London Business School

Firm heterogeneity, innovation, and value capture: Three essays

Chung Won Jennifer Tae

A thesis submitted to the London Business School for the degree of Doctor of Philosophy

April 2013

Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London Business School is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorization does not, to the best of my belief, infringe the rights of any third party.

Abstract

The underlying theme of my thesis is the role of firm capabilities and heterogeneity. Through the following three papers, I examine the role of firm heterogeneity on value migration in a sector, the financial value of innovation, and the propensity and timing of innovation adoption.

The first paper, a joint work with my advisor, considers how firm capabilities can change the industry architecture dynamics by looking at value migration, using the computer sector as an illustration. We find that the traditional industrial organization's driver of profit does *not* account for value migration, but show instead that kingpins with superior capabilities turn their segments into a 'bottleneck' and induce value migration. Although a kingpin exerts positive externalities on its peers in the short run, the inequality between a kingpin and its peers worsens over time.

My second paper looks at how firm heterogeneity affects the value of innovation. Specifically, I consider the way firm heterogeneity affects who financially benefits from innovation. The inspiration for the work comes from the financial crisis 2007-2008 during which many financial institutions underwent the unanticipated consequences of innovation and suffered financially. I find that operational capabilities, types of past exploration experience, and firm scope affect whether or not a firm can unlock the value from innovation as well as to benefit the overall firm performance.

My third paper considers how different aspects of past performance, borne out of inherent firm heterogeneity, affect adoption of innovation. I investigate the effect of feedback, possession of dynamic capabilities, and changes in external environment on whether or not, and how fast, a firm adopts innovation. I argue that firms rely more on one source of feedback than the others depending on the external environment and that this various aspects of past performance also affect the timing of adoption. I elaborate this argument with the behavioral theory of the firm and the concept of dynamic capabilities and test it on a longitudinal data on adoption of credit default swaps by the US banks.

Acknowledgement

As is usually the case with most achievements, I would never have been able to finish the PhD program on my own. If it takes a village to raise a child, I would argue that it takes a lot more than a village for someone to earn a PhD.

First and foremost, I would like to thank God for guiding me through one of the most challenging and rewarding periods of my life thus far. I know without doubt that it was through His guidance and power that I was able to start and finish the PhD program. All thanks and glory is due Him. I hope to put my degree to good use and lead a life that can demonstrate His love and majesty. Also, I thank many people who have ardently prayed for me.

Second, I must thank my family. I would like to express my gratitude to my father who has set an example for me to follow and has always been there for me to turn to in times of confusion and trouble. Dad, you have been and always will be my role model: I am blessed to have you as my dad. My mom also deserves a special thank you. As dad half-jokingly commented, you were an invisible driver behind my achievement and you qualify to claim 30% of my degree. Your physical presence in London and constant prayers from home have helped me through the most difficult period and enabled me to finish the race. I hope I make both of you proud. I thank my brother Jason for his support and never shying away from saying the right things I needed to hear. Your persistence had a huge impact on my successfully finishing the program. All in all, I love you all. I'm nothing without your unconditional love and support. Lastly, I would like to thank my relatives (my granny, aunt, uncle, and two lovely cousins) who have kept me in their prayers and shown unwavering faith in me both as a person and as a scholar. Your love and prayers are duly noted and I truly appreciate it very much.

Third, I am forever thankful to my advisor, Michael G. Jacobides. He's transformed an ambitious, yet quite emotional and un-prepared student into a decent researcher worthy of a PhD degree in Management. Michael has taught me not only the techniques of being a researcher, i.e. what is interesting, why, how it matters to others, and how this can be turned into valuable research, but also the life outside research such as classic Greek literature, opera and ballet at the Covent Garden, etc. I am deeply honored that I am the first PhD supervised by him. I hope my relationship with Michael will develop into something similar to what he shares with his PhD supervisor, Sid. I also thank other members of faculty in the department, notably Julian Birkinshaw and Phanish Puranam who have provided valuable comments and suggestions through the formation period of this thesis.

I must thank my colleagues at school who have been good comrades through the tumultuous ups and downs of a PhD program. A special mention goes to my long-time office-mate, Dr. Amandine Ody-Brasier. I don't think I would have made it this far without us sharing in the joys and pains of writing scholarly papers (and finding solace in sugar and butter, only to regret it later). I very much look forward to our co-work and lasting friendship in the future! Everyone else in the Strategy & Entrepreneurship department, Marlo Raveendran, Eucman Lee, Ramon Lecuona Torras, Maya Cara, Xu Li, and Kamini Gupta, have been very helpful and encouraging with their constructive comments on my work and emotional support. Thank you for being there and reminding me that I wasn't alone. I must also thank my non-academic friends who have patiently listened to my whining and bore out my frustrations: YK Bae, JH Choi, HH Chun, KE Han, YK Hong, JH Kim, KW Kim, YB Kwak, BY Lee, HS Oak, BM Shin, members of FOLA LG etc. (you all know who you are). Thank you for nourishing me both physically and emotionally in times of need. I love you very much and owe you guys a big one.

I must also thank the Deloitte Institute of Innovation and Entrepreneurship at the London Business School for the generous financial support for the latter two essays. Having the financial burden lifted up from my shoulders helped me fully focus on my research and explore the questions on financial innovations. I hope my essays will prove to be both theoretically interesting and managerially relevant (and be published in good journals).

There are, doubtless, many I forgot to mention, to whom I extend my apologies. To everyone who deserves my gratitude, I only wish that whatever contribution I make in the future as a researcher can at least partially make up for the love and support you have bestowed upon me. Of course, all errors and faults are my own.

TABLE OF CONTENTS

INTRODUCTION

Motivating questions

What drives value migration along a value chain of a sector? What drives value of innovations and their adoptions? And how is value capture, either within a sector or from innovations, related to firm heterogeneity? While these questions have either been pressing for an explanation or have been with us for a long time, existing answers are not fully satisfactory. This thesis will attempt to provide answers to the above questions using phenomena observed in two different industry settings. In a world of fast-paced changes in the roles and rewards of firms, a fresh take on these questions may help us both to make theoretical contributions to existing literature and to understand the changes going on in the world around us.

Objectives and potential contribution

What characterizes this dissertation, and its contribution to the literature, is the examination of three different considerations through a common lens. First, this thesis look at the role of kingpins, defined as firms with superior idiosyncratic capabilities, on the relative value capture within a sector. Rather than looking only at the competition among firms engaged in similar activities and their value capture, it also looks at the broader sector, which consists of different groups of firms that are each engaged in different activities to produce an end product, and the value distribution therein. The second consideration is financial value of innovations. This thesis examines what drives differences in the financial value of adopting innovations that makes some firms better off and others worse off. The last consideration is drivers of innovation adoption. Taking past performance of firms seriously, the thesis examines how different aspects of past performance affect the likelihood and speed of adopting innovations.

The potential contribution of this thesis is not as much the elaboration upon each of these three considerations separately. Rather, it is examining these three considerations through a common lens, namely, firm heterogeneity. The main question I am interested in is the workings of firm heterogeneity in various settings and this thesis is an attempt to explore the various facets of firm heterogeneity and capabilities and their effect, if any, on value capture and adoption of innovations at two different levels of analyses. This thesis examines the ways in which capability differentials affect value capture in *a sector* (Chapter one), value capture from an innovation *by firms* (Chapter two), and the likelihood and speed of adoption *among firms* (Chapter three). The tools used to this aim include verbal theorizing and mostly quantitative empirical analysis.

Thesis overview: Structure and methods

The structure of this three-essays type dissertation is as follows. The first chapter, a joint work with Michael G. Jacobides, explores the question on value migration. In this chapter, we consider the dynamics of value migration in the computing ecosystem from 1978 to 2005. Drawing on COMPUSTAT segment data, and on market capitalization, we modeled the entire computing ecosystem, and looked at how value migrated not only from firm to firm, but also from segment (e.g. OEMs) to segment (e.g. software or microprocessors). The paper considers economic "folklore" views that draw on traditional IO economics, and shows that sales concentration neither explains the market value of each segment, nor the way in which a market value can change. We look instead at the variance of value within each segment as the driver of market value of each segment as well as the catalyst for its change. We also consider whether the average R&D spending in a segment or the asymmetry and dispersion of R&D spending (especially the dominance of R&D from one firm) tends to help a segment. We also explore how the results from the above analysis affect other, smaller firms in the same segment.

The following two chapters both advance the considerations of value capture and sector dynamics and look back upon an important chapter of the business and financial history of our times. I have been interested in the financial crisis and the resulting debacle, and started with a careful qualitative study of the sector. While interested in the qualitative aspects of the sector, though, I have compiled an extremely comprehensive database, striving to provide something more concrete than the anecdotes, consisting of all depository institutions insured by the FDIC in the US between 2001 and 2011.

Specifically, the second chapter examines the effect of heterogeneity in firm attributes on the financial value of innovation (credit default swaps) post-adoption. I look at what drives the differences in the financial value of an innovation among adopters, both in terms of the value of innovation *per se* and its spillover effect, if any, on overall firm profitability. I look at how the quality of operational capabilities, past experience in similar activities, and the degree of specialization affect the value of innovation. Given that CDSs have proven potentially devastating for banks that undertook them, this analysis can shed new light to an important issue, as well as advance our understanding of how firms innovation adoptions affect their performance. I empirically test these ideas using the dataset on all depository institutions insured by the FDIC in the US between 1Q 2001 and 4Q 2011.

The third chapter looks at the antecedent of differences in the value of innovation by considering the drivers of adopting innovations. I examine specifically the different aspects of past performance such as feedback on financial performance and possession of dynamic capabilities from similar experience in the past to see if, and how, they affect the likelihood and speed of adopting CDSs. I also look at the effect of disruptive changes in external environment on the relationship between the drivers of adoption and actual adoption, using the height of financial crisis in 2008 to my advantage. I used the original data set used in chapter two to conduct the empirical analysis for the arguments presented here.

CHAPTER ONE

KINGPINS, BOTTLENECKS, AND VALUE DYNAMICS WITHIN A SECTOR[1]

Abstract

This paper explores the dynamics of value distribution within a sector, using data on the U.S. computer industry as an illustration. It provides exploratory quantitative evidence for the way in which conditions within the segments of a sector's value chain affect the profitability of those segments compared to the sector as a whole. To consider how value shifts from one part of the value chain (such as computer manufacturers) to another (such as software and microprocessor makers), we look at how conditions within a segment (such as software) affect changes in the value share of that segment compared to the entire sector, in terms of market capitalization. First, we find that the traditional Industrial Organization explanations based on sales concentration at the segment level do not explain how value distribution changes over time. We demonstrate instead that the presence within a segment of uniquely superior or powerful firms ('kingpins') armed with superior capabilities increases that segment's overall share of total sector value, establishing it as a 'bottleneck'. Also, while kingpins exert a positive externality on their direct competitors, their segments display increasing internal inequality over time, making the presence of kingpins a double-edged sword for their peers. These findings add flesh to the recent work on industry architectures, highlighting the interconnectedness of different segments within a sector. They also provide a structure to help us study the dynamics of 'value migration,' which has not yet attracted much academic scrutiny.

1. Introduction

As the economy is increasingly comprised of complicated, interdependent ecosystems, the interest in understanding the evolution of such systems has increased (Adner, 2012; Iansiti & Levien, 2004; Jacobides, Knudsen & Augier, 2006). And while studies of how firm and sector boundaries change are becoming more common (Baldwin, 2010; Jacobides & Winter, 2005, 2012; Luo *et al.*, 2012), the same cannot be said of analyses of how profit

---

[1] This is a joint work with Michael G. Jacobides.

patterns evolve within an industry ecosystem or architecture. While stories of "value migration" may have captured the imagination of practitioners for a while (Slywotzky & Morrison, 1997), our understanding of how and why value changes hands in an ecosystem remains limited, and no empirical work, to our knowledge, has focused on this to date. The evolution of the computer sector provides the canonical illustration of the way profit and value[2] shift from one set of specialists to another; inspired by this observation, we look at the way profit migrates from one part of the value chain[3] to another (i.e. from computer assemblers to software developers).

Our research focuses on *value* as its dependent variable, as opposed to *form* or industry demographics. Thus it complements the rich tradition on industry evolution, which has tended to look at entry and exit, firm density, concentration and emergence, innovation dynamics, life-cycle, submarkets, technological change, and, more recently, scope. It focuses on the narrower point of how value migrates between the different parts of an inter-connected system of segments, as this phenomenological orientation seems to be relevant in today's fluid industry environment.

This dynamic approach also helps to extend the strategy literature. Interestingly, while studies of profit (and its evolution) are central in that field, there has been little empirical work on how profit is distributed in interconnected sectors. Research has tended to look at "one sector at a time." In terms of the limited work on dynamics, the focus is usually on *sustainability* as opposed to evolution (see Jacobides *et al.*, 2012). Of course, analytical tools, stylized facts, and frameworks do exist, and these can inform our study of value migration. Porter's (1980) "five forces" analysis, based on Industrial Organization, (IO) for instance, would suggest that changes in value between vertically related segments are driven by differences in the market power of firms within each segment: If the firms in

2 We use the words 'profit' and 'value' synonymously, but they are not the same (see Lippman & Rumelt, 2003). In this paper, we use market capitalization to reflect profit/value. Market cap is the NPV of future profits, corresponding to *value appropriated by the firms' owners*, and thus reflects the conventional understanding of 'profit' (see Jacobides, Winter & Kassberger, 2012).

3 The term 'value chain' (Porter, 1985) was originally used for linked activities within a single firm, but has come to refer to the different activities involved to produce a final good /service across firm boundaries. Different segments make up a vertically related value chain/ecosystem: Each of the value-adding activities is termed a 'segment'. A combination of different segments to produce a final good/service is defined as a sector.

upstream segments have more power, they will end up with a bigger share of the total value add; as their power wanes, so will their share. We put the proposition that relative (oligopolistic) market power determines a sector's profit distribution to test and also look beyond it, towards industry evolution.

Specifically, we use longitudinal data *in an exploratory fashion.* Because we focus on dynamics, we can use a fixed-effects analysis of interdependent sectors without suffering from the limitations that have caused cross-sectoral IO studies to decline from the 1990s onwards. We are interested in the drivers of changing value in the industry ecosystem, and our premise is that value distribution could be driven by an alternative type of "power"– the power to shape sectors.

Drawing on our findings, we speculate that firms with this power can turn their segment into a "bottleneck" by changing the "rules of engagement". We motivate this by drawing on the recent literature on industry architecture (Jacobides *et al.*, 2006; Teece & Pisano, 2007; Ferraro & Gurses, 2009; Jacobides & Winter, 2012), which we operationalize and extend. We show that market power (as measured by sales concentration) does not explain the relative profitability of a segment, but heterogeneity in *valuation* (as measured by market capitalization) does – in particular, the dominance of one firm's market capitalization in a segment. Likewise, we argue that it is not the level of R&D, but rather the *heterogeneity* in R&D in a segment that explains its relative profitability. The more a segment has *one* firm that dominates R&D in its segment, the more *every participant* in that segment will benefit. We look at the externality of the "disproportionate power" of this dominant firm (a "kingpin") in a segment on the segment itself, both including and excluding the kingpin from the analyses. We thus look for true externalities that kingpins have on their segments' relative value.

This paper is an *exploratory quantitative* paper that examines empirical regularities in the data and offers a view consistent with the patterns that we observe. We do not provide a direct test for the theory; rather, we show that some of the existing theories do not account for the patterns we observe and propose a theory that does. We offer a fresh approach to value migration, and also an alternate conception of sectoral power that departs from the traditional economic view.

2. Theoretical background

As we noted earlier, research on industry evolution has shed light on many structural variables, including entry and exit (Audretsch, 1995; Malerba, 2002), firm density (Hannan & Freeman, 1984), concentration and emergence (Geroski, 2003), innovation dynamics (Abernathy & Utterback, 1978), life-cycle (Klepper, 1997), submarkets (Klepper & Thompson, 2006) and technological change (Nelson & Winter, 1982). However, while the theme of profit runs through all this work, it has not been explicitly considered, either theoretically or empirically, so we lack a clear analysis of how profit evolves over time. Similarly, in strategy the focus has been more on profitability in terms of statics, as opposed to the dynamics of profit (Jacobides *et al.*, 2012); in the few instances where value evolution is considered, it is in the context of one individual market or sector, as opposed to an interdependent set of segments. Much headway has been made in terms of the analysis of how interdependent segments evolve, but again, the focus has been on different topics. One strand of research focuses on scope and, of late, welfare (Jacobides & Winter, 2005, 2012), while another focuses on the interdependence of sectors and their impact on innovation (Adner, 2012; Kapoor & Adner, 2010; Kapoor & Lee, 2013).

2.1. Industry Analysis: Empirical Findings and Conjectures

In the absence of an established theory on value migration, we can look at work that has explored how profit forms. Specifically, we draw on the I/O predictions on the role of sales concentration and market power. The argument, popularized in the strategy field through Porter's (1980) "five forces" framework, is that the degrees of supplier power and buyer power both affect the focal market[4]. So, for a hypothetical sector with two segments, upstream concentration reduces the profitability of the downstream segment (given supplier power); and the upstream segment also has the advantage of its own market structure being

4 Porter's framework also considers the threat of entrants and the threat of substitutes, as well as the intensity of competition. Our proposed theory will provide a dynamic reinterpretation of this part of Porter's framework, explaining how firms' positioning along the value chain might indeed affect either potential conditions of relative entry (and mobility) in the sector, or competition intensity. Unlike Porter, though, we do not focus primarily on sales concentration and the traditional notions of market power.

oligopolistic, giving it a “double advantage” over the downstream segment. This suggests that the relative level of profitability, *especially* in vertically related segments, is based on the relative market power along the value chain.

While this analysis yields an interesting set of hypotheses, they are not, strictly speaking, based on empirical research – illustrations in Porter’s book notwithstanding.[5] Nonetheless, the idea spurred research that considers what drives profitability. A particular line of research has focused on the extent to which industry factors explain the variance in profitability – whether driven by Porter’s preferred features or other stable attributes (e.g. Rumelt, 1991; McGahan & Porter, 1997, 2003, 2005). This careful empirical work confirmed Schmalensee’s summary, based on studies before the 1980s, that “At the firm or business unit level in the U.S., industry characteristics account for only about 10–25% of the cross-section variation in accounting rates of return” (1989: 971).

Schmalensee (1989) provides the most authoritative broad review of work on cross-industry level research. He surveys both the findings that have accumulated in empirical IO since Bain’s (1951) pioneering work and the concerns over their interpretation. He takes the position that “cross-section studies can produce stylized facts that can guide theory construction and analysis of particular industries” (Schmalensee 1989: 956). He summarized the wealth of evidence produced by economists through their industry studies in stylized facts. Of particular relevance are the following stylized facts:

1. Stylized Fact 4.1: Differences among observed accounting rates of return and market/book ratios in the U.S. are generally too low to be easily reconciled with the existence of textbook monopolies. (1989: 970)
2. Stylized Fact 4.5: The relation, if any, between seller concentration and profitability is weak statistically, and the estimated concentration effect is usually small. The estimated relation is unstable over time and space and vanishes in many multivariate studies. (1989: 976)
3. Stylized Fact 4.11: In samples of U.S. firms or business units that include many industries, market share is strongly correlated with profitability; the coefficient of concentration is generally negative or insignificant in regressions including market share. (1989: 984)
4. Stylized Fact 4.12: Within particular manufacturing industries, profitability is not

5 Ghemawat, for instance, notes in his strategy textbook (2005: 23) that only five out of the 45 correlations (let alone causal links) postulated by Porter in his framework find any empirical support in the literature. Ghemawat also mentions that “a survey of empirical IO in the late 1980s – more than a decade after Porter first developed his framework – revealed that only a few of the influences that Porter flagged commanded strong empirical support”. (2005: 24)

> generally strongly related to market share. (1989: 984)

Despite their obvious interest for both economists and strategy scholars, these facts were not pursued further, and remained neglected in both teaching and research. One of the reasons for this was the shift in attention in the economics profession. As Schmalensee noted, ‘interest shifted to work on the theory of imperfectly competitive markets and, more recently, to econometric industry studies employing formal models of conduct. Industry studies are now out of fashion’. This trend remained unabated in both economics and strategy, so that, Einav & Levin (2010), in their authoritative *JEL* review of the ‘state of the field’ in terms of empirical research in IO, concluded thus:

> A final and important issue for the future of industrial organization relates to the shift from cross-industry analysis to industry studies. In his post-mortem on the cross-industry literature in industrial organization, Schmalensee (1989) pointed out that it had not taught us much about how markets actually work. After 20 years of industry studies, we know a lot about how specific industries work, but this knowledge is extremely disaggregated. We have detailed analysis on automobiles, airlines, electricity, and cement and concrete plants (which are not the same!). But this knowledge does not easily accumulate across industries. As a result, industrial organization has ceded many of the interesting and important questions about the overall organization of production in the economy to other fields such as trade and macroeconomics. It may be time to reclaim them. (2010: 162)

This relative neglect of the factors that drive industry profitability is understandable, since looking at cross-sectional data is fraught with methodological challenges. The key issues have been the complex etiology of profitability (or market capitalization), which is difficult to disentangle empirically, and the potential reverse causality identified by Demsetz (1973), i.e. that efficiency drives scale (and thus market share), as well as profitability, rendering any correlation between market share or concentration and profitability hard to interpret as evidence of oligopolistic power. Also, a cross-industry research design might tell us more about accounting differences between industries than about true heterogeneity in performance. It is this framing of the research question that provides the opportunity for our exploratory quantitative research.

2.2. Researching value distribution and migration

Moving to the research question at hand, business practitioners and academics have increasingly acknowledged that changes in one part of the value chain profoundly affect the others (Bresnahan & Greenstein, 2000) while value distribution and migration remained understudied. While some research in economics looks at the links between vertical structure and profitability, the focus is narrower and does not consider dynamics.[6] Some progress has been made, in an "appreciative research" mode, with a focus on technologically intensive sectors. Researchers have remarked that interdependence among firms engaged in different parts of the value chain stabilizes over time and results in one or a few rival "platforms": co-specialized "business ecosystems" each with their own sponsors, orchestrators, and keystone members (Gawer & Cusumano, 2002; Iansiti & Levien, 2004).

A research stream on "Global Value Chains" (GVCs) (Gereffi & Korzeniewicz, 1994; Gereffi, Humphrey & Sturgeon, 2005) has looked at how different participants and different types of firms (from different geographies) come together to organize production internationally. Earlier studies focused on the drivers behind the emergence of GVCs (e.g., Gereffi, 1994). Later work considered various arrangements in GVCs, acknowledging a variety of patterns in terms of supply structure and firms' ability to profit from them (Sturgeon, 2002; Humphrey & Schmitz, 2002). Its focus was mainly on the plight of suppliers, usually from developing countries, and their prospects of capturing more value (Gereffi & Fernandez-Stark, 2011). While this research does consider the different ways in which production can be organized and affect value capture of participating firms, it does not directly address the patterns of value distribution.

More recently, research has looked more directly at how the power and profit structures of sectors, GVCs, and ecosystems unfold. Jacobides *et al*. (2006) proposed the concept of "industry architectures", defined as the rules and roles that pertain of the division of labor – the question of "who does what" (and how), which, in turn, affects "who takes what". Drawing on the literature of innovation (Teece, 1986) and Collaborative Game Theory (CGT), they argued that the conditions within a segment of the value chain affect

6 In terms of the cross-sectional analysis of profits in the context of vertically related sectors, two tangentially related literatures exist: First, studies on successive oligopolies and double marginalization (Perry, 1978; 2007) and second, studies on vertical restraints (Dobson & Waterson, 1996). Neither directly considers the dynamics of profitability along the value chain – or even profit distribution.

that segment's share of the total profit within the sector, and determine how profitable it is to operate in that segment as opposed to others.[7] Their view is that firms with superior capabilities can shape their industry's architecture, helping to turn particular parts of the value-adding process into 'bottlenecks' (Jacobides *et al*, 2006: 1208)[8] that enable them to affect the division of profit at sector level to their advantage. This means that firms compete not only within a segment, but also across segments to increase the value of their segment within the sector. To the extent that they succeed, profits will migrate to their segment.

Ferraro & Gurses (2009) provide an application of this argument by illustrating how Lew Wasserman and his firm, MCA, used technological or regulatory turmoil change as an opportunity to change the architecture of the entertainment sector to their advantage. Pisano & Teece (2007) provide a prescriptive account of how firms in high-tech sectors should try to change their industry's architecture to ensure they benefit from their innovations, and also become more of a bottleneck.

Taken together, these recent research streams provide the building blocks of an exploratory analysis of value distribution and value migration along a sector's value chain. In particular, a carefully calibrated research design, focusing on dynamics within a segment, might help overcome some of the key impediments to date. Looking at how the *distribution of profitability changes in a set of co-dependent sectors* is methodologically more robust, phenomenologically interesting, and, we would argue, relevant to the current state of the business landscape.

3. Theory and hypothesis development

7 On the *modeling* side of economics, CGT provides a framework to explain how value is created and then shared between a set of interdependent actors (Brandenburger & Stuart, 1996; Dixit & Nalebuff, 1991). Its main argument is that a more replaceable actor, who thus adds little value to collaboration, is more restricted in its ability to capture value. This insight can be applied to the question of relative value capture in a sector, but it has not been used to address this particular question; this is what we try to do.

8 The term 'industry bottleneck' was proposed by Jacobides *et al.* (2006), but the phenomenon has been mentioned by others (Baldwin & Clark, 1997; 2000; Ferguson & Morris, 1993; Iansiti & Levien, 2004). The initial discussion of 'bottlenecks' is found in the discussion of technological progress, notably in Rosenberg (1969).

Our interest is whether and how different power dynamics within each segment of a sector affect the relative proportion of value that each segment captures when compared to the entire sector, and we look at how this *changes* over time, leading to potential value migration.

3.1. IO-based hypotheses and conjectures

We start our analysis by considering hypotheses that draw on the IO tradition, consistent with Porter and others. Both theoretical models and the empirical literature in IO build on Cournot's (1838) early insight that a restriction of output, given concentration, raises prices, leading to oligopolistic profits. Since then, sales concentration has been the focal measure for economics theory and policy alike – including the determination of market power and antitrust enforcement.

The intuition here is straightforward: The greater the increase in market power, measured by sales concentration, the greater the ability to credibly restrict output and increase prices (and profits). There have been countless variants of this, and more sophisticated forms of modeling (including game theoretic treatments of strategic interaction), as well as extensions to "umbrella pricing" by a market leader (measured in terms of sales), as in Stackelberg's (2011[1934]) model. Should the theory hold, concentration should explain not only the level of variables, but also the changes in them. Therefore,

> *Hypothesis 1a:* Increase in the *sales* concentration of a segment leads to an increase in its share of total sector profit.

In other words, relative concentration across a sector determines where the profits go: A relatively high level of concentration should be good for the segment's profit level, and the share it has when compared with the sector. This conjecture suggests that relative concentration *should* explain much of the variance in profit across a value chain.

Another expectation from traditional economics is that the level of R&D expenditure in a sector increases its ability to exert monopolistic power, since greater R&D represents an entry barrier, which is a form of "endogenous sunk cost" (Sutton, 1991).

These past investments are a source of market power, and they also reduce the intensity of competition by increasing differentiation. Thus,

> *Hypothesis 1b:* The greater the increase of the level of R&D investment in a segment, the greater the increase in its share of total sector profit.

Finally, the greater the difficulty for a firm to enter a segment (because, e.g., of the ratio of fixed costs or in terms of the assets per employee needed to compete), the greater the profitability of that segment would be – as such entry barriers suppress the rising of competitive pressure, ensuring incumbents maintain their profitability and power over potential competitors. So:

> *Hypothesis 1c:* The greater the increase of asset commitment needed to operate, and the greater the increase of fixed costs in a segment, the greater its share of total sector profit.

3.2. Dynamics along the Value Chain: Capabilities, Power and Bottlenecks

We argue that another set of forces can be at work in addition to market power. The research in industry ecosystems and architectures has demonstrated that many firms not only compete within their segments, but also change the conditions of value distribution between segments. Qualitative evidence confirms that firms do deliberately shape their ecosystem and change the "rules of the game" (e.g. Duguid, 2005; Ferraro & Gurses, 2009). The fate of a segment may depend on kingpins' ability to shape the sector to their advantage. We argue that the more a segment is dominated by kingpins (firms with disproportionate *market capitalization* and with greater rate of technological investments), the more *that segment* is likely to attract a disproportionate amount of the sector's value.

We believe that kingpins' power is not derived from their market share or output constraint, but rather on their ability to shape their ecosystem. We argue that kingpins' superior capabilities lead to higher margins and an improvement of their fortunes, in terms of market capitalization. We also argue that *substantial inequality in terms of capabilities and power within a segment* is likely to benefit the segment as a whole, i.e. kingpins exert positive externality to their segment.[9] We thus focus on whether a segment is dominated by a kingpin in terms of market capitalization.

One way a kingpin can help their segment is by setting the rules of interface with adjacent segments (Jacobides & Winter, 2005) – for example, by leading in standards negotiations or institutional arrangements. If they succeed, the segment (and the participants within it) can become the guarantor of quality, providing the "certification function" (Duguid, 2005) to end consumers – as Intel did for computers, eclipsing the power of computer makers to assure quality (e.g. "Intel Inside"). Once the kingpin helps the segment (including itself) to become the certificator of quality, other segments (and other sector participants) are rendered less important. This creates externality, allowing others in the kingpin's segment to benefit. It may even be easier for the kingpin to help establish the *segment* as opposed to just itself to become central in terms of certification game, by fear of antitrust action should it not create any externality. Thus, a kingpin can help set the industry standards to ensure that the entry barriers around its segment stay high.

Conversely, if valuations are roughly equal within a segment, firms are likely to concentrate their efforts on head-to-head competition, either because they are unable to shape the industry architecture or because they are uninterested in doing so. Increasing inequality in a segment means that one firm (*not* in terms of market share, but in terms of value) may do more than dominate its own market; it may shape the conditions in the sector, rendering *both* itself *and* other participants in its segment more valuable as a result. Thus:

> *Hypothesis 2a.* The greater the increase in inequality in value within a segment, the greater that segment's increase of share of value within the sector.

To illustrate this hypothesis, consider how the computer sector changed. Initially, IBM was *the* dominant force – not only in terms of sales concentration, but also in terms of

---

9 Since there is no direct measure of these unique capabilities and profit-making and industry-shaping potential and it is nearly impossible to get reliable, comparable, multi-segment data, we focus on the value of the firm in terms of market capitalization. Our (exploratory) theory development focuses on the features we *can* observe, and thus constitutes a "reduced form" analysis, looking at the implications of the theory for observable correlates.

value, constituting almost 42% of the total market cap of the entire sector. Soon, IBM's uniqueness (both in terms of R&D and value) started sliding, even before its market share shrunk. Its ability to control its ecosystem waned, allowing other firms to take on the mantle of the sector-wide leadership. Ultimately, both Microsoft and Intel became disproportionately valuable in their segments (more so in market value and R&D than in sales). This allowed them to turn *their* part of the value chain into a bottleneck, benefiting both themselves and other participants of that part of the sector.

The illustration suggests that kingpins should be able to create and capture value both for themselves and, indirectly, for others. Thus, our empirical testing will consider whether kingpins make their segment better off – *even when the kingpin itself is disregarded*. Thus,

> *Hypothesis 2b.* The greater a kingpin's increase in value share, the more value other firms in its segment will capture compared with the rest of the sector.

Drawing on our earlier example, we exclude Microsoft and Intel from their respective segments and determine their positive value effect on other firms in their segment. That is, we test whether there are *real* externalities to a segment resulting from the presence of a kingpin.

Our argument suggests that kingpins help their segments partly because they can drive the evolution of the sector. A big part of this is technological prowess: Clear technological leaders can set the rules of interface between segments, improving the relative position of their segment. In other words, we expect that *inequality* in technological investment between the kingpin and its peers will benefit the segment. The more R&D is concentrated with one or a few firms, the more the segment improves its fortunes. Expressed in dynamic terms, this means that:

> *Hypothesis 3a.* The greater the increase in inequality in technological investment among firms within a segment, the larger that segment's share of value within the sector.

This hypothesis is illustrated by the disproportionately heavy R&D investment made by Intel in microprocessors in the early stages, which allowed it to play a key role in standards evolution. In contrast, the significant yet largely comparable levels of R&D among chipmakers in memory and IC products led to their commoditization and left them unable to shape the sector to their advantage. We can also test the "strong form" of this hypothesis, considering whether inequality in technological investment benefits not only the segment overall, but also firms *excluding* the kingpin:

> *Hypothesis 3b.* The larger the increase in the share of technological investment a kingpin has in a segment, the greater the benefit to the other firms of that segment in terms of value capture, compared with the rest of the sector overall.

Finally, we consider the reverse causal dynamics by examining whether or not a segment being a "bottleneck" affects the inequality of value within that segment. Consistent with the industry architecture speculations, we expect a kingpin to wield more power as its segment becomes more of a bottleneck. For example, the more Microsoft and Google turn their segments into bottlenecks, the more all firms in those segments benefit from the increased strength of their segments – at the cost of increased inequality. That is:

> *Hypothesis 4a.* An increase in the share of value captured by a segment will have a positive lagged correlation with the inequality of value of firms within that segment.

Also, the more a segment becomes a bottleneck, the less the contenders in that segment try to win the technological war *within* their segment, relying on their kingpin instead. This means that as greater value is captured, the differences in R&D investment will grow ever larger:

> *Hypothesis 4b.* An increase of the share of value that each segment captures from the sector will have a positive lagged correlation with the inequality of technological investment between firms within that segment.

4. Empirical design

We conducted an exploratory quantitative analysis, aiming to test established, but broadly untested theory, and also simply to illustrate the theory advanced in the previous section.

4.1. Research Design

Our theory is versed in dynamic terms firstly because we are interested in the phenomenon of value migration, and secondly because looking at dynamics (that is, by looking at changes in both the right and the left-hand side of the equation) helps us resolve many of the problems that riddled previous work correlating profitability and structural features. We thus build on what Schmalensee (1989) observed in his concluding sentence: "it is important to note that much of the most persuasive recent work relies on non-standard data sources, particularly panel data (which can be used to deal with disequilibrium problems) and industry-specific data (which mitigate the problem of unobservable industry-specific variables.)" Looking at how the *distribution of profitability changes in a set of co-dependent sectors* through a fixed-effects model, we look not at the levels of profitability distribution, but rather at *changes* in those levels. Furthermore, we focus on a set of *causally interdependent* sectors and take their *share in terms of value* (measured by market capitalization) as our dependent variable, which is less susceptible to the distortions of accounting methods even though it incorporates stock-market expectations. Finally, we complement findings from quantitative data with qualitative data, which allows us to focus on the *process* through which profitability changes, and articulate exploratory findings to be further refined by future research.

4.2. Setting

Our choice of the computer sector as a setting was predicated on its interest, as opposed to its representativeness (Firestone, 1993). That is, we selected it *because* we have observed a dramatic shift in value distribution in the sector. The percentage of market capitalization of firms in NAICS codes 334111 (computer manufacturing) and 511210 (software developers) to the total sector value underwent dramatic change between 1978 and 2005: from 79% to 8% and from 0.01% to 31%, respectively. This sector thus provided the requisite variation that allowed us to study which segment-level conditions affect relative value capture. It represents one of the most important sectors in the US, having accounted for 9.4% of the total manufacturing value add in 2007 (Bureau of Economic Analysis). It is also similar to other sectors (e.g. mobile telecommunications) where value is currently seen to migrate in terms of its technological sophistication and intensive R&D activities, involving myriad components and parts.

4.3. Data

The data cover the period 1978–2005. Our data drew on the dataset originally gathered by Baldwin, Jacobides, and Dizaji (2006), but were substantially cleaned and checked. The data-gathering process was organized into three different stages.

First, by identifying the relevant NAICS/SIC codes, we constructed a model of the sector's value chain. Each NAICS/SIC code represents a segment that forms a part of value chain. We identified relevant codes by i) consulting the descriptions of each code listed in NAICS 1997/2002/2007 manuals from the U.S. Census Bureau, ii) tracing the NAICS codes of leading firms in the sector such as Microsoft, IBM, and Intel, and iii) identifying all NAICS codes of firms with 'computer' in their business descriptions. With the compiled list of NAICS codes, we consulted industry experts and academics to avoid both Type 1 and Type 2 errors. The complete list of NAICS codes is available upon request.

Once we had identified all the NAICS codes corresponding to the value chain, we obtained a list of all firms that listed any of the NAICS codes we had identified, both active and inactive, from COMPUSTAT's North America using the *conditional statement* section. We then cross-checked the name of the company and its main source of revenue against each NAICS code's description to ensure that only firms participating in the computer sector's value chain were included. The combination of the lists of firms belonging to each NAICS code represented all firms in the computer sector[10].

Next, we extracted numerical information on all firms included in the lists, using the unique identifiers of firms, from COMPUSTAT North America's *segment search*. We used the following information to construct variables: primary and secondary NAICS codes[11], market capitalization, sales, total assets, current assets, current liabilities, long-term debt, R&D spending (all in million USD), and number of employees (in thousands) for each firm-year. All numbers are reported at firm level apart from sales, which is reported separately for each NAICS code. For firms with more than one corresponding

10 Our data only includes firms that are publicly traded in the US and does not include firms publicly traded outside the US or private firms. These are two of our data limitations.

11 NAICS was introduced in 1997 and pre-1997 data only have SIC codes. We used the NAICS-SIC correspondence tables published by the US Census Bureau to match the codes in consistent fashion.

NAICS code, we weighted the numbers reported at the firm level with sales, the only number reported at the NAICS code-level.

Finally, we organized the numbers into a longitudinal data: NAICS codes, which represent the segments comprising a value chain, as panel and year as time. Under this setup, a firm can be represented more than once in a given year if it has more than one corresponding NAICS code.

4.4. Dependent variable

The dependent variable is the *percentage of market capitalization (segment to the sector)*[12] for each NAICS code-year (i.e., each segment-year). We calculated each *segment's* market capitalization by summing the adjusted market capitalization of all participating firms within each segment-year. We then added the market capitalization amount of all segments by year to derive the market capitalization of the entire *sector* for each year. Dividing each segment's market capitalization by the sector's total market capitalization for each year yielded the dependent variable. For the final pair of hypotheses (H4a and H4b), we used the inequality of value (independent variable for H2a) and technological investment (independent variable for H3a) within a segment as our *dependent* variable.

To conduct the 'strong tests' (H2b, H3b), we excluded the kingpin from our analysis of the share of value as a dependent variable. We identified kingpins as the firms with the highest market capitalization and excluded their market capitalization amount when calculating each segment's market capitalization. For sensitivity, we also identified kingpins on the basis of sales in the segment.

4.5. Independent variables

Market Power. We used the Herfindahl index, calculated as the sum of the squares of each firm's sales to total segment sales to examine the role of market share.[13] For technological intensity, we divided the sum of R&D spending by all firms in a segment by the number of firms in it to obtain the mean of R&D spending in each segment. We used two different

12 We use the percentage because we are interested in each segment's *relative* share of market capitalization within the sector, not its absolute amount.

13 We also tried C1 and C4 (share of top/top4 firm(s)). The results were consistent in the full models.

measures for entry barriers. First, we calculated fixed assets of all firms by deducting current assets from total assets, summing them by segment, and dividing by the number of firms in each segment. Second, we measured the asset-intensity (denoting the difficulty of entering due to capital intensity), calculated as the ratio of the sum of the segment's total assets to the total number of the segment's employees.

Inequality in value and technological investment. Inequality was calculated using the kingpin's share of market capitalization or R&D spending relative to its segment's total market capitalization or R&D spending in each segment-year. Note that the focus here is on the *distribution* of the variable as opposed to its *levels*. High values for the kingpin's share means there is a major inequality in value or technological investment among participating firms in a segment-year.

4.6. Control variables

All our models included the following control variables. To account for the size of the segment, which might affect value capture, we included both the number of firms and the total number of employees, as well as asset efficiency (a segment's total sales divided by its participants' total assets). Table 1 presents the summary statistics for the variables used to test our hypotheses.

PLACE TABLE 1 ABOUT HERE.

4.7. Robustness checks

We carried out a robustness check by running the identical models using data aggregated at both five- and six-digit NAICS codes. This allowed us to see if using finer vs. coarser "buckets" to define the segment affected our results. They did not. In addition, we created three lagged dependent variables (one, two, and three years past the base year) to ensure that the results persist over time. The results from the lagged models were similar compared to those obtained from the baseline model.

4.8. Empirical method

We specify a segment's value as a linear function of the explanatory variables: *the share of a segment's market capitalization in a sector = f (market concentration, inequality in value, or technological investments of each segment)*. Because we are using panel data, it is possible that the error terms will not be independent across time or within segments (Greene, 2008). There are potential time-dependent, macro-level factors that could affect the profitability of each segment. As we have noted above, controlling for this heterogeneity, and for the conflating effects associated with regressions of structural features on cross-sectional level of profitability measures, we focus on how the relative value share of segments changes over time (Greene, 2008; Kennedy, 2003). We thus use fixed-effects models (fixed by segment) through which we conduct within-segment estimations. Not only does the research question point to a fixed-effects model, it also offers an efficient means of dealing with non-constant variance of the errors, i.e. heteroskedasticity, stemming from the cross-sectional and temporal aspects of the pooled data. The Hausman test results also supported the use of the fixed-effects model.

5. Results

Table 2 reports the results from fixed-effects GLS estimators for both weak and strong tests at base year (t=0). The results show that there are regularities in the relationship between a certain type of power inequality within a segment and the segment's relative share of value within the sector. More results on the lagged relationships of both weak and strong tests are reported in the Appendix.

Market power hypotheses. Market share, proxied by sales concentration, does *not* predict the segment's relative value capture. Similarly, we do not find any significance to technological intensity, since the average level of R&D is not a good predictor of a segment's relative value in a sector, and nor are either of the two measures by which we test entry barriers (asset intensity and fixed assets).

Inequality in value. We find support for H2a, in which we predicted that higher inequality in value among firms within a segment would lead to higher value of the segment within the sector. The kingpin's share is a strong predictor of the segment's share of value both contemporaneously and over time. However, it seems the effect is driven mostly by the presence of the kingpin, according to the results of the 'strong test' of H2b. The correlations reported in the Appendix show that when we *exclude* the kingpin from the dependent variable, it is not clear whether the remainder of the firms in a segment can benefit from the existence of a kingpin – that is, there is no clear sign of externality.

Inequality in technological investment. We also find support for H3a. The kingpin's share has a positive sign and is statistically significant. In terms of the 'strong test' of H3b, the correlations reported in the Appendix show that when we *exclude* the kingpin from the dependent variable, the remainder of the firms in a segment can *still* benefit from the existence of a kingpin – that is, there is a clear sign of externality. The effect is consistent over time. In contrast to value, the kingpin's share in technological investment has a positive externality on the segment. This contrast in results may be attributed to the way in which kingpins turn their segments into bottlenecks, e.g. more with their technological prowess than profit or profit-generating capabilities *per se*.

PLACE TABLE 2 ABOUT HERE.

Reverse causality. Table 3 shows the results for the impact of value capture of a segment on the inequality in value within that segment over time. We find support for H4a. Higher value of a segment in a sector led to higher share of the kingpin's value within the segment over time. We also find support, albeit weak, for H4b, in which we predicted a positive relationship between a segment's share of value at t=0 and the inequality in technological investment in subsequent time periods. The kingpin's share has a positive sign and is statistically significant only in t+1.

In addition, we analyzed the effect of changes in the number of participants on value capture within a segment, as changes to value capture of a segment can induce firm entry or exit. The results show that changes in the number of participants have a positive effect on the value capture of the segment, which is the converse of what traditional IO-based theory would predict. This could mean that the growth in the value of a segment is *causing* entry of aspiring firms, who expect to find *some* protection under the umbrella of a kingpin. Results are available upon request.

PLACE TABLE 3 ABOUT HERE.

Summing up, we observe distinct patterns in how inequality among firms within a segment affects the segment's share of value. The fact that the kingpin's share is significant and robust is consistent with our theoretical expectations. The coefficients of one of our controls, mean of R&D spending, were positive in the weak test as the standard theory predicts. However, they turned negative in the strong test, implying that there really is a kingpin effect.

5.1. Illustrating our results

While our paper focuses on the quantitative evidence, we wanted to illustrate the mechanisms we referred to through one concrete example from our sample. Consider, in particular, NAICS 334112, which consists of firms primarily engaged in manufacturing computer storage devices such as hard-disk drives (HDDs), CD-ROM drives, and floppy-disk drives that allow the storage and retrieval of data. The case of computer storage device manufacturers, and HDD manufacturers in particular, illustrates how the degree of inequality in capabilities among direct competitors affects the segment's share of value in the sector. Manufacturers of HDDs compete on features such as data density and latencies, as well as smaller form factors that enable the reduction of physical sizes in computing devices – all of which require intense technological knowledge. The level of R&D investments among firms has also remained largely homogeneous, lest they put both their profitability and survival at risk. Due to the intense competition among firms within the segment, even those with somewhat superior capabilities (e.g. Western Digital and Seagate) could not use their skills to establish an industry standard, or interfaces that could help shape the sector to their advantage. For example, the ATA/SCSI interface has remained resolutely unchanged for the past three decades, which benefits only computer assemblers. The relative homogeneity in R&D investment, which hinders the emergence of kingpins by engendering relative homogeneity in future capabilities, forced the incumbents to gradually shift their focus from technological prowess to scale and price. It led to continued consolidation in the segment and, since October 2011, only three firms remain: Toshiba (10.8%), Seagate (40%), and Western Digital (49.2%). But the high concentration did not help the segment, since it was the *result* of the segment's relative impotence, and not, per the more traditional economic rationale, an opportunity for pricing power. The relative share of value of firms belonging to NAICS 334112 has remained low and relatively stable over time (between 1% and 7%). So while heterogeneity and concentration at the level of technology or capabilities, and in particular a kingpin's dominance, would have *helped* the segment, the sales concentration in the segment did not. Sales concentration seemed to have been a symptom of malaise, the result of the segment "losing out", not a predictor of success – in other words, this was an example of "defensive concentration".

6. Discussion

Our findings are consistent with Schmalensee's (1989) overview of the empirical literature, which unveiled a set of stylized facts that were hard to reconcile with traditional economic analysis. His observations were not consistent with the traditional IO approach to the dynamics of profitability, epitomized in the "five forces" framework. Our empirical finding that sales concentration, the core measure used to gauge market power, does *not* explain changes in value distribution in a sector, is theoretically important. We have tried to offer exploratory theory and evidence to show what might account for the changes in value distribution.

We are following the spirit of Schmalensee (1989), as noted in his concluding paragraph,

> This literature has also produced an impressive, if implicit, agenda for future research. It seems difficult to reconcile the set of Stylized Facts discussed above with any familiar simple view of the world; some Stylized Facts seen difficult to reconcile with each other… Future inter-industry research should adopt a modest, descriptive orientation and aim to complement case studies by uncovering robust empirical regularities that can be used to evaluate and develop theoretical tools.

Our work is focused on the dynamics of one sector, and its innovative feature is to consider an *interrelated set of vertical segments.* We cautioned that our analysis would be exploratory, in the sense that we cannot, through an analysis of one sector, infer how interdependent business ecosystems' value evolves over time. Yet the forces we uncovered in lieu of market power merit further investigation. The economy is characterized by increasingly interdependent ecosystems of firms that collaborate and compete (Adner, 2012; Iansiti & Levien, 2004; Cusumano, 2010), and the quest to explain how this affects profitability and value of firms will help keep the strategy field current and relevant.

Our findings indicate that inequality in value within a segment, and particularly the dominance of a kingpin, has a fairly robust relationship with the share of value that segment captures in its sector. These findings lend support to the emerging industry architecture literature, and to speculations on how firms shape their sectors, although we cannot test for the underlying mechanisms directly. However, we find that the differences in terms of firms' value within a segment affect the ability of that segment to make itself a bottleneck. This power is not related to the segment's market power (measured by sales concentration), but to *the variance* in firm valuation and R&D investment. So kingpins are indeed powerful, but in a way not foreseen by traditional analysis, and more congenial to the descriptions of Pisano & Teece (2007), Jacobides *et al* (2006), or Ferraro & Gurses (2009).

An important part of the "exploratory" nature of our work is that we have unearthed a set of empirical regularities and speculated on what drives them, as opposed to determining the nature and underpinnings of particular variables. This is particularly true of the driver of inequality in value within a segment, which can be a surrogate of capability differences or power (though not market power, which is directly controlled for). Proviso noted, our findings show that inequality of value, due to capability heterogeneity and technological prowess, makes a segment more valuable along the value chain. Furthermore, the more a segment becomes a bottleneck, the more unequal that segment becomes. Our results thus provide direct evidence that link the *heterogeneity* of capabilities or value in one level of analysis (the segment) to value in another, nested level of analysis (the share of the segment with respect to the sector), and show how kingpins can exert positive externalities on their peers by "growing the pie" that a segment can attract.

The analysis of the reverse causality suggests that positions of power along a value chain serve to *enhance* the dominance of a few firms, so that the bottleneck allows kingpins to tighten their grip further. So while other firms see their plight improved by a kingpin in the short term, as their segment grows in importance, over time the kingpin takes more of the value, making its dominance a double-edged sword for its peers. This observation contrasts with the "winner takes all" hypothesis (e.g. Arthur, 1989; Kelly, 1998).[14] However, this is consistent with qualitative studies (Ferraro & Gurses, 2009; Dupeyre & Dumez, 2010) and adds flesh to the anecdotal discussion in the popular press about profit-pool migration (Gadiesh & Gilbert, 1998; Slywotzky & Morrison, 1997).

In addition to providing direct evidence on whether market power (in the traditional sense) drives value dynamics in a sector, or whether there is support for hypotheses drawing on the industry architecture literature, this study has implications for different streams of work. First, it complements research on what drives variance in returns of companies (e.g. Rumelt, 1991, McGahan & Porter, 1997, 2003, 2005) by shedding light on the nature of industry/sector differences. We show that industries (or vertical segments) do matter, but because of power *distribution* rather than concentration. Our analysis is thus consistent with the findings and provides a fresh set of factors.

Second, our analysis advances the studies on industry evolution. While we know a lot about the segment-by-segment dynamics of entry and exit (Klepper, 1996, 1997), "shakeouts" (Abernathy & Utterback, 1978; Greenstein & Wade, 1998; Klepper & Simons, 2005), and industry structure (Malerba & Orsenigo, 1996; Nelson, 1994), we have a vague account of the entire sector. Our consideration of the entire industry architecture, and the relationships within it, provides an additional angle to the understanding of industry demographics. Our explicit focus on inequality within segments as a driver of sector-wide dynamics is aligned with research that looks at the drivers of differences in capabilities and their implications in a sector (Jacobides & Winter, 2012; Syverson, 2011).

Third, we complement recent work on industry architecture and global value chains (Duguid, 2005; Ferraro & Gurses, 2009; Gereffi *et al.*, 2005; Pisano & Teece, 2007), by shifting from the individual, micro-level analysis to a large-scale analysis. We offer the

14 Its argument is that a firm with superior capabilities drives out its direct competitors and eventually becomes a de facto monopoly. While we cannot rule out its possibility in a distant future, at least in our setting, the presence of a kingpin in a segment seems to benefit its direct competitors. We would speculate that one possible reason for this result is that kingpins might face regulatory pressures if they were to only benefit themselves, whereas they might be able to benefit their part of the value chain more easily.

large-scale quantitative counterpart to these studies, and provide a template for further work on value migration.

This analysis also leaves interesting questions to follow up. We need to shed light on the micro-mechanisms that underpin the quantitative evidence we highlight, using qualitative research. The question becomes, how exactly do strong players in one segment of the value chain exert a positive externality over other firms in their own segment? Also, although we speculate that inequality or other conditions within a segment and its share of value will have different relationships depending on the sector, our understanding of the underlying mechanisms is lacking. A better grasp on this would allow us to interpret the mechanism through which inequality among firms leads to a segment becoming a bottleneck. Furthermore, this research program can be complemented by formal modeling, whether in the CGT tradition (Bradenburger & Stuart, 1996; MacDonald & Ryall, 2004) or through other models of multiple-segment industry evolution that are in the making. And finally, it would be good to complement the pilot "sectoral" study with enquiries into other interconnected sectors – even though one quickly comes up against data limitations.

6.1. Limitations

This study has a number of limitations. On the theoretical level, although we identified that inequality among firms drives changes in value distribution, the question of whether this is the result of a conscious strategy remains. We cannot say whether a particular segment being a bottleneck is an unintended consequence of an individual firm's pursuit of profit, or something that firms in a segment consciously work towards, individually or through concerted action. We also avoid the question of industry architecture's endogeneity by treating it as given.

Conceptually, we consider each segment as one entity, and look at the aggregate resolution of the competitive battle as proxied, indirectly, through the inequality of participants' capabilities. Doing so takes our focus away from the struggle within each segment, such as the battle between different potential solutions, or even industry-wide architectures and the related "platform wars" (Gawer & Cusumano, 2002). Our paper is also agnostic on the *sources* of capability differences, as we treat heterogeneity as given, focusing on its implications rather than its antecedents.

On the empirical level, there are additional limitations. First, as we mentioned, we chose computers on the basis of theoretical interest, as opposed to generalizability.

Second, as we consider this sector's specificity, it is worth noting that the computer sector has fairly clearly delineated boundaries. This allows us to test the hypotheses in a constrained setting, characterized by relative stability in terms of the segments that constitute it. In many sectors, such as telecommunications and media, where we are witnessing very substantial value migration, however, the nature of the constituent segments evolves over time. This makes empirical analysis elusive, but also adds a further element of structural change that was absent from our setting.

Third, our data has its own limitations. We only look at publicly listed firms in the US market and leave out both i) private firms and ii) firms that are publicly listed elsewhere. Our data include non-US firms with ADRs (e.g. TSMC), but exclude others such as Samsung Electronics. We do not have prima facie concerns that these exclusions bias our results, and no record in action or secondary data we could think of would easily redress the problem.

Fourth, we weighed market capitalization and other measures that are identified at firm level with the sales data to transform and construct the measures to segment-level (NAICS code) data. We recognize that this arbitrarily prorates firms' value. Yet, we do not think this arbitrary choice invalidates our results and analysis, since we focus on *fixed effects*. That is, we consider how *changes* in market capitalization, prorated by sales (even if we assume an arbitrariness in prorating as a baseline), over time, links to changes in the share of value captured. If anything, a rough measure in terms of pro-rating should introduce more noise. This makes our robust results in terms of the fixed effects all the more interesting. Furthermore, not only is this practice widely used among firms for their internal managerial accounting purposes, but there also seems to be no alternative.

Fifth, in our data, we did not account for diversified firms operating in multiple industries, as opposed to being present in multiple segments of a single industry. Texas

Instruments, for instance, manufactures both semiconductors and mathematical calculators. We could not control for such firms. We only included the sales data from relevant segments and partitioned other relevant measures, only observed at firm level, by weighing them with sales. As such, we could not rule out the possibility that these firms might influence their segments in an unobserved fashion.

6.2. Concluding remarks

Limitations noted above notwithstanding, we think that this empirical analysis helps break new ground in the study of profit evolution and value migration. This exploratory quantitative study suggests that market power is not a robust predictor of value distribution, whereas the *heterogeneity* of power and capabilities and technological prowess can shape changes in the value distribution at the sector level. It also helps shift the focus from market power and sales concentration to other means by which firms shape their sectors. This suggests that a firm's superior, idiosyncratic capabilities and prowess not only positively affect its own value (market capitalization) at a given time; but also can increase the total "pie" available to the segment, making it more of a bottleneck. We demonstrate that kingpins can exert a positive externality over their peers. We also show, however, that sectors dominated by kingpins become increasingly unequal, making the presence of kingpins a double-edged sword.

By identifying new forces affecting profitability and value migration, our study helps explore new directions, by considering two facets of profitability that have received scant attention. It looks at how profitability and value evolve within a broader ecosystem or industry architecture, taking into account the entire value chain rather than focusing on just one part of it. It also helps us advance the analysis of the *mechanisms through which profits evolve over time*, and, as such, offers a first, exploratory quantitative analysis of how value migrates along the sector. By expanding the unit of analysis and examining the dynamics of profitability, we will be able to obtain a more robust and more representative theory of profitability and its evolution, and our study has offered a step in this direction.

Table 1. Descriptive statistics

		Mean	S.D.	1	2	3	4	5	6	7	8	9
1	Segment's share of value in the sector	0.04	0.12									
2	Top firm's share (market capitalization)	0.73	0.27	-0.39								
3	Top firm's share (R&D expenses)	0.73	0.29	-0.52	0.80							
4	Number of firms	32	79.4	0.66	-0.58	-0.69						
5	Sum of employees in a segment	94.9	266	0.87	-0.49	-0.58	0.71					
6	Herfindahl Index (sales)	0.63	0.34	-0.41	0.82	0.80	-0.58	-0.45				
7	Mean (R&D expenses)	58.3	163	0.04	0.05	0.02	-0.02	0.12	0.08			
8	Asset efficiency	2.26	22.8	-0.02	-0.02	0.02	-0.01	-0.02	0.07	-0.02		
9	Fixed asset	382	1058	0.01	0.06	0.03	-0.05	0.10	0.09	0.09	-0.02	
10	Asset intensity	395	1174	-0.05	0.08	0.10	-0.04	-0.05	0.09	-0.05	-0.01	-0.01

Table 2. Hypothesis testing: weak test

DV: Segment's share of value in a sector	H1a	H1b	H1c	H1c	H1	H2a	H3a	Full Model
Kingpin's share (market capitalization)						0.079***		0.073***
						(0.017)		(0.019)
Kingpin's share (R&D spending)							0.056**	0.036+
							(0.018)	(0.019)
Herfindahl index (sales)	0.004				0.005	-0.040**	-0.022	-0.054**
	(0.010)				(0.011)	(0.015)	(0.015)	(0.017)
Mean (R&D spending)		-1.12E-05			2.66E-05	3.51E-05	2.81E-05	3.54E-05
		(1.79E-05)			(4.08E-05)	(4.14E-05)	(4.1E-05)	(4.18E-05)
Fixed asset			-2.66E-06		-6.41E-06	-8.17E-06	-6.71E-06	-8.19E-06
			(2.44E-06)		(6.10E-06)	(-6.26E-06)	(6.14E-06)	(6.33E-06)
Asset intensity				-4.60E-07	-6.09E-07	-1.15E-07	-5.66E-07	-1.29E-07
				(2.04E-06)	(2.23E-06)	(2.22E-06)	(2.25E-06)	(2.24E-06)
Number of firms	2.8E-04***	2.71E-04***	2.69E-04***	2.74E-04***	2.75E-04***	2.68E-04***	3.02E-04***	2.86E-04***
	(5.4E-05)	(5.71E-05)	(5.33E-05)	(5.42E-05)	(5.89E-05)	(5.86E-05)	(5.99E-05)	(5.99E-05)
Sum of all employees	6.5E-05**	6.85E-06**	6.97E-05**	6.55E-05**	6.83E-05**	7.67E-05**	6.59E-05**	7.45E-05**
	(2.2E-05)	(2.4E-05)	(2.23E-05)	(2.24E-05)	(2.44E-05)	(2.43E-05)	(2.46E-05)	(2.46E-05)
Asset efficiency	-1.73E-05	-1.37E-05	-1.42E-05	-1.14E-05	-1.95E-05	4.04E-05	1.50E-05	5.84E-05
	(9.0E-05)	(9.6E-06)	(8.94E-05)	(9.2E-05)	(9.96E-05)	(9.97E-05)	(1.01E-04)	(1.02E-04)
Constant	0.021**	0.027***	0.024***	0.025***	0.026***	-0.004	0.001	-0.018
	(0.007)	(0.003)	(0.003)	(0.003)	(0.008)	(0.010)	(0.011)	(0.012)
N	729	636	720	695	616	605	601	590
F-value	22.71***	19.69***	22.72***	21.54***	11.05***	12.38***	10.75***	11.31***

Standard errors in parentheses. + ($p<0.1$), *($p<0.05$), **($p<0.01$), ***($p<0.001$)

Table 2 (cont'd): Hypothesis testing (strong test)

DV: Segment's share of value in a sector (excluding kingpin's value)	H1a	H1b	H1c	H1c	H1	H2b	H3b	Full Model
Kingpin's share (market capitalization)						0.033		0.016
						(0.023)		(0.025)
Kingpin's share (R&D spending)							0.070**	0.066**
							(0.023)	(0.025)
Herfindahl index (sales)	0.001				-0.002	-0.021	-0.037*	-0.044*
	(0.013)				(0.015)	(0.020)	(0.019)	(0.022)
Mean (R&D spending)		1.02E-05			-1.20E-04*	-1.26E-04*	-1.19E-04*	-1.27E-04*
		(2.10E-05)			(4.71E-05)	(4.85E-05)	(4.73E-05)	(4.88E-05)
Fixed asset			5.47E-06+		2.16E-05**	2.29E-05**	2.14E-05**	2.31E-05**
			(3.01E-06)		(7.05E-06)	(7.34E-06)	(7.08E-06)	(7.39E-06)
Asset intensity				-8.85E-08	6.09E-07	1.20E-06	1.05E-06	1.33E-06
				(3.20E-06)	(3.35E-06)	(3.39E-06)	(3.37E-06)	(3.42E-06)
Number of firms	-2.88E-04***	-2.85E-04***	-2.79E-04***	-2.88E-04***	-2.87E-04***	-2.90E-04***	-2.52E-04**	-2.55E-04**
	(6.89E-05)	(6.93E-05)	(6.81E-05)	(6.78E-05)	(7.08E-05)	(7.14E-05)	(7.20E-05)	(7.31E-05)
Sum of all employees	1.46E-05	1.05E-05	4.52E-06	1.47E-05	1.20E-05	1.62E-05	1.04E-05	1.20E-05
	(3.00E-05)	(3.13E-05)	(3.05E-05)	(3.00E-05)	(3.14E-05)	(3.18E-05)	(3.15E-05)	(3.20E-05)
Asset efficiency	9.79E-05	1.00E-04	1.04E-04	1.03E-04	1.06E-04	1.29E-04	1.48E-04	1.56E-04
	(1.12E-04)	(1.13E-04)	(1.10E-04)	(1.11E-04)	(1.15E-04)	(1.17E-04)	(1.17E-04)	(1.19E-04)
Constant	0.057***	0.060***	0.056***	0.059***	0.060***	0.047***	0.030*	0.026
	(0.009)	(0.004)	(0.004)	(0.004)	(0.010)	(0.013)	(0.015)	(0.016)
N	563	495	558	537	484	475	473	464
F-value	6.20***	6.03***	7.01***	6.20***	4.77***	4.51***	5.27***	4.78***

Standard errors in parentheses. + (p<0.1), *(p<0.05), **(p<0.01), ***(p<0.001)

Table 3. Hypothesis testing: reverse causality

DV: Inequality within a segment	H4a: Kingpin's share (market cap)			H4b: Kingpin's share (R&D)		
	t+1	t+2	t+3	t+1	t+2	t+3
Segment's share of value in a sector	0.323**	0.212+	0.161	0.247*	0.188	0.150
	(0.116)	(0.126)	(0.136)	(0.112)	(0.123)	(0.134)
Herfindahl index (sales)	0.444***	0.365***	0.293***	0.390***	0.320***	0.252***
	(0.032)	(0.035)	(0.037)	(0.032)	(0.034)	(0.037)
Mean (R&D spending)	-7.09E-05	-1.82E-04	-1.53E-04	-3.25E-04**	-5.28E-04***	-5.41E-04***
	(1.23E-04)	(1.33E-04)	(1.41E-04)	(1.18E-04)	(1.33E-04)	(1.42E-04)
Fixed asset	6.49E-06	1.84E-05	1.76E-05	3.55E-05*	5.44E-05**	5.83E-05**
	(1.78E-05)	(1.90E-05)	(2.02E-05)	(1.68E-05)	(1.90E-05)	(2.05E-05)
Asset intensity	-1.77E-06	-1.20E-05	-5.94E-06	2.53E-06	5.49E-07	2.02E-06
	(6.04E-06)	(7.33E-06)	(7.65E-06)	(5.95E-06)	(7.57E-06)	(7.98E-06)
Number of firms	-3.34E-05	7.50E-06	1.11E-04	-5.70E-04***	-5.46E-04**	-4.19E-04*
	(1.66E-04)	(1.79E-04)	(1.92E-04)	(1.61E-04)	(1.75E-04)	(1.89E-04)
Sum of all employees	-1.11E-04	-1.07E-04	-1.48E-04	4.84E-05	4.97E-05	1.70E-05
	(7.18E-05)	(8.18E-05)	(9.20E-04)	(6.97E-05)	(7.99E-05)	(9.05E-05)
Asset efficiency	-3.22E-04	-4.96E-04+	-3.39E-04	-4.51E-04+	-3.08E-04	-2.18E-04
	(2.68E-04)	(2.82E-05)	(2.94E-04)	(2.63E-04)	(2.79E-04)	(2.89E-04)
Constant	0.441***	0.488***	0.522***	0.499***	0.534***	0.562***
	(0.021)	(0.023)	(0.025)	(0.021)	(0.023)	(0.025)
N	565	532	500	551	509	473
F-value	27.25***	16.51***	9.48***	25.88***	17.25***	10.38***

Standard errors in parentheses. + (p<0.1), *(p<0.05), **(p<0.01), ***(p<0.001)

APPENDIX

1. Hypothesis testing: lagged relationships (weak tests)

DV: Segment's share of value in a sector (F1)	H1a	H1b	H1c	H1c	H1	H2a	H3a	Full Model
Kingpin's share (market capitalization)						0.074***		0.068***
						(0.018)		(0.019)
Kingpin's share (R&D spending)							0.054**	0.037+
							(0.019)	(0.019)
Herfindahl index (sales)	0.003				0.004	-0.038*	-0.023	-0.053**
	(0.010)				(0.012)	(0.016)	(0.015)	(0.018)
Mean (R&D spending)		-7.75E-06			2.64E-05	3.61E-05	2.95E-05	3.74E-05
		(2.17E-05)			(4.54E-05)	(4.61E-05)	(4.57E-05)	(4.66E-05)
Fixed asset			-2.17E-06		-5.61E-06	-7.52E-06	-5.94E-06	-7.59E-06
			(2.84E-06)		(6.45E-06)	(-6.58E-06)	(6.49E-06)	(6.65E-06)
Asset intensity				-4.48E-07	-5.48E-07	-4.64E-08	-5.00E-07	-5.84E-08
				(2.09E-06)	(2.29E-06)	(2.28E-06)	(2.31E-06)	(2.32E-06)
Number of firms	3.30E-04***	3.25E-04***	3.23E-04***	3.28E-04***	3.29E-04***	3.21E-04***	3.54E-04***	3.39E-04***
	(5.57E-04)	(5.95E-05)	(5.55E-05)	(5.63E-05)	(6.13E-05)	(6.09E-05)	(6.23E-05)	(6.23E-05)
Sum of all employees	5.02E-06	7.21E-06	8.77E-06	5.07E-06	6.62E-06	1.55E-05	4.22E-06	1.33E-05
	(2.42E-05)	(2.68E-05)	(2.48E-05)	(2.48E-05)	(2.72E-05)	(2.71E-05)	(2.73E-05)	(2.74E-05)
Asset efficiency	-1.05E-05	-7.67E-06	-7.78E-06	-4.93E-06	-1.09E-05	4.49E-05	2.26E-05	6.34E-05
	(9.20E-05)	(9.83E-05)	(9.15E-05)	(9.39E-05)	(1.02E-04)	(1.02E-05)	(1.04E-04)	(1.04E-05)
Constant	0.026***	0.033***	0.029***	0.030***	0.032***	0.004	0.008	-0.009
	(0.007)	(0.003)	(0.003)	(0.003)	(0.008)	(0.010)	(0.012)	(0.013)
N	676	590	669	647	576	568	562	554
F-value	15.70***	13.57***	15.68***	14.96***	7.67***	8.91***	7.67***	8.25***

Standard errors in parentheses. + (p<0.1), *(p<0.05), **(p<0.01), ***(p<0.001)

DV: Segment's share of value in a sector (F2)	H1a	H1b	H1c	H1c	H1	H2a	H3a	Full Model
Kingpin's share (market capitalization)						0.066***		0.061**
						(0.019)		(0.020)
Kingpin's share (R&D spending)							0.047*	0.032
							(0.019)	(0.020)
Herfindahl index (sales)	8.61E-05				3.77E-05	-0.038*	-0.023	-0.051**
	(0.010)				(0.013)	(0.017)	(0.016)	(0.018)
Mean (R&D spending)		-3.77E-06			1.70E-05	0.00002.58	1.98E-05	2.72E-05
		(2.36E-05)			(4.82E-05)	(4.92E-05)	(4.86E-05)	(4.98E-05)
Fixed asset			-1.20E-06		-3.48E-06	-5.38E-06	-3.76E-06	-5.45E-06
			(3.08E-06)		(6.82E-06)	(-7.00E-06)	(6.88E-06)	(7.09E-06)
Asset intensity				-4.57E-07	-5.17E-07	-2.90E-07	-4.61E-07	-2.76E-07
				(2.44E-06)	(2.67E-06)	(2.67E-06)	(2.70E-06)	(2.70E-06)
Number of firms	3.94E-04***	3.94E-04***	3.92E-04***	3.95E-04***	3.94E-04***	3.86E-04***	4.16E-04***	4.01E-04***
	(5.74E-05)	(6.14E-05)	(5.72E-05)	(5.82E-05)	(6.33E-05)	(6.31E-05)	(6.44E-05)	(6.46E-05)
Sum of all employees	7.70E-05**	-7.62E-05*	-7.50E-05**	-7.71E-05**	-7.66E-05*	-6.75E-05*	-7.85E-05**	-6.9E-05*
	(2.65E-05)	(2.94E-05)	(2.71E-05)	(2.72E-05)	(2.98E-05)	(2.98E-05)	(3.01E-05)	(3.02E-05)
Asset efficiency	-8.20E-06	-9.51E-06	-8.84E-06	-6.05E-06	-6.86E-06	4.28E-05	2.22E-05	5.90E-05
	(9.32E-05)	(9.95E-05)	(9.25E-05)	(9.52E-05)	(1.03E-04)	(1.04E-04)	(1.05E-04)	(1.06E-04)
Constant	0.035***	0.041***	0.036***	0.037***	0.042***	0.018	0.022+	0.006
	(0.007)	(0.004)	(0.003)	(0.003)	(0.008)	(0.011)	(0.012)	(0.013)
N	632	552	627	603	539	531	526	518
F-value	13.14***	11.37***	13.09***	12.50***	6.35***	7.16***	6.20***	6.56***

Standard errors in parentheses. + (p<0.1), *(p<0.05), **(p<0.01), ***(p<0.001)

DV: Segment's share of value in a sector (F3)	H1a	H1b	H1c	H1c	H1	H2a	H3a	Full Model
Kingpin's share (market capitalization)						0.063**		0.059**
						(0.019)		(0.021)
Kingpin's share (R&D spending)							0.056**	0.027
							(0.018)	(0.021)
Herfindahl index (sales)	-0.006				-0.007	-0.043*	-0.022	-0.054**
	(0.011)				(0.013)	(0.017)	(0.015)	(0.019)
Mean (R&D spending)		5.74E-06			2.45E-05	3.07E-05	2.81E-05	3.21E-05
		(2.46E-05)			(4.88E-05)	(5.00E-05)	(4.1E-05)	(5.06E-05)
Fixed asset			-6.30E-08		-3.36E-06	-4.95E-06	-6.71E-06	-4.98E-06
			(3.27E-06)		(6.97E-06)	(-7.18E-06)	(6.14E-06)	(7.26E-06)
Asset intensity				-3.57E-07	-4.05E-07	-2.25E-07	-5.66E-07	-2.59E-07
				(2.47E-06)	(2.67E-06)	(2.67E-06)	(2.25E-06)	(2.71E-06)
Number of firms	4.59e-04***	4.66E-04***	4.63E-04***	4.63E-04***	4.61E-04***	4.52E-04***	3.02E-04***	4.65E-04***
	(5.82E-05)	(6.24E-05)	(5.81E-05)	(5.94E-05)	(6.43E-05)	(6.43E-05)	(5.99E-05)	(6.59E-05)
Sum of all employees	-1.66E-04***	-1.69E-04***	-1.66E-04***	-1.66E-04***	-1.69E-04***	-1.59E-04***	6.59E-05**	1.6E-04***
	(2.84E-05)	(3.14E-05)	(2.90E-05)	(2.92E-05)	(3.20E-05)	(3.21E-05)	(2.46E-05)	(3.26E-05)
Asset efficiency	-2.60E-06	-1.08E-05	-1.02E-05	-7.30E-06	1.10E-06	4.74E-05	1.50E-05	6.04E-05
	(9.27E-05)	(9.87E-05)	(9.19E-05)	(9.50E-05)	(1.03E-04)	(1.03E-04)	(1.01E-04)	(1.06E-04)
Constant	0.047***	0.049***	0.043***	0.045***	0.054***	0.032**	0.001	0.022
	(0.007)	(0.004)	(0.003)	(0.003)	(0.008)	(0.011)	(0.011)	(0.014)
N	592	518	588	561	504	496	601	484
F-value	16.40***	14.20***	16.23***	15.41***	7.91***	8.28***	10.75***	7.44***

Standard errors in parentheses. + (p<0.1), *(p<0.05), **(p<0.01), ***(p<0.001)

2. Hypothesis testing: lagged relationships (strong tests)

DV: Segment's share of value in a sector (excluding kingpin's value) F1	H1a	H1b	H1c	H1c	H1	H2b	H3b	Full Model
Kingpin's share (market capitalization)						0.041+		0.026
						(0.023)		(0.025)
Kingpin's share (R&D spending)							0.067**	0.060*
							(0.023)	(0.025)
Herfindahl index (sales)	-2.68E-04				-0.005	-0.029	-0.039*	-0.050*
	(0.014)				(0.015)	(0.020)	(0.019)	(0.022)
Mean (R&D spending)		1.96E-06			-1.17E-04*	-1.20E-04*	-1.14E-04*	-1.2E-04*
		(2.46E-05)			(5.07E-05)	(5.21E-05)	(5.09E-05)	(5.25E-05)
Fixed asset			5.02E-06		1.93E-05**	1.94E-05**	1.90E-05**	1.95E-05**
			(3.43E-06)		(7.19E-06)	(7.43E-06)	(7.23E-06)	(7.49E-06)
Asset intensity				-6.01E-09	4.03E-07	1.09E-06	8.30E-07	1.22E-06
				(3.18E-06)	(3.32E-06)	(3.35E-06)	(3.34E-06)	(3.38E-06)
Number of firms	-2.64E-04***	-2.62E-04***	-2.54E-04***	-2.64E-04***	-2.68E-04***	-2.74E-04***	-2.35E-04**	-2.4E-04**
	(6.95E-04)	(6.91E-05)	(6.87E-05)	(6.75E-05)	(7.06E-05)	(7.10E-05)	(7.18E-05)	(7.27E-05)
Sum of all employees	-6.02E-06	-7.48E-06	-1.57E-05	-5.62E-06	-4.94E-06	2.08E-06	-6.52E-06	-1.73E-06
	(3.20E-05)	(3.32E-05)	(3.27E-05)	(3.16E-05)	(3.33E-05)	(3.37E-05)	(3.35E-05)	(3.40E-05)
Asset efficiency	1.02E-04	1.00E-04	1.05E-04	1.01E-04	1.05E-04	1.36E-04	1.44E-04	1.58E-04
	(1.11E-05)	(1.11E-04)	(1.10E-04)	(1.09E-04)	(1.14E-04)	(1.15E-04)	(1.16E-04)	(1.17E-04)
Constant	0.058***	0.061***	0.057***	0.059***	0.063***	0.049***	0.035*	0.029+
	(0.010)	(0.005)	(0.004)	(0.004)	(0.010)	(0.013)	(0.015)	(0.016)
N	525	463	522	502	455	449	444	438
F-value	6.21***	6.15***	6.74***	6.35***	4.54***	4.40***	4.97***	4.53***

Standard errors in parentheses. + (p<0.1), *(p<0.05), **(p<0.01), ***(p<0.001)

DV: Segment's share of value in a sector (excluding kingpin's value) F2	H1a	H1b	H1c	H1c	H1	H2b	H3b	Full Model
Kingpin's share (market capitalization)						0.034		0.02
						(0.023)		(0.026)
Kingpin's share (R&D spending)							0.061*	0.056*
							(0.024)	(0.025)
Herfindahl index (sales)	-4.00E-03				-3.00E-03	-0.022	-0.035+	-0.043+
	(0.013)				(0.015)	(0.021)	(0.020)	(0.023)
Mean (R&D spending)		1.80E-05			-3.68E-05	-3.37E-05	-3.43E-05	-3.3E-05
		(2.65E-05)			(5.35E-05)	(5.52E-05)	(5.39E-05)	(5.57E-05)
Fixed asset			4.48E-06		8.95E-06	8.15E-06	8.69E-06	8.27E-06
			(3.52E-06)		(7.57E-06)	(7.85E-06)	(7.62E-06)	(7.93E-06)
Asset intensity				1.56E-07	3.32E-07	7.81E-07	7.49E-07	9.67E-07
				(3.29E-06)	(3.50E-06)	(3.53E-06)	(3.53E-06)	(3.57E-06)
Number of firms	-2.01E-04**	-1.91E-04**	-1.90E-04**	-1.97E-04**	-1.95E-04**	-2.00E-04**	-1.65E-04*	-1.70E-04*
	(6.74E-05)	(7.02E-05)	(6.68E-05)	(6.77E-05)	(7.21E-05)	(7.27E-05)	(7.36E-05)	(7.47E-05)
Sum of all employees	-4.66E-05	-5.33E-05	-5.49E-05	-4.62E-05	-5.20E-05	-4.59E-05	-5.30E-05	-4.90E-05
	(3.29E-05)	(3.57E-05)	(3.36E-05)	(3.35E-05)	(3.60E-05)	(3.65E-05)	(3.63E-05)	(3.69E-05)
Asset efficiency	7.08E-05	6.52E-05	6.86E-05	6.51E-05	6.71E-05	9.26E-05	1.03E-04	1.14E-04
	(1.07E-04)	(1.11E-04)	(1.05E-04)	(1.08E-04)	(1.14E-04)	(1.17E-04)	(1.17E-04)	(1.19E-04)
Constant	0.062***	0.063***	0.059***	0.062***	0.065***	0.052***	0.040**	0.035*
	(0.009)	(0.005)	(0.004)	(0.004)	(0.010)	(0.013)	(0.015)	(0.017)
N	493	435	491	470	427	421	416	410
F-value	6.13***	5.70***	6.51***	5.89***	3.40**	3.19**	3.74**	3.32**

Standard errors in parentheses. + (p<0.1), *(p<0.05), **(p<0.01), ***(p<0.001)

DV: Segment's share of value in a sector (excluding kingpin's value) F3	H1a	H1b	H1c	H1c	H1	H2b	H3b	Full Model
Kingpin's share (market capitalization)						0.024		0.009
						(0.024)		(0.026)
Kingpin's share (R&D spending)							0.062*	0.060*
							(0.024)	(0.026)
Herfindahl index (sales)	-0.005				-0.003	-0.017	-0.035+	-0.039+
	(0.014)				(0.016)	(0.021)	(0.020)	(0.023)
Mean (R&D spending)		4.77E-05+			-3.76E-05	-4.50E-05	-3.49E-05	-4.4E-05
		(2.74E-05)			(5.35E-05)	(5.53E-05)	(5.39E-05)	(5.58E-05)
Fixed asset			9.74E-06**		1.44E-05+	1.48E-05+	1.42E-05+	1.50E-05+
			(3.68E-06)		(7.64E-06)	(7.94E-06)	(7.70E-06)	(8.01E-06)
Asset intensity				3.32E-07	5.34E-07	8.76E-07	8.63E-07	9.81E-07
				(3.28E-06)	(3.49E-06)	(3.53E-06)	(3.53E-06)	(3.57E-06)
Number of firms	-1.62E-04*	-1.43E-04*	-1.42E-04*	-1.58E-04*	-1.47E-04*	-1.52E-04*	-1.16E-04	-1.20E-04
	(6.73E-05)	(7.05E-05)	(6.64E-05)	(6.78E-05)	(7.21E-05)	(7.27E-05)	(7.36E-05)	(7.47E-05)
Sum of all employees	-8.02E-05*	-9.68E-05*	-9.85E-05**	-7.95E-05*	-9.49E-05*	-8.90E-05*	-9.66E-05*	-9.40E-05*
	(3.45E-05)	(3.75E-05)	(3.50E-05)	(3.51E-05)	(3.78E-05)	(3.83E-05)	(3.81E-05)	(3.88E-05)
Asset efficiency	1.59E-04	1.57E-04	1.56E-04	1.54E-04	1.59E-04	1.77E-04	1.93E-04+	1.97E-04+
	(1.05E-04)	(1.09E-04)	(1.03E-04)	(1.06E-04)	(1.13E-04)	(1.15E-04)	(1.15E-04)	(1.17E-04)
Constant	0.065***	0.065***	0.059***	0.063***	0.065***	0.056***	0.040**	0.038*
	(0.010)	(0.005)	(0.004)	(0.005)	(0.011)	(0.014)	(0.015)	(0.017)
N	463	408	588	439	399	393	388	382
F-value	7.20***	7.23***	16.23***	6.89***	4.60***	4.09***	4.77***	4.16***

Standard errors in parentheses. + (p<0.1), *(p<0.05), **(p<0.01), ***(p<0.001)

CHAPTER TWO

THE CURATE'S EGG: FIRM HETEROGENEITY AND THE VALUE OF ADOPTING INNOVATION IN THE US BANKING INDUSTRY, 2001–2011

Abstract

This paper investigates the effect of firm heterogeneity on the financial value of innovation. It provides quantitative evidence on how differences in firm capabilities and attributes affect the financial value of innovation itself and overall firm performance, using data from all FDIC-insured depository institutions in the US between 2001 and 2011. I show that better past performance allows firms to realize more value from innovation. I also demonstrate that while past experience of utilizing innovations does not affect the value of innovation, the incidence of past exploration positively affects it, alluding to the existence of redeployable capabilities. I find that broader firm scope negatively affects the value of innovation. Lastly, I find that firms' ability to unlock value from an adopted innovation and their ability to use it to improve overall performance are independent of each other, i.e. higher value of innovation does not automatically translate into enhanced overall firm performance. This paper contributes to the literature on the performance implications of innovation by identifying the factors that make an innovation valuable (or not) and determining whether or not that value contributes positively to overall firm performance.

1. Introduction

The financial crisis of 2007–2008 showed that the value[1] of innovation can be misleading. Some financial innovations appeared profitable, and the number of firms that adopted them increased over time. When the financial crisis put these firms' true performance in the spotlight, however, it turned out that while a few adopters had benefited financially, others had suffered from the *same* innovation. That is, the value of innovation was not homogeneous, but heterogeneous in terms of both magnitude and direction. Existing studies, however, have implicitly assumed that an innovation's value is predetermined (e.g. Bikhchandani, Hirschleifer, & Welch, 1998; Rao, Greve, & Davis, 2001) and monolithic, with variance observed only in terms of its magnitude

[1] The word 'value' in this paper refers to financial value, i.e. contribution to revenue generation and profitability. Consequently, 'good' innovations denotes those that yield positive financial gains to their adopters, while 'bad' innovations yield financial losses.

(Rogers, 1995). There have been studies on how idiosyncratic resource deployment to activities can lead to performance heterogeneity (e.g. Barney, 1986), but the idea has not been explicitly applied and tested on the heterogeneous value of innovation. The possibility of an innovation being simultaneously good and bad has been underexplored and, as a result, the drivers of such differences have not been studied much.

In the US, the repeal of the Glass-Steagall Act in 1999 enabled commercial banks and other depository institutions to expand their scope beyond traditional interest-income activities. For example, they could offer investment banking services and operate trading desks dealing in equities and bonds, including FICC (fixed income, commodities, and currency) derivatives. This opened up opportunities for commercial banks to adopt financial innovations such as Credit Default Swaps (CDSs). Gradually, the number of adopters of financial innovations increased, as did the nominal amount outstanding of those innovations. Some adopters enjoyed financial gain from innovation, at least temporarily, whereas others did not. During the financial crisis, many of these adopters suffered, along with bigger and more heavily involved investment banks such as Merrill Lynch and Lehman Brothers, while a very few firms walked away largely unscathed. Since the adopted innovation (CDSs) was identical, why was its value to adopters so variable?

In trying to answer that question, I consider the role of firm heterogeneity (Penrose, 1959). Capabilities are a key driver of profitability: a firm with superior idiosyncratic capabilities can outperform its competitors. Literature on evolutionary economics posits that firm routines and capabilities are developed over time through firms' behavior, making them path-dependent (Nelson & Winter, 1982) and idiosyncratic. This idiosyncrasy in evolutionary path results in different attributes, since firms differ in terms of which of their routines and capabilities need to be changed, and which do not. On the basis of these arguments, I conjecture that idiosyncratic firm capabilities and attributes drive the differences in the value of innovation. This approach allows me to argue that the 'compatibility' between an innovation and the capabilities and attributes of potential adopters determines the value of that innovation. To examine this relationship, I undertake a quantitative analysis using an unusually rich dataset derived from the regulatory reports of all FDIC-insured depository institutions in the US between 1Q 2001 and 4Q 2011. This provides an interesting setting to study the dynamics of innovation, since the financial services sector – like other service sectors – has been largely neglected by innovation researchers (for an exception, see Pennings & Harianto, 1992).

This study will probe what drives the direction and magnitude of the value of innovation among firms. In doing so, I will look at the value of innovation *per se* and overall performance separately. This enables me to identify the conditions that make an innovation financially beneficial or otherwise in itself (Jacobides & Winter, 2012), but also how those conditions affect the overall performance of each adopter of the innovation. That is, I can look at whether the value of innovation always 'spills over' to improve overall firm performance, or if firms need special capabilities to make this happen.

This paper is structured as follows. I begin by reviewing existing research on innovation. I then propose and test hypotheses on how different firm capabilities and attributes affect the value of innovation for non-innovator adopters. I examine the evidence in the US banking sector, which was the inspiration for this research. Based on the findings, I conclude by linking back to the literature, outlining limitations, identifying avenues for future research, and discussing implications for theory and practice.

2. Theoretical background

There is a wealth of literature on innovation, covering topics such as who innovates, how innovation diffuses, and how innovation affects competition between firms and throughout the industry over time. I focus on the stream of literature that is most relevant to the topic of this paper: the performance implications of innovation.

2.1. Technology innovation and firm performance

Innovation has long been a central concern to management scholars. Following the Schumpeterian tradition (1934), scholars have focused on the relationship between innovation and industry evolution, notably in the study of industry life cycles and changes in technologies (Abernathy & Utterback, 1978; Klepper, 1997). Others have examined how technological innovations affect firm performance, both for the innovator and for their competitors (Christensen, 1997; Henderson & Clark, 1990; Tushman & Anderson, 1986). Relatedly, some scholars have studied how market dynamics of supply and demand, i.e. opportunities to financially benefit, motivate firms to adopt innovations or to innovate themselves (Gilbert & Newbury, 1982; Geroski, 2003).

Many studies have examined the drivers of innovation performance, often taking patent filing or forward citations as measurements. Researchers have looked at how interorganizational alliances, M&A activities, or openness to different processes affect innovation (e.g. Stuart, 2000; Ahuja & Katila, 2001; Laursen & Salter, 2005). While these studies further our understanding of factors that motivate innovation among firms or enhance the quality of innovation, they focus on innovation as an outcome and what drives it. They do not explicitly consider the financial implications of innovation (see Ernst, 2001 for an exception). Other scholars have considered the conditions under which past innovation can hurt the performance of innovators in the future. Tushman and Anderson (1986) categorized the types of innovation that firms undertake at t=0 and how subsequent innovation from competitors can benefit/harm the focal firm in later periods. Focusing on product characteristics, Henderson & Clark (1990) noted that the type of product-architecture innovation a firm has undertaken can hinder further necessary innovation and hurt performance. Christensen (1997), in his study of the hard disk drive industry, noted that earlier innovation and the financial success that it brought can hurt the innovator's performance in the future due to fear of cannibalization or customer demand.

The findings of most technology innovation studies imply that innovation, regardless of its type or characteristics, has important competitive and performance implications for innovators, adopters, and non-adopters. Because successful innovators can shape the competitive environment to their advantage (Grove, 1999; Jacobides, Knudsen & Augier, 2006; Jacobides & Tae, 2013), much focus has been placed on firms' ability to innovate. With radical innovation, incumbents lose out to new entrants. With incremental innovation, incumbents are better off than new entrants. While this alludes to the heterogeneous value of innovation, the literature on technological innovation has assumed that innovators themselves almost always have the advantage over those who adopt their innovation. This innovator/adopter dichotomy identifies one source of heterogeneity in the value of innovation, but goes no further than that. To ensure competitiveness and survival, firms are assumed either to innovate or to quickly adopt innovations of others; how well they do so determines the magnitude in value of innovation. The contrast between innovators and adopters, moreover, underplays the inherent heterogeneity among adopters and its effect on their performance – even though there may be more variation in their fortunes than there is between adopters and innovators. Some adopters are competent ‘fast seconds’ (Markides & Geroski, 2005), whereas others fail to adopt efficiently or effectively (Hannan & Freeman, 1984; Miller & Chen, 1994). Because it assumes the superiority of innovators, the literature on technology innovation cannot adequately explain how an innovation can be simultaneously ‘good’ and ‘bad’

2.2. Firm heterogeneity and diffusion of innovation

Unlike the literature on technology innovation, the literature on diffusion of innovation has explicitly looked at the drivers of innovation adoption. The standard theory considers the characteristics that make the firm more or less likely to adopt (e.g. Baum, Calabrese & Silverman, 2000; Greve, 1998). For example, organizational structure (Zaltman, Duncan & Holbek, 1973; Damanpour, 1991), size (Frambach & Schillewaert, 2002), and availability of cash (Rogers, 1995) have been identified as drivers of adopting innovation. Studies have also shown that major technological innovations, in general, are adopted more rapidly. This usually means early adoption by firms with high technological capabilities (Dewar & Dutton, 1986), although others have implied that some innovations are adopted regardless of firm’s capabilities (e.g. Cohen & Levinthal, 1990). In addition to firm capabilities, research has also highlighted the role of physical (geographical) proximity (Strang & Soule, 1998). There are studies that show that adoption of innovation happens more quickly over short distances (McKendrick, Doner, & Haggard, 2000) and that interfirm networks facilitate diffusion (Davis & Greve, 1997; Beckman & Haunschild, 2002).

In sum, the literature on innovation diffusion identifies firm heterogeneity and social influence from other adopters as the main drivers of diffusion. While recognizing that firm heterogeneity affects the adoption of innovation, the literature implicitly assumes that the value of innovation is monolithic. That is, whoever adopts an innovation can expect to realize some, to a varying degree, value from it. Even studies that relax this notion assume that value will differ only in magnitude rather than direction (Rogers, 1995). However, there are many instances that have manifested vastly different values, sometimes with opposite signs; they include MP3 technology (e.g. Apple vs. Sony) and toning shoes (e.g. Reebok vs. Sketchers). So firm heterogeneity, which affects the likelihood of innovation adoption, might also affect the value of innovation. Works on the resource based view (RBV), have alluded to this mechanism by pointing out that idiosyncratic deployment of resources (e.g. Barney, 1986) firms possess leads to heterogeneity in performance. In other words, deployment of different capabilities and whether or not firms have a specific capability can vary the value adopters capture from innovations (Helfat & Raubitschek, 2000). The literature on diffusion of innovation, by highlighting the 'bright side' of innovation and its value, has nonetheless sidestepped the question of what drives this variance.

Notwithstanding the contributions made by existing studies on technological innovation and diffusion of innovation, they are insufficient to address one of the important aspects of innovation, i.e. the heterogeneity in the financial value of innovation. There is always the possibility that the value of innovation will never be fully appropriated as anticipated, but bring about disruption and confusion to the existing set of routines and capabilities. I acknowledge this possibility and allude that the reason behind this unexpected outcome is also due to firm heterogeneity. Setting this possibility aside, we do not know much about why some adopters make more money than others or why some even lose money. In other words, what makes the same innovation yield different financial value to adopters has not been explicitly considered.

By explicitly looking at the drivers of value of innovation, this paper will expand existing theories on innovation and, more importantly, explain why some adopters benefit financially from innovation while others do not. In addition, by considering the value of innovation and its contribution to overall firm performance separately, I will examine whether or not the value of innovation is positively associated with firm performance. The identification of the above boundary conditions will help us better understand the dynamics of innovation and its effect on adopting firms' financial performance. This study will thus contribute to recent research efforts to explore the contingencies of adoption outcomes (Greve & Taylor, 2000; Kim & Miner, 2007; Miner et al., 1999).

3. Theory development

In the following, I explicate in detail the mechanisms through which firm heterogeneity, manifest in different indicators that are measurable, drives the variance in the financial value of innovation for adopters both in terms of its value per se and its effect on overall firm performance.

3.1. Firm heterogeneity and value of innovation

I begin my argument with the idea that the firm's existing capabilities[2], reflected in its past performance, are one of the drivers of heterogeneity in innovation value. Differences in performance have long been attributed to heterogeneity in firm capabilities (Penrose, 1959, Peteraf, 1993). Accordingly, firms with better past performance are considered to have superior capabilities in general. Firms with superior capabilities use them not only outperform their competitors, but also to acquire other types of capability more easily (Henderson & Cockburn, 1994), such as those necessary to benefit from innovation.

Firms with better past performance have the advantage of time compression diseconomies (Dierickx & Cool, 1989). Superior capabilities take time to develop; once they are developed, they cannot be imitated by others immediately. In evolutionary economics, firms are thought to undergo constant market tests, which serve as a selection mechanism and a source of motivation for firms to act in certain ways to ensure their survival (Nelson & Winter, 1982). Once established, routines persist and solidify over time unless they prove ineffective for solving the problem at hand (Simon, 1962).

Consequently, firms with better past performance can maintain the upper hand against their peers as long as there is no dramatic change in the basis of competition that makes every existing capability obsolete or irrelevant. Even when similar sorts of routines and capabilities are required for the innovation across every adopter, those with better past performance still fare better.

[2] In this paper, I use the term 'capabilities' to refer to operational capabilities, defined as 'a high-level routine (or collection of routines) that, together with its implementing input flows, confers upon an organization's management a set of decision options for producing significant outputs of a particular type' (Winter, 2000: 983). In this definition, the term 'routine' refers to a 'repetitive pattern of activity' (Nelson & Winter, 1982: 97). An operational capability generally involves performing an activity, such as manufacturing a particular product, using a collection of routines to execute and coordinate the variety of tasks required to perform the activity (Helfat & Peteraf, 2003: 999).

The value of an explorative behavior like innovation cannot usually be fully appropriated straight away, even in cases where the firm already has the right routines and capabilities. The time needed to realize value from innovation differs among firms, and past performance can serve as a benchmark indicating how quickly firms might achieve it. This implies that firms with relatively poor past performance cannot unlock the potential value of innovation effectively and efficiently, or translate it into financial gain.

Better past performance also provides accumulated slack resources, which can alleviate negative performance problems straight after adoption (George, 2005). Slack resources enable firms to enjoy the 'grace period,' i.e. time to discover how to benefit from innovation, without any threat to survival from financial setback. Therefore, the value of innovation will be higher for adopters with better past performance.

> *Hypothesis 1.* Pre-adoption performance of adopters will be *positively* associated with the value of innovation *ex post.*

Firms also exhibit differences in past experience in their exploration. Exploration covers a range of phenomena denoted by terms such as 'search', 'variation', 'risk taking', 'experimentation', 'play', 'flexibility', 'discovery', 'innovation', etc. (March, 1991: 71). Experience in general leads to learning in routines and capabilities related to that particular experience, i.e. experiential learning (Levitt & March, 1988), and makes firms effective and/or efficient in utilizing them over time. However, the fact that adopters have engaged in exploration in the past does not guarantee them higher value from new innovations ex ante. The value of an innovation is discovered after adopters have undergone a process of 'trial and error' to develop a routine that successfully withstands the selection process (Nelson & Winter, 1982). However, experiences of different kinds, over time, constitute a set of endowments (Levinthal & Myatt, 1994) from which firms can develop or improve their routines. Similarly, past experience in exploration can leave firms with latent (dormant) capabilities that have not been utilized heavily, but nonetheless exist among a set of routines. Some of these capabilities can be applied to an innovation – that is, they are redeployable (Helfat & Peteraf, 2003). Firms with past experience in exploration can try to tap into absorptive capacity (Cohen & Levinthal, 1990) to maximize the value of newly adopted innovation. However, the mere existence of exploration experience in the past and its spillover effect on performance with new exploration has been called into question (e.g. Zollo, 2009; Zollo & Reuer, 2010).

Repeated action, in contrast to one-off action, enables firms to get better at developing and using new routines and capabilities, i.e. to learn from repeated experience (Herriott, Levinthal & March, 1985; Levitt & March, 1988) and develop dynamic capabilities (Teece, Pisano, & Shuen, 1997). One such repeated action is repeated adoption of innovation. Adopters with more experience in adopting innovations than others would be better equipped to introduce a new innovation quickly. This can provide an advantage to firms with more experience: all else being equal, they will enjoy higher value from an innovation.

Another kind of repeated action is the continued utilization of previously adopted innovation. Adopters who had successfully integrated innovation into their daily operations and generated financial benefit from it would possess routines and capabilities necessary for successful implementation and integration, which those who had not done so would lack. This can provide an advantage to adopters who have experienced continued utilization of previously adopted innovation, all else being equal, against those who have not made much use of previously adopted innovation.

Both types of repeated actions (adoption and utilization), and their implications, are consistent with the argument that it is the success of past experience that matters (e.g. Haunschild & Miner, 1997; Levinthal & March, 1993). Since success is what matters, what is considered a success becomes an important issue. Managers can wrongly believe that their past endeavor was a success when in reality it was not. This would lead to the so-called superstitious learning (Zollo, 2009) whereby firms lack the needed resources and capabilities necessary for success but think they possess them. In sum, this implies that managers' tendency to positively re-frame past behavior regardless of the actual outcome will matter as much as the actual outcome from past experience. However, whether or not firms have the necessary capabilities will become visible from the way adopted innovations are utilized. That is, better utilization of previously adopted innovations will indicate the presence of necessary capabilities to financially benefit from the newly adopted innovations. Therefore, I expect both repeated innovation adoption and repeated utilization of past innovation to affect the value of innovation post adoption.

> *Hypothesis 2a.* The number of previously adopted innovations will be *positively* associated with the value of innovation *ex post.*
> *Hypothesis 2b.* The better utilization of previously adopted innovations will be *positively* associated with the value of innovation *ex post.*

Another aspect of firm heterogeneity is difference in firm scope.[3] Firms in a market do not necessarily have the same scope of products or operations. Rather, some concentrate on one particular product or operation, while others have multiple products or operations.

Managers at more specialized firms (narrow scope) do not require capabilities in dividing their resources and attention between multiple products or operations, which would be essential for their counterparts at more generalized firms (broader scope). Because successful adoption and implementation of innovations requires commitment of resources and managerial attention (Ocasio, 1997), the differences in the scope of firms will affect how effectively such commitments are made. Dividing resources and attention among multiple products or operations is part of well-established routines for managers at firms with broader scope, and this can shorten the period from adoption to implementation. Since managers at firms with narrower scope need time to develop these routines and capabilities, their counterparts at firms with broader scope will be in a better position, at least in the short term, to extract higher financial benefit from innovations.

Additionally, firm scope determines the number of market interfaces a firm can have. Having more market interfaces can give firms an advantage in terms of information (Jacobides & Billinger, 2006). Since they can tap into more data from multiple sources, they can achieve increased market responsiveness and stronger impetus for change. Unless an innovation is directly related to the areas where firms with narrower scope already have in-depth knowledge, be it product-specific routines or redeployable capabilities, they will not be able to benefit as much from the innovation. Because the chances of firms being able to redeploy existing routines

[3] I am indifferent to the vertical or horizontal scope of the firm. My interest is in the number of market interfaces firms have, regardless of where those interfaces may be located. In my empirical setting, this indifference does not pose any problems as I focus explicitly on products with one interface.

and capabilities instantly to newly adopted innovation are slim, I expect that firm scope will positively affect the value of innovation.

> *Hypothesis 3*. Pre-adoption firm scope will be *positively* associated with the value of innovation *ex post*.

4. Research design

4.1. Empirical setting

The setting of this paper is the US banking sector, which was at the heart of the financial crisis of 2007–2008. Beginning in the early 2000s, financial institutions in the US started to experience exponential growth in their profits, exemplified by CAGR of 30% in ROE for some firms. Behind such growth were financial innovations such as credit derivatives[4]. When the financial crisis struck, numerous borrowers defaulted on their payments, and buyers of Credit Default Swaps (CDSs) as an insurance against such defaults demanded payment from the sellers, one of which was AIG. AIG was unable to meet all its CDS obligations, and was ultimately rescued by the US government. Other government bailouts also involved banks using financial innovations such as CDSs. Some observers have thus blamed the entire financial crisis on the proliferation of financial innovations. For example, Paul Krugman commented in a New York Times op-ed (2007) that '… policy makers left the financial industry free to innovate — and what it did was to innovate itself, and the rest of us, into a big, nasty mess.' Paul Volcker, former chairman of the Federal Reserve in the US, and Lord Turner, chairman of the Financial Services Authority in the UK, also voiced their opinion that unregulated financial innovation was a major cause of the crisis.

Credit derivatives are bilateral financial contracts with payoffs linked to a credit-related event such as non-payment of interest, a credit downgrade, or a bankruptcy filing. A bank can use a credit derivative to transfer some or all of the credit risk of a loan to another party, or to take on additional risks. In principle, credit derivatives are tools that enable banks to manage their portfolio of credit risks more efficiently.

[4] Some may argue that credit derivatives, and CDSs in particular, are not innovation in the strictest sense. I have two justifications for defining CDSs as an innovation. First, I turn to the definition of innovation given by Schumpeter (1934): a specific social activity (function) carried out within the economic sphere and with a commercial purpose by 'new combinations of new or existing knowledge, resources, equipment and so on' (Schumpeter 1934, pp. 65). Second, bankers familiar with the product and its mechanics have confirmed during my field interviews that banking industry participants do indeed regard CDSs as an innovation.

CDSs[5] represent the largest part of the credit derivatives market. Originally developed as a tool to minimize the losses of lenders against borrowers' default, CDSs had initially seemed a valuable innovation, or at least a harmless one. Regulators and bankers alike believed that they made banks sounder. Alan Greenspan, the former head of the Federal Reserve System, opined that credit derivatives and other complex financial instruments had contributed 'to the development of a far more flexible, efficient, and hence resilient financial system than existed just a quarter-century ago.' (Greenspan, 2004) The popularity of CDSs soared in the 2000s: whereas the nominal outstanding value of CDSs in 1998 was US$300 billion, by 2007 the figure was at US$62.2 trillion. Although the use of credit derivatives was not widespread among participants of the financial services sector (e.g. depository institutions, private equity, hedge funds, etc.), the number of credit derivatives held by investment banks and universal banks that did use them was extremely large (usually more than 90% of the entire market share). And despite there being more depository institutions that adopted CDSs than investment banks and universal banks combined, their presence in the entire CDS market was weak (never exceeding 10% of market share). Nonetheless, the income generated from CDSs and their effect on the bottom line differed greatly among depository institutions that had adopted them.

In this paper, among all the financial innovations available for adoption since 1999, I focus on one particular product that has received much attention during the financial crisis: Credit default swaps (CDS). Because most CDSs were traded over-the-counter, i.e. between the involved parties without going through a clearinghouse, no two CDSs were the same. Each CDS contract was highly customized to cater to the specific needs of the involved parties. Moreover, the knowledge on its mechanics in the market and how the involved parties could profit from it was not openly available and not standardized or codified, i.e. highly tacit. Any depository institutions that adopted CDSs started out from a level playing field and had to acquire/develop the necessary capabilities by participation. Its mechanics being highly tacit and the product

[5] Credit Default Swaps (CDSs) are private contracts between two parties in which the buyer of protection agrees to pay premiums to a seller of protection over a set period. There are no regulatory capital requirements for the seller of protection. CDSs were originally created in the mid-1990s as a means to transfer credit exposure for commercial loans and to free up regulatory capital in commercial banks. By entering into a CDS, a commercial bank shifted the risk of default to a third party, and this transferred risk did not count against their regulatory capital requirements. Speculation became rampant in the market such that sellers and buyer of CDSs were no longer owners of the underlying asset (bond or loan), but were just 'betting' on the possibility of a credit event occurring with a specific asset.

rarely standardized make CDSs one of the ideal financial innovations to examine the heterogeneity in the value of innovations.

4.2. Data

I use Call Reports and Thrift Regulatory Forms submitted quarterly to the FDIC, FDR, OCC, or OTS by all FDIC-insured depository institutions in the US between 1Q 2001 and 4Q 2011. Because it is mandatory for all FDIC-insured depository institutions to fill out these forms, the data is consistent and comparable both across time and firms. The reports contain detailed information including financial statements, firms' asset characteristics, their demographic and institutional characteristics, etc. The unusual amount of detailed information enables me to consider the drivers of differences in value of innovation post adoption. The data contains information on all depository institutions, which totals approximately 8,000 unique entities (fluctuating ±3% from year to year) in the US for 44 quarters, and provides more than 350,000 unique observations. This huge dataset enables me to consider banks that adopted innovation exclusively without any concerns over sample size. Additionally, having no sample bias increases my confidence in the results.

In some cases, I used the numbers originally reported in the initial dataset as variables, but also calculated different measures using the base data to better reflect the construct of interest. I coded the detailed information on demographic and institutional characteristics such as ownership structures (being a part of a bank holding company or a financial holding company), primary regulatory agency (Federal Reserve, FDIC, OCC, and former OTC), location (50 US states), size (total assets, number of offices, number of employees), etc. so as to be able to test whether they influence the relationship I was interested in.

4.3. Variables

Dependent variables. I have two sets of dependent variables for all hypotheses. First, I consider the value of innovation itself using trading account gains, which are defined as net gains and losses from trading derivative contracts that were recognized during the accounting period. Second, I consider the spillover effect of the innovation's value on overall performance using operating pretax cash flow (weighted by total assets). Operating pretax cash flow is defined as earnings before income taxes and extraordinary items plus interest on subordinated notes and debentures. This measure has been used in finance literature (e.g. Cornett, Mehran & Tehranian, 1998; Cornett, Ors & Tehranian, 2002) to evaluate the performance of banks. The reason I use two different dependent variables is because I have no prima facie evidence that the ability to extract value from innovation and the ability to improve overall firm performance through innovation are the same. As such, I expect different results depending on the type of dependent variable used.

To account for the probable time lag between the adoption and its effect on profitability, I forwarded dependent variables by one quarter and one year. This also addresses the serial autocorrelation issue, i.e. binary variable CDS may be correlated with error terms that affect the value of innovation. For comparison purposes, identical models were run with no forwards on dependent variables.

Independent variables. For Hypothesis 1, I used the three-quarter running average of net income as an independent variable. For Hypothesis 2a, I calculated the level of past experience in innovation as follows. First, I created a dummy variable: 1 if bank has inter-state operations, 0 otherwise. Second, I created a count variable of all non-traditional non-interest income activities banks adopted prior to adopting CDSs. They include income derived from investment banking, venture capital/private equity activities, servicing mortgages, credit cards, and other financial assets held by others, securitization transactions (other than servicing), and insurance-related activities. I then added the first and second set of numbers. For Hypothesis 2b, I used the nominal value of incomes derived only from investment banking, venture capital/private equity activities, servicing, securitization transactions, and insurance-related activities (weighted by total assets). For Hypothesis 3, I used the asset concentration hierarchy to measure the firm scope. This binary measure indicates whether or not a bank's assets in a certain area (e.g. agriculture, commercial & industrial, international, housing) exceed 25% of its total assets. Because all firms report interest income, non-interest income, and additional non-interest income, an ordinal variable indicating participation in each cannot capture the differences in firm scope. I thus use the differences in asset scope to capture firm scope.

Control variables. I include a variety of control variables pertaining to organizational and institutional characteristics that may affect both the dependent and independent variables.

The variables are i) geographical location (50 US states), ii) the primary regulatory agency determined by the charter type (four categories: Fed, FDIC, OCC, OTC), iii) bank charter class (five categories), iv) a part of a bank/financial holding company (binary; 1=yes, 0=no), v) ownership (binary; 1=stock, 0=non-stock), vi) the size of the firm (total assets, logged for distributional properties), vii) seasonality (1: 1Q, 2: 2Q, 3: 3Q, 4: 4Q), and viii) financial crisis (binary; 1: 2007–2008, 0: otherwise). To address the potential seasonality issue where certain numbers in financial reporting are unusually larger or smaller in a specific quarter, I include the seasonality categorical variable for quarterly data.

Whether or not a firm is more risk seeking or more risk averse can affect how much value it can extract from an innovation, e.g. high risk, high return. That is, each firm's risk propensity is likely to affect how 'aggressively' they participate in the newly entered CDS market and in turn, yield more/less gains. In my earlier empirical analyses, I included a variable on risk propensity (natural logarithm of net charge-offs to total assets) in order to address this possibility. It was never significant in any of the models, so I excluded it.

Empirical reasons aside, the characteristics of depository institutions provide another reason this may not be an issue. Depository institutions consists of regional banks that have multiple offices in a state or across the state border, municipal banks that have one or two offices in the same geographical area (same county), and savings institutions that caters to the town or the city they are located in. Because these institutions are highly localized in terms of their daily operations and their performance is directly linked to the community and its economic well-being, they focus on what is known as the 'traditional banking:' lending money to small local businesses, investing in municipal bonds, etc. As such, I have confidence that firms included in my samples will not show much variance in their risk appetite even after some of them enter the CDS market. I nonetheless acknowledge that this can potentially be an issue.

After the financial crisis, it was well documented in the popular press that many financial institutions had manipulated their accounting records, taking advantage of regulatory grey areas. This is a potential concern for the analysis, as I cannot separate those firms whose numbers were manipulated from those whose were not. I try to address this problem by using the three-quarter running average instead of a specific quarter's performance figure, so that a sudden change in performance due to changes in accounting practices does not drive my results. Also, since the data comes from mandatory regulatory filings, I expect the calculation methods, whether manipulated or not, to remain consistent over time. This, however, does not account for the inherent self-selection bias. I acknowledge this as one of the empirical limitations of this study.

4.4. Empirical method

For all the hypotheses, I used the fixed effects (within) models. I specify a bank's performance as a linear function of the explanatory variables:

DV = f (ε_i; αt + β_1CDS + β_jExplanatory variables + β_{j+1}CDS * Explanatory variables)

where αt is the year effect, β_js are the coefficients to be estimated, and ε_i is the error term. Because I am using panel data, it is possible that the error terms will not be independent across time or within banks (Greene, 2008). There are potential time-dependent, macro-level factors that could affect the profitability of each bank. Due to the huge number of unique firms present in the data, the control variables I include in the models cannot account for all the unobserved heterogeneity that can affect the outcome of interest. Because I am unable to identify and measure the effects described above, there is potential for a systematic component to be embedded in the error term, which violates OLS assumptions (Kennedy, 2003). Fixed or random effects may be used to correct for violations of this sort (Greene, 2008). Because I am interested in how the value of innovation (and its effect on overall performance) changes over time, I use fixed-effects models (fixed by banks) through which I conduct within-segment estimations. Not only does the research question point to a fixed-effects model, it also offers an efficient means of dealing with non-constant variance of the errors, i.e. heteroskedasticity, stemming from the cross-sectional and temporal aspects of the pooled data. The Hausman test results also supported the use of the fixed-effects model in place of the random-effects model.

Robustness checks. First, I used four different measures of past performance (ROE, ROA, interest income, net interest margin) in testing H1 to ensure that the choice of variable did not affect the results. The results did not change except for minor fluctuations in statistical significance. Second, I used a different dependent variable (net income) to measure overall firm performance. The rationale behind was the same as the first robustness check. This did not change the results. Third, I conducted an identical analysis using annualized figures to ensure that my results were not driven by the handling of the data. Because a large number of observations on both cross-section and time dimensions may distort the asymptotic properties of these models and lead to spuriously significant results (Wooldridge, 2002), it is desirable to aggregate the data to avoid a potential non-conservative (hence undesired) bias in my estimations. I annualized the data in the following way. For stock numbers, I used the figures reported in the fourth quarter of every year. For flow numbers, I calculated the mean and the median of figures reported between 1Q and 4Q each year. The same procedure was then carried out to construct variables for the analysis.

5. Results

Table 1 provides the descriptive statistics and correlations of all independent variables. The results of the analyses are summarized in Tables 2 to 5 (lagged relationships). In general, the results show that firm heterogeneity has a significant effect on the value of innovation. Some effects are as expected, while others are in the opposite direction, further supporting my earlier conjecture that the value of innovation is not unidirectional. The results illustrate that the value of innovation is neither monolithic nor fixed ex ante, but determined post-adoption by adopters' capabilities and attributes.

INSERT TABLE 1 ABOUT HERE.

5.1. Results

Past performance. Hypothesis 1 examines the influence of past performance, which proxies for existing operational capabilities, on the value of innovation post-adoption. The results show that firms with better past performance do not necessarily enjoy higher value from innovation.

I find support for H1. I find that higher net income in the past three quarters positively affects the value of innovation *per se*, i.e. trading gains and losses from derivatives. The size of the coefficient is noticeably large (18.694) with strong statistical significance ($p<0.01$). I get similar results even when the dependent variable is overall firm performance, measured by pretax operating cash flow. The size of the coefficient is larger for the overall firm performance (44.018), but its statistical power is slightly reduced ($p<0.05$). Past performance, which proxies for the quality of firms' operational capabilities, seems to enable firms both to capture higher value from innovation and to relay that value to enhance overall performance.

Past experience in exploration. Hypothesis 2 looks at past exploration behavior and its effect on the value of innovation. I expected more past experience in exploration, both in terms of the number of explorations (H2a) and their utilization *ex post* (H2b), to increase the value of innovation. My results suggest that the benefits of past experience in exploration are not straightforward.

I find no support for H2a. Contrary to what I expected, the level of past exploration negatively affects the value of innovation *per se*, i.e. trading gains and losses. The sign of the coefficient is negative although it lacks statistical significance. The coefficient for the number of past explorations has an expected positive sign, but does not have statistical significance when the dependent variable measures the overall firm performance with pretax operating cash flow. I also find no support for H2b. The results are opposite to what I find for H2a: the utilization of exploration in the past positively affects the value of innovation *per se*, although its effect on the overall firm performance is negative. As was the case for H2a, both coefficients lack statistical significance. In sum, it is difficult to draw any inferences on whether or not different types of past exploration affect the value of innovation.

INSERT TABLES 2, 3, 4 AND, 5 ABOUT HERE.

Firm scope. Hypothesis 3 considers the effect of firm scope and managers' ability to allocate attention on the value of innovation. The results show that the effect of firm scope and managerial capability on the value of innovation is twofold.

I find no support for H3 when the dependent variable is trading gains and losses from derivatives, i.e. the value of innovation *per se*. The sign of the coefficient is negative, but the coefficient lacks statistical significance. On the other hand, I find strong support when the dependent variable is overall firm performance (pretax operating cash flow). Not only is the size of coefficient large, with the sign in the expected direction (29.325), it is statistically significant ($p<0.001$). One possible explanation is that superior managerial capability regarding division of resources and attention can help to maximize profit at the firm level by effectively incorporating innovation, but not necessarily unlocking the value from innovation *per se*. In other words, while capabilities nurtured through firm scope can improve the performance of the firm as a whole, they cannot influence the value of each innovation.

Full models. Perhaps unsurprisingly, the results in full models reflect those in previous restricted models, although there are minor changes to the size of coefficients and their statistical significance. I find strong support for H1a for both dependent variables, do not find support for either H2a or H2b, and find support for H3 only when the dependent variable is the overall firm performance (pretax operating cash flow).

The comparison of results using different dependent variables (trading gains and losses from derivatives and pretax operating cash flow) gives me confidence in the robustness of the results and their implications.

6. Discussion

The preliminary findings suggest there is a systematic connection between firm capabilities and the financial value of innovation post-adoption.

The findings indicate that heterogeneity in firm capabilities and attributes greatly affects the value of innovation for adopters, manifest in their post-adoption performance. I find that firms with better past performance do enjoy higher value from innovation than other adopters. Firms with better past performance not only enjoy higher value from the innovation *per se*, but are also able to use such value to improve overall performance.

Second, I show that different types of repeated action regarding exploration have different, and maybe opposite effects on the value of innovation per se and overall firm performance. Having frequently engaged in exploration in the past can sometimes hinder the realization of value from innovation. In contrast, the extent to which past exploration is currently being utilized does not seem to affect the value of innovation, regardless of how it is measured. I also find that managerial capability of attention allocation, necessitated by firm scope, positively affects the value of innovation.

Together, the capabilities and attributes analyzed in this paper suggest that firm heterogeneity drives the value of innovation. It is particularly noteworthy that some capabilities/attributes negatively affect the value of innovation, which undermines the economic rationale behind the adoption. More interestingly, the opposite results for the same variable in models with different dependent variables indicate that the financial value of innovation *per se*, i.e. the ability to generate income from innovation, does not automatically translate into better overall firm performance. What enables firms to extract value from innovation does not always guarantee that such value will benefit the firm as a whole. It seems, at least from the results of the above analysis, that the firm capabilities/attributes that maximize the value of innovation and those that transform that value into something good for the entire firm are different. Such dynamics are both theoretically meaningful and managerially relevant, and merit further attention.

Collectively, I show that firm heterogeneity, through path-dependent capabilities and routine development and provision of information, plays an important role in determining the value of innovation. Some capabilities yield higher value from the innovation, but superiority in some types of capabilities/attributes can actually reduce the value of innovation. This demonstrates that heterogeneity among firms matters, not only in understanding the competitive dynamics of firms, but also in explaining why some firms benefit more from the same innovation than others. For example, the number of past explorations was a predictor of decrease in the value of innovation, while past performance in core activity was a predictor of increase in the value of innovation. Inasmuch as a firm can use its capabilities to maximize the upsides of such attributes, the value of innovation for the focal firm can exceed that of other adopters even when the innovation is open, i.e. available for any firms to adopt.

The results of my empirical analysis implicitly support the notion of asset stock accumulation and time compression diseconomies (Dierickx & Cool, 1989). As the capabilities considered in this paper take time to develop and improve, having the right capabilities to deploy and enjoy higher value from innovation at the outset can be a source of sustained competitive advantage (Barney, 1986). The disadvantages of those who lack such capabilities are perhaps most palpable in the fact that they are powerless to overcome their shortcomings even when they are fully aware of which capabilities/attributes hinder their extraction of maximum value from the innovation.

This study has looked at a setting where abundant anecdotal evidence allowed for theory development and testing: the deregulation of US banking and the financial crisis that shed light on the fate of banks that adopted various financial innovations, exemplified by CDSs. I recognize that the generalizability of my findings is questionable, especially in terms of technology-related innovation and sectors where firm interdependencies are not as dramatic as they are in the banking sector. It would be a valuable extension of this study to examine whether the same firm capabilities have the same, different or no effect on the value of innovation in other settings. Because there is no substantial upfront fixed cost associated with the adoption of the products I studied, the relationships discussed in this paper may be less applicable, or even completely inapplicable, to innovations in the manufacturing sector, for example. This interesting avenue of research is well outside the scope of this paper.

6.1. Contributions

The explanation offered in this paper complements the existing innovation literature in three ways. First, it broadens the focus by studying a setting that is concerned with service provision, as opposed to being technology-driven. Second, it highlights the heterogeneity in value of innovation in a stream of literature that has largely focused on the universal benefits of innovation. Lastly, and most importantly, it explicates why and when some adopters of innovation can benefit while others cannot.

Innovation literature has primarily focused on technology – or, more broadly, on manufacturing sectors. Taking advantage of the recent financial crisis and a controversial innovation that was central to it, I broaden the empirical horizon of a stream of research that has generally neglected the financial services sector – and other service sectors (Pennings & Harianto, 1992). I find that the dynamics surrounding the value of innovations in technology-intensive sectors and those in the financial services sector are different. This may be due to various factors at different levels (e.g. national, industry, firm). Research into how and why service innovation differs from manufacturing innovation would thus be a promising area for future research.

I also shed new light on the value of innovation. In the study of topics such as the speed at which innovations spread (Geroski, 2000; Gruber, 2001), why firm adopt (DiMaggio & Powell, 1983; Tolbert & Zucker, 1983), and what happens when firms refuse to take part in diffusion (Abrahamson, 1991), the value of innovation has been implicitly assumed to be homogeneous across a population of firms. Although the heterogeneous value of innovation has recently been recognized (e.g. Greve & Taylor, 2000; Kim & Miner, 2007; Miner et al., 1999), studies that explicitly consider heterogeneity in the value of innovation are rare. This paper illustrates why the same innovation can be beneficial or detrimental even when the adoption was voluntary, indicating adopters had ex ante belief that they could extract value. In particular, it points to the possible explanation of why some seemingly well-suited firms do not benefit from innovation when other firms do.

Finally, this study contributes to the broader innovation literature by considering what makes an innovation valuable (or not). It does so by considering the effect of existing operational capabilities, types of past experience in exploration, and firm scope on the value of innovation. I also contribute to the literature by separating the value of innovation into i) the value of innovation per se (measured, in my study, by trading account gains) and ii) its impact on overall firm performance (measured by operating pretax cash flow). It is usually assumed that the former will have an additive effect on the latter, but my results suggest otherwise. Further investigation into how and why the value of innovation affects overall firm performance (for better or worse) will be a valuable addition to the literature.

6.2. Limitations

This paper is subject to two key limitations. First, there is the question of generalizability. The research question was inspired by the phenomenon observed, i.e. the financial crisis and the role played by financial innovations, and the dataset was chosen for its uniqueness rather than its representativeness (Firestone, 1993). The results corresponded with what the popular press had observed and reported, giving some credit to the patterns I observed. Applying the findings of this analysis to different settings in the future will, regardless of the outcome, remedy this limitation.

Second, my analysis focused on depository institutions, leaving out other financial services institutions such as investment banks and insurance companies. It is a well-known fact that investment banks such as Lehman Brothers and Bear Stearns, as well as insurance companies, most notably AIG, played major roles in the near-meltdown of the financial system. Despite their considerable involvement in the event, I had no choice but to exclude them due to data limitations: any detailed information on the activities of these institutions was difficult to obtain, and no publicly available information on these institutions was as comprehensive, comparable, or consistent as the data on depository institutions.

6.3. Concluding remarks

This paper looks at four different firm capabilities/attributes that could easily be numerically measured to study the drivers of heterogeneity in value of innovation. It examines the influence of these capabilities/attributes on changes in trading gains and losses from derivatives (the value of innovation per se) and pretax operating cash flow (the value of innovation in terms of overall firm performance). The robust relationship manifest in my results betters our understanding of the dynamics of innovation, particularly how and why some adopters benefit financially and others do not. Specifically, it offers an explanation on why heterogeneity in value arises from identical innovation.

The repercussions of the financial crisis are still continuing – notably, an attempt to rein in innovations such as CDSs is under way – and I believe this paper will also be interesting and useful for practitioners. My empirical results contribute to the ongoing debate on banking by providing quantitative evidence, which has so far been lacking. By presenting the results of a large-scale data analysis, this paper can aid the debate on financial innovations and whether they add value. The findings can also help practitioners to better understand the value of financial innovations. My field interviews with bankers revealed that many of them felt sure that they could benefit from adopting innovations. Therefore, my findings help practitioners better understand and predict what innovations are likely to yield more benefit to their firms, and how their current strengths can affect the value of innovation.

With the global financial sector still reeling from the financial crisis, there is much food for thought in the way that firm attributes, developed over a long period, can put a firm on the wrong behavioral trajectory and ultimately wreak havoc. Not only is this of interest for bankers and regulators, but it offers a very promising avenue for future scholarly contributions and research.

Table 1. The descriptive statistics

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	CDS related income	1															
2	Pretax operating cashflow	0.55	1														
3	CDS_either	0.05	0.07	1													
4	mean_3Q_net income	0.00	0.02	-0.01	1												
5	number_exploration	0.05	0.09	0.71	0.01	1											
6	usage_exploration	0.00	0.02	0.07	0.24	0.05	1										
7	firm_scope	0.00	0.02	-0.06	0.01	-0.05	-0.02	1									
8	state	0.01	0.01	0.02	0.02	0.04	0.01	0.05	1								
9	regulator	0.02	0.03	0.67	0.00	0.53	0.07	-0.01	0.08	1							
10	bank charter type	0.00	-0.01	0.20	-0.01	0.17	-0.01	-0.04	0.01	-0.04	1						
11	bank holding company	0.01	0.01	-0.47	0.01	-0.23	-0.06	0.03	-0.04	-0.26	-0.17	1					
12	ownership	0.01	0.01	-0.41	0.01	-0.29	0.01	0.03	-0.03	-0.23	-0.27	0.42	1				
13	ln(total assets)	0.11	0.20	0.13	0.01	0.44	-0.03	-0.07	0.00	0.14	0.08	0.09	0.02	1			
14	firm age	0.03	0.03	0.03	0.02	0.15	-0.06	0.13	0.08	0.05	0.06	0.06	-0.20	0.01	1		
15	seasonality	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1	
16	crisis	-0.01	0.00	0.00	-0.01	-0.03	0.00	-0.04	0.00	-0.01	0.00	0.01	0.00	0.04	0.00	0.00	1
	mean	1.59	10403	0.10	0.01	1.61	0.01	0.13	25.34	1.81	2.31	0.71	0.93	11.84	24818	2.48	0.18
	std. dev.	82.71	222668	0.31	0.05	1.59	0.07	0.34	13.76	1.07	1.16	0.45	0.25	1.37	15879	1.13	0.39

Table 2. Hypothesis testing: The value of innovation *per se*

DV: Trading gains and losses Quarter lag	Model 1 Controls only	Model 2 binary_CDS	Model 3 H1	Model 4 H2a	Model 5 H2b	Model 6 H3	Model 7 Full model
cds_either		3.033+	3.366+	4.884+	2.967+	3.191+	6.314*
		(1.67)	(1.72)	(2.75)	(1.67)	(1.68)	(2.83)
mean_3Q_net income			0.737				0.830
			(2.98)				(2.98)
cds_either * mean_3Q_net income			18.694**				19.750**
			(6.44)				(6.76)
number_exploration				0.135			0.133
				(0.19)			(0.19)
cds_either*no_exploration				-0.472			-0.674
				(0.51)			(0.53)
usage_exploration					-1.667		-1.888
					(3.11)		(3.29)
cds_either*usage_exploration					3.810		0.094
					(4.23)		(4.58)
firm_scope						0.036	0.034
						(0.43)	(0.44)
cds_either*firm_scope						-2.070	-2.343
						(1.49)	(1.52)
state	0.248*	0.247*	0.220*	0.246*	0.248*	0.247*	0.218*
	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)	(0.10)	(0.11)
regulatory agent	2.739***	2.297***	2.141***	2.316***	2.301***	2.282***	2.165***
	(0.45)	(0.51)	(0.53)	(0.52)	(0.51)	(0.51)	(0.53)
bank charter	-3.055***	-3.060***	-2.881***	-3.056***	-3.059***	-3.061***	-2.877***
	(0.31)	(0.31)	(0.32)	(0.31)	(0.31)	(0.31)	(0.32)
bank holding company	0.133	0.243	0.297	0.254	0.238	0.251	0.317
	(0.65)	(0.66)	(0.68)	(0.66)	(0.66)	(0.66)	(0.68)
ownership	-0.148	-0.181	-0.085	-0.256	-0.178	-0.193	-0.209
	(1.55)	(1.55)	(1.60)	(1.55)	(1.55)	(1.55)	(1.60)
ln(asset)	0.137	0.115	-0.042	0.099	0.123	0.120	-0.067
	(0.31)	(0.31)	(0.33)	(0.31)	(0.31)	(0.31)	(0.34)
firm age	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	0.00	0.00	0.00	0.00	0.00	0.00	0.00
seasonality	-0.073	-0.073	-0.089	-0.073	-0.072	-0.073	-0.090
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
crisis	-1.691***	-1.693***	-1.727***	-1.697***	-1.693***	-1.695***	-1.736***
	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)
cont.	-13.972**	-13.158**	-11.392*	-13.094**	-13.244**	-13.152**	-11.041*
	(4.36)	(4.38)	(4.62)	(4.39)	(4.38)	(4.39)	(4.64)
Obs	355383	355383	344501	355383	355383	355383	344501
F	22.97	21.00	16.56	17.59	17.57	17.67	11.31
P>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses. * (p<0.05), ** (p<0.01), *** (p<0.001)

Table 3. Hypothesis testing: The value of innovation *per se* (cont'd)

DV: Trading gains and losses Year lag	Model 1 Controls only	Model 2 binary_CDS	Model 3 H1	Model 4 H2a	Model 5 H2b	Model 6 H3	Model 7 Full model
cds_either		4.946**	4.643*	1.714	4.904**	4.194*	1.479
		(1.81)	(1.87)	(2.93)	(1.81)	(1.81)	(3.02)
mean_3Q_net income			-6.371				-5.269
			(10.46)				(10.65)
cds_either * mean_3Q_net income			7.743				5.904
			(12.05)				(12.40)
number_exploration				0.109			0.13
				(0.20)			(0.20)
cds_either*no_exploration				0.678			0.49
				(0.54)			(0.55)
usage_exploration					-1.432		-1.195
					(3.48)		(3.75)
cds_either*usage_exploration					2.58		2.34
					(4.58)		(5.02)
firm_scope						-0.012	-0.013
						(0.45)	(0.47)
cds_either*firm_scope						10.478***	10.169***
						(1.59)	(1.63)
state	0.284*	0.283*	0.274*	0.285*	0.284*	0.283*	0.275*
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
regulatory agent	2.985***	2.275***	2.293***	2.170***	2.278***	2.347***	2.278***
	(0.48)	(0.55)	(0.57)	(0.55)	(0.55)	(0.55)	(0.57)
bank charter	-3.306***	-3.310***	-3.342***	-3.319***	-3.309***	-3.304***	-3.343***
	(0.33)	(0.33)	(0.34)	(0.33)	(0.33)	(0.33)	(0.34)
bank holding company	0.134	0.302	0.314	0.313	0.30	0.27	0.29
	(0.70)	(0.70)	(0.73)	(0.70)	(0.70)	(0.70)	(0.73)
ownership	-0.948	-1.005	-0.981	-0.851	-1.003	-0.945	-0.798
	(1.65)	(1.65)	(1.71)	(1.65)	(1.65)	(1.65)	(1.71)
ln(asset)	-0.117	-0.150	-0.310	-0.170	-0.146	-0.173	-0.354
	(0.33)	(0.33)	(0.36)	(0.33)	(0.33)	(0.33)	(0.36)
firm age	0.000***	0.000***	0.001***	0.001***	0.000***	0.000***	0.001***
	0.00	0.00	0.00	0.00	0.00	0.00	0.00
seasonality	-0.029	-0.029	-0.040	-0.031	-0.028	-0.028	-0.043
	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.09)
crisis	-1.507***	-1.508***	-1.578***	-1.499***	-1.508***	-1.494***	-1.558***
	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)
cont.	-12.932**	-11.663*	-10.348*	-12.185*	-11.702*	-11.819*	-10.993*
	(4.72)	(4.74)	(5.02)	(4.75)	(4.75)	(4.75)	(5.04)
Obs	330468	330468	319925	330468	330468	330468	319925
F	21.95	20.50	16.39	17.30	17.11	21.02	13.38
P>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses. * (p<0.05), ** (p<0.01), *** (p<0.001)

Table 4. Hypothesis testing: The value of innovation on *overall firm performance*

DV: Pretax operating cash flow Quarter lag	Model 1 Controls only	Model 2 binary_CDS	Model 3 H1	Model 4 H2a	Model 5 H2b	Model 6 H3	Model 7 Full model
cds_either		-24.282***	-25.654***	-33.472***	-24.387***	-26.514***	-36.237***
		(4.91)	(5.07)	(8.08)	(4.92)	(4.92)	(8.34)
mean_3Q_net income			67.942***				67.702***
			(8.79)				(8.80)
cds_either * mean_3Q_net income			44.080*				52.534**
			(19.00)				(19.94)
number_exploration				-0.175			-0.05
				(0.55)			(0.57)
cds_either*no_exploration				2.140			2.019
				(1.50)			(1.55)
usage_exploration					10.542		8.165
					(9.13)		(9.71)
cds_either*usage_exploration					-1.942		-20.893
					(12.42)		(13.51)
firm_scope						0.008	0.101
						(1.25)	(1.30)
cds_either*firm_scope						29.325***	25.522***
						(4.36)	(4.49)
state	3.117***	3.120***	2.877***	3.126***	3.121***	3.123***	2.881***
	(0.30)	(0.30)	(0.31)	(0.30)	(0.30)	(0.30)	(0.31)
regulatory agent	4.550***	8.083***	8.098***	7.883***	8.086***	8.296***	8.063***
	(1.32)	(1.50)	(1.56)	(1.51)	(1.50)	(1.50)	(1.57)
bank charter	-7.770***	-7.734***	-7.563***	-7.754***	-7.736***	-7.713***	-7.555***
	(0.91)	(0.91)	(0.95)	(0.91)	(0.91)	(0.91)	(0.95)
bank holding company	-3.099	-3.976*	-3.826+	-3.986*	-3.982*	-4.089*	-3.898+
	(1.92)	(1.93)	(2.01)	(1.93)	(1.93)	(1.93)	(2.01)
ownership	2.387	2.649	3.12	3.052	2.651	2.81	3.658
	(4.54)	(4.54)	(4.71)	(4.55)	(4.54)	(4.54)	(4.72)
ln(asset)	5.657***	5.836***	5.278***	5.843***	5.912***	5.768***	5.153***
	(0.91)	(0.91)	(0.99)	(0.91)	(0.91)	(0.91)	(0.99)
firm age	0	0	0	0	0	0	0
	0.00	0.00	0.00	0.00	0.00	0.00	0.00
seasonality	-0.348	-0.35	-0.455+	-0.353	-0.349	-0.347	-0.456+
	(0.23)	(0.23)	(0.24)	(0.23)	(0.23)	(0.23)	(0.24)
crisis	-3.501***	-3.484***	-3.562***	-3.456***	-3.491***	-3.439***	-3.492***
	(0.71)	(0.71)	(0.72)	(0.71)	(0.71)	(0.71)	(0.72)
cont.	-119.558***	-126.073***	-116.422***	-126.917***	-126.749***	-126.486***	-117.353***
	(12.79)	(12.86)	(13.62)	(12.89)	(12.87)	(12.88)	(13.68)
Obs	355383	355383	344501	355383	355383	355383	344501
F	28.848	28.409	29.33	23.846	23.866	27.779	21.788
P>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses. * (p<0.05), ** (p<0.01), *** (p<0.001)

Table 5. Hypothesis testing: The value of innovation on *overall firm performance* (cont'd)

DV: Pretax operating cash flow	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Year lag	Controls only	binary_CDS	H1	H2a	H2b	H3	Full model
cds_either		-27.080***	-28.422***	9.005	-27.081***	-27.436***	11.073
		(5.42)	(5.60)	(8.77)	(5.42)	(5.43)	(9.06)
mean_3Q_net income			161.033***				155.345***
			(31.38)				(31.95)
cds_either * mean_3Q_net income			-120.922***				-113.377**
			(36.14)				(37.17)
number_exploration				-0.36			-0.269
				(0.59)			(0.61)
cds_either*no_exploration				-7.925***			-8.747***
				(1.61)			(1.66)
usage_exploration					13.622		6.175
					(10.41)		(11.26)
cds_either*usage_exploration					-7.785		-9.652
					(13.72)		(15.06)
firm_scope						-0.885	-1.127
						(1.35)	(1.40)
cds_either*firm_scope						4.54	0.023
						(4.75)	(4.89)
state	3.690***	3.691***	3.180***	3.674***	3.692***	3.692***	3.158***
	(0.33)	(0.33)	(0.34)	(0.33)	(0.33)	(0.33)	(0.34)
regulatory agent	4.066**	7.954***	8.132***	8.952***	7.951***	7.992***	9.201***
	(1.44)	(1.64)	(1.70)	(1.65)	(1.64)	(1.64)	(1.71)
bank charter	-6.522***	-6.502***	-6.311***	-6.408***	-6.504***	-6.507***	-6.228***
	(0.99)	(0.99)	(1.03)	(0.99)	(0.99)	(0.99)	(1.03)
bank holding company	-0.466	-1.387	-1.158	-1.437	-1.384	-1.406	-1.203
	(2.09)	(2.10)	(2.19)	(2.10)	(2.10)	(2.10)	(2.19)
ownership	-0.115	0.197	0.581	-1.471	0.195	0.239	-1.153
	(4.92)	(4.92)	(5.11)	(4.93)	(4.92)	(4.93)	(5.12)
ln(asset)	1.790+	1.972*	1.1	2.077*	2.038*	1.955*	1.205
	(0.99)	(0.99)	(1.08)	(1.00)	(1.00)	(0.99)	(1.09)
firm age	0.001**	0.001***	0.001***	0.001**	0.001***	0.001***	0.001**
	0.00	0.00	0.00	0.00	0.00	0.00	0.00
seasonality	0.058	0.055	-0.022	0.077	0.057	0.054	0.01
	(0.25)	(0.25)	(0.26)	(0.25)	(0.25)	(0.25)	(0.26)
crisis	-11.032***	-11.024***	-11.114***	-11.120***	-11.030***	-11.032***	-11.234***
	(0.77)	(0.77)	(0.78)	(0.77)	(0.77)	(0.77)	(0.78)
cont.	-118.879***	-125.829***	-108.555***	-121.027***	-126.423***	-125.328***	-102.807***
	(14.13)	(14.19)	(15.05)	(14.23)	(14.20)	(14.22)	(15.11)
Obs	330468	330468	319925	330468	330468	330468	319925
F	42.786	41.007	33.185	36.66	34.347	34.262	24.008
P>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses. * (p<0.05), ** (p<0.01), *** (p<0.001)

Appendix

1. Hypothesis testing: The value of innovation *per se* (DV without lags)

DV: Trading gains and losses Baseline (t=0)	Model 1 Controls only	Model 2 binary_CDS	Model 3 H1	Model 4 H2a	Model 5 H2b	Model 6 H3	Model 7 Full model
cds_either		3.137+	2.997+	-6.670*	3.009+	3.670*	-5.304+
		(1.62)	(1.69)	(2.68)	(1.62)	(1.63)	(2.79)
mean_3Q_net income			0.519				0.663
			(2.97)				(2.97)
cds_either * mean_3Q_net income			17.793**				16.619*
			(6.42)				(6.73)
number_exploration				0.162			0.101
				(0.18)			(0.19)
cds_either*no_exploration				2.147***			1.950***
				(0.50)			(0.52)
usage_exploration					-1.226		-1.515
					(3.01)		(3.27)
cds_either*usage_exploration					6.236		3.038
					(4.12)		(4.54)
firm_scope						0.053	0.065
						(0.42)	(0.43)
cds_either*firm_scope						-6.714***	-6.829***
						(1.44)	(1.50)
state	-0.015	-0.015	0.109	-0.010	-0.014	-0.016	0.115
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
regulatory agent	2.521***	2.065***	2.131***	1.779***	2.071***	2.013***	1.834***
	(0.44)	(0.50)	(0.52)	(0.50)	(0.50)	(0.50)	(0.52)
bank charter	-2.749***	-2.755***	-2.983***	-2.780***	-2.754***	-2.758***	-3.007***
	(0.30)	(0.30)	(0.31)	(0.30)	(0.30)	(0.30)	(0.31)
bank holding company	0.028	0.142	0.130	0.167	0.134	0.173	0.172
	(0.63)	(0.64)	(0.67)	(0.64)	(0.64)	(0.64)	(0.67)
ownership	0.318	0.286	-0.427	0.737	0.291	0.250	-0.081
	(1.50)	(1.50)	(1.56)	(1.50)	(1.50)	(1.50)	(1.56)
ln(asset)	0.096	0.072	0.275	0.026	0.096	0.088	0.258
	(0.30)	(0.30)	(0.33)	(0.30)	(0.30)	(0.30)	(0.33)
firm age	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
seasonality	-0.019	-0.019	0.009	-0.024	-0.018	-0.019	0.001
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
crisis	-1.711***	-1.713***	-1.599***	-1.678***	-1.715***	-1.723***	-1.579***
	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)
cont.	-7.159+	-6.314	-9.127*	-7.544+	-6.552	-6.274	-10.107*
	(4.20)	(4.22)	(4.51)	(4.23)	(4.22)	(4.23)	(4.53)
Obs	366349.00	366349.00	351842.00	366349.00	366347	366349	351842
F	20.74	19.05	16.13	17.88	16.141	17.812	12.959
P>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses. * (p<0.05), ** (p<0.01), *** (p<0.001)

2. Hypothesis testing: The value of innovation on *overall firm performance* (DV without lags)

DV: Pretax operating cash flow Baseline (t=0)	Model 1 Controls only	Model 2 binary_CDS	Model 3 H1	Model 4 H2a	Model 5 H2b	Model 6 H3	Model 7 Full model
cds_either		-20.643***	-21.610***	-46.630***	-21.385***	-22.700***	-47.642***
		(4.74)	(4.97)	(7.83)	(4.74)	(4.75)	(8.19)
mean_3Q_net income			71.040***				67.453***
			(8.72)				(8.73)
cds_either * mean_3Q_net income			42.725*				18.767
			(18.84)				(19.74)
number_exploration				0.007			-0.003
				(0.53)			(0.56)
cds_either*no_exploration				5.860***			5.303***
				(1.46)			(1.53)
usage_exploration					68.421***		71.686***
					(8.79)		(9.61)
cds_either*usage_exploration					-10.513		-28.321*
					(12.04)		(13.33)
firm_scope						-0.138	0.087
						(1.22)	(1.27)
cds_either*firm_scope						25.927***	28.670***
						(4.21)	(4.39)
state	2.412***	2.415***	2.441***	2.430***	2.425***	2.418***	2.461***
	(0.29)	(0.29)	(0.30)	(0.29)	(0.29)	(0.29)	(0.30)
regulatory agent	4.101**	7.104***	7.277***	6.437***	7.131***	7.302***	6.922***
	(1.27)	(1.45)	(1.52)	(1.46)	(1.45)	(1.45)	(1.53)
bank charter	-7.610***	-7.574***	-7.729***	-7.636***	-7.597***	-7.560***	-7.782***
	(0.87)	(0.87)	(0.92)	(0.87)	(0.87)	(0.87)	(0.92)
bank holding company	-3.956*	-4.709*	-4.413*	-4.684*	-4.754*	-4.827**	-4.537*
	(1.85)	(1.86)	(1.97)	(1.86)	(1.86)	(1.86)	(1.97)
ownership	3.559	3.774	1.300	4.946	3.782	3.909	2.435
	(4.39)	(4.39)	(4.58)	(4.39)	(4.39)	(4.39)	(4.59)
ln(asset)	7.265***	7.419***	8.108***	7.360***	7.925***	7.358***	8.436***
	(0.88)	(0.88)	(0.96)	(0.88)	(0.88)	(0.88)	(0.97)
firm age	-0.001*	-0.001*	-0.001**	-0.001*	-0.001**	-0.001*	-0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
seasonality	0.065	0.063	0.040	0.052	0.072	0.066	0.039
	(0.23)	(0.23)	(0.24)	(0.23)	(0.23)	(0.23)	(0.24)
crisis	-1.171	-1.153	-0.869	-1.064	-1.200	-1.114	-0.786
	(0.69)	(0.69)	(0.71)	(0.69)	(0.69)	(0.69)	(0.71)
cont.	-110.410***	-115.970***	-117.591***	-118.798***	-120.662***	-116.165***	-124.440***
	(12.26)	(12.33)	(13.25)	(12.35)	(12.34)	(12.35)	(13.30)
Obs	366349	366349	351842	366349	366347	366349	351842
F	26.001	25.302	29.845	22.584	29.996	24.494	27.483
P>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses. * (p<0.05), ** (p<0.01), *** (p<0.001)

3. Robustness check 1: Different independent variable for H1

DV: Trading gains and losses	Model 1		Model 2		Model 3	
H1: mean_3Q_ROE	t=0		t+1		t+4	
cds_either	2.990+	-5.288+	3.257+	6.489*	4.557*	1.591
	(1.69)	(2.79)	(1.72)	(2.83)	(1.87)	(3.02)
mean_3Q_ROE	0.007	0.007	0.006	0.006	-0.886	-0.812
	(0.07)	(0.07)	(0.07)	(0.07)	(1.16)	(1.16)
cds_either * mean_3Q_ROE	2.385***	2.230**	5.523***	5.614***	3.619+	3.407+
	(0.70)	(0.71)	(1.15)	(1.18)	(2.00)	(2.05)
number_exploration		0.099		0.132		0.128
		(0.19)		(0.19)		(0.20)
cds_either*no_exploration		1.937***		-0.742		0.446
		(0.52)		(0.53)		(0.55)
usage_exploration		-1.450		-1.822		-1.450
		(3.27)		(3.28)		(3.69)
cds_either*usage_exploration		4.866		0.925		1.386
		(4.44)		(4.50)		(4.93)
firm_scope		0.065		0.038		-0.011
		(0.43)		(0.44)		(0.47)
cds_either*firm_scope		-6.795***		-2.281		10.145***
		(1.50)		(1.52)		(1.63)
state	0.111	0.117	0.223*	0.221*	0.272*	0.272*
	(0.10)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
regulatory agent	2.134***	1.841***	2.149***	2.182***	2.295***	2.282***
	(0.52)	(0.52)	(0.53)	(0.53)	(0.57)	(0.57)
bank charter	-2.984***	-3.009***	-2.888***	-2.883***	-3.347***	-3.347***
	(0.31)	(0.31)	(0.32)	(0.32)	(0.34)	(0.34)
bank holding company	0.118	0.157	0.279	0.297	0.316	0.289
	(0.67)	(0.67)	(0.68)	(0.68)	(0.73)	(0.73)
ownership	-0.415	-0.070	-0.027	-0.164	-0.943	-0.770
	(1.56)	(1.56)	(1.60)	(1.60)	(1.71)	(1.71)
ln(asset)	0.280	0.275	-0.031	-0.050	-0.325	-0.374
	(0.33)	(0.33)	(0.33)	(0.34)	(0.36)	(0.36)
firm age	0.000***	0.000***	0.000***	0.000***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
seasonality	0.010	0.002	-0.089	-0.089	-0.040	-0.043
	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
crisis	-1.597***	-1.578***	-1.724***	-1.734***	-1.571***	-1.551***
	(0.24)	(0.24)	(0.24)	(0.24)	(0.26)	(0.26)
cont.	-9.263*	-10.336*	-11.777*	-11.453*	-10.145*	-10.715*
	(4.51)	(4.53)	(4.62)	(4.64)	(5.03)	(5.05)
N	351833	351833	344493	344493	319919	319919
F	16.211	13.040	17.490	11.930	16.626	13.516
P>F	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses. * (p<0.05), ** (p<0.01), *** (p<0.001)

3. Robustness check 1: Different independent variable for H1 (cont.d)

DV: Pretax operating cash flow	Model 1		Model 2		Model 3	
H1: mean_3Q_ROE	t=0		t+1		t+4	
cds_either	-22131.983***	-47683.770***	-26928.676***	-35308.249***	-29105.006***	11928.172
	(4969.64)	(8200.12)	(5075.53)	(8342.99)	(5609.73)	(9068.34)
mean_3Q_ROE	208.81	205.784	212.89	212.857	17430.315***	16860.866***
	(197.61)	(197.57)	(199.00)	(198.99)	(3470.17)	(3473.92)
cds_either * mean_3Q_ROE	14734.293***	13348.405***	37073.134***	37908.651***	7688.92	10620.958+
	(2065.52)	(2078.95)	(3402.37)	(3468.46)	(5995.66)	(6156.58)
number_exploration		-37.436		-83.591		-269.883
		(555.48)		(566.90)		(613.47)
cds_either*no_exploration		5170.672***		1518.375		-9066.867***
		(1527.14)		(1551.23)		(1662.38)
usage_exploration		75990.751***		12405.360		14163.463
		(9596.25)		(9690.29)		(11066.54)
cds_either*usage_exploration		-23205.931+		-22558.447+		-23679.449
		(13030.59)		(13267.73)		(14782.23)
firm_scope		11.612		47.937		-1096.209
		(1272.10)		(1298.07)		(1396.34)
cds_either*firm_scope		28916.221***		25980.929***		-238.159
		(4393.54)		(4485.24)		(4889.17)
state	2462.343***	2481.020***	2902.933***	2906.813***	3202.759***	3176.234***
	(303.85)	(303.82)	(312.33)	(312.36)	(344.81)	(344.85)
regulatory agent	7441.016***	7109.970***	8287.684***	8323.262***	8151.363***	9253.303***
	(1520.06)	(1531.48)	(1557.04)	(1569.09)	(1700.27)	(1712.83)
bank charter	-7758.137***	-7825.441***	-7629.341***	-7614.133***	-6343.928***	-6256.590***
	(921.85)	(921.84)	(945.94)	(946.08)	(1032.85)	(1032.98)
bank holding company	-4592.915*	-4707.346*	-4042.627*	-4128.031*	-1244.182	-1266.715
	(1966.25)	(1966.52)	(2009.14)	(2009.78)	(2186.69)	(2187.36)
ownership	1385.072	2511.666	3541.081	3984.375	766.617	-1011.638
	(4580.96)	(4588.47)	(4709.07)	(4717.26)	(5113.48)	(5122.41)
ln(asset)	8408.215***	8786.602***	5608.331***	5519.783***	1476.313	1550.697
	(964.66)	(970.45)	(987.09)	(992.92)	(1081.72)	(1087.59)
firm age	-0.939***	-0.880**	-0.112	-0.056	1.247***	1.006**
	(0.28)	(0.28)	(0.29)	(0.29)	(0.32)	(0.33)
seasonality	36.551	38.008	-458.568+	-457.149+	-20.963	11.706
	(240.56)	(240.66)	(242.63)	(242.78)	(260.54)	(260.70)
crisis	-845.270	-772.017	-3528.555***	-3468.283***	-11148.242***	-11266.146***
	(708.95)	(709.50)	(720.99)	(721.60)	(776.87)	(777.36)
cont.	-119329.306***	-126502.747***	-119939.874***	-120868.937***	-114788.417***	-108581.250***
	(13250.76)	(13301.53)	(13622.99)	(13677.58)	(15088.64)	(15156.77)
Obs	351833	351833	344493	344493	319919	319919
F	24.948	25.331	30.809	22.805	34.856	25.356
P>F	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses. * (p<0.05), ** (p<0.01), *** (p<0.001)

4. Robustness check 2: Different dependent variable (overall firm performance)

DV: Net income	Model 1		Model 2		Model 3	
H1: mean_3Q_ROE	t=0		t+1		t+4	
cds_either	-18094.036***	-41399.061***	-19931.681***	-31717.042***	-19123.189***	-272.253
	(3684.67)	(6080.07)	(3768.74)	(6194.94)	(4155.00)	(6716.90)
mean_3Q_ROE	172.788	170.952	176.279	176.347	12743.439***	12433.437***
	(146.52)	(146.49)	(147.76)	(147.75)	(2570.27)	(2573.13)
cds_either * mean_3Q_ROE	11559.111***	10604.923***	28181.711***	28702.562***	6321.212	7921.173+
	(1531.45)	(1541.46)	(2526.37)	(2575.44)	(4440.85)	(4560.17)
number_exploration		98.395		91.342		-75.746
		(411.86)		(420.94)		(454.39)
cds_either*no_exploration		4841.910***		2346.170*		-4286.120***
		(1132.32)		(1151.84)		(1231.32)
usage_exploration		51418.876***		10893.630		11314.949
		(7115.25)		(7195.35)		(8196.97)
cds_either*usage_exploration		-16369.806+		-18460.452+		-17522.5
		(9661.68)		(9851.71)		(10949.17)
firm_scope		-36.406		-34.567		-881.891
		(943.21)		(963.86)		(1034.27)
cds_either*firm_scope		17757.740***		18055.990***		6571.783+
		(3257.64)		(3330.44)		(3621.40)
state	1280.203***	1296.300***	1678.874***	1684.963***	2027.023***	2013.801***
	(225.29)	(225.27)	(231.91)	(231.93)	(255.39)	(255.43)
regulatory agent	6026.607***	5605.588***	6463.068***	6301.373***	6340.960***	6896.782***
	(1127.03)	(1135.53)	(1156.15)	(1165.10)	(1259.35)	(1268.69)
bank charter	-5172.919***	-5232.429***	-5119.261***	-5121.853***	-4843.281***	-4799.534***
	(683.49)	(683.51)	(702.39)	(702.49)	(765.00)	(765.13)
bank holding company	-3060.021*	-3112.983*	-2419.198	-2457.789+	15.767	-8.709
	(1457.85)	(1458.10)	(1491.85)	(1492.32)	(1619.63)	(1620.18)
ownership	1622.035	2647.787	3769.395	4343.26	408.063	-376.315
	(3396.49)	(3402.17)	(3496.63)	(3502.72)	(3787.43)	(3794.16)
ln(asset)	5185.086***	5405.996***	2979.138***	2882.173***	160.968	169.999
	(715.23)	(719.55)	(732.95)	(737.28)	(801.21)	(805.58)
firm age	-0.604**	-0.530*	0.043	0.119	0.903***	0.794**
	(0.20)	(0.21)	(0.21)	(0.22)	(0.24)	(0.24)
seasonality	16.736	11.545	-324.460+	-329.589+	-25.887	-10.359
	(178.36)	(178.44)	(180.16)	(180.27)	(192.98)	(193.10)
crisis	-1020.975+	-953.151+	-3059.250***	-2999.108***	-8605.573***	-8658.295***
	(525.64)	(526.07)	(535.36)	(535.81)	(575.41)	(575.79)
cont.	-67834.932***	-73334.925***	-69935.612***	-71323.173***	-66180.864***	-63190.029***
	(9824.59)	(9862.58)	(10115.50)	(10156.04)	(11175.81)	(11226.61)
N	351833	351833	344493	344493	319918	319918
F	20.335	20.936	27.176	20.388	34.782	24.281
P>F	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses. * (p<0.05), ** (p<0.01), *** (p<0.001)

CHAPTER THREE

WHICH FLYING GOOSE LEADS THE V?
INNOVATION ADOPTION AND ITS SPEED IN THE US BANKING INDUSTRY, 2001–2011

Abstract

I investigate the mechanisms through which different aspects of past performance affect whether and when a firm adopts an innovation. Using past financial performance as a source of performance feedback, and past experience in explorative behavior as a proxy for inherent dynamic capabilities, I argue that firms generally rely more on past experience than on past financial performance in deciding how quickly to adopt an innovation. The influence of past experience on this decision is felt even when we account for the factors that are known to expedite adoption (such as adoption by similar firms and geographical proximity). I also show that changes in the external environment affect which aspects of past performance firms rely on for their adoption decisions. I test these arguments using longitudinal data on the adoption of credit default swaps by US depository institutions between 2001 and 2011.

1. Introduction

Firms do not adopt an innovation simultaneously, so the adoption of innovations is typically spread or 'diffused' over time. In studying the dynamics of this diffusion, researchers have primarily focused on identifying factors that expedite diffusion, such as adopter characteristics (Damanpour, 1991; Rogers, 1995; Frambach & Schillewaert, 2002), geographical proximity (Strang & Soule, 1998; McKendrick, Doner, & Haggard, 2000), and interfirm networks (Davis & Greve, 1997; Beckman & Haunschild, 2002). This helps us understand what drives innovation to spread throughout a population of firms. In terms of adopter characteristics, scholars have looked at the effect of size or cash availability, but little attention has been paid to the role of past performance or related aspects such as underlying firm capabilities and feedback. As a result, we know little about the way past performance affects firms' decisions to adopt innovations. Specifically, we have only a limited understanding of how feedback or having relevant capabilities, both borne out of past behavior, influences the adoption of innovations. This paper focuses on the 'performance' aspect of firm characteristics and the ways in which it affects the adoption of innovations.

The behavioral theory of the firm (Cyert & March, 1963; March & Simon, 1958) and its extension to evolutionary economics (Nelson & Winter, 1982) explain change as a consequence of feedback on heterogeneous firms' performance or fitness, both of which are characterized by specific routines and capabilities. In this model, managers make changes to firm behavior only when they are faced with a problem, which they identify through feedback, i.e. actual performance against a pre-determined aspiration level. Since the adoption of innovations entails change to firms' existing routines and capabilities, feedback will influence whether or not firms adopt the innovations of others. This approach allows me to argue that adoption is a change in firm behavior instigated by a feedback 'cue'.

When positive or negative feedback on performance drives behavioral change, the benchmark for evaluating such feedback, i.e. aspiration level, plays an important role. Cyert & March (1963: 123) suggested that firms determine their aspiration level on a goal variable as a function of: i) the aspiration level in the previous period, ii) the firm's experience with respect to that goal, and iii) the experience of a reference group with respect to that goal. Many studies have looked at how firms react both to the recent performance of a focal firm and to that of comparable firms (e.g. Greve, 1998; Lant, 1992; Mezias et al., 2002). More specifically, behavioral studies of strategic change or risk-taking have usually used the historical performance of comparable firms (Massini et al., 2005; Porac et al., 1999) and how it compares to that of the focal firm.

Firms' performance also reflects their inherent capabilities. Scholars have argued that a unique combination of specialized and complementary resources and capabilities leads to superior performance (Peteraf, 1993; Wernerfelt, 1984). Extending this idea further, Teece, Pisano, & Shuen (1997) introduced dynamic capabilities: firms' ability to nurture, assess, and reform their own capabilities. This work suggests that developing the competency to change competencies is what enables sustainable superior performance. The dynamic capabilities view thus provides an interesting angle on the adoption of innovations: does the presence of existing capabilities from past explorative behavior overpower feedback as a driver?

By examining the effect of different aspects of past performance on the likelihood and speed of adoption, I can offer a more complete analysis and complement studies that have looked at other adopter characteristics. Moreover, by considering different types of feedback, I can establish which ones are more important in the decision to adopt innovations. This approach can also explain how firms perceive adoption of innovations: as a solution to a problem presented by feedback, or as a means to exploit existing dynamic capabilities. Finally, I can complement existing studies on diffusion by simultaneously considering some of the factors that we already know have an influence on the adoption decision. Thus the study can be extended beyond the basic institutional explanation on adoption.

The primary goal of this paper is to explore how different aspects of past performance affect the likelihood and speed of innovation adoption. I argue that firms receive different feedback depending on which aspect of their past behavior is being examined. This feedback, in turn, affects firms differently with regards to whether and when they adopt innovation. I also argue that the existence of previous capabilities affects the adoption. I aspire to expand the literature on adoption and diffusion of innovations with particular focus on past performance, feedback, and capabilities and their role on firm evolution (Jacobides & Winter, 2012). I undertake a quantitative analysis using an unusually rich dataset that includes all FDIC-insured depository institutions who were potential adopters of an identical innovation in the US between 1Q 2001 and 4Q 2011. Using the financial crisis that took place between 2007 and 2008, I also consider if there are any contingencies involved in the mechanisms through which different aspects of past performance affect the adoption of innovations.

This paper is structured as follows. I begin by reviewing existing research on the diffusion of innovation. I then propose hypotheses on how firms' multiple feedback signals and inherent capabilities arising from different aspects of past performance affect the likelihood and timing of innovation adoption. I test the hypotheses using the dataset on the US banking sector, which was the inspiration for this research. Based on the findings, I conclude by linking back to the literature, outlining limitations, identifying avenues for future research, and discussing implications for theory and practice.

2. Theoretical background

Innovation has long been a central concern to management scholars. Following the Schumpeterian tradition (1934), scholars have studied the relationship between innovation and industry evolution (e.g. Abernathy & Utterback, 1978; Klepper, 1997), and, within that theme, the diffusion of innovation. Here I provide a selective analysis of research relevant to this paper.

2.1. How innovation spreads, and why

The standard theory of the diffusion of innovation considers adopter characteristics (e.g. Baum, Calabrese & Silverman, 2000; Greve, 1998) that make the firm more or less likely to adopt. For example, organizational structure (Zaltman, Duncan & Holbek, 1973; Damanpour, 1991), size (Frambach & Schillewaert, 2002), and availability of cash (Rogers, 1995) have been identified as drivers of adopting innovation. Studies have also shown that major technological innovations are generally adopted sooner by firms with superior technological capabilities (Dewar & Dutton, 1986). Cohen & Levinthal (1990) suggested that some innovations may spread rapidly when the potential value to be unlocked is high, and when potential adopters possess the significant capability to absorb external knowledge. That is, optimal timing of adoption often depends on the resource base of the firm (Lieberman & Montgomery, 1998).

Other researchers have found that the diffusion of innovations is more rapid over short physical distances (Burns & Wholey, 1993; Rao, Davis, & Ward, 2000; McKendrick, Doner, & Haggard, 2000; D'Aunno, Succi, & Alexander, 2000) or that interorganizational networks facilitate innovation diffusion (Davis & Greve, 1997; Kraatz, 1998; Haunschild & Beckman, 1998; Ahuja, 2000; Tsai, 2001). Such findings, however, must be approached with caution, because many of the innovations examined are not critically important to the firms who adopt them.

Most work on the diffusion of innovations looks at the factors that expedite adoption rather than those that inhibit it. However, as Gatignon & Robertson (1989) argued, 'non-adoption is not the mirror image of the adoption decision.' Potential adopters may have actively decided to reject the innovation, passively decided to reject it, or failed to progress through certain stages of the adoption process yet (Nabih *et al.*, 1997). As a result, little is known about the factors that affect non-adoption (for an exception, see Stevens *et al.*, 1989).

However, some studies have looked at inhibiting factors. For instance, Zander and Kogut (1995) examined whether the type of knowledge embedded in an innovation predicts how quickly it spreads to other firms, and found that more easily codified and teachable innovations were transferred sooner. Another study examined whether different understanding or different incentives explained the failure of independent firms to imitate routines used by successful franchise organizations, finding that the understanding of effects had the greatest impact (Knott, 2003). This study also showed that valuable routines did not spread widely even when they were well described.

Taken together, the above research sheds light on the factors, both external and internal, that influence the speed at which firms adopt innovation. The factors identified have tended to be sociology-oriented, highlighting the mimetic isomorphism in the diffusion process. Consequently, the potential influence of firms' previous behavior has received relatively little attention, and our understanding of what actually drives the initial adoption of an innovation is very limited.

2.2. Why firms change, and when

Evolutionary economics (Nelson, 1991; Nelson & Winter, 1982) and the behavioral theory of the firm (Cyert & March, 1963; March & Simon, 1958) propose the attributes that lead to changes in firm behavior. Evolutionary economics tells us that firms' patterns of behavior persist over time unless there is a strong enough stimulus for change.

The literature on the behavioral theory of the firm points out that firms use short-run feedback as a trigger to action in order to avoid uncertainty. Such feedback is determined against a benchmark, termed an 'aspiration level'. As there are many ways to measure performance, it is assumed that a firm can obtain multifarious, heterogeneous feedback. Scholars assume that decisions are made by solving a series of problems as they arise. As such, decision rules emphasize short-run reaction to short-run feedback (Cyert & March, 1963: 119). If feedback on a firm's current *modus operandi* suggests it is no longer adequate, the firm makes a change. Faced with negative feedback, the firm can either change (e.g. adopt an innovation) or simply revise its aspiration level downwards so that future feedback will be positive.

In evolutionary economics, firms are regarded as undergoing continuous market tests, which serve as a selection mechanism and a motivation for firms to act in certain ways (Nelson & Winter, 1982). Developing a pattern of behavior takes time and, once routines are established, it does not require much deliberation to act on them. Because of the tendency for actors to ‘satisfice’ with respect to their established propensities of behavior, established routines do not change unless there is a compelling reason (Simon, 1963).

The presence and behavior of peers can also have an effect on whether or not firms adopt an innovation. That is, adoption can be a ‘fad’ among a population of firms (Abrahamson & Rosenkopf, 1997; Abrahamson & Fairchild, 1999). Firms observe others’ behavior and mimic it, with the imitation effect spreading over time. This suggests that adoption is at least partly institutional (mimetic) from start to finish. Because firms can only observe adoption and its outcome among their peers, late adopters can draw incorrect inferences and commit systematic mistakes of adopting innovations based on incorrect/imperfect information, i.e. imperfect replication (Winter & Szulanski, 2001), when they lack the actual ‘ingredients’ to benefit from adoption (Abrahamson, 1991). This mimicry becomes more pronounced over time because latecomers regard early adopters as *role models* (Greve 1996, 2009; Haveman, 1993).

Dynamic capabilities may be another driver of change. These capabilities, built through experience (Teece *et al*. 1997, p. 528), enable a firm to change and adapt to new environments. Generating such capabilities requires enough experience that they are stored ‘in new patterns of activity, in “routines”’ (Teece *et al*. 1997, p. 520). In other words, firms develop capabilities and routinize the adaptation itself over time (Winter, 2003). Once these capabilities and routines are in place, firms are motivated to exploit them to the fullest. In this sense, firms with extensive experience in explorative behavior, who have thus developed dynamic capabilities, will be more open to adopting innovations (a kind of explorative behavior) as they become available.

By considering other explanations for behavioral change in firms in addition to those cited above, this paper can help to expand the discussion on the role of past performance on diffusion of innovation.

3. Theory development

I examine the way in which two aspects of past performance – feedback and past experience – affect the adoption of innovations. In so doing, I examine different types of feedback and experience to determine exactly what drives adoption. I also look at the effect of changes in the external environment on the abovementioned drivers of adoption. Specifically, I consider how i) feedback on past financial performance and ii) possession of dynamic capabilities from past experience affect firms' decision to adopt innovations. Then, I consider if and how the changes in the external environment affect the drivers of innovation adoption.

3.1. Financial performance and feedback

There are rational, market-based explanations for firms' motivation to adopt or innovate based on supply or demand (Gilbert & Newbury, 1982; Geroski, 2003). The assumption is that firms have perfect information of both the demand and supply needs of the market, and that this allows rational decision-making. In the real world, however, perfect information is rare. Rather, because firms have imperfect information, decision rules emphasize observable and measurable information in the form of short-run feedback (Cyert & March, 1963: 119). If the feedback is positive, firms maintain the status quo. In a similar vein, evolutionary economics informs us that firms' patterns of behavior persist over time (Nelson, 1991; Nelson & Winter, 1982), so that it takes a strong stimulus to make them drop a routinized behavior. Taken together, these ideas suggest that firms will not change their behavior or engage in exploration until they see a warning sign – i.e. negative feedback.

I argue that negative feedback on a firm's *overall* performance is a key driver of adopting an innovation. Good performance indicates that there is no 'problem' to be solved. High-performing firms have no immediate need to do something new, although they may be nearing the efficiency frontier in utilizing their existing routines and capabilities, i.e. exploitation. However, because firms will not get negative feedback until their performance hits a plateau, they are unlikely to 'explore' (March, 1991) *ex ante*, for example by adopting a readily available innovation. However, if firms get negative feedback that calls for an 'immediate' reaction, they may overlook the initial problems associated with the adoption of innovation because they are 'standing on a burning platform'. Reversing the danger signs then becomes the center of managerial attention (Ocasio, 1997) and a rationalization for disrupting existing routines and introducing a novel element. Firms with poor financial performance, resulting in negative feedback, are more likely to adopt a readily available innovation – and to adopt it quickly (Harrison and March, 1984; Barney, 1986).

Following the same logic, positive feedback on a firm's *main source of profit*[1] will inhibit adoption of an innovation. Although superior capabilities are positively associated with the easier acquisition of new capabilities (Henderson & Cockburn, 1994), they are also a source of positive feedback, and therefore do not drive the acquisition of new capabilities. Over time, continual positive feedback makes the responsible routines more inert and rigid than those that receive occasional negative feedback (Leonard-Barton, 1992; Chakravarthy & Doz, 2007). In other words, these routines' importance and superiority can turn them into competency traps (Levitt & March, 1988; Levinthal & March, 1993), resulting in the firm continually exploiting its superior capabilities at the expense of possible exploration. Another disadvantage for firms with superior capabilities is the accumulated asset stock that enabled superior performance in their main source of profit (Dierickx & Cool, 1989). Developing superior capabilities is time-consuming. Once developed, they can neither be imitated nor quickly replaced, leaving the firm in a competency trap whereby inertia impedes change to existing routines, or the creation of new ones (Freeman & Hannan, 1984). This may inhibit the adoption of innovations that require changes in existing routines and development of new capabilities.

> *Hypothesis 1a.* Negative feedback on overall firm performance will *increase* the likelihood and speed of adopting an innovation.
> *Hypothesis 1b.* Positive feedback on performance in a firm's main source of profit will *decrease* the likelihood and speed of adopting an innovation.

3.2. Past experience and dynamic capabilities

I argue that a different aspect of performance, specifically past experience in exploration, can also affect the likelihood of adopting an innovation. Research on the diffusion of innovation suggests that differences in risk propensity and capability determine the order of adoption (Rogers, 1995). However, there is no *prima facie* reason to believe that these characteristics will only determine the order of adoption – they may also determine whether or not firms adopt. A firm's past experience in exploration, and adopting innovations in particular, is a good indicator of both, since it manifests the firm's attitude toward risk/uncertainty and its ability to benefit from the adoption.

---

[1] This activity can be thought of as a 'cash cow' in the BCG matrix. In my argument, however, it does not matter whether the activity is a high-margin, high-market share one or not – just whether it accounts for the majority of the firm's profit.

Much prior work on organizational learning has found that the accumulation of experience leads to performance improvement (e.g. Argote 1999, Herriott *et al.* 1985). That is, the more innovations a firm adopted in the past, the better it will be in adopting innovations in the future. Amburgey & Miner (1992), in line with this, found that experienced firms are likely to be involved in the same type of strategy/behavior as they were in the past. Although the characteristics of innovations adopted in the past and those being considered for adoption may differ, firms with past experience will be able to draw on existing, redeployable capabilities (Helfat & Peteraf, 2003), i.e. absorptive capacity (Cohen & Levinthal, 1990), when they adopt innovations, giving them an advantage.

In addition, the repeated adoption of innovations in the past will have enabled firms to develop dynamic capabilities (Teece *et al*., 1997), i.e. the ability to continuously nurture, assess, and reform their own capabilities. Firms who have adopted many innovations will be able to carry on adopting them, and do it well. In other words, there may be an element of routinization in the adoption of innovations over time through accumulated experience that other firms are unable or unwilling to undertake due to the costs involved in developing such 'patterns' (Winter, 2003). Firms resist change because it is time-consuming to nurture, assess, and reform their existing capabilities and develop new routines. But those with dynamic capabilities will be least resistant, and most open to change. Firms with more experience in adopting innovations are also more likely to be early adopters, because they will perceive innovations as opportunities to exploit their existing dynamic capabilities (March, 1991). Also, much experience in the past can result in firms' managers viewing the past in a more positive light (McGrath, 1999) and be more willing to adopt innovations quickly. In other words, managerial hubris (Roll, 1986) can expedite adoption: When managers are aware that such capabilities require extensive experience and cannot be purchased from markets, thus generating time compression diseconomies (Dierickx & Cool, 1989), they consider themselves to be in a better position than their peers. Thus,

> *Hypothesis 2.* More past experience in adopting innovation will *increase* the likelihood and speed of adopting an innovation.

3.3. Feedback and dynamic capabilities

A firm that has repeatedly succeeded in adopting and integrating innovation into its operations will probably have superior dynamic capabilities and routines. Moreover, it would also have received positive feedback from the experience. On the other hand, firms that fared less well with adoption in the past would have negative feedback. Although the spillover effect of past experience on future performance has been questioned (e.g. Zollo, 2009; Zollo & Reuer, 2010), it is possible that firms will read too much into feedback on past experience, affecting their view of future behavioral change or the utilization of the capabilities that were involved. Experience and feedback provide an opportunity to learn, but similar feedback can be interpreted differently by different firms, partly due to differences in learning capability (e.g. Cohen & Levinthal, 1990; Miner & Mezias, 1996). This leads them to draw different inferences for behavior in the future. Therefore, there can be both virtuous cycles and vicious cycles at work between feedback and the quality of (dynamic) capabilities (Pisano, Bohmer, & Edmondson, 2001). Initial positive (negative) feedback may promote more (fewer) adoptions. This leads to more (less) experience, which, in turn, provides more (fewer) opportunities to develop relevant capabilities. As a result, when engaging in the same behavior, e.g. adoption of innovations, firms end up with further positive (negative) feedback. Those with initial negative feedback are more likely to wait until the innovation is sufficiently widespread to 'legitimize' its adoption and make its implementation more codified. Adoption at this late stage represents significantly lower risk and uncertainty. In summary, the interaction between utilizing dynamic capabilities to adopt innovations in the past and the feedback from doing so will, independent of feedback on financial performance, affect the likelihood and speed of adopting innovations. Therefore,

> *Hypothesis 3*. Positive feedback on previously adopted innovations will *increase* the likelihood and speed of adopting an innovation.

3.4. External environment and adoption

The competitive environment provides firms with feedback on what they do and how well they (seem to) do it. Once established, the heterogeneity in profitability of different firms is not easily changed due to the fit between the market and well-established routines (Nelson & Winter, 1982) unless there is a challenge to the status quo such as an innovation. However, adopting innovations involves significant uncertainty about the payoffs to the firm. Observing peers lets the focal firm see how other firms perceive this uncertainty (Levitt & March, 1988; Greve, 1996). The more salient and consistent the information received, the more likely the focal firm is to mimic its peers. This would entice potential adopters to imitate and adopt the innovation quickly, leading to the emergence of management 'fads' (Abrahamson, 1991).

Limited resources mean that firms cannot observe the adoption behavior of every firm in the industry, or its outcome. Rather, they select a number of firms to serve as a reference group (Cyert & March, 1963: 123; Massini *et al.*, 2005). Reference firms are usually similar to the focal firm in terms of their size, existing *modus operandi*, or geographical location. Many studies on diffusion of innovation have found that firms adopt innovations more quickly when similar firms (e.g. Frambach & Schillewaert, 2002) and those located close by (e.g. Rao *et al.*, 2000; McKendrick *et al.*, 2000) have adopted them. In other words, firms in the reference group function not only as sources of information, but also as role models. Therefore,

> *Hypothesis 4a.* A larger number of similar firms adopting an innovation will *increase* the likelihood and speed of adopting the same innovation.
> *Hypothesis 4b.* Greater geographical distance between a firm and its peers will *decrease* the likelihood and speed of adopting an innovation.

3.5. Changes to the external environment and adoption

What happens if the whole market is disrupted? That is, what if the external environment changes dramatically, affecting every firm? Several studies have asserted that firms' strategic adaptations co-evolve with changes in the environment (Lewin, Long, & Carroll, 1999; McKelvey, 1999; Tan & Tan, 2005). In their study of US rail deregulation, Smith & Grimm (1987) noted that firms who changed their strategies for the new environment performed better than those who didn't. These studies imply that changes in environment necessitate adaptation through different strategies and actions.

The same can be said of adopting innovations: Firms will base their decisions on changes in their environment lest the adopted innovation fails to bring about the anticipated outcome. The financial crisis of 2007–2008 was an abrupt change to the environment in which depository institutions operated, and firms lost faith in their existing guidelines as a result. Both zero-level (operational) and dynamic capabilities *à la* Winter (2003) were disrupted, and 'businesses as usual' became impossible. Financial performance was no longer a reliable indicator of success and relative superior capabilities could not be used. This loss of faith led to a breakdown in the systematic relationship between the expected drivers of adopting innovation and adoption itself. Moreover, with financial innovations being blamed for the crisis, firms may have shied away from innovation regardless of what the expected drivers of adoption implied. In other words, fear of stakeholder disapproval delegitimized the adoption of innovation. Therefore,

> *Hypothesis 5.* The relationship between the drivers of adopting innovations and the likelihood and speed of doing so will *break down* after a change in the external environment.

These five hypotheses will allow me to show how adoption of innovations is driven by different motivations – feedback, existing capabilities, and/or institutional factors. This will help us understand which firms are likely to lead the way in innovation, and which will follow them, rather like geese flying in a 'V' formation.

4. Research design

4.1. Empirical setting

The setting of this paper is the US banking sector, which was at the heart of the financial crisis of 2007–2008. The setting of this paper is the US banking sector, which was at the heart of the financial crisis of 2007–2008 and offers an ideal setting to address my research question. With the repeal of the Glass-Steagall Act in 1999, commercial banks and other depository institutions in the US were allowed to engage in investment banking, brokerage, and trading activities that were once off limits. This gave banks the option of adopting financial innovations that had previously been monopolized by investment banks.

Beginning in the early 2000s, financial institutions in the US started to experience exponential growth in their profits, exemplified by CAGR of 30% in ROE for some firms. Behind such growth were financial innovations such as credit derivatives[2] . When the financial crisis struck, numerous borrowers defaulted on their payments and those who purchased CDS as

---

[2] Some may argue that credit derivatives, and CDS in particular, are not innovation in the strictest sense. I have two explanations for defining CDS as an innovation. First, I turn to the definition of innovation given by Schumpeter (1934): a specific social activity (function) carried out within the economic sphere and with a commercial purpose by *"new combinations" of new or existing knowledge, resources, equipment and so on* (Schumpeter 1934, pp. 65). Second, bankers familiar with the product and its mechanics have confirmed during my field interviews that the banking industry participants consider this product as an innovation.

an insurance against such defaults demanded payment from the sellers of CDS. A number of major government bailouts during the crisis involved banks excessively using financial innovations such as CDSs. Some observers have thus blamed the entire financial crisis on the proliferation of financial innovations. For example, Paul Krugman commented in one of his New York Times Op-ed (2007) that "… policy makers left the financial industry free to innovate — and what it did was to innovate itself, and the rest of us, into a big, nasty mess." Paul Volcker, former chairman of the Federal Reserve in the US, and Lord Turner, chairman of the Financial Services Authority in the UK, also voiced their opinion that unregulated financial innovation was a major cause of the crisis.

Credit derivatives are bilateral financial contracts with payoffs linked to a credit-related event such as non-payment of interest, a credit downgrade, or a bankruptcy filing. A bank can use a credit derivative to transfer some or all of the credit risk of a loan to another party or to take on additional risks. In principle, credit derivatives are tools that enable banks to manage their portfolio of credit risks more efficiently. The largest part of the credit derivatives market is the Credit Default Swaps[3] (CDS) market. Originally developed as a tool to minimize losses of lenders against borrowers' default, CDSs, at first, had seemed valuable innovation, or at least harmless. Regulators and bankers alike believed that they make banks sounder. Alan Greenspan, the former head of the Federal Reserve System, voiced that credit derivatives and other complex financial instruments have contributed "to the development of a far more flexible, efficient, and hence resilient financial system than existed just a quarter-century ago." (Greenspan, 2004)

In this paper, among all the financial innovations available for adoption since 1999, I focus on Credit default swaps (CDS). The popularity of CDSs soared in the 2000s: whereas the nominal outstanding value of CDS in 1998 was US$300 billion, by 2007 the figure was at US$62.2 trillion.

---

[3] Credit Default Swaps (CDS) are a private contract between two parties in which the buyer of protection agrees to pay premiums to a seller of protection over a set period of time. There are no regulatory capital requirements for the seller of protection. Credit Default Swaps (CDS) were originally created in the mid-1990s as a means to transfer credit exposure for commercial loans and to free up regulatory capital in commercial banks. By entering into CDS, a commercial bank shifted the risk of default to a third-party and this shifted risk did not count against their regulatory capital requirements. Speculation became rampant in the market such that sellers and buyer of CDS were no longer owners of the underlying asset (bond or loan), but were just "betting" on the possibility of a credit event of a specific asset.

Because most CDSs were traded over-the-counter, i.e. between the involved parties without going through a clearinghouse, no two CDSs were the same. Each CDS contract was highly customized to cater to the specific needs of the involved parties. Moreover, the knowledge on its mechanics in the market and how the involved parties could profit from it was not openly available and not standardized or codified, i.e. highly tacit. Any depository institutions that adopted CDSs would need to acquire/develop the necessary capabilities by participation. With such challenge of not having readily available recipe for routines and capabilities to utilize CDSs make them one of the ideal financial innovations to examine what firm adopts innovations and why.

4.2. Data

I use Call Reports and Thrift Regulatory Forms submitted quarterly to the FDIC, FDR, OCC, or OTS by all FDIC-insured depository institutions in the US between 1Q 2001 and 4Q 2011. Because it is mandatory for all FDIC-insured depository institutions to fill out these forms, the data is consistent and comparable both across time and firms. The reports contain detailed information including financial statements, firms' asset characteristics, their demographic and institutional characteristics, etc. The unusual amount of detailed information enables me to consider the drivers of differences in value of innovation post adoption. The data contains information on all depository institutions, which totals approximately 8,000 unique entities (fluctuating ±3% from year to year) in the US for 44 quarters, and provides more than 350,000 unique observations. This huge dataset enables me to consider banks that adopted innovation exclusively without any concerns over sample size. Additionally, having no sample bias increases my confidence in the results.

In some cases, I used the numbers originally reported in the initial dataset as variables, but also calculated different measures using the base data to better reflect the construct of interest. I coded the detailed information on demographic and institutional characteristics such as ownership structures (being a part of a bank holding company or a financial holding company), primary regulatory agency (Federal Reserve, FDIC, OCC, and former OTC), location (50 US states), size (total assets, number of offices, number of employees), etc. so as to be able to test whether they influence the relationship I was interested in. In this paper, among all the financial innovations available for adoption since 1999, I focus on one particular product that has received much attention during the financial crisis: Credit default swaps (CDS).

4.3. Variables

Dependent variables. I have a binary dependent variable for all hypotheses. The variable takes a value of 1 if an entity is engaged in the CDS market, 0 otherwise. ‘Engagement’ is defined as having a net position in the market that does not equal zero. It takes a value of 0 otherwise. I am indifferent to the manner of engagement: that is, I do not distinguish between guarantors and beneficiaries of CDSs. Event times are accurate to the nearest quarter; unfortunately, I do not have data at the monthly level. A bank remains at risk of adoption until its net position in the CDS market becomes non-zero, or it exits the data.

Independent variables. For Hypothesis 1a, I used the three-quarter running average of return on equity (ROE), which has been the favored measure of performance by banks. ROE is defined as the ratio of net income to total equity. For Hypothesis 1b, I used the three-quarter running average of net interest income, which is defined as the difference between interest and dividends earned on interest-bearing assets and interest paid to depositors and other creditors. Interest has traditionally been the main source of income for depository institutions, who primarily acted as intermediaries in the financial market.

It was well documented in the popular press that many financial institutions had manipulated their accounting records, taking advantage of regulatory grey areas. This is a potential concern for the analysis, as I cannot separate those firms whose numbers were manipulated from those whose were not. I try to address this problem by using the three-quarter running average instead of a specific quarter’s performance figure, so that a sudden change in performance due to changes in accounting practices does not drive my results. Also, since the data comes from mandatory regulatory filings, I expect the calculation methods, whether manipulated or not, to remain consistent over time. This, however, does not account for the inherent self-selection bias. I acknowledge this as one of the empirical limitations of this study. The use of three-quarter running average also ensures that seasonality (repeated unusual performance in a specific period compared to the rest of the year) does not affect the results.

For Hypothesis 2, I calculated the past instances of adopting an innovation with the following method. First, I created a dummy variable: 1 if a bank has inter-state operations, 0 otherwise. Second, I created a count variable of all non-traditional non-interest income activities banks adopted prior to adopting CDSs. These include income derived from investment banking, venture capital/private equity activities, servicing mortgages, credit cards, and other financial assets held by others, securitization transactions (other than servicing), and insurance-related activities. Then, the first and second sets of numbers were added.

For Hypothesis 3, I use the nominal value of incomes derived only from investment banking, venture capital/private equity activities, servicing, securitization transactions, and insurance-related activities. This number is a proxy for the feedback firms received on their previous adoption of innovations and the changes in the quality of relevant capabilities.

For Hypothesis 4a, I use a count variable to identify similar firms that had adopted CDSs. In the US, all depository institutions fall into one of the five categories by charter type, depending on their title (commercial bank vs. savings bank), geography of charter (federal vs. state), and membership of the Federal Reserve (yes or no): N, SM, NM, SB, and SA[4]. Within each category, I counted the cumulative number of depository institutions who had adopted CDSs by the previous quarter. For Hypothesis 4b, I used the distance between a bank and its FDIC regulatory offices[5], of which there are eight across the US (Boston, New York, Atlanta, Memphis, Chicago, Kansas City, Dallas, San Francisco), each dealing with geographically proximate states. I used the zip code of each bank and that of the respective FDIC office to get the shortest distance (in kilometers) between the two locations, and took natural logarithms for distributional properties.

Control variables. I include a variety of control variables pertaining to organizational and institutional characteristics that may affect both the dependent and independent variables.

---

[4] N stands for nationally (federally) chartered commercial banks that are also members of the Federal Reserve. SM stands for state-chartered commercial banks that are members of the Federal Reserve. NM stands for state-chartered commercial banks that are non-members of the Federal Reserve. SB stands for state-chartered savings bank. SA stands for federally- or state-chartered savings associations.

[5] In most of the cases, FDIC regional offices are located in the largest nearby city, which is also the place with the highest number of depository institutions. One exception is San Francisco: Los Angeles is bigger and also has more institutions. However, as I could not pinpoint a zip code that can represent the information centre of LA, I could not calculate the distance using LA as an alternative. However, I do not have any reason to believe that this change would have changed my results. The issue is, nonetheless, noted.

The variables are i) firm scope (binary: 1=generalist, 0=specialist), ii) the primary regulatory agency (four categories: Fed, FDIC, OCC, OTC), iii) a part of a bank/financial holding company (binary: 1=yes, 0=no), iv) ownership (binary: 1=stock, 0=non-stock), v) firm age, vi) firm size (natural logarithm of total assets), and vii) risk propensity (natural logarithm of net charge-offs to total assets). Because the Cox proportional hazard model fully controls for variables that vary over time but not across firms, I do not include year dummies or the overall economy of the US: Even if included, the effects would not be identified, since the variables will be dropped from the model. In addition, my data consists of depository institutions of US origin operating within the US: I therefore expect them to be exposed to the same macroeconomic conditions.

4.4. Methods

To test my hypotheses, I use the Cox proportional hazard model (Cox, 1972), which has been used in the longitudinal study of various events taking place such as foreign entry timing, venture formation, and geographical expansion. The semiparametric event history model accounts for both discrete events and continuous timescale data, allows time-dependent explanatory variables, performs stratified analyses to adjust for subset differences in a sample, and identifies both cross-sectional and longitudinal effects (Allinson, 1995). The model yields efficient estimates as compared to a parametric proportional hazards model even when the data come from the parametric model (Efron, 1977). Furthermore, it does not require any underlying distribution to be specified, being more general in nature. These properties make the model particularly suitable for my data.

The years leading up to the financial crisis (2001–2008) and its aftermath (2008–2011) are tested separately, using the censoring technique in Cox models (Allinson, 1995). The year 2008 was incorporated in both models, since this is when the most dramatic events of the financial crisis took place (for example, the fire sale of Bear Stearns to JPMorgan Chase, the collapse of Lehman Brothers, the bailout of AIG, and the takeover of Merrill Lynch by the Bank of America). This censoring allows me to test Hypothesis 5. To account for differences in political, economic, or social conditions within each state, I ran a stratified model with states as strata. To get more conservative results, I used robust standard errors clustered by each bank.

Finally, because there are ties (two or more subjects having the same event time) in the data set, I use the Breslow approximations to the partial log-likelihood.

Robustness checks. First, I used a different measure of past financial performance (net income) in testing H1a to ensure that the choice of variable does not affect the results. Second, I used a different measure of main source of income (total interest income) for H1b so that the potential role played by operational efficiency is eliminated: net interest income is total interest income minus total interest expenses. For these two robustness checks, I used the three-quarter running average to maintain consistency in analysis and to address the potential concerns mentioned above regarding the manipulation of accounting. For both H1a and H1b, I used the difference between a firm's ROE or net interest income and the average of that measure across its peers in the past quarter. This was to ensure that different sources of feedback based on aspiration level (historic vs. industry average) do not affect the results. Peers were defined as depository institutions in the same state with the same charter type. I took the natural logarithm of the numbers for the distributional properties after treating the negative numbers. The results are reported in the Appendices and discussed briefly below.

5. Results

5.1. Results

Table 1 provides descriptive statistics for the variables used in the analysis. Table 2 reports analysis from the entire sample period (1Q 2001–4Q 2011) and Tables 3 and 4 report results from the pre- (1Q 2001–4Q 2008) and post-crisis (1Q 2008–4Q 2011) periods, respectively. The results show that different aspects of past performance have varying effects on the likelihood and speed of adoption. The results also illustrate that the changed external environment can negate the effects observed in the period before the change.

PLACE TABLE 1 ABOUT HERE.

Model 1 in each table has only control variables and gives a set of results that are also consistent in later specifications.

Feedback on past financial performance. H1a hypothesized that feedback on past financial performance will negatively affect both the likelihood and speed of adopting innovations. Model 2 in each table contains analyses that test this hypothesis. The effect of the average of past three quarters' return on equity (ROE) on the likelihood and speed of adopting CDSs is in the expected direction. In both the entire sample and the pre-crisis subsample, the signs of coefficients are negative, as expected, and are statistically significant ($p<0.05$ and $p<0.10$ respectively). Thus, H1a is supported. However, in the post-crisis subsample, although the sign of the coefficient is in expected direction, it is not statistically significant. The loss of significance in the post-crisis subsample shows that feedback's effect on innovation adoption is negligible, consistent with H5.

H1b hypothesized that positive feedback on a firm's main source of income will reduce the likelihood and speed of adopting innovations. Model 3 in each table contains analyses that test this hypothesis. Although the signs of coefficients in all samples are in the expected direction (negative), none of them are statistically significant. Therefore, H1b is not supported.

Dynamic capabilities from past experience. H2 hypothesized that having dynamic capabilities developed from past experience in adopting innovations will positively affect the likelihood and speed of adopting innovations. Model 4 in each table contains analyses that test this hypothesis. In both the entire sample and the pre-crisis subsample, the sign of the coefficients is in the expected direction (positive) and the coefficients are statistically significant ($p<0.001$). Thus, H2 is supported. In the post-crisis subsample, however, the coefficient is not significant although its sign is in expected direction. It seems the effect of having dynamic capabilities matters less (or not at all) when the external environment changes for the worse, supporting H5.

Feedback and dynamic capabilities. H3 hypothesized that positive feedback on previously adopted innovations will positively affect the likelihood and speed of adopting innovations. Model 5 in each table contains analyses that test this hypothesis. Similar to the results obtained for H2, the hypothesis is supported in the entire sample and the pre-crisis subsample with the expected sign (positive) and statistical significance ($p<0.01$). Therefore, H3 is supported. In the post-crisis subsample, however, the coefficient is statistically insignificant and its sign is not in the expected direction, consistent with H5.

PLACE TABLES 2, 3, AND 4 ABOUT HERE.

Effect of the external environment. H4a hypothesized that the more similar firms adopt innovations, the more likely it is a focal firm will expedite its adoption. Model 6 in each table contains analyses that test this hypothesis. In all samples, the sign of the coefficients is positive, as expected, but the coefficient in the post-crisis sample lacks statistical significance. Thus, both H4a and H5 are supported.

H4b hypothesized that geographical proximity will have a positive effect on the likelihood and speed of adopting innovations. Model 7 in each table contains analyses that test this hypothesis. In all samples, the sign of coefficients is negative, as expected, but the coefficient in the post-crisis sample, once again, lacks statistical significance. Therefore, both H4b and H5 are supported.

Full models. Model 8 in each table enters all independent variables to see if the effects can be parsed out. In the entire sample, every independent variable maintains the same sign as in restricted models but only the variables for H1b and H4a are statistically significant. Consequently, both Wald Chi-square and Log pseudolikelihood are considerably smaller compared to the restricted models. In the pre-crisis subsample, the variables also maintain the signs exhibited in restricted models. In this case, however, only the variables for H3 and H4a remain statistically significant, and weakly so ($p<0.10$). In the post-crisis subsample, the sign of one variable (feedback and dynamic capabilities for H3) changes from negative to positive. Moreover, it becomes significant in the full model ($p<0.05$). Although none of the other independent variables are significant in restricted models, variables for H1a and H1b also turn significant in the full model.

5.2. Robustness checks

Additional models were also estimated and the results are reported in the Appendices. First, H1a and H1b were analyzed using a different benchmark: whereas Models 2 and 3 in Tables 2 to 4 used historical performance as a measure of feedback, Models 1 and 2 in Appendices 1–3 used the industry average in the previous period (quarter) as a measure of feedback. The results are not obtained for ROE due to collinearity (entire sample) or flat regions resulting in missing likelihood (pre- and post-crisis subsamples). For the main source of income, the results are identical to what was reported in Tables 2 to 4: Net interest income does not inhibit the likelihood and speed of adopting innovations. Model 5 reports the result of full models where three substitute independent variables were entered.

Second, H1a was analyzed using a different measure of financial performance – namely, net income (Model 3). Just as with ROE, the sign of coefficients is in the expected direction (negative) and statistically significant, both for the entire sample and the pre-crisis subsample. In the post-crisis subsample, not only is the sign of the coefficient in the opposite direction, but the coefficient also lacks statistical significance. Similarly, H1b was analyzed using total interest income instead of net interest income (Model 4). In all samples, the signs of the coefficient are in the opposite direction to what was expected (positive). Moreover, the coefficients in the entire sample and pre-crisis subsample are statistically significant ($p<0.10$ and $p<0.05$ respectively). The results show that H1b is not supported regardless of which measure is used. Model 6 in Appendices 1–3 reports a full model with the above two substitutions.

6. Discussion

The findings suggest there is a systematic connection between different aspects of past performance and the adoption of innovations. Having dynamic capabilities developed from adopting innovations in the past played a far more important role than feedback from past financial performance. The differences in pre- and post-crisis numbers confirm that the various drivers of innovation adoption based on past performance are contingent on the external environment.

First, the findings indicate that feedback from financial performance has a fairly robust relationship with the decision on whether and when to adopt innovation. In line with the behavioral theory of the firm (Cyert & March, 1960) and evolutionary economics (Nelson & Winter, 1982), I find that positive feedback on past financial firm performance decreases the likelihood and speed of adopting CDSs. However, I also find that positive feedback on the main source of income, which is directly related to each firm's most superior capability, does not have any effect on whether or when firms adopt CDSs. This suggests that, at least in this paper's setting, firms are not hindered by competency traps (Levitt & March, 1988) or organizational inertia (Hannan & Freeman, 1984) when they consider adopting innovations. In other words, firms who must react quickly to short-term negative feedback on financial performance are more likely to speedily adopt CDSs. This suggests that firms react differently to different feedback indicators, highlighting the importance of recognizing those that actually affect firm behavior such as adopting innovations.

Second, the analysis also indicates that firms rely heavily on the capabilities developed from their past experience and the feedback they received on using those capabilities when considering whether and when to adopt an innovation. I find that firms with superior dynamic capabilities, proxied by the number of instances of adopting innovations or new practices, are likely to quickly adopt CDSs. Moreover, firms that have successfully derived financial benefit from using those capabilities, regardless of the number of instances, are likely to quickly adopt CDSs. In terms of the size of the coefficients, the interaction between feedback and dynamic capabilities far outweighed feedback on either of the financial performance measures analyzed, implying that firms' capabilities loom larger than their financial performance when they think about adopting innovations. This may be a story of experiential learning (Zollo & Winter, 2003) or having dormant, but redeployable (dynamic) capabilities better suited for successful adoption (Cohen & Levinthal, 1990; Helfat & Peteraf, 2003).

Third, I find that the external economic environment plays a major role in determining whether or not firms heed their past performance. Using the financial crisis as a catalyst that disrupted the economic environment where banks operate, I show that the factors that would have promoted or inhibited adoption of CDSs before the crisis lost their effect after it. This finding seems intuitive and is consistent with the argument that emphasizes the 'fit' between environment and firm behavior, i.e. firms need to change their strategies and behavior when their environment changes. In line with this argument, my results shed light on the volatility of factors that influence behavioral change in firms. Recognizing that firms rely on different 'cues' to change their behavior or adopt innovations depending on the broader economic condition, and identifying those cues, can deepen our understanding of the dynamics of behavioral change.

Collectively, this paper shows that the adoption of an innovation, and its speed, is affected by more than just financial performance or institutional pressure that promotes mimetic behavior (Greve, 2011). Rather, feedback on financial performance, having dynamic capabilities developed through past experience, and positive feedback from using such capabilities come together to dictate whether and when firms adopt innovations. The inclusion of institutional factors did not negate the effects mentioned above. Higher numbers of adopters who share similar characteristics (in terms of location and bank charter) and geographical proximity to a dense population of firms, regardless of those firms' rate of adoption, are shown to expedite the adoption of CDSs. Moreover, the change in the external environment changed the effect of the abovementioned drivers. This highlights that various aspects of firms' past performance matter, not only in terms of individual firms' competitiveness, but also in terms of how they behave when faced with a choice such as adopting innovations. It implies that because past decisions and experience lead to firm heterogeneity over time through changes in firm routines and capabilities (Jacobides & Winter, 2012), an exclusive set of firms that meet all the criteria to adopt innovations as soon as they are available can emerge over time. This mean that firms embrace and integrated innovations in a particular order, and each firm's place in this sequence affects its performance (Pisano *et al.*, 2001). Early adopters' fortunes can be continuously improved through superior capabilities (e.g. absorptive capacity and dynamic capabilities) and positive feedback emanating from the experience. Meanwhile, late adopters may suffer from the vicious cycle of lacking capabilities leading to negative feedback, depriving them of opportunities to improve and develop the necessary capabilities. Repeated over time, this may lead to a Matthew effect (Merton, 1968) in who benefits the most from innovations.

The contribution of this study lies in identifying different drivers of innovation adoption that have been previously underexplored – namely, feedback on financial performance and the possession of dynamic capabilities developed through past experience.

This research deepens our understanding of feedback. While we know a lot about the effect of feedback on firms' propensity to take risks (Levinthal & March, 1993), lapse into active inertia (Sull, 2005) or fall prey to competency traps (Levitt & March, 1988) in the short run, and firms' tendency to 'satisfice' at a certain level (Nelson & Winter, 1982; Simon, 1962), we have only a vague account of positive feedback's role on behavioral change. The explicit focus on different sources of feedback as drivers of behavioral change provides a counterintuitive example of how the lack of an imminent problem to solve can motivate firms to explore by adopting innovations.

Second, this paper sheds light on the role of dynamic capabilities (Teece *et al.*, 1997). The ability to review, renew, and reconfigure existing capabilities to suit the changing external environment enables firms to adopt innovations. Moreover, their success in doing so, accumulated over time, leads to further chances to develop dynamic capabilities and expedite the adoption of new opportunities such as innovations. By focusing on the role of dynamic capabilities in the adoption of innovations, I provide a concrete example of how dynamic capabilities can help firms sustain their competitive advantage in a fast-changing environment.

Third, this study complements work on diffusion of innovation. It builds on existing literature that has examined the phenomenon with more of a sociological perspective, which mainly looked at the speed at which innovations spread across a population of firms (Geroski, 2000; Gruber, 2001), why they spread (DiMaggio & Powell, 1983; Tolbert & Zucker, 1983), and what happens when firms refuse to take place in diffusion (Abrahamson, 1991). Focusing explicitly on the role of past performance and its various aspects, I provide an additional angle, besides institutional factors, from which to study the diffusion of innovation.

In addition, I help to expand the literature by looking at a less-studied type of innovation. Although there are many types of innovation, very little empirical work has studied it in a non-technological setting (see Myatt & Levinthal, 1995; Pennings & Harianto, 1995; Pisano et al., 2001 for exceptions). By looking at the adoption of innovation in the realm of financial services, I complement the extensive existing literature on technology diffusion and technology-related product diffusion. However, this also opens up the possibility of limiting the generalizability of the findings. Unlike many technological innovations, CDSs did not require massive initial financial investment. Capital constraints being one of the factors that affect the behavior of firms (e.g. endogenous sunk cost à la Sutton (1991)), this characteristic may have played an important role in whether or not depository institutions adopted CDSs. It would be an interesting avenue for further research to compare and contrast how similar or dissimilar adoption patterns emerge with regards to other financial innovations or innovations that do not require much capital at the beginning.

Lastly, this paper has practical implications for managers and policy makers. My findings clearly show how disappointing financial performance and the richness of past experience drive the adoption of innovation. Given that banks did not know who had entered the CDS market apart from the large investment banks, the results of this paper can help managers at banks predict who might become their competitors when an innovation becomes available. Also, the findings can help policymakers devise regulatory environments that do not hinder competition with regards to new financial innovations among market participants, but still safeguard systemic stability. Knowing who is likely to adopt innovations, when, and for what reasons will help both practitioners and policymakers make better, more informed decisions.

This paper has limitations pertaining to the data set. Because I used the reports filed with the FDIC, only depository institutions are included in my data. In other words, I do not have data on investment banks, who were more actively and extensively involved in the CDS market. There was no easy answer to remedy this problem with publicly available accounting data, because they are reported at the consolidated level. My field interviews with practitioners also confirmed that information on the involvement of large investment banks in the CDS market is not available to the general public. Despite the practical impossibility of addressing this problem, the shortcoming must be noted. Similarly, my data was limited to the US institutions, leaving aside the possibility that foreign depository institutions could be active in the CDS market. It would be a valuable exercise to see if the findings of this paper on the US can be replicated in another country such as the UK.

Additionally, I have only focused on the drivers of adoption, leaving aside the implications of adoption. If different aspects of past performance affect who adopts innovations and when, it is also possible that this underlying firm heterogeneity, both in terms of financial performance and development of relevant capabilities, can affect who benefits from the adopted innovation. It might also be that while some firms benefit from an innovation, other firms are harmed by it. The speed of adoption can also play a role. An exploration of how adopters fare after they adopt an innovation is a promising topic for future research.

Third, this study has looked at a setting where abundant anecdotal evidence allowed for theory development and testing: the deregulation of US banking and the financial crisis that shed light on the fate of banks that adopted various financial innovations, exemplified by CDSs. I recognize that the generalizability of my findings is questionable, especially in terms of technology-related innovation and sectors where firm interdependencies are not as dramatic as they are in the banking sector. Because there is no substantial up-front fixed cost associated with adoption of CDSs, the relationships discussed in this paper may not be wholly applied or even not applicable at all to innovations in manufacturing sector, for example. It is an interesting avenue of research, but well outside the scope of this paper.

Table 1. Descriptive statistics

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 CDS adoption (binary)	1													
2 3Q mean_ROE	-0.005	1												
3 3Q mean_NetIncome	-0.180	0.014	1											
4 No. of past exploration	0.707	-0.001	-0.199	1										
5 Usage of past exploration	0.059	0.002	0.028	0.068	1									
6 Adoption by similar firms	0.698	-0.003	-0.129	0.493	0.028	1								
7 Geographical proximity	-0.070	-0.002	0.053	-0.086	-0.007	-0.027	1							
8 Ownership type (binary)	-0.467	0.006	0.167	-0.331	0.007	-0.364	0.109	1						
9 Regulatory agent	0.513	-0.006	0.055	0.266	0.035	0.390	0.055	-0.150	1					
10 Part of bank holding co. (binary)	-0.315	0.005	-0.112	-0.007	-0.010	-0.254	-0.010	0.308	-0.491	1				
11 Firm scope (binary)	-0.059	-0.004	-0.075	-0.023	-0.013	-0.051	0.045	0.041	-0.107	0.187	1			
12 Firm age	-0.069	-0.004	0.049	-0.104	-0.064	-0.012	0.090	-0.068	0.212	-0.307	-0.056	1		
13 Ln (total assets)	0.161	0.008	-0.088	0.471	0.027	0.068	-0.190	-0.012	0.092	0.060	-0.100	-0.017	1	
14 Ln (risk propensity)	-0.016	-0.026	0.174	0.023	0.075	-0.024	-0.009	0.059	-0.006	0.030	0.050	-0.039	0.104	1
Obs	372969	349457	349495	372969	372969	372969	372969	372969	372969	372969	372969	363376	372969	372969
Mean	0.077	0.053	0.025	1.387	0.002	1.495	8.932	0.940	2.104	0.606	0.144	33529	11.684	0.082
S. D.	0.266	1.271	0.008	1.466	0.020	6.363	0.819	0.237	1.017	0.489	0.351	11729	1.193	0.004

Table 2. Hypothesis testing: Entire sample (1Q 2001–4Q 2011)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
overall firm performance		-0.135*						-0.331
		(0.07)						(0.22)
main source of income			-26.591					-33.380+
			(18.60)					(19.88)
number of past experience				0.609***				0.046
				(0.03)				(0.13)
usage of past experience					1.878**			1.553
					(0.70)			(2.90)
adoption by similar firms						0.005***		0.821*
						(0.00)		(0.87)
geographic distance							-0.080**	-0.121
							(0.03)	(0.09)
ownership	-0.351***	-0.638	-0.69	-0.307***	-0.363***	-0.343***	-0.352***	0.102
	(0.04)	(0.62)	(0.59)	(0.04)	(0.04)	(0.04)	(0.04)	(0.94)
regulator	1.869***	0.726***	0.773***	1.101***	1.864***	1.837***	1.871***	-0.055
	(0.12)	(0.18)	(0.17)	(0.10)	(0.12)	(0.12)	(0.12)	(0.16)
part of bank holding company	-1.134***	-1.302***	-1.177***	-0.593***	-1.134***	-1.106***	-1.133***	-0.604
	(0.13)	(0.33)	(0.34)	(0.11)	(0.13)	(0.12)	(0.13)	(0.40)
firm_scope	-0.466***	-0.526	-0.543	-0.217*	-0.463***	-0.456***	-0.454***	-0.474
	(0.10)	(0.38)	(0.38)	(0.10)	(0.10)	(0.10)	(0.10)	(0.40)
firm_age	4.05E-07	-7.23E-06	-6.53E-06	1.39E-06	1.03E-06	3.58E-07	1.33E-06	-2.24E-06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln_asset	0.249***	0.878***	0.825***	0.049*	0.252***	0.246***	0.239***	0.827***
	(0.02)	(0.07)	(0.07)	(0.02)	(0.02)	(0.02)	(0.02)	(0.13)
ln_risk_propensity	4.249	-25.672	-9.163	3.641	2.468	6.353	5.099	3.552
	(10.56)	(40.11)	(37.41)	(8.31)	(10.78)	(9.85)	(10.54)	(22.56)
Log pseudolikelihood	-3295.63	-295.75	-301.19	-3188.07	-2193.81	-3293.73	-3293.74	-237.99
Wald_Chi2	1746.69***	199.98***	188.81***	2245.05***	1754.48***	1918.79***	1726.30***	187.14***
N	334437	320853	320865	334437	334437	334437	334437	320853

Robust standard errors (clustered by firm_id) in parentheses.
+ (p<0.10), * (p<0.05), ** (p<0.01), *** (p<0.001)

Table 3. Hypothesis testing: Pre-crisis sample (1Q 2001–4Q 2008)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
overall firm performance		-0.118						-0.338
		(0.07)						(0.28)
main source of income			-18.086					-19.904
			(19.55)					(20.63)
number of past experience				0.598***				0.057
				(0.03)				(0.13)
usage of past experience					1.833**			3.677+
					(0.69)			(2.23)
adoption by similar firms						0.004***		0.845+
						(0.00)		(0.47)
geographic distance							-0.074**	-0.073
							(0.03)	(0.11)
ownership	-0.320***	-0.662	-0.716	-0.287***	-0.332***	-0.313***	-0.321***	0.161
	(0.04)	(0.63)	(0.61)	(0.04)	(0.04)	(0.04)	(0.04)	(1.00)
regulator	1.925***	0.800***	0.843***	1.140***	1.919***	1.894***	1.926***	0.04
	(0.13)	(0.17)	(0.17)	(0.10)	(0.13)	(0.13)	(0.13)	(0.17)
part of bank holding company	-1.106***	-1.242***	-1.128***	-0.576***	-1.106***	-1.082***	-1.105***	-0.595
	(0.13)	(0.33)	(0.33)	(0.11)	(0.13)	(0.13)	(0.13)	(0.42)
firm_scope	-0.447***	-0.611	-0.629	-0.209*	-0.444***	-0.437***	-0.436***	(0.37)
	(0.10)	(0.40)	(0.40)	(0.10)	(0.10)	(0.10)	(0.10)	(0.40)
firm_age	5.57E-07	-7.46E-06	-6.95E-06	1.49E-06	1.19E-06	5.20E-07	1.40E-06	-2.52E-06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln_asset	0.230***	0.843***	0.795***	0.040*	0.234***	0.227***	0.221***	0.764***
	(0.02)	(0.08)	(0.08)	(0.02)	(0.02)	(0.03)	(0.02)	(0.14)
ln_risk_propensity	-1.357	-107.235**	-87.308*	-2.721	-3.276	0.731	-0.543	-65.631
	(10.08)	(39.69)	(42.26)	(7.06)	(10.28)	(9.47)	(10.10)	(48.11)
Log pseudolikelihood	-3253.25	-268.5	-274.32	-3153.35	-3251.51	-3251.65	-3251.69	-220.36
Wald_Chi2	1695.03***	158.60***	144.88***	2176.49***	1703.13***	1887.08***	1675.32***	156.54***
N	242227	229023	229035	242227	242227	242227	242227	229023

Robust standard errors (clustered by firm_id) in parentheses.
+ (p<0.10), * (p<0.05), ** (p<0.01), *** (p<0.001)

Table 4. Hypothesis testing: Post-crisis subsample (1Q 2008–4Q 2011)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
overall firm performance		-0.009						-0.008**
		(0.04)						(0.00)
main source of income			-71.116					-153.184*
			(54.56)					(70.50)
number of past experience				0.483				0.102
				(0.37)				(0.30)
usage of past experience					-7.614			7.217*
					(43.81)			(3.58)
adoption by similar firms						1.439		1.621
						(1.29)		(1.39)
geographic distance							-0.113	-0.252
							(0.22)	(0.24)
ownership	0.367	0.370	0.699	0.079	0.389	-1.178	0.491	-0.296
	(1.76)	(1.76)	(1.83)	(1.76)	(1.82)	(2.05)	(1.75)	(3.25)
regulator	0.653	0.651	0.535	0.528	0.654	-0.231	0.631	-0.688
	(0.45)	(0.45)	(0.56)	(0.39)	(0.44)	(0.43)	(0.45)	(0.66)
part of bank holding company	-3.373***	-3.362***	-3.227***	-3.467***	-3.370***	-3.473***	-3.368***	-3.109**
	(0.73)	(0.73)	(0.88)	(0.86)	(0.73)	(0.75)	(0.73)	(0.96)
firm_scope	-0.189	-0.184	-0.147	-0.351	-0.180	-11.812	-0.181	-10.934
	(1.04)	(1.04)	(1.07)	(0.92)	(1.04)	(12.68)	(1.04)	(14.60)
firm_age	-1.75E-05	-1.75E-05	-7.70E-06	-1.45E-05	-1.74E-05	-1.18E-05	-1.51E-05	-9.27E-06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln_asset	1.332***	1.330***	1.326***	1.030***	1.337***	1.696***	1.289***	1.806**
	(0.17)	(0.17)	(0.21)	(0.31)	(0.19)	(0.23)	(0.21)	(0.53)
ln_risk_propensity	5.712	5.448	12.389	16.128	6.487	-16.761	10.193	4.822
	(41.16)	(41.33)	(43.98)	(34.42)	(42.17)	(70.62)	(41.23)	(71.99)
Log pseudolikelihood	-34.97	-34.94	-33.7	-33.67	-34.96	-23.68	-34.87	-19.58
Wald_Chi2	104.63***	104.83***	129.65***	138.30***	104.59***	119.73***	158.44***	126.29***
N	130124	129589	129589	130124	130124	130124	130124	129589

Robust standard errors (clustered by firm_id) in parentheses.
+ (p<0.10), * (p<0.05), ** (p<0.01), *** (p<0.001)

Appendix 1. Robustness checks: Entire sample (1Q 2001–4Q 2011)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	ln_relative_roe	ln_relative_nim	netinc_3q_mean	intinc_3q_mean	Full model with M1/M2	Full model with M3/M4
overall firm performance	41.664		-26.278		27.99545	-21.545*
	(38.32)		(17.36)		(40.41)	(9.11)
main source of income		7.161***		3.45E-07	5.326***	2.95E-07
		(1.55)		(0.00)	(1.27)	(0.00)
number of past experience					0.598***	0.04
					(0.03)	(0.12)
usage of past experience					1.415***	2.825
					(0.33)	(4.31)
adoption by similar firms					0.002	0.823*
					(0.00)	(0.37)
geographic distance					-0.084**	-0.08
					(0.03)	(0.10)
ownership	-0.353***	-0.328***	-0.595	-0.696	-0.301***	0.112
	(0.04)	(0.04)	(0.61)	(0.61)	(0.04)	(0.96)
regulator	1.857***	1.893***	0.741***	0.759***	1.105***	-0.063
	(0.12)	(0.12)	(0.17)	(0.17)	(0.10)	(0.17)
part of bank holding company	-1.147***	-1.188***	-1.341***	-1.210***	-0.667***	-0.657
	(0.13)	(0.13)	(0.33)	(0.33)	(0.12)	(0.39)
firm_scope	-0.468***	-0.446***	(0.48)	(0.53)	-0.196*	-0.425
	(0.10)	(0.10)	(0.37)	(0.37)	(0.09)	(0.40)
firm_age	3.96E-07	-4.16E-07	-5.64E-06	-7.93E-06 rm_age	1.72e-06	-3.37E-06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln_asset	0.251***	0.218***	0.894***	0.768***	0.023	0.802***
	(0.02)	(0.02)	(0.07)	(0.10)	(0.02)	(0.15)
ln_risk_propensity	4.032	-1.492	-35.322	-33.653	-1.969	-22.15
	(10.56)	(10.85)	(35.76)	(42.45)	(8.97)	(34.09)
Log pseudolikelihood	-3292.88	-3287.59	-290.31	-301.23	-3178.45	-235.94
Wald_Chi2	1753.93***	1681.32***	213.52***	219.00***	2211.72***	206.13***
N	334427	334437	320853	320865	334427	320853

Robust standard errors (clustered by firm_id) in parentheses.
+ (p<0.10), * (p<0.05), ** (p<0.01), *** (p<0.001)

Appendix 2. Robustness checks: Pre-crisis subsample (1Q 2001–4Q 2008)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	ln_relative_roe	ln_relative_nim	netinc_3q_mean	intinc_3q_mean	Full model with M1/M2	Full model with M3/M4
overall firm performance	omitted due to		-25.518		ommitted due to	-22.032*
	collinearity		(17.31)		collinearity	(9.38)
main source of income		7.642***		5.07e-07*	5.703***	4.37E-07
		(1.55)		(0.00)	(1.27)	(0.00)
number of past experience					0.587***	0.06
					(0.03)	(0.14)
usage of past experience					1.404***	5.507*
					(0.33)	(2.27)
adoption by similar firms					0.001	0.834
					(0.00)	(0.47)
geographic distance					-0.077**	-0.013
					(0.03)	(0.13)
ownership	-0.322***	-0.295***	-0.637	-0.732	-0.280***	0.162
	(0.04)	(0.04)	(0.62)	(0.62)	(0.04)	(1.03)
regulator	1.912***	1.951***	0.818***	0.834***	1.147***	0.041
	(0.13)	(0.13)	(0.17)	(0.17)	(0.10)	(0.17)
part of bank holding company	-1.120***	-1.162***	-1.275***	-1.142***	-0.653***	-0.628
	(0.13)	(0.14)	(0.34)	(0.33)	(0.12)	(0.41)
firm_scope	-0.447***	-0.425***	-0.570	-0.615	-0.186*	-0.336
	(0.10)	(0.10)	(0.40)	(0.40)	(0.09)	(0.41)
firm_age	5.47E-07	-2.73E-07	-6.16E-06	-8.94E-06	1.73E-06	-4.81E-06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln_asset	0.232***	0.199***	0.860***	0.700***	0.014	0.699***
	(0.02)	(0.02)	(0.08)	(0.10)	(0.02)	(0.16)
ln_risk_propensity	-1.515	-8.690	-106.557**	-138.675**	-10.272	-113.402
	(10.13)	(10.10)	(41.09)	(47.96)	(7.78)	(60.88)
Log pseudolikelihood	-3250.66	-3244.58	-263.71	-272.68	-3143.82	-216.68
Wald_Chi2	1702.46***	1622.25***	163.67***	185.98***	2135.42***	172.91***
N	242217	242227	229023	229035	242217	229023

Robust standard errors (clustered by firm_id) in parentheses.
+ (p<0.10), * (p<0.05), ** (p<0.01), *** (p<0.001)

Appendix 3. Robustness checks: Post-crisis subsample (1Q 2008–4Q 2011)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	ln_relative_roe	ln_relative_nim	netinc_3q_mean	intinc_3q_mean	Full model with M1/M2	Full model with M3/M4
overall firm performance			9.821			43.022*
			(23.07)			(19.82)
main source of income		6.385		6.56E-08		-8.52E-09
		(23.39)		(0.00)		(0.00)
number of past experience						0.080
						(0.36)
usage of past experience						-118.294
						(131.48)
adoption by similar firms						1.82
						(1.74)
geographic distance						-0.484+
						(0.26)
ownership		0.290	0.306	0.340		-0.914
		(1.97)	(1.81)	(1.90)		(2.37)
regulator	flat region:	0.664	0.669	0.656	flat region: missing LL	-0.447
	missing LL	(0.47)	(0.45)	(0.46)		(0.48)
part of bank holding company		-3.367***	-3.401***	-3.359***		-3.892***
		(0.72)	(0.69)	(0.72)		(1.00)
firm_scope		-0.205	-0.208	-0.192		-15.229
		(1.04)	(1.04)	(1.03)		(17.36)
firm_age		-1.97E-05	-1.82E-05	-1.83E-05		-1.45E-05
		(0.00)	(0.00)	(0.00)		(0.00)
ln_asset		1.298***	1.338***	1.312***		1.807***
		(0.26)	(0.17)	(0.27)		(0.50)
ln_risk_propensity		5.255	14.080	5.570		32.15
		(41.95)	(54.26)	(41.51)		(77.26)
Log pseudolikelihood		-34.94	-34.91	-34.94		-21.97
Wald_Chi2		117.10***	103.32***	124.65***		158.10***
N		130124	129589	129589		129589

Robust standard errors (clustered by firm_id) in parentheses.
+ (p<0.10), * (p<0.05), ** (p<0.01), *** (p<0.001)

CONCLUSION

In a world where the fate of firms has become more volatile and unpredictable and where profit/value emerges, disappears, and migrates rapidly in ever-changing business ecosystems, a study of the actual drivers of value capture is more than a response to a major question in strategy; it is a real issue with significant implications for practitioners. On the other hand, the fact that research on innovations has not explored much beyond the value and diffusion of technology- and manufacturing-related contexts leaves the generalizability of existing theories in question. This creates a challenge and an opportunity to explore the mechanisms of existing theories and develop new ones, informed by the phenomena observed in the real world.

The findings of the first chapter support the thesis that kingpins (i.e. dominant firms in terms of market capitalization, which proxies for firm capabilities) can help shape the industry architecture of their sectors, benefitting not only themselves, but also the rest of the firms within their vertical segments. Thus, heterogeneity and the power of kingpins are associated with the creation of bottlenecks and the patterns of profit migration in a business ecosystem. We also find that kingpins, useful as they may be for the segment in the short run (lifting 'all boats' up, as it were), accentuate the inequality in their segment over time, making them a double-edge sword. The paper thus not only challenges the "folklore" of market concentration as a driver of value, but also offers an alternative consistent with the data.

In the second chapter, I find that firm heterogeneity, through path-dependent capabilities and routine development and provision of information, plays an important role in determining the value of innovation. Some capabilities yield higher value from the innovation, but superiority in some types of capabilities/attributes can actually reduce the value of innovation. This demonstrates that heterogeneity among firms matters, not only in understanding the competitive dynamics of firms, but also in explaining why some firms benefit more from the same innovation than others. For example, the number of past explorations was a predictor of decrease in the value of innovation, while past performance in core activity was a predictor of increase in the value of innovation. Inasmuch as a firm can use its capabilities to maximize the upsides of such attributes, the value of innovation for the focal firm can exceed that of other adopters even when the innovation is open, i.e. available for any firms to adopt.

Finally, the results of last chapter show that the adoption of an innovation, and its speed, is affected by more than just financial performance or institutional pressure that promotes mimetic behavior (Greve, 2011). Rather, feedback on financial performance, having dynamic capabilities developed through past experience, and positive feedback from using such capabilities come together to dictate whether and when firms adopt innovations. The inclusion of institutional factors did not negate the effects mentioned above. Moreover, the change in the external environment changed the effect of the abovementioned drivers. This highlights that various aspects of firms' past performance matter, not only in terms of individual firms' competitiveness, but also in terms of how they behave when faced with a choice such as adopting innovations. It implies that because past decisions and experience lead to firm heterogeneity over time through changes in firm routines and capabilities (Jacobides & Winter, 2012), an exclusive set of firms that meet all the criteria to adopt innovations as soon as they are available can emerge over time. This mean that firms embrace and integrated innovations in a particular order, and each firm's place in this sequence affects its performance (Pisano *et al.*, 2001). Repeated over time, this may lead to a Matthew effect (Merton, 1968) in who benefits the most from innovations.

With this thesis, I tried to offer novel explanations, taking firm heterogeneity as the main driver of the outcomes to phenomena observed in the real world. In the first chapter, I empirically demonstrated that existing theory of value capture does not fully explain the value migration in a sector and offered an alternative explanation that is in line with the evidence. By taking inspiration from the recent financial crisis and the discussions on financial innovations, I expanded the literature on innovation both in terms of context and theory. I contribute to the diversifying of settings in which innovations are studied by looking at financial innovations (CDSs). In addition, I also offer novel explanations as to why some firms financially benefit from adopting an innovation while others lose and how differences in past experience affects the likelihood and speed of adopting an innovation. My goal in all three papers was to find phenomena in the real world that is theoretically worth studying and managerially relevant, explore the explanatory power of existing theories in those phenomena, build a new theory, and offer insights that can help managers in the real world.

While it is often said that there are tradeoffs between managerial relevance (usefulness to practitioners) and theoretical and analytical rigor (academic contribution), this is clearly not the case in the study of dynamics of value migration or the antecedents and consequences of adopting an innovation. The on-going tug of war among Apple, Samsung, Google, and Microsoft illustrates that value migration is an important part of strategy dynamics and profit distribution. Similarly, the continued discussion and efforts to understand and prevent another near-meltdown of the financial services industry by setting up eligibility for certain *modus operandi* and standardization of financial innovations highlight how firm behavior towards innovations, driven mainly by 'cues' emanating from the past, can wreak havoc to the entire sector.

In sum, this thesis, by focusing on a core set of questions which both provide a new theoretical perspective and look at fascinating, little understood phenomena, tried to better understand the various roles of firm heterogeneity. With the constant evolution in the industry architecture of various sectors such as telecommunications and pharmaceuticals and the ever-increasing number of innovations that firms can potentially adopt, the topics considered in this thesis not only belong to the forefront of research , but they will also grow in importance to practitioners.

REFERENCES

Abernathy WJ, Utterback JM. 1978. Patterns of innovation in technology. *Technology Review* **80**(7): 40-47.

Abrahamson, E. 1991. Managerial fads and fashions: The diffusion and rejection of innovations. *Academy of Management Review* **16**: 586-612.

Abrahamson E, Rosenkopf L. 1997. Social network effects on the extent of innovation diffusion: A computer simulation. *Organization Science* **8**: 289-309.

Adner R. 2012. *The Wide Lens: A New Strategy for Innovation*. Portfolio/Penguin: London.

Ahuja G, Katila R. 2001. Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal* **22**(3): 197-220.

Argote L. 1999. *Organizational Learning: Creating, Retaining, and Transferring Knowledge*. Kluwer Academic Publishers: Norwell, MA.

Arthur WB. 1989. Competing technologies, increasing returns, and lock-in by historical events. *The Economic Journal* **99**(394): 116-131.

Audretsch DB. 1995. *Innovation and Industry Evolution*. The MIT Press, Boston, MA.

Bain JS. 1951. Relation of profit rate to industry concentration: American manufacturing, 1936-1940. *Quarterly Journal of Economics* **65**(3): 293-324.

Baldwin CY, Clark KB. 1997. Managing in an age of modularity. *Harvard Business Review* **75**(5): 84-93.

Baldwin CY, Clark KB. 2000. *Design Rules: The Power of Modularity*. The MIT Press: Boston, MA.

Baldwin CY, Jacobides MG, Dizaji R. 2006. From the Structure of the Value Chain to the Strategic Dynamics of Industry Sectors. *Academy of Management Annual Meeting 2006*. Available at http://www.people.hbs.edu/cbaldwin/DR2/JBDIndustryArchitectureCYB.pdf

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

Baum JA, Calabrese T & Silverman BS. 2000. Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology. *Strategic Management Journal* **21**(3): 267-294.

Beckman CM, Haunschild PR. 2002. Network learning: The effects of partners' heterogeneity of experience on corporate acquisitions. *Administrative Science Quarterly* **47**(1), 92-124.

Bikhchandani S, Hirschleifer D & Welch I. 1998. Learning from the behavior of others: Conformity, fads, and informational cascades. *Journal of Economic Perspectives* **12**: 151-170.

Brandenburger AM, Stuart HW, Jr. 1996. Value-based business strategy. *Journal of Economics and Management Strategy* **5**(1): 5-24.

Bresnahan T, Greenstein S. 1999. Technological Competition and the Structure of the Computing Industry. *Journal of Industrial Economics* **47**: 1-40.

Bureau of Economic Analysis US. Gross Domestic Product (GDP) by Industry, Vol. 2009.

Christensen CM. 1997. *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail*. Harvard Business Press: Boston, MA.

Cohen WM, Levinthal DA. 1990. Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly* **35**(1): 128-152.

Cornett MM, Mehran H & Tehranian H. 1998. Are financial markets overly optimistic about the prospects of firms that issue equity? Evidence from voluntary versus involuntary equity issuances by banks. *Journal of Finance* **53**(6): 2139-2159.

Cornett MM, Ors E & Tehranian H. 2002. Bank performance around the introduction of a Section 20 subsidiary. *Journal of Finance* **57**(1): 501-521.

Cournot AA. 1838. *Cournot Recherches sur les principes mathématiques de la théorie des richesses* Hachette: Paris.

Cyert RM, March JG. 1963. *A Behavioral Theory of the Firm*. Prentice-Hall Inc.: Englewood Cliffs, NJ.

Damanpour F. 1991. Organizational innovation: A meta-analysis of effects of determinants and moderators. *Academy of Management Journal* **34**(3): 555-590.

Danneels E. 2002. The Dynamics of Product Innovation and Firm Competences. *Strategic Management Journal* **23**(12): 1095-1121.

Davis GF, Greve HR. 1997. Corporate elite networks and governance changes in the 1980s. *American Journal of Sociology* **103**(1): 1-37.

Denrell J, Fang C & Winter SG. 2003. The economics of strategic opportunity. *Strategic Management Journal* **24**(10): 977-990.

Dewar RD, Dutton JE. 1986. The adoption of radical and incremental innovations: an empirical analysis. *Management Science* **32**: 1422-1433.

Dierickx I, Cool K. 1989. Asset stock accumulation and sustainability of competitive advantage. *Management Science* **33**: 1504-1511.

DiMaggio PJ, Powell WW. 1983. The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review* **48**(2): 147-160.

Dixit AK, Nalebuff BJ. 1991. *Thinking Strategically: Competitive Edge in Business, Politics and Everyday Life* (1 ed.). W W Norton & Co: London.

Dobson PW, Waterson M. 1996. Vertical restraints and competition policy. Research Paper (12 ed.), Office of Fair Trading: London.

Duguid P. 2005. Networks and knowledge: The beginning and end of the Port commodity chain, 1703-1860. *Business History Review* **79**(3): 453-466.

Dupeyre C, Dumez H. 2009. The role of architectural players on coopetition: The case of the US defense industry. In LR Frederic, Y Said (Eds.), *Coopetition: Winning Strategies for the 21st Century*. Edward Elgar: Cheltenham.

Einav L, Levin J. 2010. Empirical industrial organization: A progress report. *Journal of Economic Perspectives* **24**(2): 145–162.

Ernst H. 2001. Patent applications and subsequent changes of performance: evidence from time-series cross-section analyses on the firm level. *Research Policy* **30**(1): 143-157.

Ferguson CH, Morris CR. 1993. How architecture wins technology wars. *Harvard Business Review* **71**(2): 86-96.

Ferraro F, Gurses K. 2009. Building architectural advantage in the US motion picture industry: Lew Wasserman and the Music Corporation of America. *European Management Review* **6**(4): 233-249.

Firestone, W. A. 1993. Alternative arguments for generalizing from data. *Educational Research*. **22**(4): 16–23.

Frambach RT, Schillewaert N. 2002. Organizational innovation adoption: a multi-level framework of determinants and opportunities for future research. *Journal of Business Research* **55**(2): 163-176.

Gadiesh O, Gilbert JL. 1998. Profit pools: A fresh look at strategy. *Harvard Business Review* **76**(3): 139-147.

Gawer A, Cusumano MA. 2002. *Platform Leadership: How Intel, Microsoft, and Cisco drive industry innovation*. Harvard Business School Press: Cambridge, MA.

Gereffi G. 1994. The Organization of Buyer-Driven Global Commodity Chains: How U.S. Retailers Shape Overseas Production Networks. In G Gereffi, M Korzeniewicz (Eds.), *Commodity Chains and Global Capitalism*. Praeger: Westport, CT. 95-122.

Gereffi G, Fernandez-Stark K. 2011. Global Value Chain Analysis: A Primer. *Center on Globalization, Governance & Competitiveness, Duke University*. Available at http://www.cggc.duke.edu/pdfs/2011-05-31_GVC_analysis_a_primer.pdf: Durham, NC

Gereffi G, Humphrey J, Sturgeon T. 2005. The governance of global value chains. *Review of International Political Economy* **12**(1): 78 – 104.

Gereffi G, Korzeniewicz M. 1994. *Commodity Chains and Global Capitalism*. Praeger: Westport, CT.

George G. 2005. Slack resources and the performance of privately held firms. *Academy of Management Journal* **48**(4): 661-676.

Geroski P. 2000. Models of technology diffusion. *Research Policy* **29**(4-5): 603-625.

Geroski P. 2003. *The Evolution of New Markets*. Oxford University Press: Oxford, UK.

Ghemawat P. 2005. *Strategy and the Business Landscape: Core Concepts* (2 ed.). Prentice Hall: Englewood Cliffs, NJ.

Gilbert RJ, Newbury DM. 1982. Preemptive patenting and the persistence of monopoly. *American Economic Review*. **72**: 514-526.

Greene WH. 2008. *Econometric Analysis* (6 ed.). Pearson Education: London.

Greenspan A. 2004. Economic flexibility. Before the HM Treasury Enterprise Conference, London, England. Remark delivered on 24 January 2004.

Greenstein SM, Wade JB. 1998. The product life cycle in the commercial mainframe computer market, 1968-1982. *RAND Journal of Economics* **29**(4): 772-789.

Greve H. 1998. Managerial cognition and the mimetic adoption of market positions: What you see is what you do. *Strategic Management Journal*, **19**: 967-988.

Greve, HR. 2003. *Organizational Learning from Performance Feedback: A Behavioral Perspective on Innovation and Change*. Cambridge University Press: Cambridge, UK.

Greve, HR. 2009. Fast and expensive: The diffusion of a disappointing innovation. *Strategic Management Journal* **32**: 949-968.

Greve HR, Taylor A. 2000. Innovations as catalysts for organizational change: Shifts in organizational cognition and search. *Administrative Science Quarterly* **45**(1): 54-80.

Grove AS. 1999. *Only the Paranoid Survive: How to Exploit the Crisis Points that Challenge Every Company*. Crown Books, New York, NY.

Gruber H. 2001. The diffusion of mobile telecommunications services in the European Union**.** *European Economic Review* **45**(3): 577-588.

Hannan, MT, Freeman, J. 1984. Structural inertia and organizational change. *American Sociological Review*: 149-164.

Haveman HA**.** 1993. Follow the leader: Mimetic isomorphism and entry into new markets. *Administrative Science Quarterly* **38**: 593-627.

Haunschild PR, Miner AS. 1997. Modes of interorganizational imitation: The effects of outcome salience and uncertainty. *Administrative Science Quarterly* **42**: 472-500.

Helfat CE, Peteraf MA. 2003. The Dynamic Resource-Based View: Capability Lifecycles. *Strategic Management Journal* **24**(10): 997-1010.

Helfat CE, Raubitschek RS. 2000. Product Sequencing: Co-Evolution of Knowledge, Capabilities and Products. *Strategic Management Journal* **21**(10/11): 961-979.

Henderson RM, Clark KB. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly* **35**: 9-30.

Henderson RM, Cockburn I. 1994. Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management Journal* **15** (S1): 63 – 84.

Herriott, SR, Levinthal, D & March, JG. 1985. Learning from experience in organizations. *American Economic Review* **75**: 298-302.

Humphrey J, Schmitz H. 2002. How does insertion in global value chains affect upgrading in industrial clusters? *Regional Studies* **36**(9): 1017-1027.

Iansiti M, Levien R. 2004. *The Keystone Advantage: What the New Dynamics of Business Ecosystems Mean for Strategy, Innovation, and Sustainability*. Harvard Business School Press: Boston, MA.

Jacobides MG, Billinger S. 2006. Designing the boundaries of a firm: From “make, buy, or ally” to the dynamic benefits of vertical architecture. *Organization Science* **17**: 249-261.

Jacobides MG, Knudsen T & Augier M. 2006. Benefiting from innovation: Value creation, value appropriation, and the role of industry architecture. *Research Policy* **35**(8), 1200-1221.

Jacobides MG, Tae CJ. 2013. Kingpins, bottlenecks and value dynamics within a sector. Working paper, London Business School.

Jacobides MG, Winter SG. 2005. The co-evolution of capabilities and transaction costs: explaining the institutional structure of production. *Strategic Management Journal* **26**(5): 395-413.

Jacobides MG, Winter SG. 2012. Capabilities: Agency, structure and evolution. *Organization Science* **23**(5), 1365-1381.

Jacobides, MG, Winter, SG & Kassberger, SM. 2012. The dynamics of wealth, profit and sustainable advantage. *Strategic Management Journal,* Early view, May, DOI: 10.1002/smj.1985

Kapoor R, Adner R. 2012. What firms make vs. what they know: How firms' production and knowledge boundaries affect competitive advantage in the face of technological change. *Organization Science* **23**(5): 1227-1248.

Kapoor R, Lee, JM. 2013. Coordinating and competing in ecosystems: how organizational forms shape new technology investments. *Strategic Management Journal* **34**(3): 274-296.

Kelly K. 1998. *New Rules for the New Economy: Ten Radical Strategies for a Connected World.* Penguin Books: New York, NY.

Kennedy P. 2003. *A Guide to Econometrics.* MIT Press: Cambridge, MA.

Kim JY, Miner AS. 2007. Vicarious learning from the failures and near-failures of others: Evidence from the US commercial banking industry. *Academy of Management Journa*l **50**(3): 687-714.

Klepper S. 1996. Entry, exit, growth, and innovation over the product life cycle. *The American Economic Review* **86**(3): 562-583.

Klepper S. 1997. Industry life cycles. *Industrial and Corporate Change* **6**(1): 145-182.

Klepper S, Simons KL. 2005. Industry shakeouts and technological change. *International Journal of Industrial Organization* **23**(1-2): 23-43.

Krugman P. 2007. Innovating our way to financial crisis. In *Op-Ed Column, New York Times* (3 December). Accessed on 14 July, 2012.

Laursen K, Salter A. 2005. Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms. *Strategic Management Journal* **27**(2): 131-150.

Leonard-Barton, D. 1992. Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal* **13**(S1): 111-125.

Levinthal DA, March JG. 1993. The myopia of learning. *Strategic Management Journal* **14**(S2): 95-112.

Levinthal DA, Myatt J. 1994. Co-evolution of capabilities and industry: The evolution of mutual fund processing. *Strategic Management Journal* **15**(S1): 45-62.

Levitt B, March JG. 1988. Organizational learning. *Annual Review of Sociology* **14**: 319-340.

Lieberman MB, Montgomery DB. 1988. First-mover advantages. *Strategic Management Journal* **9**(S1): 41-58.

Lippman SA, Rumelt RP. 2003. A bargaining perspective on resource advantage. *Strategic Management Journal* **24**(11): 1069-1086.

MacDonald G, Ryall MD. 2004. How do value creation and competition determine whether a firm appropriates value? Management Science **50**(10): 1319-1333.

Malerba F. 2002. Sectoral systems of innovation and production. Research policy **31**(2): 247-264.

Malerba F, Orsenigo L. 1996. The dynamics and evolution of industries. *Industrial and Corporate Chang*e **5**(1): 51-87.

March JG. 1991. Exploration and exploitation in organizational learning. *Organization Science* **2**: 71-87.

Markides CC, Geroski PA. 2005. *Fast Second: How Smart Companies Bypass Radical Innovation to Enter and Dominate New Markets*. Jossey-Bass: San Francisco, CA.

McGahan AM., Porter ME. 1997. How Much Does Industry Matter, Really? *Strategic Management Journal* **18**: 15-30.

McGahan AM., Porter ME. 2003. The emergence and sustainability of abnormal profits. *Strategic Organization* **1**: 79-108.

McGahan AM., Porter ME. 2005. Comment on ‘Industry, corporate and business-segment effects and business performance: A non-parametric approach’ By Ruefli And Wiggins. *Strategic Management Journal* **26**(9): 873-880.

McGrath RG. 1999. Falling forward: Real options reasoning and entrepreneurial failure. *Academy of Management Review* **24**(1): 13-30.

McKendrick D, Doner RF & Haggard S. 2000. *From Silicon Valley to Singapore: Location and Competitive Advantage in the Hard Disk Drive Industry*. Stanford University Press: Stanford, CA.

Miller D, Chen MJ. 1994. Sources and consequences of competitive inertia: A study of the US airline industry. *Administrative Science Quarterly*: 1-23.

Miner AS, Kim JY, Holzinger I & Haunschild P. 1999. Fruits of failure: organizational level failure and population level learning. In *Advances in Strategic Management: Population Level Learning and Industry Change*, Miner A, Anderson P (eds). JAI Press: Stamford, CT: 187-220.

Nelson RR. 1991. Why do firms differ, and how does it matter? *Strategic Management Journal* **12**: 61-74.

Nelson RR. 1994. The co-evolution of technology, industrial structure, and supporting institutions. *Industrial and Corporate Change* **3**(1): 47-63.

Nelson RR, Winter SG. 1982. *An Evolutionary Theory of Economic Change*. Harvard University Press: Cambridge, MA.

Ocasio W. 1997. Towards an attention-based view of the firm. *Strategic Management Journal* **18**(S1): 187-206.

Pennings JM, Harianto F. 1992. Technological networking and innovation implementation. *Organization Science* **3**(3): 356-382.

Penrose ET. 1959. *The Theory of the Growth of the Firm*. John Wiley & Sons: New York, NY.

Perry MK. 1978. Vertical Integration: The Monopsony Case. *The American Economic Review* **68**(4): 561-570.

Peteraf MA. 1993. The cornerstones of competitive advantage: A resource-based view. *Strategic Management Journal* **14**(3): 179-191.

Pisano GP, Teece DJ. 2007. How to capture value from innovation: Shaping intellectual property and industry architecture. *California Management Review* **50**: 278–296.

Porter ME. 1980. C*ompetitive Strategy*. The Free Press: New York.

Rao H, Greve HR, & Davis GF. 2001. Fool's gold: Social proof in the initiation and abandonment of coverage by Wall Street analysts. *Administrative Science Quarterly* **46**: 502-526.

Rogers EM. 1995. *Diffusion of Innovations* (4th ed.) Free Press: New York, NY.

Roll R. 1986. The hubris hypothesis of corporate takeovers. *Journal of Business*, 197-216.

Rosenberg N. 1969. The direction of technological change: Inducement mechanisms and focusing devices. *Economic Development and Cultural Change* **18**(1): 1-24.

Rumelt RP. 1991. How much does industry matter? *Strategic Management Journal* **12**(3): 167-185.

Schmalensee R. 1985. Do markets differ much? *American Economic Review* **75**(3): 341.

Schmalensee R. 1989. Inter-Industry Studies of Structure and Performance. In R Schmalensee R Willig (Eds.), *Handbook of Industrial Organization*. Elsevier: Amsterdam.

Schumpeter JA. 1934. *The Theory of Economic Development*. Harvard University Press: Cambridge, MA.

Shamsie J, Martin X & Miller D. 2009. In with the old, in with the new: Capabilities, strategies, and performance among the Hollywood studios. *Strategic Management Journal* **30**(13): 1440-1452.

Simon HA. 1962. The architecture of complexity. *Proceedings of the American Philosophical Society* **106**: 467-482.

Slywotzky A, Morrison D. 1997. *The Profit Zone: How Strategic Business Design Will Lead You to Tomorrow's Profits*. John Wiley & Sons: New York.

Sorenson O, Audia PG. 2000. The social structure of entrepreneurial activity: Geographic concentration of footwear production in the United States, 1940-1989. *American Journal of Sociology* **2**: 424-462.

Strang D, Soule SA. 1998. Diffusion in organizations and social movements: From hybrid corn to poison pills. *Annual Review of Sociology* **24**: 265-290.

Stuart TE. 2000. Interorganizational alliances and the performance of firms: A study of growth and innovation rates in a high-technology industry. *Strategic Management Journal* **21**(8): 791-811.

Sturgeon TJ. 2002. Modular production networks: A new American model of industrial organization. *Industrial and Corporate Change***11**(3): 451-496.

Sutton J. 1991. *Sunk Costs and Market Structure: Price Competition, Advertising, and the Evolution of Concentration*. The MIT Press: Cambridge, MA.

Syverson C. 2011 What determines productivity? *Journal of Economic Literature* **42**(2): 326-365.

Teece DJ. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy* **15**(6): 285-305.

Teece DJ, Pisano G, & Shuen A. 1997. Dynamic capabilities and strategic management. *Strategic Management Journal* **18**(7): 509–533.

Tolbert PS, Zucker LG. 1983. Institutional sources of change in the formal structure of organizations: The diffusion of civil service reform, 1880-1935. *Administrative Science Quarterly* **28**: 22-39.

Tushman ML, Anderson P. 1986. Technological discontinuities and organizational environments. *Administrative Science Quarterly* **31**(3): 439-465.

Von Stackelberg H. 2011. *Market Structure and Equilibrium*. Springer: Heidelberg. English translation of H Von Stackelberg H. 1934. *Marktform und Gleichgewicht.* Springer-Verlag: Wien and New York.

Winter SG. 2003. Understanding Dynamic Capabilities. *Strategic Management Journal* **24**(10): 991-995.

Winter SG, Szulanski G. 2001. Replication as strategy. *Organization Science* **12**(6): 730-743.

Wooldridge JM. 2002. *Econometric Analysis of Cross-Section and Panel Data.* MIT Press: Cambridge, MA.

Zaltman G, Duncan R, & Holbek J. 1973. *Innovations and Organizations*. Wiley & Sons: New York, NY.

Zollo M. 2009. Superstitious learning with rare strategic decisions: Theory and evidence from corporate acquisitions. *Organization Science* **20**(5): 894-908.

Zollo M, J Reuer. 2010. Experience spillovers across corporate development activities. *Organization Science* **21**(6): 1195-1212.