmetic operations at 125,000 calculations per second.<sup>31</sup> In comparison, 55 years later, in 2008, Intel announced the world's

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<sup>31</sup> Source: University of Manchester Computer Science Archives

first computer with over 2 billion transistors on a single chip and which operates at clock speeds between 1.2 to 2 GHz.<sup>32</sup>

Thus, in 55 years, the number of transistors which may be incorporated into a single computer has increased by a factor of 10 million, a remarkable rate of advance that has led to the rapid evolution of signal processing as a GPT. This rate of technical advance is even more astounding when one compares the processing speed of single-chip DSPs to microcontrollers, a specialized form of microprocessor-based computer on a single chip (Nebeker 1998c). From 1980 to 1995, the performance of single-chip DSPs increased by about three orders of magnitude (a factor of improvement of nearly 1,000 times) in comparison to the performance of microcontrollers (Frantz and Papamichalis 1996). The remarkable and unprecedented rate of technological advancement in signal processing may account for the occurrence of substantial errors in threat perception and opportunity recognition among firms in the industry. These errors in assessing threats and opportunities may, in turn, contribute the magnitude and direction of the numerous surprises encountered by firms in the industry.

#### *Timeline and Milestones in Modern Signal Processing, 1948-1974*

Although the critical technologies which led to the formalization of the field of signal processing first emerged in 1948, *it was not until 26 years later that the first commercially available digital signal processing (DSP) chips were actually produced.* In 1973, TRW produced the first “DSP engine” which was designed for classified U.S. military applications and was not commercially available. The first commercially available off-the-shelf DSP chips were introduced the next year

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<sup>32</sup> Sources: Intel and Physorg <http://www.physorg.com/news121350597.html>

in 1974 by Advanced Micro Devices as the Am2901 family of discrete logic chips (Strauss 2007). In the period from 1948 to 1974, a number of unexpected or surprising technical advances occurred in information theory, transistors, and computing which were essential to the development of the first DSP chips.

These advances and related market events such as the entry of new companies and products are summarized chronologically in Tables 17,18, 19, and 20, with major developments impacting signal processing highlighted (see shaded blocks) throughout.

Table 17. Timeline of Events in the Field of Signal Processing,<sup>33</sup> 1948-1949

Year	Information Theory	Transistors	Computing
1948	<ul style="list-style-type: none"> <li>At Bell Labs in the U.S., Claude Shannon publishes foundations of information theory.</li> <li>Claude Shannon, Bernard Oliver and John Pierce publish fundamentals of Pulse Code Modulation (PCM).</li> <li>Richard Hamming introduces error correction codes</li> <li>Maurice Bartlett introduces statistical techniques for spectrum estimation.</li> </ul>	<ul style="list-style-type: none"> <li>Bell Labs announces the invention of the transistor by researchers John Bardeen, Walter Brattain and William Shockley.</li> <li>Raytheon CK703 is first commercially available transistor.</li> <li>Junction transistor theory developed by William Shockley at Bell Labs.</li> </ul>	<ul style="list-style-type: none"> <li>At the University of Manchester in England, Frederic Williams and Tom Kilburn demonstrate the Small-Scale Experimental Machine (SSEM), the first stored-program computer.</li> </ul>
1949	<ul style="list-style-type: none"> <li>Shannon's <i>Communication Theory of Secrecy Systems</i> is declassified.</li> <li>Marcel J. E. Golay introduces Golay codes for forward error correction.</li> <li>John Tukey introduces statistical techniques for the spectral analysis of random processes.</li> </ul>	<ul style="list-style-type: none"> <li>"Type A" point contact transistor enters limited production at Bell Labs.</li> <li>W. MacWilliams builds the Transistor Gating Matrix at Bell Labs, using 40 "Type A" transistors; this is the first functional transistor application.</li> </ul>	<ul style="list-style-type: none"> <li>BINAC, the Binary Automatic Computer, is designed for Northrop Aircraft Company by the Eckert-Mauchly Computer Corporation (EMCC), which was the first computer company. BINAC was the first stored-program computer in the US, and the world's first commercial digital computer.</li> </ul>

<sup>33</sup> I compiled this set of tables (Table 17-20) from multiple sources, including Nebeker (1998a, b, c) and Verdu (1998). For additional details and more in-depth timelines for information theory, transistors and computing, see also <http://www.historyofscience.com>, [http://www.intel.com/museum/online/hist\\_micro/hof/](http://www.intel.com/museum/online/hist_micro/hof/), <http://www.sciencetimeline.net>, and <http://www.asc-cybernetics.org/foundations/timeline.htm>.



Table 18. Timeline of Events in the Field of Signal Processing, 1950-1959

Year	Information Theory	Transistors	Computing
1950-1959	<p><b>1951</b></p> <ul style="list-style-type: none"> <li>David A. Huffman invents Huffman encoding, a method of finding optimal prefix codes for lossless data compression for any set of symbols; the algorithm is eventually used for compressing data in everything from compact discs to interplanetary spacecraft (Waldrop, 2001).</li> </ul> <p><b>1955</b></p> <ul style="list-style-type: none"> <li>Peter Elias introduces convolutional codes.</li> </ul> <p><b>1956</b></p> <ul style="list-style-type: none"> <li>Noam Chomsky publishes "Three Models for the Description of Language" and introduces two key concepts: the hierarchy of syntactic forms, and transformational-generative grammar theory; Chomsky expands on these ideas in <i>Syntactic Structures</i> (1957).</li> <li>Norbert Wiener publishes <i>The Human Use of Human Beings</i>.</li> <li>Ross Ashby publishes <i>Introduction to Cybernetics</i>.</li> </ul> <p><b>1957</b></p> <ul style="list-style-type: none"> <li>Eugene Prange first discusses cyclic redundancy codes.</li> </ul> <p><b>1958</b></p> <ul style="list-style-type: none"> <li>A joint United States and European committee is formed to create a universal programming language, 'Algorithmic Language,' or 'Algol.' the precursor of 'Pascal.' In the course of creating Algol, John Backus and Peter Naur invented 'Backus-Naur notation' for giving the formal definition of a programming language.</li> </ul> <p><b>1959</b></p> <ul style="list-style-type: none"> <li>Raj Chandra Bose and Dwijendra Kumar Ray-Chaudhuri, and independently the next year Alexis Hocquenghem, present BCH codes.</li> </ul>	<p><b>1950</b></p> <ul style="list-style-type: none"> <li>First grown junction transistor created at Bell Labs.</li> </ul> <p><b>1951</b></p> <ul style="list-style-type: none"> <li>30 Companies licensed by Western Electric to manufacture transistors.</li> <li>First alloy junction transistors developed at GE and RCA.</li> </ul> <p><b>1952</b></p> <ul style="list-style-type: none"> <li>Texas Instruments (TI) enters semiconductor business by licensing transistor from Western Electric (Bell Labs).</li> <li>Hearing aids become first commercial product to use transistors; Raytheon produces 10,000 CK718 hearing aid transistors.</li> <li>GPC markets the first commercial grown junction transistor (2517 series).</li> </ul> <p><b>1953</b></p> <ul style="list-style-type: none"> <li>Total U.S. transistor production for the year is 1,000,000 units.</li> </ul> <p><b>1954</b></p> <ul style="list-style-type: none"> <li>Regency and TI develop and market the first all-transistor radio (TR-1).</li> <li>TI markets the first commercial silicon transistor (900 series).</li> </ul> <p><b>1956</b></p> <ul style="list-style-type: none"> <li>Shockley, Bardeen and Brattain awarded the Nobel Prize for the invention of the transistor.</li> </ul> <p><b>1957</b></p> <ul style="list-style-type: none"> <li>Fairchild semiconductor division founded by former scientists from Shockley Semiconductor Laboratory.</li> </ul> <p><b>1958</b></p> <ul style="list-style-type: none"> <li>Jack Kilby invents integrated circuit at TI.</li> </ul> <p><b>1959</b></p> <ul style="list-style-type: none"> <li>Texas Instruments introduces first commercial integrated circuit (IC).</li> </ul>	<p><b>1950</b></p> <ul style="list-style-type: none"> <li>Alan Turing proposes the Turing Test to decide if a computer is exhibiting intelligent behavior.</li> <li>Sperry Rand builds the first commercially-available data processing machine, the UNIVAC I.</li> </ul> <p><b>1951</b></p> <ul style="list-style-type: none"> <li>IBM decides to produce their first electronic computer, the 701. It is a machine for scientific applications and IBM eventually sells nineteen of these machines.</li> </ul> <p><b>1952</b></p> <ul style="list-style-type: none"> <li>EDVAC (Electronic Discrete Variable Computer) completed at the Institute for Advanced Study, Princeton, USA (by Von Neumann and others).</li> </ul> <p><b>1953</b></p> <ul style="list-style-type: none"> <li>An Wang invents the magnetic core computer memory.</li> <li>IBM announces the development of the 702, a version of the 701 designed for business rather than scientific applications.</li> </ul> <p><b>1954</b></p> <ul style="list-style-type: none"> <li>IBM announces the 704. It is the first commercially available computer to incorporate indexing and floating point arithmetic as standard features. The 704 also features a magnetic core memory, far more reliable than its predecessors' memories.</li> </ul> <p><b>1956</b></p> <ul style="list-style-type: none"> <li>Nathaniel Rochester and John H. Holland publish computer programs which simulated neural networks.</li> </ul> <p><b>1957</b></p> <ul style="list-style-type: none"> <li>Commercial transistorized computers, including the UNIVAC Solid State 80 and the Philco TRANSAC S-2000, are introduced. These inaugurate the so-called second generation of electronic computers.</li> </ul>

Table 19. Timeline of Events in the Field of Signal Processing, 1960-1969

Year	Information Theory	Transistors	Computing
1960-1969	<p><b>1960</b></p> <ul style="list-style-type: none"> <li>Irving S. Reed and Gustave Solomon propose Reed-Solomon codes.</li> <li>Bernard Widrow and Marcian "Ted" Hoff develop the Least-Means-Squares (LMS) algorithm for adaptive filtering.</li> </ul> <p><b>1962</b></p> <ul style="list-style-type: none"> <li>Robert G. Gallager proposes Low-density parity-check codes; they are unused for 30 years due to technical limitations.</li> </ul> <p><b>1964</b></p> <ul style="list-style-type: none"> <li>Leonard Kleinrock publishes his 1962 PhD thesis <i>Communication Nets: Stochastic Message Flow and Delay</i>, providing a mathematical theory of packet data network communications.</li> </ul> <p><b>1965</b></p> <ul style="list-style-type: none"> <li>James W. Cooley and John Tukey rediscover the Fast Fourier Transform (FFT) algorithm originally formulated by Carl Friedrich Gauss in 1805 and describe how to implement it on a computer.</li> </ul> <p><b>1966</b></p> <ul style="list-style-type: none"> <li>John Stockham and Howard Helms independently invent fast convolution, which combines the FFT with digital filtering and convolution.</li> </ul> <p><b>1967</b></p> <ul style="list-style-type: none"> <li>Andrew Viterbi reveals the Viterbi algorithm, making decoding of convolutional codes practicable.</li> <li>Bishnu Atal and Manfred Schroeder invent adaptive predictive coding (APC) which enables efficient coding of speech signals for transmission over communications networks.</li> <li>Atal also invents linear predictive coding (LPC), an extension of APC which is used in the compression, recognition and synthesis of speech signals.</li> </ul> <p><b>1968</b></p> <ul style="list-style-type: none"> <li>Elwyn Berlekamp invents the Berlekamp-Massey algorithm; used for decoding BCH and Reed-Solomon codes.</li> <li>Chris Wallace and David M. Boulton publish the first of many papers on Minimum Message Length (MML) statistical and inductive inference.</li> </ul>	<p><b>1961</b></p> <ul style="list-style-type: none"> <li>TI delivers the first integrated circuit computer to the U.S. Air Force. The advanced experimental equipment has a total volume of only 6.3 cubic inches and weighs only 10 ounces. It provides the identical electrical functions of a computer using conventional components which is 150 times its size and 48 times its weight, which also was demonstrated.</li> </ul> <p><b>1964</b></p> <ul style="list-style-type: none"> <li>Texas Instruments in partnership with Zenith Radio introduces the first consumer product containing an integrated circuit--a hearing aid.</li> </ul> <p><b>1965</b></p> <ul style="list-style-type: none"> <li>Future Intel co-founder Gordon Moore observes the exponential growth in the number of transistors per integrated circuit and predicts that this trend will continue. The press calls this "Moore's Law."</li> </ul> <p><b>1966</b></p> <ul style="list-style-type: none"> <li>Robert H. Dennard of IBM invents Dynamic Random Access Memory (DRAM) cells— one-transistor memory cells that store each single bit of information as an electrical charge in an electronic circuit. The technology permitted major increases in memory density.</li> </ul> <p><b>1967</b></p> <ul style="list-style-type: none"> <li>Texas Instruments files the patent for the first hand-held electronic calculator, invented by Jack S. Kilby, Jerry Merryman, and Jim Van Tassel. This miniature calculator employed a large-scale integrated array containing the equivalent of thousands of discrete semiconductor devices.</li> </ul> <p><b>1968</b></p> <ul style="list-style-type: none"> <li>Robert Noyce, Gordon Moore and Andrew Grove found Intel. The company is originally incorporated under the name of NM Electronics.</li> </ul> <p><b>1969</b></p> <ul style="list-style-type: none"> <li>Marcian "Ted" Hoff designs the first microprocessor, an integrated circuit semiconductor chip which was able to receive instructions and send data.</li> </ul>	<p><b>1960</b></p> <ul style="list-style-type: none"> <li>The Advanced Research Projects Agency (ARPA) of the United States Defense Department increases funding for research on computing.</li> <li>IBM introduces a transistorized version of its vacuum-tube-logic 709 computer, the 7090. It was the first commercially available general purpose computer with transistor logic, and it became the most popular large computer of the early 1960s.</li> </ul> <p><b>1961</b></p> <ul style="list-style-type: none"> <li>TI builds the first computer specifically designed for signal processing, the TI187, which is used to analyze seismic data, although not in real-time.</li> </ul> <p><b>1962</b></p> <ul style="list-style-type: none"> <li>Douglas Engelbart of Stanford Research Institute completes his report, <i>Augmenting Human Intellect: A Conceptual Framework</i>, for the Air Force Office of Scientific Research.</li> </ul> <p><b>1964</b></p> <ul style="list-style-type: none"> <li>IBM announces the System/360 family, the first IBM computers capable of both commercial and scientific applications. All IBM 360s ran the same operating system -- OS/360. Previously each computer model required a different operating system.</li> <li>RCA announces the Spectra series of computers, which run the same software as IBM's 360. The Spectra computers were the first commercial computers to use integrated circuits.</li> </ul> <p><b>1964</b></p> <ul style="list-style-type: none"> <li>Pres Eckert and John Mauchly receive a general patent on the stored-program electronic computer. Sperry Rand Univac, owner of the patent, charged a 1.5 percent royalty for all electronic computers sold by all companies except IBM, with which it had previously cross-licensed patents.</li> </ul> <p><b>1968</b></p> <ul style="list-style-type: none"> <li>Douglas Engelbart of Stanford Research Institute demonstrates an "oNLine System" (NLS), the features of which include hypertext, text editing, screen windowing, and email.</li> </ul>

Table 20. Timeline of Events in the Field of Signal Processing, 1970-1974

Year	Information Theory	Transistors	Computing
1970-1974	<p><b>1970</b></p> <ul style="list-style-type: none"> <li>Valerii Denisovich Goppa introduces Goppa codes, A new class of linear correcting codes.</li> </ul>	<p><b>1970</b></p> <ul style="list-style-type: none"> <li>Gilbert Hyatt files a patent application entitled Single Chip Integrated Circuit Computer Architecture based on work begun in 1968. This was the first general patent on the microprocessor. Twenty years later in 1990, the U.S. Patent Office awarded the patent, but was overturned in 1995.</li> </ul>	<p><b>1970</b></p> <ul style="list-style-type: none"> <li>MIT Lincoln Labs develops the Fast Digital Processor (FDP), the first real-time DSP computer, which performed signal processing tasks about 100 time faster than the general-purpose computers of the era. A more powerful version was introduced in 1974 for speech processing.</li> </ul>
	<p><b>1971</b></p> <ul style="list-style-type: none"> <li>Thomas Kailath and Enders Robinson publish a number of papers on statistical techniques for optimal design of filters and systems for reducing noise in signal transmissions.</li> </ul> <p><b>1972</b></p> <ul style="list-style-type: none"> <li>Thomas Parks and James McClellan and introduce the Parks-McClellan algorithm for designing and implementing efficient and optimal finite impulse response FIR filters.</li> <li>James K. Baker and Fred Jelinek introduce statistical techniques which enable speech recognition by automated systems.</li> <li>Franklin Cooper introduces new techniques for analyzing speech patterns and synthesizing speech signals based on principles of acoustics and human auditory perception.</li> <li>J. Justesen proposes Justesen codes, an improvement of Reed-Solomon codes.</li> </ul> <p><b>1973</b></p> <ul style="list-style-type: none"> <li>James Flanagan proposes adaptive differential pulse code modulation (ADPCM), which exploited the fact that a small sample of speech can be predicted fairly accurately from preceding samples. ADPCM was adopted as a new standard for encoding speech in 1984.</li> <li>David Slepian and Jack Wolf discover and prove the Slepian-Wolf coding limits for distributed source coding.</li> </ul>	<ul style="list-style-type: none"> <li>Intel announces the Intel 1103, the world's first commercially available Dynamic Random Access Memory (DRAM) chip (1K bit pMOS dynamic RAM ICs).</li> </ul> <p><b>1971</b></p> <ul style="list-style-type: none"> <li>TI announces a new standard one-chip MOS/LSI calculator logic circuit to make full electronic calculators available for the mass consumer market. The chip incorporates all of the logic and memory circuits to perform complete 8-digit 3-register calculator functions, including full precision add, subtract, multiply, and divide operations. The chip was priced at less than \$20.</li> <li>Intel announces the first microprocessor, the 4-bit 4004, designed by Federico Faggin.</li> </ul> <p><b>1972</b></p> <ul style="list-style-type: none"> <li>Intel introduces the eight-bit, 8008 microprocessor.</li> </ul> <p><b>1974</b></p> <ul style="list-style-type: none"> <li>Intel announces the 8080 eight-bit microprocessor. It will power the MITS Altair 8800 designed by H. Edward Roberts, the first truly inexpensive personal computer. Within a year the 8800 will be designed into hundreds of different products.</li> </ul>	<p><b>1971</b></p> <ul style="list-style-type: none"> <li>C. Gordon Bell and Allen Newell publish <i>Computer Structures: Readings and Examples</i>, a systematized presentation of the principles governing the design of computer systems.</li> <li>IBM's first operational application of speech recognition enables customer engineers servicing equipment to "talk" to and receive "spoken" answers from a computer that can recognize about 5,000 words.</li> </ul> <p><b>1973</b></p> <ul style="list-style-type: none"> <li>The Alto computer system is operational at Xerox PARC. Conceptually the first personal computer system, it eventually featured the first WYSIWYG (What You See is What You Get) editor, a graphic user interface (GUI), networking through Ethernet, and a mouse.</li> </ul> <p><b>1974</b></p> <ul style="list-style-type: none"> <li>IBM builds the first prototype computer (the 801) employing RISC (Reduced Instruction Set Computer) architecture. Based on an invention by John Cocke, RISC simplified the instructions given to run computers, making them faster and more powerful.</li> </ul>

### *The Role of Computational Complexity in Driving Technological Adoption*

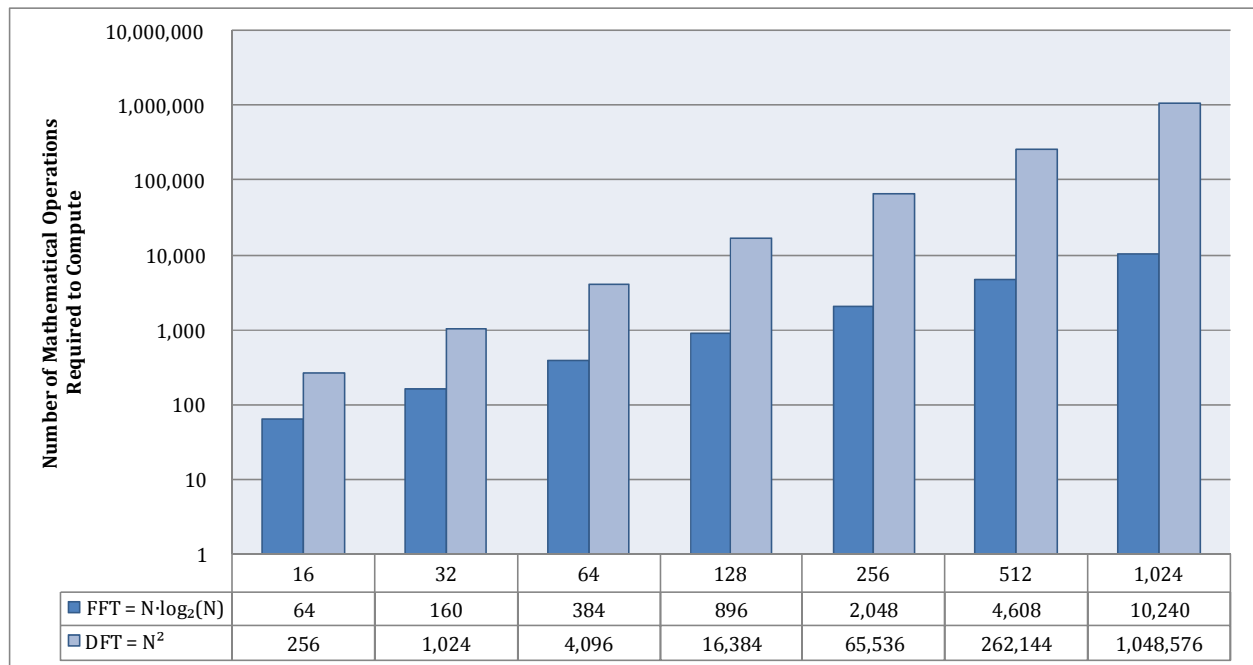
A careful review of the preceding timeline of events impacting signal processing offers some valuable insights regarding the largely unpredictable and surprising evolution of DSP as a GPT. Advances in information theory sometimes led directly to improvements in computing architectures, which were then quickly implemented in commercial products made possible by the latest transistor devices. However, this process was rarely linear or as straightforward as it might appear from the retrospective summary (Tables 17-20) compiled in this study. For example, some innovations such as David Huffman's 1951 invention of Huffman coding for lossless data compression were quickly adopted and remain in use even today (Huffman 2006). However, Peter Elias' 1955 more computationally complex invention of convolutional codes (Elias 1955) was not practical to implement until 12 years later with Andrew Viterbi's 1967 development of the Viterbi algorithm for decoding (Viterbi 1967). In a more extreme case, Robert Gallager's 1962 invention of low-density parity-check codes was not usable until 30 years later due to technical limitations and computational complexity (Richardson and Urbanke 2003).

In addition, some innovations were actually rediscoveries of earlier inventions. In these situations, the source of the surprise was that information was unintentionally lost and then found. Perhaps the most notable of example of rediscovery in signal processing is James Cooley's and John Tukey's (1965) formulation of the Fast Fourier Transform (FFT) which was originally discovered by Carl Friedrich Gauss over one hundred and sixty years earlier c.1805

(Heideman et al. 1985).<sup>34</sup> What made Cooley's and Tukey's version of the FFT spread so quickly was the ease of implementation in the computers available at the time (Cooley 1992). The FFT, which enables the frequency domain processing of the time domain representation of physical signals (Cooley 1987; Cooley and Tukey 1965) in real-time, is absolutely fundamental to all signal processing applications in use today (Rader and Brenner 1976).

Figure 8 below utilizes a brief numerical example to illustrate the significance of the FFT as a mathematical innovation.<sup>35</sup>

Figure 8. The Computational Complexity of Fast Fourier Transform (FFT) in Comparison to the Discrete Fourier Transform (DFT)



<sup>34</sup> (Heideman et al. 1985) According to the authors, the treatise of interest was entitled "Theoria Interpolationis Methodo Nova Tractata". It was published only posthumously in Volume 3 of the collected works of Gauss in 1866, but was originally written, most likely, in 1805.

<sup>35</sup> Note that scale on the Y-axis is logarithmic, each increment is an increase in order of magnitude (a factor of 10).

Prior to the discovery of the FFT, the Discrete Fourier Transform (DFT) was the best known method for generating a frequency-domain representation of a sampled signal. Here, the variable  $N$  corresponds to the length of the sampled signal; the greater the length, the higher the value of  $N$ . As the value of  $N$  on the X-axis (in the figure below) increases from  $N=16$  to  $N=1024$  (corresponding to an increase the sample length), the number of mathematical operations (multiplications and additions) required to compute the FFT increases from 64 to a value of 10,240 (an increase by a factor of 160 times). In comparison, the number of mathematical operations required to compute the DFT increases from 256 to 1,048,576 (an increase by a factor of 4,096 times). The net result is that for a sample length of  $N=1024$ , the DFT is exactly 102.4 times more computationally complex than the FFT.<sup>36</sup>

Thus, as shown in the preceding numerical example, the impact of the FFT as a mathematical innovation was a dramatic reduction in the computational complexity of the most fundamental algorithm required for every signal processing application. The “thought experiments” that were previously only possible on paper could actually be tested and validated through “numerical experiments” by efficiently programming the available computing power (Cooley 1992). This enabled scientists and engineers to prototype and implement a variety applications in fields ranging from sonar systems for underwater navigation to seismic monitoring systems for oil exploration. Perhaps the most surprising and fascinating aspect about the FFT is that it was rediscovered multiple times and in multiple forms by a number of scientists working in different

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<sup>36</sup> Obtained by dividing 1,048,576 by 10,240.

disciplines. Table 21 below summarizes the known instances of the initial discovery computationally efficient alternatives to the DFT.

Table 21. Discovery and Rediscovery of Computationally Efficient Alternatives to the DFT<sup>37</sup>

Generalizability	Input Sequence Lengths (Acceptable Values of $N$ )	Researcher(s) and Year of Initial Discovery
<b>Most General</b>	Any composite integer	Gauss – 1805, Cooley & Tukey – 1965 (FFT)
	Any integer with relatively prime factors	Thomas – 1948, Good – 1958, Winograd – 1976
	$2^n \cdot K$ , $3^n \cdot K$	Stumpff – 1939
<b>Least General</b>	$2^n \cdot K$	Runge – 1903
	$2^n$	Danielson & Lanczos – 1942
	4, 8, 16, 32	Smith – 1846
	12	Carlini – 1828, Everett – 1923

Remarkably, over a 160 year span of time, from 1805 to 1965, at least 7 different alternatives to the DFT were discovered by 11 different researchers or pairs of researchers. The most generalizable approach, the FFT, which was developed by Cooley and Tukey in 1965, was actually a rediscovery of the comparable work of Gauss from 1805 (Cooley 1987). *The unintentional loss and rediscovery of this vital know-how may have contributed to errors in threat perception and opportunity recognition among potential developers of signal processing technology and may account for the occurrence of surprises during the course of the emergence of the scientific field and industry.*

<sup>37</sup> I modified the original table entitled “Principal Discoveries of Efficient Methods of Computing the DFT” on page 272 of (Heideman et al. 1985) The modified table indicates the overall generalizability of each alternative in terms of the allowed values for the input sequence lengths.

### *The Role of Key Inventors in Generating More than One Type of Innovation*

In addition to the rediscovery of the FFT, the original contributions of a select group of researchers who spanned two or more areas of innovation (mathematical, material, and/or architectural) were also significant in the evolution of signal processing. For example, in 1960, Marcian “Ted” Hoff developed the Least-Means-Squares (LMS) algorithm (Widrow and Stearns 1985) with his doctoral advisor, Bernard Widrow, as part of his Ph.D. dissertation (Hoff 1962). The LMS algorithm is perhaps second only to the FFT in terms of its widespread use in signal processing applications as an adaptive filtering mechanism (Widrow and Haykin 2003). Later, in 1969, Hoff was an early employee at Intel as is credited with co-inventing the microprocessor with Federico Faggin and Stan Mazor.<sup>38</sup> Hoff contributed to key developments in both information theory and transistors and it is impossible to discern how much influence his invention in one domain had on his subsequent invention in another related domain. Similarly, at Bell Labs in 1948, John Pierce developed the methodology of pulse code modulation (PCM) with Bernard Oliver and Claude Shannon while also managing the team of John Bardeen, Walter Brattain and William Shockley when they conducted the series of experiments that led to the invention of the transistor. Based on the analysis presented thus far on the unpredictable evolutionary path of signal processing, the description below appears to appropriately characterize mathematical, material, and architectural innovation in this field.

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<sup>38</sup> Source: Intel Corporation, <http://inventors.about.com/od/mstartinventions/a/microprocessor.htm>



Models that depict innovation as a smooth, well-behaved linear process badly mis-specify the nature and direction of the causal factors at work. Innovation is complex, uncertain, somewhat disorderly, and subject to changes of many sorts. (Kline and Rosenberg 1986)

Furthermore, as Stephen Kline and Nathan Rosenberg explain, “The process of innovation must be viewed as a series of changes in a complete system not only of hardware but also of market environment, production facilities and knowledge, and the social contexts of the innovation organization”(Kline and Rosenberg 1986). In Kline and Rosenberg’s (1986) framework, “Commercial innovation is controlled by two distinct sets of forces that interact with one another in subtle and unpredictable ways.” The two sets of forces are *market forces* and *technological forces* and they are closely interconnected on multiple levels. Thus, understanding the evolution of signal processing as a GPT also requires the careful measurement and analysis of the interaction of market forces and technological forces over time. The non-deterministic nature of this interaction may generate errors in organizational beliefs about the field of signal processing and these errors may produce surprise in less resilient organizations. In the next section, I examine both sets of forces and their effect on the emergence and growth of DSP firms and the DSP industry as a whole.

### **DSP as a Global High-Technology Industry, 1974-2008**

As described earlier, the field of signal processing has its roots in the breakthroughs in information theory, transistors and computing which occurred in 1948. Over 26 years passed before the first *commercially available* off-the-shelf DSP chips were introduced in 1974 by Advanced Micro Devices as the Am2901 family of discrete logic chips; in the 34 subsequent years that passed from the

introduction of the first off-the-shelf DSP chips, the total size of the DSP industry grew from virtually zero to over \$27 billion in total revenues in 2008 (Strauss 2008).<sup>39</sup>

### Initial Generation of Commercial DSP

In the period from 1974-2008, DSP technology underwent six major changes in technology regimes, represented by six new generations of technology. After Advanced Micro Devices' introduction of the Am2901 family of DSP chips in 1974, the next major milestone was the introduction of the Speak and Spell™ educational toy by Texas Instruments (TI) in 1978 (Frantz 1982). Market and technological forces interacted synergistically, demonstrating that DSP could be used to create a new class of consumer products that would eventually transform the way we live. The Speak and Spell™ incorporated the non-programmable TMS280, the *first single-chip implementation of a DSP algorithm and was the first widely used mass market consumer product to utilize DSP technology* (Strauss 2007).<sup>40</sup> The introduction of the Speak and Spell™ surprised TI and its competitors in the emerging DSP industry by demonstrating that consumer applications of signal processing could be enormously profitable for firms even in comparison to military applications of the technology. In the same year, 1978, AMI Semiconductor announced the *first programmable DSP*, the S2811 (Strauss 2007), but was beaten to the market by Intel, which introduced the 2920 DSP chip which was designed by Marcian "Ted" Hoff (the

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<sup>39</sup>Estimates are for all DSP silicon, which includes general purpose programmable DSP chips and embedded DSP chips. See Appendix for Profiles and a Comparison of DSP Firms.

<sup>40</sup> According to Strauss (2007), prior to the introduction of the TMS280, all DSP algorithms required multiple chips for implementation.

co-inventor of the LMS algorithm for adaptive filtering in 1960 and the Intel 4004, the *first microprocessor* in 1969).

### 1st Generation of Commercial DSP

After the introduction of these early single-chip DSPs by TI, AMI, and Intel, the first major shift in DSP technology occurred in 1980 with the introduction  $\mu$ PD7720 by NEC and the DSP-1 by AT&T (Lee 1988, 1989). The significance of both chips is that they were the *first DSPs based on the Harvard architecture*, a computer architecture which separates data and memory buses for real-time operation.<sup>41</sup> The result of adopting this architecture is that both chips were sufficiently powerful for real-time processing of audio signals. Because AT&T's DSP-1 chip was only available for internal use until 1985, NEC's  $\mu$ PD7720 was the *first practical off-the-shelf DSP chip for use in real-time audio applications* (Strauss 2007).

### 2nd Generation of Commercial DSP

The second substantial improvement in DSP chip technology occurred during 1983-1987 when Texas Instruments, Toshiba, Fujitsu, Matsushita and AT&T all introduced DSP chips which incorporated the single-cycle multiplier-accumulator (MAC) function, *which effectively doubled the bandwidth of these DSPs versus previous chips* (Lee 1988, 1989). The AT&T DSP32 which was introduced internally in 1984 and externally in 1986 had the added distinction of being the *first floating-point DSP chip available in the commercial market*.<sup>42</sup>

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<sup>41</sup> [http://www.pic24micro.com/harvard\\_vs\\_von\\_neumann.html](http://www.pic24micro.com/harvard_vs_von_neumann.html)

<sup>42</sup> Source: AT&T, Lucent, and Agere company historical timelines

### Subsequent Generations of Commercial DSP

The third wave of technological change in DSP chip technology occurred in the years 1987-1990, when a number of vendors, most notably Zoran and Analog Devices introduced DSP chips *featuring reconfigurable memory, increased parallelism, and expanded instruction sets, all of which improved the overall flexibility of the DSP chips.* (Strauss 2007). These chips were primarily used for military applications. Vendors also focused on optimizing their earlier first-generation floating-point chip designs. The fourth wave of DSP technology from 1990-1994 was marked by the *introduction of integer operational capabilities, optimization of chips for commonly used algorithms, smaller chip sizes and faster processing speeds.*<sup>43</sup> Several vendors introduced their second-generation of floating point DSP chips and their second-generation of integer DSP chips. The fifth wave of DSP technology from 1994-1998 featured *the inclusion and of numerous functions which optimized DSPs for use in cell phones and wireless infrastructure.*

The sixth and most recent wave of DSP technology from 1999-2006 was *characterized by a fundamental change in chip architecture, the first DSP chips based on VLIW (Very Large Instruction Word) and superscalar architectures were introduced.*<sup>44</sup> The benefit of this new architecture was the ability to efficiently handle more complex algorithms for a variety of signal processing

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<sup>43</sup> Source: Motorola's DSP56156 product data sheet.

<sup>44</sup> Source: ZSP, LSI Logic.

applications in audio, video, wireless and multimedia products.<sup>45</sup> The current generation of DSP products reflects continued improvement in increasing the processing speed, flexibility and capabilities of fixed-point, floating-point, and integer DSPs over time along with the density improvements expected with Moore's Law and the fabrication cost increases expected with Moore's Second Law (discussed in the next section). Table 22 below summarizes the six generations of DSP technology and key market drivers during the commercialization phase of the industry from 1974-2008.

Table 22. Generations of DSP Technology and Market Drivers<sup>46</sup>

Years	Generation	Technological Changes	Market Drivers
1974-1980	0	First single-chip implementation of a DSP algorithm	Military applications, Consumer applications-Speak and Spell
1980-1983	1	First DSPs based on the Harvard architecture	Audio applications
1983-1987	2	Doubled bandwidth; First floating-point DSP	Audio and communications applications
1987-1990	3	Reconfigurable memory, increased parallelism, and expanded instruction sets, all of which improved the overall flexibility	Military applications, imaging
1990-1994	4	Integer operational capabilities, optimization of chips for commonly used algorithms, smaller chip sizes and faster processing speeds	Communications applications
1994-1998	5	Optimized for use in cell phones and wireless communications infrastructure.	Wireless applications
1998-2006	6	First VLIW and superscalar architectures for efficiently handling complex algorithms	Wireless and multimedia applications
2006-	Current	Continued improvement in processing speed, flexibility, capabilities, and density	Audio, video, wireless and multimedia applications

<sup>45</sup> Source: Discussion with former members of the technical staff at ZSP Corporation.

<sup>46</sup> For details on each generation of DSP technology, see Strauss (2007).

As shown in Table 22, the nature of the technological changes and the key market drivers were different from one generation of DSP to another. *Architectural improvements over six generations of technology have facilitated the opening of new markets for a broad range of DSP applications.* Although a consumer application, Speak and Spell™, captured the imagination of the market in the initial phase, it was military applications that provided the significant early market demand. This demand gradually shifted over time to audio and communications applications and then more specifically to wireless and multimedia applications. The current market demand is for audio, video, wireless and multimedia applications across multiple sectors of the economy, but is still driven primarily by wireless phones. In addition to the market forces described here, technological forces also played an important role in shaping the evolution of DSP and are examined in the next section.

*Moore's Second Law and Gene's Law: Addressing What Moore's Law Left Out*

As described earlier in this study, Moore's Law states that the number of transistors on a chip doubles every 18-24 months. The emergence of merchant foundries reflects an industry phenomenon that has come to be known as Moore's Second Law, described below.<sup>47</sup>

Rising fixed costs give rise to Moore's Second Law: as the cost of transistors comes down, the cost of fabs goes up, albeit not at quite the same rate. In 1966 a new fab cost \$14m. By 1995 the price had risen to \$1.5 billion. Today, says Intel, the cost of a leading-edge fab exceeds \$6 billion, including all the preparatory work. And the Taiwanese Semiconductor Manufacturing Company (TSMC) has built two "GigaFabs" for between \$8 billion and \$10 billion each, which would buy you four nuclear power stations. The output of such

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<sup>47</sup> [http://research.microsoft.com/en-us/um/people/gray/Moore\\_Law.html](http://research.microsoft.com/en-us/um/people/gray/Moore_Law.html)

monsters depends on the mix of products, but they each could easily churn out 3 billion chips a year.<sup>48</sup>

Thus, ever-increasing costs have fueled the need for increasing specialization to achieve sufficient economies of scale in each stage of the value chain. This has led to the proliferation of merchant foundries and fabless semiconductor companies in all sectors of the market including DSP.<sup>49</sup> The DSP industry as a whole has benefited from this reconfiguration of inter-firm alliances. Only when the economics of the semiconductor industry made the costs of owning and operating their own internal foundry prohibitive for all but the largest integrated device manufacturers (IDMs), did an active market for technology in DSP truly emerge. Based on previous studies on the economics of Moore's Law (Tuomi 2002), the conventional wisdom about the semiconductor industry in general is that *the reconfiguration of inter-firm networks has substantially increased the diversity and rate of material innovation, thereby enabling organizations to overcome the performance barriers implicit in such technical benchmarks*. However, this conclusion is somewhat controversial, and it is not universally shared, especially by leading DSP experts. Beyond Moore's

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<sup>48</sup> "The Semiconductor Industry: Under New Management," *The Economist*, April 2, 2009

<sup>49</sup> In this study, and in standard industry terminology, an *integrated producer* or *integrated device manufacturer* (IDM) is a semiconductor company which designs, manufactures, and sells chips - integrated circuit (IC) products. The term integration refers to the fact that design and manufacturing of the IC are both done in-house. A *foundry* is a semiconductor company which manufactures ICs. IDMs have their own foundries or *fabs* for manufacturing ICs and these are typically referred to as "internal" or "captive" foundries, since they only produce chips for internal markets. "Merchant" or "pure-play" foundries are semiconductor companies that do not design their own chips but fabricate chips for other firms called *fabless* semiconductor companies, which focus only on designing chips. Thus one way to conceptualize the three types of companies, IDMs, foundries, and fabless semiconductor companies is that IDMs compete with dyads of fabless semiconductor companies that partner merchant foundries to produce chips. See (Yoon and Malerba 2009) [http://asialics6.ust.hk/essays/2b/Yoon\\_Minho\\_015\\_Feb23.pdf](http://asialics6.ust.hk/essays/2b/Yoon_Minho_015_Feb23.pdf). See also (Teece 2006).

Law and Moore's Second Law, Gene Frantz,<sup>50</sup> a Texas Instruments' Principal Fellow, has proposed the eponymous Gene's Law, to address what he and many other industry participants and observers view as a significant shortcoming of Moore's Law. Frantz was the program manager for the Speak & Spell™ learning aid, and development team leader for all of the early speech products for TI; he has been at the forefront of commercializing signal processing over several technology generations. *Gene's Law states that the power dissipation of semiconductor chips including DSPs will be reduced at approximately the same rate that performance increases.* As described below, and in contrast to the prevailing wisdom, *Frantz believes that architectural innovation, rather than material innovation, has been the primary means through which chip design engineers have dealt with the limitations of Moore's Law.* Thus, in the DSP industry, different organizations may have dramatically different beliefs about the expected trajectories of the three types of innovations (mathematical, material, and architectural), which may lead to surprises if the actual introduction of innovations does not conform to the prior expectations of firms.

Most experts see Moore's Law continuing to follow the path it has held for nearly half a century. But there are things that Moore did not tell us about ICs that threaten the validity of his law. In terms of performance, as measured in terms of clock speed, we effectively fell of the 18-month cycle of doubling nearly a decade ago. Then, how does performance continue to increase, I hear you ask. Well,

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<sup>50</sup> From Gene Frantz's official bio: "Gene Frantz is presently responsible for finding new opportunities and creating new businesses utilizing TI's signal processing technology. In recognition of his leadership role in establishing TI as the world's leading DSP solutions provider, Frantz was elected as TI's Principal Fellow in 2002, a privilege enjoyed by less than 0.1 percent of TI's technical personnel."



we've managed to compensate for it with innovations in architecture such as deeper and deeper pipelines.<sup>51</sup>

Mahesh Mehendale, TI Fellow at Texas Instruments India, concurs with this assessment and posits that going forward, architectural innovation will play an even greater role in driving performance improvement, as indicated in his comments below.

The net result of this is that moving forward Gene's law cannot hold good riding on Moore's law but rather it will have to hold good in spite of Moore's law. Just as in the past whenever Moore's law was threatened, innovations and breakthroughs in the semiconductor manufacturing process have helped keep it on track, in case of Gene's law the breakthroughs will have to come from innovations at circuit design and architecture levels. Just as Moore's law took us from micrometer to nanometer, Gene's law will take us from volts to millivolts. As long as it makes business sense, technologists will find a way to make Gene's law hold true. So as I gaze at the technology trends crystal ball, it shows me this simple prediction: "Moore's law will hold good as long as Gene's law holds good".<sup>52</sup>

As discussed at the outset of this study, technical benchmarks such as Moore's Law may indeed be a self-fulfilling prophecy (see Table 15). As the ongoing and unresolved debate between proponents of Moore's Law and Gene's Law demonstrates, technologies such as DSP may evolve in ways that are not predicted by and even contradict these established benchmarks (Tuomi 2002). Unpredictability in technological evolution or seemingly contradictory technology trends may lead to errors in organizational beliefs which may ultimately result in surprising consequences for competing firms.

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<sup>51</sup> Gene Frantz, "What Moore Didn't Tell Us About ICs" TI Video360 Blog, <http://blogs.ti.com>

<sup>52</sup> [http://www.vlsiconference.com/vlsi2009/mess\\_mahesh.html](http://www.vlsiconference.com/vlsi2009/mess_mahesh.html)

## **Discussion and Summary of Historical Analysis**

A diverse and ongoing mixture of mathematical, material, and architectural innovations have shaped the evolution of signal processing from its ancient origins in Egypt to its current state as a multi-billion dollar global high-technology industry. From c. 2500 B.C., when the combination of the Palermo Stone, nilometers, and human stone carvers constituted the essential components of a primitive DSP — to the present day, when semiconductor-based DSP chips are used in virtually every digital application involving communications, audio, voice, video, image, and sensory data — the technological and economic importance of signal processing has grown exponentially.

If the birth of modern signal processing can be traced back to a single year, it is 1948, when three major research breakthroughs occurred: the introduction of information theory, the invention of the transistor, and the demonstration of the first stored-program computer. If the birth of modern signal processing can be traced back to a single organization, it is Bell Labs, which served as an intellectual crossroads for early scientific leaders who sought to build a unified information theory firmly grounded in mathematics and physics. The formalized and axiomatic nature of signal processing stemmed from its information-theoretic roots. This intrinsic characteristic of signal processing as mathematical science enabled conceptual exploration and practical application through the active combination and recombination of thought experiments and numerical experiments. Conducting these numerical experiments was largely made possible through the rediscovery by James Cooley and John Tukey in

1965 of the Fast Fourier Transform (FFT) originally discovered by Carl Friedrich Gauss in 1805. If the successful commercialization of modern signal processing can be traced back to a single innovation, it is the rediscovery of the FFT.

Although the critical innovations which led to development of signal processing first emerged in 1948, it was not until 26 years later, in 1974, that the first commercially available DSP chips were actually produced, representing a significant lag between the initial mathematical innovations, and the subsequent architectural innovations which were further constrained by the technical limits of material innovations. From 1974-2008, a series of architectural improvements over six generations of technology facilitated the opening of new markets for a broad range of DSP applications and led to the reconfiguration of industry alliances, particularly between fabless DSP companies and their merchant foundries. While most semiconductor industry participants believe that material innovation was the primary factor in overcoming the performance barriers inherent in technical benchmarks such as Moore's Law during this time frame, some noted DSP experts believe that architectural innovation was the main driver.

This difference in perspective has not yet been reconciled but may nevertheless offer some valuable general insights for managers and researchers interested in the evolution of GPTs and their role in the formation and growth of knowledge-intensive industries. For example, although mathematical innovations are typically rigorously formalized and highly axiomatic, their impact on subsequent architectural innovations may be largely unpredictable and may

generate errors which lead to surprises for firms. Without computationally efficient methods for conducting natural experiments to test the predictions of thought experiments, there may be a substantial lag between the discovery of a mathematical concept and its eventual instantiation in the form of a commercially available product.

While empirically-observed technical benchmarks may provide a useful framework for prioritizing and making resource allocation decisions among the different types of innovations (mathematical, material, and architectural), the causal mechanisms underlying these distinct types of innovation may be difficult to isolate and may interact in entirely unexpected and occasionally contradictory ways. In particular, dramatic changes in the materials themselves, as a physical building block, may radically alter the long-term trajectory of innovation. The history of signal processing is replete with examples of the unintentional loss and rediscovery of mathematical innovations, the unanticipated lag between architectural and mathematical innovations, and the unexpected rearrangement of firm alliances. All of these factors may contribute to a chaotic industry environment in which firm errors in threat perception and opportunity recognition are not only possible but highly probable. This may make the signal processing industry ideally suited to the study of strategic surprise.

In a fascinating preview of future possibilities in the advancement of DSP, recent studies have speculated that in the coming decades, the main materials for constructing DSPs will not be semiconductors made of silicon, but more exotic materials made of organic elements. In the future, DSP systems may be

grown, rather than fabricated and be comprised of “chemical substrates, cells, organisms, or even DNA” and may even operate “without the use of electrical currents” (Tsaftaris and Katsaggelos 2008).

While this speculation may sound like science fiction, future observers may regard today’s DSP chips to be as primitive in comparison to organic-based DSP systems as modern observers regard the stone-based DSP system of the ancient Egyptians. Perhaps an intriguing new mixture of mathematical, material, and architectural innovations awaits future signal processing researchers. Molecular biologists, genetic engineers, biophysicists, and organic chemists may someday join computer scientists, electrical engineers, transistor physicists and information theorists in influencing the ongoing evolution of the field of signal processing in surprising new ways.

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