THE CREATION AND PERFORMANCE OF CLASSIFICATION SCHEMES:
RATING SYSTEMS IN UNITED STATES BROKER-DEALERS, 1993-2000

by

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ABSTRACT

In the past few years, organizational researchers have found a renewed interest in categorization and its consequences. Most research focuses on the consequences of categorization for the categorized objects, arguing that a clear identity is important for users to understand (and thus value) an object. In my dissertation, I shift the perspective from the users and the categorized objects to focus on the creator of the classification scheme. I question the commonly held assumption that categories are created to reduce ambiguity and structure the world for users. In the first part of my dissertation, I suggest conditions under which a categorizer might create an ambiguous classification scheme rather than an unambiguous one. I argue that the ambiguity of the classification scheme depends on the categorizer's relationship with the objects it rates, its relationship with many different types of users, and its status relative to other categorizers within the industry. By doing so, I move the focus away from the results of categorization to the antecedent of it. Users frequently question whether an object has been correctly placed in a classification scheme, but they must also question whether the scheme itself has been created strategically by the categorizer. In the second part of my dissertation, I examine the performance of the categorizer as a result of its classification scheme. While strategic behavior may help an organization achieve its objectives, in the long run, there may be negative consequences for a categorizer when the meaning of a classification scheme cannot be understood. I argue that overly ambiguous classification schemes lead to decreases in customer accounts. In addition, I measure the linguistic network position of individual schemes to illuminate how the usage of different schemes within an organizational field affects all firms in the industry. I use equity rating systems (for example, "buy, sell, hold") in the United States during the years 1993-1999 as a setting in which to test my hypotheses.

CHAPTER 1

INTRODUCTION

1.1 Overview

Research on categorization has exploded over the past decade, with scholars examining areas ranging from borders of countries (Sahlins, 1991), to technological breakthroughs and stock market categorization (Benner, 2007), to whether or not poor Americans are "deserving" or "undeserving" of welfare (Steensland, 2006). Categorization invites study because categories underlie almost all of human thought. The act of categorizing places like things with like so as to better understand the world around us. Individuals develop categories to understand everything from time (before and after) to what to eat (fruits, vegetables, dairy, meat). Groups develop categorizations of insiders and outsiders. No matter what is being analyzed, at its essence, categorization is about creating meaning (Durkheim & Mauss, 1972 (1963); Levi-Strauss, 1983). Meaning occurs not only through an assessment of the attributes of a set of objects within a single category, but also through an understanding of the interplay of all possible categories (Bowker & Star, 2000; Goodman, 1992). We learn as much about an object by knowing what it is not as we do by knowing what it is.

Categorization is particularly important to organizations. Categories help them understand the market in which they compete as well as the actions available to them. Organizations develop informal categories to define the appropriate band of competitors and to differentiate themselves from others (Porac, Thomas, & Baden-Fuller, 1989). These categories reinforce an organization's identity and fend off imitation

(Swaminathan, 1998). In addition to informal categories created by organizations, organizations are also affected by formal classification schemes, in which they or their products are classified by an outside entity (Douglas, 1986). Unlike other categorizations, classification schemes, which include industry directories, rating systems, and product guides, are created with the explicit knowledge that they will be employed by a set of users different from the entity that created them.   For example, SIC codes identify industry membership, which can have a wide impact on a firm's activities. Mergers between competitors or firms seen as operating within the same industry require special approval from the government, and may require divestitures of certain areas of a firm's activities. Because of such potential influence, classification schemes play a vital role in organizational life.

My dissertation focuses on these classification schemes. Specifically, I look at the equity rating systems ("Buy, Hold, Sell" for example) used by United States broker-dealers. Since they are created by outsiders, classification schemes help to order markets by creating structures through which market actors and their products can be observed and understood by consumers (Hsu, 2006b; Hsu & Podolny, 2005; Rao, Monin, & Durand, 2005; Zuckerman, 1999). In this sense, they are interpretive devices for users' decision making, because users see them as a helpful way in which to view a particular landscape of objects. Within a classification scheme, objects that are difficult to classify or that blur boundaries are devalued because users cannot understand them. As a result, the message to objects is plain: develop a clear identity in order to receive the maximum benefits of classification. For users, too, the norms of classification suggest that schemes are created to improve clarity and understanding.

While the perspective of the classified objects and the users has been strongly elaborated in the literature on classification schemes, the role of the categorizer has been generally ignored. The categorizer creates and maintains the classification scheme and does the classifying. Furthermore, in markets, there is often competition among categorizers who purvey multiple schemes, each offering alternative interpretations of a given market. In my dissertation, I adopt the perspective of the categorizer in exploring the creation and performance of the classification scheme. At its essence, categorization is about creating meaning, which occurs through both the relationship of a given object to others within its category (the focus of prior literature) and also through the interplay of all possible categories within a given scheme (the focus of my dissertation). Thus far, the composition of the classification scheme itself has been largely taken for granted. The assumption is that the collection of categories which constitutes the scheme is always unambiguous—yet little research has examined this. In fact, ambiguous classification schemes can and do exist. Without understanding why these schemes are created and how they perform, we understand only part of the effects of categorization.

My dissertation addresses this gap by asking two questions: (1) why are ambiguous classifications schemes created? and (2) does the composition of the classification schemes impact categorizer performance? The first question addresses the critical issue of needing to relate individual categories to others within a given scheme. The second addresses the ability of classification schemes, however they are created, to generate meaning in a complex world. In addition, I extend the scope of prior research by considering multiple classification schemes of different categorizers. This allows me to address the important issue of competition, and how competition among categorizers

affects the creation and maintenance of classification schemes, and thus the meaning of a particular industry. Categorizers compete with each other for users of the classification scheme and for objects to categorize.

In Part I of my dissertation, I examine the composition of the classification scheme itself. My starting point is prior research that has focused on the role of ambiguity in categorized objects. In general, this research points to an ambiguity discount: objects which are difficult to classify have poorer performance because they are less understood. This has been shown in the stock market, where companies that have confusing identities trade for lower than comparable firms which can be more easily described (Zuckerman 1999, Zuckerman 2004); in early credit ratings, where firms with ambiguous identities received lower credit ratings than both hybrid and single business firms (Ruef and Patterson 2007); in French gastronomy, where restaurants using both nouvelle and classic techniques receive fewer stars than specialists (Rao et al., 2005), and in the film industry, where actors who do not have a recognizable type work less often than those who do in the early stages of their career (Zuckerman 2004).

Focusing on the ambiguity of categorized objects seems to assume that, were an object only unambiguous, it could be placed in its appropriate category and it would be understood. For this to happen, however, the classification scheme must also be unambiguous. Understanding cannot occur if the classification scheme itself is not clear. I challenge this assumption of clarity by detailing why a categorizer might create an ambiguous classification scheme rather than an unambiguous one. I define an ambiguous classification scheme as one where a single object could be correctly placed in multiple categories (Ruef 2007, Abbott 1997). I suggest that the ambiguity of the classification

scheme depends on the categorizer's relationship with the objects it rates, its relationship with many different types of users, and its status within the industry. By doing so, I move the focus away from the results of categorization to the antecedent of it. Users must ask not only if a scheme is used correctly, but also if it has been created in such a way that understanding is possible. Furthermore, I examine the availability of ambiguity as a strategy. Theoretically, any organization can choose to be ambiguous, but in practice, ambiguity may be available only to certain kinds of organizations.

In Part II, I consider the impact of the scheme on the categorizer's performance. While Part I suggests that categorizers may create ambiguous classification schemes when it is beneficial to the categorizer, Part II examines whether there are consequences for such choices. Ambiguity is a double edged sword: while organizations benefit from creating ambiguity ((Leifer, 1991; March, 1994; Padgett & Ansell, 1993; White, 1992), audiences discount it. I suggest that the relationship of ambiguity and performance follows an inverted U: too little ambiguity hamstrings the organization, but too much dissuades audience members. However, the performance of the scheme is also impacted by the similarity of the scheme to other schemes. To examine this, I build a linguistic network to examine how the labels given to individual categories within a single classification scheme connect across all possible classification schemes. I contrast the similarity of the scheme with categorizers who have the exact same scheme as other categorizers. While using a prevalent scheme gives a categorizer legitimacy, it shifts the locus of competition to the use of the scheme—to the categorizer's ability to share information and categorize objects.

By focusing on the performance of the categorizer, I shed light on an undertheorized area. Much is known about the performance of individual objects as the result of their categorization, but little is known about whether or not the classification scheme impacts the performance of the categorizer that creates it. Each classification scheme represents a way of seeing a particular world of objects—a culturally influenced meaning system beyond simply conveying information. I argue that this way of seeing has material impact for categorizers, in terms of customer response. At a higher level, my dissertation points to larger cultural influences on firm performance: strategy matters, but that strategy influenced by how knowledge is conveyed within the bounds of the classification scheme.

1.2 Literature

My approach is rooted in the literature of categorization. While I focus primarily on sociological approaches of categorization as reflecting social processes, I also use literature from linguistics and cognitive psychology to address issues of language and how meaning is understood from words and from categorized objects. I augment this with literature from strategy dealing with the importance of performance, the effects of competition and choices of differentiation within a market setting. For both theory sections, I use literature on ambiguity in sociology, economics, and linguistics to elaborate the creation and the reception of classification schemes.

1.3 Setting

I use equity rating systems of United States broker-dealers between the years of 1993-1999 as a setting to test my hypotheses. Broker-dealers create rating systems for categorizing the equities of publicly traded firms. These classification systems are based on quality. While most classification schemes are based on three possible types of ratings, positive, neutral, and negative (often typified as 'buy, hold, sell'), in fact a great deal of variation in the makeup of the scheme and the category labels exist. As a result, this allows me to test not only how an individual scheme is created, but also how alternative schemes might be created. Prior research on classification schemes has often been limited to an examination of a single scheme. My sample contains over four hundred firms, which provides significant variation.

I focus on the years from 1993 to 2000 because in 2000, the industry began to face significant changes. The Glass-Steagall Act was repealed in late 1999, allowing commercial banks to enter into investment banking for the first time since before the depression. In addition, a series of scandals rocked the industry in 2001, starting with the fall of Enron and later MCI Worldcom, but also as the result of the exposure of incriminating emails from a number of highly rated analysts. These emails suggested that analysts were recommending stocks in public while privately disparaging them. As a result of these events and the ensuing Global Equities Settlement, the rules guiding equity analysis changed greatly. 1992 through 1994 begins a shift in the landscape of broker-dealers, as some began to focus on investment banking as a revenue source rather than simply appealing to potential investors. This shift in audience may be captured in the performance of the classification scheme.

Focusing on rating systems during this time period allows me to examine classification schemes as they might operate "in the wild," without coercive pressures to control the kind of classification scheme that any firm created.

1.4 Structure of the Dissertation

The structure of my dissertation is narrative in form. I begin with a review of relevant literature. I then suggest a series of hypotheses predicting when organizations will create ambiguous classification schemes. I follow this with hypotheses that examine the effects of classification choices on performance. I explain the methods and measures that I use. I will conduct my analyses and then conclude.

CHAPTER 2

THEORETICAL DEVELOPMENT

This chapter begins the theoretical development for the hypotheses discussed in

chapters 3 and 4. I specifically focus on two literatures: the literature on categorization

and the literature on ambiguity within organizations and across individuals. The

literature on categorization as it has been used in psychology, sociology, and

organizations is examined first. Then, I move to a subset of the literature on

categorization, specifically categorizers as critics, or those whose classification schemes

are used to determine object quality. Finally, I synthesize these research streams.

2.1 Overview of Categorization

Categories are pervasive. National borders, grades in school, tax brackets—all

are divisions of the world. Categories structure the world around us by answering the

question, "What is this?" Categorization (also known as classification) is, at its heart, the

process of understanding a series of objects by grouping some of them together and

separating them from others (Zerubavel, 1991, 1996). A category or classification is a "a

spatial, temporal, or spatio temporal segmentation of the world" (Bowker et al., 2000).

At least three roles participate in categorization. The first role is that of the

category creator. This entity develops the taxonomy of categories. For the purposes of

this dissertation, this role shall be called the categorizer. The second role is that of the

objects that are categorized. Anything is a candidate for categorization. Thus,

categorized objects can include humans, organizations, or inanimate objects such as

equities, animals, or plants as well as ideas and time. They occupy, often in groups, individual categories within a classification scheme. For the purposes of this dissertation, I shall call these objects. The third role is the entity that uses the classification scheme. Individuals, groups and organizations extract information from looking at what objects are placed in a classification scheme. I shall call these users. For example, when looking at automobile classification, *Car & Driver* Magazine would be a categorizer, an individual wanting to buy a car would be a user, and BMW would be an object.[1]

These roles may be played by distinct actors, or a single actor or group of actors may play multiple roles. For example, cliques in elementary school are created by the students themselves. A particular group of students (usually members of an in-group) then categorize other students. The "popular" students decide who is popular and who is not. In this case, the "popular" students are categorizers, users, and objects. Other students are also objects because they are classified as unpopular. They may also be users of the scheme to the extent that they know who is "popular" and change their action accordingly. In business, the United States government creates an industry classification scheme that groups businesses according to what industry they are in. This classification scheme is used by individuals. In this example, the government is the categorizer, businesses are objects, and individuals (such as PhD students) are users.

The simplest categorical division is a binary, in-group/out-group definition, but there may be many separate categories created to define a given set of objects or experiences. Groups of categories that order certain kinds of objects are considered

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[1] My interest is in the individuals and organizations that have agency in the process of categorization. It is possible for an object to create many objects that can be classified. For example, BMW has several models of cars that could be classified in Car and Driver magazine. The cars have no agency, and cannot complain, for example, if they are miscategorized. Only BMW or its representatives can do that. It is also possible that the object itself may be categorized, for example, the company BMW belongs in the category 5012 in SIC codes. In this case, BMW acts on its own behalf if it wishes to respond to the SIC codes.

schema. When that schema is created and maintained by an official or institutionalized actor, it is called a classification scheme (Lounsbury & Rao, 2004). Classification schemes differ from other kinds of categories in two ways. First, the roles of user, object, and categorizer are usually distinct. Second, the set of possible categories is defined and known. In a formal classification scheme, categorizers make a choice from a set of objects, and cannot add or subtract categories at will. This is in sharp contrast to informal categories, such as strategic groups, niche theories in ecological research, and psychological studies of human categorization. In informal classification, categories are socially constructed, and can appear and disappear at will. For example, humans constantly use an array of different categories, blending and changing them with ease (Hsu, 2006b; Hsu et al., 2005). New industries arise where none were before, solidified through producers, media mentions, and customer awareness (Kennedy, 2005). In the literature on strategic groups, such groups exist only when some quality of the group contributes to performance, and thus groups may be constructed or destructed based on a variety of dimensions (Dranove, Peteraf, & Shanley, 1998). In a formal classification scheme, the creation or removal of a category is not so easily done, and is subject to both technical and strategic considerations (Lounsbury et al., 2004). Since multiple categories are visible in a formal classification scheme, they are especially useful areas of inquiry for understanding how categories come about. In addition, they provide opportunities for understanding the structure of the scheme itself.

Classification schemes can be vertical or horizontal or a combination of both. Vertical classifications schemes imply a hierarchy of order, where one or more categories are above other categories (Schwartz, 1981). Examples of vertical classification schemes

include grades in school, quality ratings, and caste systems. Horizontal classification schemes are attributional based categories, where one category is not necessarily better or more advanced than another. Horizontal classification schemes include product directories, restaurant guides, and SIC codes. However, horizontal categories may have some elements of vertical categories, given that value or status is often placed upon certain categories. For example, although job classifications are generally considered horizontal categories, some job categories are considered more prestigious than others.

The process of categorizing involves at least two parts: the creation of the classification scheme and the use of it. Literature focusing on the creation of classification schemes examines the underlying structure of the categories created. It seeks to understand why and how categories are created. The second division, the use of the scheme, studies how categories are enacted. This branch seeks to understand how categories are used and takes for granted the underlying set of categories. It also examines the consequences of such use. The vast majority of work centers on the use of categories, with special emphasis on the consequences for categorization, particularly in terms of those being classified.

Because the roles of users, objects and categorizers are often played by single actors, most theoretical work discusses both usage and creation together. For example, in Durkheim's work on signs, he considers the creation and deployment of tribal totems to be a reflection of the social divisions between different tribes (Durkheim, 1995; Durkheim et al., 1972 (1963)). Yet, the processes of creation and use are conceptually distinct even though the roles may be blended. First, the same system can be used for many purposes. For example, racial classification systems separate humans into

categories based on historical origin. Although they all look similar, systems of racial

classification can be used in vastly different ways. The same racial classification system

that allows affirmative action also allows apartheid regimes. In addition, category

creation is defining a vision for seeing a landscape of objects. Category use examines

which options are chosen and what is placed in each category. Because humans and their

institutions are categorizers, there is fallibility in the implementation of the classification

schemes. Furthermore, there is meaning in the creation of the system. Separating and

examining each part of the process allows researchers to understand these meanings.

2.2 Use of Categories

Research dealing with the usage of a classification scheme focuses first on which

objects are placed in which individual category as well as the consequences of such

placement. Once a set of categories have been created, objects are placed within them

through a process of 'lumping and splitting' (Lounsbury et al., 2004; Zerubavel, 1996).

Lumping involves grouping things together based on some attributes as defined by the

category into which they are placed. Splitting involves the separation of objects in one

category from objects in another. The degree to which these processes work hinges on

the distinctness of the individual categories. Where there are sharp categorical

boundaries, lumping and splitting is a fairly routine and consistent process. However,

when categorical boundaries are less clear, classification becomes difficult (Lamont &

Fournier, 1992; Lamont & Molnar, 2002; Rao et al., 2005).

Two theories offer explanations for the process of lumping objects together.

Aristotelian categorization posits that an object is placed in a category based on a set of

defined attributes which exist, much like a list of requirements (Bowker et al., 2000).
The object either possesses these attributes or does not. In this binary world, possession
of attributes means automatic inclusion in the category, while lack of possession means
automatic exclusion from the category. For example, in the category "Sports that use
spherical objects," croquet, baseball, and shot put belong, but cycling, football, and
gymnastics are excluded.   Prototypical categorization, on the other hand, argues that
categorization occurs without a list of required attributes. Instead, objects are placed into
a category based on their similarity to an idealized type. Thus, seating devices with four,
three, and two legs may all fit into the category "chair." Aristotelian categorization tends
to create categorical absolutes, while prototypical categorization has a greater potential
for confusion. This occurs because associations across categorizers may not always be
consistent, and as more things are associated with the category, the identity of the
category may be come unclear. Consider the pictures of objects in Figure 2.1.
All are possible values for the category "chair" based on association of different elements,
but not all of them are necessarily chairs. The drawing is not a tangible object to sit upon,
nor is the numbered chair sculpture.

The question of whether Aristotelian or prototypical categorization more closely
resembles the way humans actually categorize has been the subject of lively debate,
particularly in psychological research. In general, researchers believe that humans
categorize largely through prototypical association, examining an object and comparing it
to already classified objects. This makes sense, given that cognitive categories created by
humans are flexible divisions created and used by a single individual. Consistency in
human categorization may be helpful for a given person's cognition, but not absolutely

necessary. In the case of firms, the literature on strategic groups suggests that managers of firms engage in constant pairwise comparisons of their firm to others using some strategic dimension, discarding dissimilar firms while remembering similar ones. These groupings may then be communicated with other managers within the firm to generate a firm level cognition of who is in or out of the strategic group (Peteraf & Shanley, 1997). Conversely, in formal classification schemes, Aristotelian, rule based classification often occurs, since many different people or groups within a single categorizer are likely to use the scheme. Rules-based classification, in theory, provides better likelihood that objects will be consistently placed in the appropriate category.

2.2.1 Consequences of Categorization

Being placed in a category has immediate consequences not only for categorized objects, but also for users. In general, the consequences of categorization can be divided into three groups: cognitive, social, and technical. Cognitive consequences involve those consequences that affect how users understand the objects in a particular category. Social consequences involve how objects are influenced by being placed in a particular category. Technical consequences focus on how users allocate resources based on categorization.

Cognitive Consequences

Awareness. Being placed in a classification scheme creates awareness of the objects that are categorized. Since categories structure the world around us, being placed within a category determines the world "worth knowing." Objects that are not categorized are often treated as if they do not exist (Bowker et al., 2000; Zerubavel, 1991).

Order. Categorization creates order (Douglas & Hull, 1992; Estes, 1994; Zhao, 2005). Objects within a particular category are placed there because they are to be seen as similar to each other. As a result, categorization creates order, by defining what is like what. This order often becomes the standard for interpreting how objects relate to each other. As a result, alternative classifications or ways of seeing may not be seen once a particular categorization system is in use.

Social Consequences

Behavioral Expectations. When something is categorized it creates a set of expectations about future actions. This occurs because of the association of attributes with a particular category. Thus, mass media films perform worse in art house movie theatres because art house theatres create an expectation of the kind of work being shown (Zuckerman, Tai-Young, Kalinda, & James von, 2003b). Likewise, "craft beers" need to be created in small batches and not sourced from mass producers in order to succeed because the conception of a craft beer is an antithesis to scale production (Carroll & Swaminathan, 2000; Swaminathan, 1998).

Behavioral expectations may occur because of the labeling that accompanies the individual categories (Becker, 1997 (1963)). For example, an innovation categorized as architectural will be tremendously concerning to incumbent producers, even though it seems to be continuing current practices—because these types of innovations destroy the product architecture used by incumbent producers lack expertise (Henderson and Clark 1990). Labeling theory deals with this notion particularly, arguing that simply by classifying an object in a particular way, humans can influence the behavior and

perceptions of that object. For example, Becker argues that simply labeling an individual

as a criminal increases the propensity for criminal acts (Becker, 1997 (1963)).

Identity. For categorized objects, the act of being placed in a category confers an

identity because it establishes a social or symbolic boundary around those in a particular

category (Bowker et al., 2000; Douglas, 1986; Tajfel & Turner, 1986; Zerubavel, 1996).

Whether socially created or drawn from some perceived reality, attributes are the basis of

categorization. Irrespective of what is put into it, the category itself has an identity based

on these attributes as they are a set of expectations of what the category is. To the extent

that objects within a particular category are social objects, whether individuals or

organizations, they reinforce the identity conferred by the category attributes by created

shared expectations and codes for fellow category members. Thus, Scottish knitwear

producers know that they create "top quality cashmere pullover and cardigan sweaters"

and furthermore see themselves as unique in doing so (Porac et al., 1989). Members of

their group have certain requirements, such as geographic location in a certain part of

Scotland, fully fashioned sweater technology, and high quality yarns knit in a classic

style. Within members of the group, there is a shared sense of understanding and a

tendency to minimize threats to the group. In addition, the act of being grouped creates a

shared sense of identity among all of those who have that identity, whether or not they

know each other (Sahlins, 1991). A study of British school children, for example, found

that they tried to create favorable disparities in distribution of rewards toward members

of their own group—even when they did not know specifically who was in their in-group

(Tajfel et al., 1986).

Legitimacy Closely connected to identity is the notion of legitimacy. As mentioned before, the attributes that define categories bring with them a set of expectations about how other objects in the category will behave. Category membership requires adherence to this set of expectations. Objects that conform to these expectations are considered legitimate by external audiences (Suchman, 1995; Zhao, 2005; Zuckerman, 1999). Legitimacy is desirable for individuals and organizations because it helps them accrue resources which are necessary for survival (DiMaggio & Powell, 1983; Powell & Maggio, 1991; Suchman, 1995). In addition, the meaning of an individual or organization is enhanced when it is perceived as legitimate. Legitimate forms are seen as "more meaningful, more trustworthy, and more predictable"(Suchman, 1995). Illegitimate behavior, that which is inconsistent with prevailing norms for group membership, can lead to expulsion from the group.

Status The overall categorization scheme creates a status order. This occurs because of the social value that users place on objects in some categories, whether or not the classification scheme is horizontal or vertical. This nonmonetary value is determined by privileging certain attributes or qualities above others. Because of this comparative nature, the status created is inherently relational (Bourdieu, 1984). Status can also be achieved, such as when categories are determined by technical characteristics or accomplishments (Podolny, 1993).

Technical Consequences

Value Categorization can influence the financial value of the categorized object. The act of being categorized also determines some amount of value on a particular object, depending on which category it is placed in. For example, stocks that are difficult to

categorize trade at a discount relative to those that are easier to categorize (Zuckerman, 1999). Stocks that are downgraded see their price fall (Lin & McNichols, 1998; Mikhail, Walther, & Willis, 1999; O'Brien, McNichols, & Lin, 2005; Stickel, 1992; Womack, 1996).

Resources. Categorization may influence resource procurement and allocation. For example, dividing people into categories of income determines who should pay what taxes. Thus, fiscal policy in the Nixon era created divisions between "deserving" and "undeserving" poor (Steensland, 2006). The "deserving" poor, were, as their name implied, worthy of receiving financial assistance. The undeserving poor, on the other hand, were not.

2.2.2 Strategic Use of Categories

Because of the important consequences of categorization, a large body of research has suggested that categories can be used strategically—that is, that the placement of objects within a category can occur to benefit certain objects. For example, Porac et al examined firms creating referent groups of comparable firms when discussing CEO compensation, as required by law (Porac, Wade, & Pollock, 1999). While the intended notion of the law was for firms to identify with similar firms in their industry, the researchers found that organizations that paid their CEO more than the industry average were likely to carefully select a reference group based not on similarity of firm but on compensation, so that their behavior seemed well in line with expected behavior. As a result, the firm in question would seem to be acting appropriately within a categorical boundary. Several studies have also documented occurrences of favorable classification. For example, Hayward and Boeker (and others) have documented that some stock market

analysts place stocks in a more favorable rating category when their firms also do underwriting business in those industries (Hayward & Boeker, 1998; Kessler, 2004; Lin et al., 1998; McNichols & O'Brien, 1997).

However, all of this research takes the underlying categories as a given. That is, it asks, given that categories exist, how are they used? Yet the way in which categories are created may in fact have an impact on how they are used. In the next section, I explore research that discusses how and why categories are created.

2.3 The Creation of Categories

2.3.1 How Categories are Created

The act of category creation itself occurs in one of three ways: invention, borrowing, and encounter (McAdam, Tarrow, & Tilly, 2001). Each suggests a particular way in which categories are created—either as the product of a human mind responding to a need to make sense of the world, or as individuals responding to the categories of others. Invention occurs because a new category is created in response to a new set of objects. This supports a view of categories as individually created unique objects: humans have the capability to determine that some objects do not fit into the current order, and act independently to develop or expand their current schemes. Encounter describes the process that occurs when pre-existing categorical notions are blended together to form a new category, such as the categories of truck and car converging to create the new category of minivan (Rosa, Porac, Runser-Spanjol, & Saxon, 1999). Borrowing is the process of noticing a category in use by another entity and appropriating

it for oneself. This implies a distinctly social notion of categorization—and one in which

categorizers compare their own schemas to those of other categorizers to see how they fit.

The debate of how and why categories are created has captivated philosophers

from the early Greeks and the enlightenment, and has been joined by empirical

researchers from psychology and sociology. Present day studies have broadened to

include animals in an effort to understand what occurs simply as a part of mental

processing and what might be distinctly human: pigeons can distinguish between

categories with training, as can rats, monkeys, and horses (Aydin & Pearce, 1994; Hanggi,

1999; III, Orduna, & Nowak, 2005; Makino & Jitsumori, 2007). As computer

programming has become more integrated with everyday activities, machines have begun

to categorize as well.

Philosophers and early social theorists argued that categories are innately created

within a single human being—that is, that categories are a process of invention. Kant

suggested that individuals even in the wild would create categories in order to facilitate

thinking. The first categories, he argued, were temporal and spatial distinctions (Bowker

et al., 2000). These categories (past,present; near, far) were the foundational basis for

other distinctions by which individuals understood and perceived their world. Categories

arose and were created whenever new things were encountered as a sorting process.

Research and theory in developmental psychology suggest that children develop

categories as a way of understanding (Piaget, 1955). Studies with infants have noted that

individuals do seem to innately categorize even before they can express themselves.

Experiments show that 8 month old babies understand that similar objects should behave

in similar ways (Needham, Cantlon, & Holley, 2006). Keys and key rings are objects

that are familiar to babies; when these objects are separated unexpectedly, babies are surprised, showing that they associated the two together (Needham, 2001; Needham et al., 2006). As humans grow, their classification schemes become more sophisticated—simple categories such as "dog" are replaced by more specific ones such as "collie" (Blewitt, 1983).

In addition, different individuals may categorize differently. For example, trees are classified differently depending on whether one is a college student, horticulturist, or member of an indigenous tribe (Estes, 1994; Zhao, 2005). These differences occur because individuals select different attributes upon which to base their classification. These differences are distinctly social differences. That is, an individual horticulturist may create a difference classification scheme than a college student, but in general, horticulturists have different understanding of trees than the average college student. Similarly, the indigenous tribe may create a classification system not only because of different perceptions of what trees are, but because trees have a different meaning to them (Levi-Strauss, 1968, 1983).

A long tradition in sociology focuses on this notion that categorization is not just some innate human capacity but instead, the result of social interaction that molds and facilitates the creation of categories. Durkheim proposed that categories are a part of daily life because categories exist in social life. "The first logical categories were social categories; the first classes of things were classes of men, into which these things were integrated. It was because men were grouped, and thought of themselves in the form of groups, that in their ideas they grouped other things…" (Durkheim et al., 1972 (1963)). Humans live in communities, and share categories among regions which may not be

necessarily reproduced throughout other regions. Rather than simply noting the difference between different individuals, sociologists have focused on how this social interaction allows for the creation of categories in the first place.

The social notion of grouping is important simply because so many plausible methods of categorizing a set of objects are possible. Wine is classified differently in different areas of the world, even though the ingredients for wine-making do not vary (Zhao, 2005). Consumers and car producers develop different classification schemes for automobiles (Rosa et al., 1999). "The dictionaries of the French textile industry show that classifications emanating from administrative institutions have a territorial base while those emanating from manufacturing institutions focus on production" (Lamont et al., 1992). While money seems like a simple category of a single currency, in fact humans categorize money based on purpose in their home lives (Zelizer, 1989). Thus rent money is separate from food money, and wives' money is separate from their husbands. These examples show that while classification schemes are ostensibly developed based on attributes of different objects to be classified, *which* attributes form the basis of that distinction is determined by social groups (Starr, 1992).

Furthermore, not only do different groups determine different attributes as the appropriate ones upon which to build a system, but also different groups may come together to create the system in the first place. These groups create categories either for themselves or in conversation with all members of a field (Becker, 1982; Peteraf et al., 1997). In the first case, a group may create a cognitive representation of what it means to be in a particular category. For example, Scottish knitwear producers see themselves as a distinct type of knitwear manufacturer (Porac et al., 1989). This distinction was created

by the manufacturers themselves; customers and suppliers may not necessarily see this division. In other instances, categories may appear as the result of conversation and consultation within a field. For example, what constitutes high art is determined not solely by a single artist, but instead by the intersection of artists, gallery owners, museum curators, and patrons (Becker, 1982; Varnedoe, 1990). These groups negotiate what becomes high art and what remains merely pop art or folk art.

In addition, third parties may help solidify or publicize classification schemes. Third parties may simply publicize categories that are already being considered by users or those being categorized (Kennedy, 2005). This publicity serves to solidify categories as meaningful and appropriate. For example, media publicity about nascent categories of automobiles creates an understanding of new categories of automobile(Rosa et al., 1999). Media also help solidify competitive groups and the players within an industry by linking together particular objects (Kennedy, 2005).

2.3.2 Individual Categories vs. Groups of Categories

The prior discussion centered largely on the creation of individual categories. Yet categories may also appear in groups—that is, as part of a classification scheme. Classification schemes differ slightly from cognitive categories used by individuals or groups to understand their world. Classification schemes are created by fiat, either by institutions, individuals, or organizations. Institutions with legitimate authority create sets of categories because they wield power over the objects they wish to categorize (Douglas, 1986). Thus, governments can create systems of apartheid based on racial classifications (Bowker et al., 2000). However, while schemes can be created that

disadvantage others, institutionally created classification schemes need not be negative or oppressive. Part of the benefits of having legitimate authority is the ability to create systems that can be adopted and used by those connected to the institution. Tax brackets, grades in schools and the like also help create societal order.

Formal classification schemes can also be created by organizations or individuals that wish to order a particular set of objects and then communicate that classification scheme to a set of users. Organizations creating classification schemes act as market intermediaries when these schemes encompass objects that they do not produce or control. Thus, newspapers, investment analysts, guide book creators, directory publishers and the like create classification schemes which they then impose on groups of objects (films, companies, restaurants, mutual funds) to be categorized for the benefits of the users (readers, investors, tourists). When the objects being categorized are difficult to understand, these categorizers often take the role of expert interpreters, helping disparate groups understand particular categories by performing an evaluation of the objects within a particular category. For example, restaurant critics evaluate whether restaurants are good or bad (Rao et al., 2005).

2.3.3 Why Categories Are Created

The preceding discussions have all, implicitly or explicitly, been based on the notion that categories are created to improve understanding of the technical or social aspects of a particular world for users, objects, and categorizers. While the process of categorization is understood, the ultimate issue of why categories are created remains an undertheorized one. The common notion is that categories are created for improved

cognition via clear boundaries (Bowker et al., 2000; DiMaggio, 1987; Estes, 1994). That is, separate from any plans of use of the classification scheme, the individual categories are designed to improve cognition by separating some objects from other objects.

Categories are also the basis of social ordering. Indigenous tribes, for example, create categories to improve their understanding of their place in the world (Levi-Strauss, 1968)). Elites in social circles promote 'high art' to cement their superior social position (DiMaggio, 1987). Governments create systems of apartheid to privilege certain groups of people over others (Bowker et al., 2000). Even though the reasons behind the creation of these categories may be for self interest, the functional form of the categories is designed to create clarity among the different divisions. For example, apartheid groups focus on rules such as the "one drop" rule to make a strong distinction against black and white. The racial division of human beings is based on physical attributes designed to clarify who is in one group and who is in another. Elites working to create art forms advertise specifically about what genres are their domain (classical music, opera, abstract art), because in order to be distinct from others, their artwork must also be distinct from more general representations (DiMaggio, 1987; DiMaggio & Pettit, 1999).

Furthermore, descriptions of how categories are created (invention, borrowing, and encounter) suggest that categories are created only when current categories do not match the cognitive needs of those using them (McAdam et al., 2001). Thus, citizens in towns that have changed borders due to war or other issues develop new, blended social categories of citizenships as their old categories no longer work (Sahlins, 1991). Mutual fund directories retire categories that no longer capture the different kinds of funds

currently being available, while adding new categories as new funds become available (Lounsbury et al., 2004).

Most research, in fact, focuses on the results of categorization precisely because the answer to, "why are categories created?" has been automatically assumed to be for improved understanding—that is, categories, are a cognitive simplification device. As a result, most researchers focus on the consequences of categorization, taking the creation of categories for granted. However, this leaves open the possibility that categories may not always exist for reasons of improving cognition.

One empirical example highlights this possibility by examining when categories change or disappear. Lounsbury and Rao studied a mutual fund directory to determine when categories were created or reconstituted (Lounsbury et al., 2004). They found that the directory paid attention to powerful mutual fund companies in deciding whether or not to keep a category which had few members. Categories dominated by powerful mutual fund companies lasted longer than those that did not have such members. The authors suggest that this was because of the mutual dependence between the creator of the directory, who needed mutual funds in order to publish the directory, and the mutual fund firms, which wanted to be listed in a way that made them most favorable. This suggests that created categories may remain even if they are no longer improving cognition. However, it does not directly address the possibility of categorizers creating categories for strategic reasons. In fact, research has in general ignored the possibility that categories could be created strategically, in the form of ambiguous categories which do not add to understanding.

2.4 The Role of the Classification Scheme

The possibility of the creation of ambiguous categories has important implications for our understanding of classification in general. Categories gain meaning not simply for their own attributes in isolation, but also because of attributes across the entire scheme (Zerubavel, 1991, 1996). Categories have meaning in relation to other categories. For example, we understand a chair not only by knowing the attributes of a chair, but also knowing that a chair is not a table, bird, or car. This example separates chairs from many different kinds of objects. But one could imagine a classification scheme that separates chairs from tables, dressers, and sofas. And one could imagine a further scheme that separated chairs into side chairs and armchairs. Without understanding the entire scheme of categories, it is difficult to understand what aspect of meaning is being discussed.

Focusing on classification schemes offers a unique way to address the issue of referent categories. While classification schemes have been studied as a particular type of classification, they have generally been overlooked by researchers, who focus more on informal categories, or, when using classification schemes as a data source, focus on categories within a classification scheme as if they are informal categories representing a larger cognitive map (Lounsbury et al., 2004; Rao & Monin, 2007; Rao et al., 2005; Zuckerman, 1999). Classification schemes offer a unique perspective on categorization research in general because they offer an entire scheme of fixed categories—that is, the appropriate referent categories for understanding are included for classification schemes. Classification schemes also benefit because the roles of categorizer, object, and user are separated, allowing the potential to examine the influence of these roles separately.

2.5 Conclusion

Categorization underlies much of human thought and action. Lumping and splitting objects has important consequences not only for users of the categories, but also for the objects as well. For categorized objects, categorization determines and solidifies their identity, how they are valued, and what resources accrue to them. It helps chart a course of acceptable action for them. For users, categorization determines the expectations they have for individual objects, the value of those objects, and identifies the objects that are to be known.

Most research on categorization takes the underlying categories as a given, focusing instead on the consequences of categorization. That is, studies that examine the consequences of categorization assume that the underlying categories clearly convey information about the categorized objects. This is because classification is generally perceived to be an act of cognitive simplification. Categories are created for improving the understanding of the categorized objects. However, research has shown that categories remain in use even when they may no longer be giving information. This occurs when keeping those categories is vital to preserving power relationships between the categorizers and the categorized. While this occurs after the categories have been created, such events leave open the possibility that categories may be created strategically in addition to being used strategically.

My dissertation addresses this gap by suggesting that organizations can and do create categories for reasons other than improving cognition in certain situations. By focusing on classification schemes, I am able to examine when categories may be created for strategic reasons. By doing so, I am also able to highlight the role of the categorizer.

Prior literature has addressed actions of categorizers, noting that institutions, for example, impose categories by virtue of their legitimate power. In the following chapters, I focus on the perspective of the categorizer in the creation of the classification scheme.

In addition to examining when strategic category creation may occur, I also push the literature further by examining the implications of this behavior, which has thus far been ignored by researchers. Categorizers may indeed strategically create classification schemes, but what impact does this have on users? Users are typically seen as the ultimate reason for the scheme in the first place: classification schemes help users of the scheme better understand their world—hence why issues of inappropriate use of categories become extremely important when they are revealed. Yet no research has examined the effect of strategic action on customer response.

CHAPTER 3

HYPOTHESES, I

3.1 Overview

As suggested in the prior chapter, research on the act of classification has greatly

increased the understanding of categorized objects, and in particular, the behavior of

those objects as a result of their classification. Yet such a focus often ignores both the

categorizer and the composition of the classification scheme itself. As a result, most

research focuses on issues of placement: if the object is unambiguous, it can be placed

in a category and thus understood. Such reasoning implies that each category is clearly

defined. Yet categories within a scheme may be overlapping or unclear. In these cases,

the meaning of any individual category in isolation may seem plausible, but when placed

in juxtaposition with other categories, the meaning of the categories becomes confused.

I call such schemes ambiguous. Formally defined, an ambiguous classification scheme is

one where individual categories overlap in meaning, allowing a single object to be placed

in multiple categories without violating any of the rules of the classification scheme

(Ruef 2007, Abbott 1997).[2] That is, ambiguous classification schemes have overlapping

categories, while unambiguous classification schemes have categories that do not overlap.

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[2] It is important to clarify between ambiguous *creation* of classification schemes and ambiguous *usage* of classification schemes. Ambiguous category creation involves creating a set of categories which are not analytically distinct from each other. Ambiguous *usage* of a classification scheme occurs when many objects with dissimilar attributes are lumped into the same category. For example, when organizations declining in market share and with no profits are rated a "Market Outperformer," and organizations with high profits and increasing market share are also rated a "Market Outperformer," the category of "Market Outperformer" is used in an ambiguous manner. On the other hand, when "Market Outperformer" exists in the same classification scheme as "Overweight" and "Buy," the classification scheme itself can be said to be ambiguously *created*, because the same organization can be placed in multiple categories. My paper concerns the <u>creation</u> of ambiguous classification schemes, not the ambiguous use of categories.

This is because meaning occurs not only through an assessment of the attributes of a set of objects within a single category, but also through an understanding of the interplay of all possible categories (Bowker et al., 2000; Goodman, 1992; Porac & Thomas, 1994).

This chapter brings into focus the issue of classification scheme creation through a focus on the composition of the scheme. By examining the conditions under which categorizers create ambiguous classification schemes, I begin to fill the gap in our understanding of classification scheme creation, but also in our understanding of categorizer decision making in the first place. While ambiguous classification schemes could occur by accident, the fact that classification schemes are created, not discovered, leaves open the possibility of strategic action. In this chapter, I suggest situations in which the creator of a scheme might deliberately choose to create an ambiguous classification scheme, rather than a clear one.

In the following sections, I adopt the perspective of the categorizer in exploring some explanations for why ambiguous schemes are created. Categorizers create classification schemes, yet their role has been largely ignored in the research on organizational classification (but see Lounsbury & Rao 2004 for an exception). I examine how interactions between categorizers, objects and users as well as the interactions among multiple categorizers may influence the level of ambiguity in the classification scheme. I suggest that ambiguity increases when there is a conflict of interest between the categorizer and its users as well as when the categorizer occupies an elite position in the market for classification.

3.2 Users, Objects, and Classification Scheme Creation

Even though a classification scheme is a frame with a point of view determined by the categorizer, its creators take into account both user and object expectations when designing the scheme. Users assume that classification schemes are objective (Bowker et al., 2000; Lounsbury et al., 2004). Users also expect classification schemes to clarify the meaning of a set of objects, although the taxonomy of an individual classification scheme may be left to the discretion of the categorizer (Lounsbury et al., 2004). While users want a classification scheme that allows them to discriminate between objects, the objects focus more on the potential usage of the scheme.[3] Classified objects want to be portrayed the way they see themselves, usually in the best possible classification.

In many classification schemes, the categorizer is separated from its users and the objects it classifies because the classification scheme is either non-revenue generating or generates revenue solely from user subscriptions. In these situations, the categorizer is somewhat insulated from any pressures of objects for favorable classification. In an idealized situation, the categorizer would simply look at the world of objects and would then place them in the appropriate categories according to the tenets of the classification scheme.

A conflict of interest, however, often exists between the categorizer and the users because objects may also be customers of categorizers. It may be difficult for a categorizer to objectively classify an object if it has a relationship with it. In practice, categorizers may accept payment from objects for services tangential to the classification, in addition to any revenues they may receive from users. For example, firms may pay Google and other search engines to increase their position so that they appear as a

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[3] Again, object represents the organization that creates what is categorized. For example, in stock market classification, the future performance of the stock is what is being classified, but it is the company whose stock is being evaluated that wants to be favorably classified.

member of a particular category or as well-placed within a particular category. Users then interpret this as a best match. Categorizers may offer advertising opportunities, such as when newspapers accept advertisements from movies that they then rate. Categorizers may provide objects with advising services, generating revenue from their expertise in particular categories or through auxiliary services within the firm. For example, brokerage firms may underwrite or offer consulting services to companies whose stocks they also rate as part of their objective market analysis. While such behavior allows the categorizer to generate multiple lines of revenue, it may also influence the categorizer to classify in ways that allow the categorizer maximum benefit, even at the possible expense of users.

This conflict of interest is further exacerbated by the power dynamics between objects and categorizers (Lounsbury et al., 2004). When there are multiple categorizers in a particular market, the object can threaten to take its ancillary business elsewhere. It can also refuse to give access to firm information for the categorizer, which can have implications for the categorizer's ability to classify the object. This can result in user dissatisfaction with the categorizer.

One way for categorizers to manage the push from objects for favorable classification is to classify some objects more favorably than they deserve. For example, some investment firms rate stocks more favorably than other raters when they have an underwriting relationship with the company whose stock they are rating (Hayward et al., 1998). Merrill Lynch and Salomon Smith Barney (Citigroup) both faced scandals when they rated stocks positively while disparaging them in private. Such activity, if discovered, has reputational and financial ramifications. Both of these firms paid large

fines and the analysts in question were barred from working in the securities industry. Furthermore, such behavior risks alienating users, who expect objects to be honestly categorized.

Another way to deal with the pressures to classify objects in a particular way is to create a classification scheme that will create multiple opportunities for classification—that is, an ambiguous classification scheme. Ambiguity in general often has negative connotations due to a strong human preference for clarity. Several studies show that the value of clarity is nontrivial. In experimental settings, subjects have an ambiguity discount (that is, the price at which they are willing to place a bet given ambiguous rather than clear probabilities) ranging between 5% and 20% (Bernasconi & Loomes, 1993; MacCrimmon & Larsson, 1979; Yates & Zukowski, 1976) and at least one study up to 60% (Becker & Brownson, 1964). A study of auditors and the users of financial statements found that users reacted conservatively to ambiguous probabilities when determining whether or not potential future loss should be included in an auditor's report (Nelson & Kenney, 1997). Examining the stock market, (Zuckerman, 1999) finds that large diversified firms which cannot be easily categorized by analysts trade at a discount to those firms whose purpose is clear. While this is not evidence of an ambiguity premium, it is evidence that investors pay less for the equities of firms they do not understand. Ruef and Patterson find that ambiguous firms (denoted by a description including a miscellaneous object) received lower credit ratings than those whose descriptions were clear (Ruef & Patterson, 2007). Gould argued that violence occurs when audiences cannot tell the difference between their position and another. That is,

violence occurs as the result of confusion about social roles as perceived by those who enact those roles (Gould, 2003).

Yet ambiguity (including ambiguous classification schemes) can also be beneficial to organizations because of the way that humans process it. At the level of the individual, the ability to be ambiguous is associated with increased performance and the preservation of role, status, or credibility. These benefits occur when actors are able to craft an action or group of words with a sufficient amount of vagueness. Both of these benefits come from allowing a single action to be interpreted favorably. This increase in performance comes from the reduction of constraints in responding to a situation. That is, ambiguity allows an actor to be flexible in his adaptation, while clarity often constrains him to a clearly identifiable role.

This positive benefit of ambiguity has many empirical examples. Chess players, for example, who can maintain many lines of play within a single arrangement of pieces, perform better than those who choose a single line of action (Leifer, 1991). These better performing players still make single moves, but each move is an advance in "many games at once." The strategy of remaining ambiguous until they find a situation where there is a clear best move allows them to respond better to their opponent. Cosimo de Medici's influential leadership was possible because he was able to maintain an ambiguous profile (Padgett et al., 1993). A single action by Cosimo had many possible meanings, and so different audiences could interpret the meaning differently, and favorably, for their own situation. Established actors perform better when they are able to become generalists later in their career (Zuckerman, Kim, Ukanwa, & Rittmann, 2003a). Although role specialization helps them become known, as they gain experience,

the number of roles to which they are appropriate dwindles. Those who are able to break free from their specialized role identity have more opportunities for new projects.

Inside organizations, ambiguity can be seen as a way of building coalitions. Ambiguity may be "essential to organizing" because it allows multiple interpretations by multiple audiences (Eisenberg, 1984). When ambiguous agendas are set, all actors feel that their goals are being taken into account, and consensus is easier to achieve (March, 1994). Ambiguous contracts allow the possibility of change and interpretation as projects evolve, and may allow for better outputs than specified contracts (Mukerji, 1998).

Ambiguity can also be used as a tactic to deal with external audiences of an organization. Organizations often use ambiguous communication when dealing with potentially damaging situations because they want to avoid offending multiple audience members (Shuetz 1990). Ambiguity forces audiences to rely on their own interpretations for meanings. These interpretations are usually consistent with the user's current worldview (DiMaggio, 1997; Goss & Williams, 1973; Sellnow & Ulmer, 1995). Thus, the creator of ambiguity is able to benefit because its users will develop divergent interpretations. Ambiguity allows an organization to be flexible, while clarity often constrains it to a clearly identifiable role. As a result, actors who successfully use ambiguity are often able to increase their performance by increasing their options in responding to a situation (Leifer, 1991; Padgett et al., 1993).

An ambiguous classification scheme allows a categorizer many different ways to classify a particular object. An ambiguous scheme may allow categorizers to placate objects by creating several possible categories in which it might fit. This action reinforces the relationship it has with the object, but it also allows it to keep users who

will create their own meaning for the ambiguous categories. Theatre critics may divide some theatres into experimental and avant-garde. Such a scheme allows a production to be 'correctly' placed in multiple categories, leaving open the opportunity for the show to be the best "experimental" show of the year, even though it was similar to many shows labeled avant-garde. This keeps advertising theatres happy, and maintains the newspaper's ability to gain valuable and newsworthy information from the theatre companies. In equity rating systems, having multiple overlapping categories allows investment banks to place equities into a positive-sounding category or create movement within categories, which can appear favorable even if the equity is not the strongest performer relative to others that also receive positive ratings. As a result, the investment bank reinforces its relationship with lucrative underwriting and banking clients. Investors interpret differences between the categories and use the writing within the research report to justify their decisions.

The ambiguity of the classification scheme is likely to increase as the categorizer has more and more of a conflict of interest relative to its size. Although audiences may tolerate ambiguity, they have a threshold for valuing it. Too much ambiguity results in devaluation (Becker et al., 1964; Bernasconi et al., 1993; Camerer & Weber, 1992). If the activity creating the conflict of interest is a rare event, categorizers should be less likely to take the risk of being discounted by being overly ambiguous, as the benefit to pleasing a few objects is less likely to outweigh the potential cost of alienating multiple users. As there are more conflict of interest relationships, however, both the pressure to maintain these relationships as well as the benefits for doing so increase and may equal or outweigh the desire to serve the users.

This suggests the following hypothesis:

H1: The greater the relationships creating a conflict of interest for the categorizer, the greater the ambiguity of the classification scheme.

3.3 The Role of Other Categorizers

The prior hypothesis focused on how incentives might encourage a single organization to use an ambiguous classification scheme to deal with users and objects. However, the effect of conflict of interest is likely to vary according to the status of the categorizer itself. This occurs because of the inherent risk of choosing ambiguity as a strategy.

In classification, ambiguity is an attractive option to categorizers with a conflict of interest because it allows them flexibility and control (White, 1992). While audiences are likely to attempt to develop a meaning for the classification scheme, they may not be able to do so. When audiences are unable to determine a meaning for an ambiguous experience, they are likely to discount it altogether (Mukerji, 1998; Pulford & Colman, 2007). As the ambiguity of the classification scheme increases, categorizers risk alienating users even as they may placate the objects that they classify. The ability to share information in an accessible way to users is the hallmark of a good classification scheme—as well as adherence to norms of classification, which suggest that self-serving classification is taboo (DiMaggio, 1987). In order to gain acceptance for their classification scheme, categorizers need users to accept an ambiguous classification scheme. Categorizers with a conflict of interest can develop a more ambiguous classification scheme to the extent that they are higher status because of the role status

plays in user acceptance. This occurs because users are most willing to tolerate ambiguity from a high status categorizer.[4] Thus, while having a conflict of interest may encourage categorizers to create ambiguous schemes, the effect of conflict of interest varies by status.

In general, status is most valuable in markets where quality cannot be clearly observed (Podolny, 1994; Podolny, 1993). Industries where firms act as market intermediaries by creating classification schemes, such as in financial services, are ones in which quality is inherently uncertain. The need for a classification scheme in the first place indicates that information may be difficult to obtain or correctly interpret. Classification schemes are created by organizations when a set of objects is uncertain. They are designed to give clarity to that world. However, the categorizers themselves operate in an uncertain environment because the metrics for evaluating quality among categorizers are frequently contentious (Elsbach & Kramer, 1996; Espeland & Stevens, 1998b; Stake, 2006). In these situations, status is a helpful way to discern between different actors.

In general, higher status has been shown to give many benefits to those who possess it. High status actors have increased market share and increased margins on their sales (Podolny, 1993; Podolny & Phillips, 1996). They are leaders in market activities

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[4] My focus here is on the moderating relationship that status has on conflict of interest. It is not clear that high status actors would, independent of a conflict of interest, desire to create ambiguous classification schemes. With higher status also comes the desire to protect and enhance that status, which often means that high status actors are more likely to choose a course of action that preserves their status, rather than one that might risk destroying it (Podolny 2008). Schemes labeled as ambiguous may be interpreted as self-serving, and thus may negatively affect the reputation of the categorizer, much as deliberate mis-categorization might. On the other hand, high status actors may desire the flexibility that an ambiguous classification scheme would provide. Rather than examining the role of status, which has been exhaustively studied in other settings, my main interest is in arguing that classification schemes are created for strategic reasons, and thus I focus solely on the conflict of interest relationship and the effect of status within the frame of that conflict of interest.

(Lounsbury, 2002; Podolny & Stuart, 1995; Sanders & Tuschke, 2007). These benefits accrue to the high status actor because other marketplace participants perceive them to be valuable in part because of their high regard, not just through their actions or observed quality. In fact, market actors and outsiders are biased in favor of high status actors (Benjamin & Podolny, 1999; Hovland, Janis, & Kelley, 1953). In experimental data, individuals rated the statements attributed to high status actors as more trustworthy and of higher quality than the exact same statements attributed to lower status actors (Hovland et al., 1953). As a result of this high regard, high status actors have a certain amount of flexibility in their actions. High status actors, more so than middle status actors, can make choices precisely because their status affords them a certain shield (Phillips & Zuckerman, 2001; Sanders et al., 2007).

In classification, for categorizers with a conflict of interest, ambiguous classification schemes may allow them flexibility in the face of categorized objects; however, such classification schemes may be interpreted as creating intentional confusion. Those categorizers that are also high status can create an ambiguous classification scheme that still attracts users. This occurs because users are still likely to desire an affiliation with a high status partner even if they do not understand the actions of that actor because such affiliations improve their own status (Benjamin et al., 1999; Chung, Singh, & Lee, 2000). Thus, users may substitute the status of the categorizer for an understanding of the scheme itself. Instead of evaluating the scheme on its ability to clarify the world, they assume that because a high status actor created it, it must be valuable. In this way, high status categorizers with a conflicts of interest can be even

more ambiguous than their low status counterparts because the attention focused on their actions is likely to be perceived in a favorable light.

Conversely, firms with heavy conflict of interest relationships but lower status firms may see a benefit to ambiguity, but the risks of choosing such a scheme are greater for them than they are for high status firms. In general, low status firms are thought to operate largely invisibly within a marketplace (Benjamin et al., 1999; Phillips et al., 2001). While it is true that a more ambiguous classification scheme by a low status firm may not be noticed by the market at large, such an action is likely to be noticed by current users. With fewer users and less visibility than higher status firms, categorizers cannot risk the possibility that users may discount the scheme because it is ambiguous, even though such a scheme may give them flexibility to placate categorized objects. The loss of users is more devastating for these firms because they have fewer options for attracting new ones. Fewer users also may discourage ancillary services the categorizer may wish to offer to categorized objects, for which visibility through the classification scheme is a priority. Furthermore, even users who stay may be less willing to pay for the services of the lower status categorizer. Thus, a low status brokerage firm with underwriting business (a conflict of interest) risks losing its brokerage clients if it chooses an ambiguous scheme, and such schemes may also cause it to lose underwriting business as well, since underwriting clients want the visibility created by a (favorable) rating and analyst coverage.

The prior discussion suggests that status has a moderating effect on conflict of interest.

H2*:* The interaction between status and conflict of interest is positive:

categorizers with high levels of conflict of interest and high status will create

more ambiguous classification schemes than other actors.

3.4 Alternative Explanations

This chapter suggests that categorizers may strategically create ambiguity.

However, there may be other reasons that ambiguous classification schemes may appear.

First, ambiguous classification schemes may appear because of categorizer inexperience.

That is, categorizers may want to create clear classification schemes, but may not

understand how to do so, or may believe that their scheme is readily interpretable when in

fact audiences do not understand it. Second, ambiguous classification schemes may

simply reflect the difficulties of categorizing a particular set of objects. If the objects

have many different facets, and categorizers feel that they need to address them all, a

classification scheme may become ambiguous simply through the inclusion of multiple

elements. I will control for these alternative explanations in my models.

3.5 Summary

This chapter argues that while prevailing theories of categorization suggest that

categories are designed for perceptual clarity by users, in fact, when organizations are

categorizers, clarity may not always be the intention. Ambiguous classification schemes

can occur when categorizers have a conflict of interest between their own interests and

that of their users, but this effect varies by the status of the categorizer. This chapter has

focused on reasons internal to the categorizer that may lead a categorizer to choose

ambiguity. While having a conflict of interest or many users creates the incentives for

ambiguity, status may create the opportunity for ambiguity. The prescription from this chapter seems to be that all categorizer that can should attempt to be as ambiguous as possible, since ambiguity allows them flexibility. But is this true? While the choice to create any scheme may be free, the performance of that classification scheme does not rest solely within the categorizer's control. The next chapter discusses what determines the impact of the scheme on the categorizer's ability to attract users. By looking at ambiguity and other factors as they relate to the performance of the categorizer, it is possible to shed light on whether ambiguity is the best strategy.

CHAPTER 4

THEORY AND HYPOTHESES, II

4.1 Overview

The prior chapter of the dissertation suggested that classification schemes, in some situations, would be created ambiguously, rather than in a way that increases the clarity of the categorized objects. I hypothesized that categorizers likely to create ambiguous schemes were those who had both the incentive (via a conflict of interest) and the ability (via high status) to do so. Ambiguous classification schemes allowed these categorizers to be attractive to particular categorized objects by creating many different ways to classify objects.

In this chapter, I turn to the larger question of whether these actions have an impact on user attention. That is, classification schemes are generally considered to be created as clarification devices that help structure markets of classified objects (Bowker et al., 2000; Douglas et al., 1992; Zhao, 2005). Scheme creators act as critics of a particular market, providing information and simplifying cognition for users (customers) of that market (Hsu et al., 2005; Zuckerman, 1999). Investors use equity rating systems to differentiate between multiple equities. Diners use restaurant classifications to understand what kinds of cuisine exist in a given locale and how good those restaurants may be. Drivers use product guides to learn the difference between different types of vehicles.

Prior research has focused strongly on the information benefits of classification schemes. Classification schemes make different kinds of objects commensurable by placing them in the same category (Breiger, 2005; Espeland & Stevens, 1998a): both The Spotted Pig, a pub, and Babbo, an upscale restaurant by famed chef Mario Batali, rate a single star in the latest edition of the Michelin Guide. Group membership provides a reference group, allowing users to better understand the actions of an object in a particular category by the actions of other objects within that category. To continue the prior example, diners expect a high quality of food from both The Spotted Pig and Babbo, because both belong to the same category. Having experienced food at one or the other, they would have similar expectations via the category membership.

For objects categorized within a classification scheme, category membership helps define legitimate actions for them, and separates other actions or attributes as unacceptable for membership (Porac et al., 1994; Porac et al., 1989). The act of categorization itself is important as it renders categorized objects known—being difficult to categorize results in users of the scheme devaluing objects, at best, or not knowing about them at all, at worst (Rao et al., 2005; Ruef et al., 2007; Zuckerman, 1999). For example, in the 1990s, firms that de-diversified often cited analysts not understanding how to categorize them as a factor in their decision to restructure the firm (Zuckerman, 2000). Category membership also helps firms understand the competitive landscape, knowing which firms are competitive threats and which operate using different strategic principles (Peteraf et al., 1997).

Thus, it is well-established that the information contained within a classification scheme—that is, the <u>use</u> of a classification scheme, is beneficial to users and categorized

objects. Yet the value of the classification scheme itself to those who create it is not as clear. If the Michelin Guide used something other than its 0 to 3 star rating, would diners still buy it? In the prior chapter, I suggested that organizations strategically create classification schemes. But do such schemes affect the performance of the organization that creates it? And more generally, does the configuration of the classification scheme matter for the categorizers at all?

I answer this question by examining the performance of the categorizer as determined by aspects of its scheme. Performance is perhaps the fundamental strategic outcome: most theories of strategic management attempt to uncover what drives increased performance, whether that is survival, profits, or return on assets. In this chapter, I focus on user response, measured here as customer accounts. At some level, most measures of performance capture customer response, as measured in return on assets or profit, because customers are usually the ones providing the revenue of an organization. Thus, customers are at the very heart of any organization—without them, the organization may cease to exist. Rather than focusing on accounting based measures, I focus on actual customer (user) accounts because classification schemes are designed to capture user attention and assist users. Therefore, measuring their departure or arrival is an accurate measure of the performance of the categorizer[5].

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[5] My focus on the change in customer accounts is based on the assumption that the goal of most categorizers is to increase their customer accounts. It is theoretically possible that some categorizers may wish to pursue activities that would improve performance without increasing the number of customer accounts. For example, categorizers might attempt to change the net value of their existing accounts, or they might choose to switch customer segments in a way that would result in a net loss of customers. In general, however, categorizers rely on customers who purchase their products by fee. The only way for these categorizers to increase revenues is to increase customer numbers. It is possible that categorizers that focus on certain customer segments might tend to rely relatively heavily on increasing customer accounts, while other categorizers tend to rely on other methods of improving performance. For example, brokerage firms that focus on retail clients may find it easier to increase customer accounts than those focused primarily on institutional customers. I will control for these different foci in the ensuing investigations.

Focusing on the effects of the classification scheme on user response also complements research which has suggested that categorizers may be self interested, but has not examined how users respond to such behavior. Research has suggested that categories within classification schemes may be maintained in order to preserve important relationships between the categorized objects and the categorizer (Lounsbury et al., 2004). Such behavior benefits the categorizer by maintaining its access to potential objects to place in the classification scheme. Categorizers have also received fines for deliberately miscategorizing objects, such as those levied on equity research firms by the 2001 Global Research Settlement (Kessler, 2004; Reingold, 2006). Yet it is not clear whether users notice or respond to such actions.

That categorizer actions would lead to increases or decreases in performance (as measured by user attention) is hardly a novel idea when looked at more generally. Choices by firms in terms of product mix, location, and service form the basis of studies in strategy (Poppo & Zenger, 1998; Ruef, 1997; Teece, Pisano, & Shuen, 1997). These are augmented by studies which suggest customers respond to reputational concerns, departing when they feel associations with a firm might taint their own reputation (Jensen, 2006). Yet it is not clear that a classification scheme is necessarily like these other firm activities. Firms that work as critics are usually seen as competing on information: the ability to give thorough, timely, or unique information, and accurately grouping objects within a particular category (Hsu, 2006b; Shrum, 1991). Thus, the drivers of performance might be logically seen as the information or the use of the scheme. The configuration of that scheme has, thus far, been taken for granted.

In this chapter, I argue that the configuration of the classification scheme does indeed matter for the categorizers who create them. I suggest that the scheme itself serves two purposes: first, it is an ordering device. As a result, schemes which do not order well lose users. Second, the scheme is a cultural artifact. Choice of a scheme links categorizers with an industry and furthermore provides a set of legitimate groupings that help users appropriate value and understand the organizations that create the schemes in addition to the information provided within the scheme itself. In particular, drawing on literature from institutional theory as well as understanding of cognitive schemas, I examine how the legitimacy, similarity, and ambiguity of the scheme affect the change in customer accounts from year to year.

It is important to place boundary conditions around this investigation. My argument applies to situations in which a formal classification scheme has been created by an organization for the purpose of ordering a particular market. These classification schemes include rating systems, product directories, restaurant guides, and so on. In each of these cases, organizations create schemes because the objects that will be placed within the classification scheme are complex to understand, and markets for valuing them may be uncertain. These categorizers hope to attract users (customers) who will use their classification scheme as part of a larger decision-making process.

4. 2 Classification Schemes as Ordering Devices

As I have discussed in prior chapters, a classification scheme is a set of categories which divide a given world of objects into (ideally) discrete boxes (Bowker et al., 2000). This occurs through a process of "lumping and splitting"—like objects are grouped

together and separated from unlike objects (Zerubavel, 1991, 1996). Users who encounter a classification scheme can look at the different objects and take action based on their assessment of the different groupings. Thus, the categories themselves serve as devices which highlight similarities among members of the same category, while differentiating them from other categories (Hsu, Negro, & Perretti, 2007).

In the prior chapter, ambiguity described the relationship of individual categories within a scheme to each other. Given that this relationship may have an impact on the comprehension of categories within the scheme, choosing such a scheme may also have an impact on firm performance, to the extent that users may prefer schemes that they can develop a meaning for. Ambiguity works on a continuum. At one end is a scheme that is completely distinct, with harsh boundaries between the categories. As the category boundaries are increasingly blurred, the ambiguity of the scheme increases. I hypothesize an inverted U relationship between ambiguity and performance.

Classification schemes that create harsh boundaries around a given set of categories are likely to best differentiate the categories within the scheme. That is, schemes for which there is a clear definitional boundary should most easily differentiate objects. Yet in reality, such harsh boundaries are often difficult to maintain, due to the fact that categorized objects often share or borrow attributes with objects in other categories (Rao et al., 2005; Rao & Sivakumar, 1999; Sahlins, 1991). For example, restaurants which wanted to incorporate elements of nouvelle cuisine and classical French cooking slowly eroded the purity of those categories, causing difficulty in rating those restaurants (Rao et al., 2007; Rao et al., 2005). As a result, particularly in classification markets where objects are uncertain, especially distinct classification

schemes may be difficult to deploy, as objects may be complex. While users may appreciate the idea of clear boundaries, once objects are placed into them, the categories may become confusing.

As defined in the prior chapter, a classification scheme with many overlapping categories, such that an object with a single set of characteristics can match multiple categories at once, is said to be ambiguous. While user perceptions of a distinct classification scheme seem obvious, user perceptions of an ambiguous one are less clear. This occurs because, when first presented with ambiguity, most individuals attempt to develop a meaning for the ambiguous communication (Eisenberg, 1984; Sellnow et al., 1995; Ulmer & Sellnow, 1997). The interpretation developed tends to be consistent with the worldview of the individual (DiMaggio, 1997; Sellnow et al., 1995). Thus, organizations that create ambiguous communications can appeal to multiple stakeholders with conflicting demands.

However, other research suggests that, when faced with overwhelming ambiguity, rather than develop their own worldview, individuals tend to discount the ambiguous communication entirely, making it less valuable than a clearer alternative. That is, many people exhibit strategic ambiguity aversion (Pulford et al., 2007; Segal, 1987; Viscusi & Chesson, 1999). This is likely to be especially true in situations where users of the scheme can imagine clearer alternatives. Thus, when faced with a single ambiguous classification scheme, an individual might attempt to develop a meaning for the scheme. On the other hand, when alternatives for schemes exist, a user may be less likely to develop an explanation, and may instead discount the scheme altogether. This suggests that there is a threshold for ambiguous classification schemes: a certain amount of

ambiguity, and users may interpret it as nuance. Too much ambiguity, and users interpret it as nonsense.

Thus, in an uncertain market with competition, at low levels of ambiguity, the classification scheme is constraining, and distinct bins lead to problems with placement, which may lead to user dissatisfaction. Moderately ambiguous schemes, on the other hand, can be favorably interpreted by multiple parties, who tend to see the categories as matching their world view. On the other end of the continuum, highly ambiguous schemes, particularly in a competitive market, are easily discounted for clearer alternatives. Thus:

> **H3:** The relationship between ambiguity and customer accounts follows an inverted U: at low and high levels of ambiguity, the change in customer accounts is lower than at moderate levels of ambiguity.

4.3 Classification Schemes and Similarity

Competition among the schemes of different categorizer creates a market for classification. Categorizers compete for users on at least three dimensions: the composition of the scheme, the ability of the categorizer to place objects in the scheme, and the information they convey to users within the scheme itself. But unlike markets for tangible products, such as cars or hotels, the market for classification schemes is first a competition of meaning. That is, before categorized objects are shared with users, the categorizer must settle on the kind of scheme it will use to examine those objects. The prior hypothesis examined how the categories within a particular scheme may affect customer response. In this section, I examine how the relationship of those category

choices to other categorizers' choices affect customer response. That is, users make decisions based on their understanding of a particular scheme, but they also compare that scheme to other schemes that may occur.

The classification scheme represents a particular view for sorting a given set of objects. Categorizers choose both the number of categories and the labels that identify those categories—as well as attributes that define category membership. These choices can be culturally rooted (Bowker et al., 2000; Durkheim et al., 1972 (1963); Varnedoe, 1990) as well as strategic (Lounsbury et al., 2004; Porac et al., 1999). As a result, classification schemes for the same kinds of objects often differ across different categorizers. For example, the classification scheme for wines in France focuses on geographic production area, while the classification scheme for wines in America focuses on grape varietal (Zhao, 2005). Each scheme could easily have chosen the other— different French wines use different kinds of grapes, and American wines can be distinguished according to the state in which they are produced. The choice of the scheme, then, represents a choice about the salient attributes to describe a given set of objects and the level at which to describe them (Bowker et al., 2000). French wine, for example, focuses on a domain, rather than individual cities or larger regional areas.

Yet beyond the objects that are categorized, classification schemes create a way of sorting categorizers as well. Whenever there are multiple categorizers in a given market, the classification scheme becomes a way for categorizers to differentiate or assimilate to other categorizers' conceptions of the categorized objects. Markets are socially constructed through producers' examinations of each other's choices (White, 1981). The choices of a producer based on dimensions in the market signal to others

what kind of organization it is. For White, these dimensions were price and quality. But for others, there have been other dimensions, including service, geography and styling (Baum & Haveman, 1997; Porac et al., 1994; Porac et al., 1989). The collective result of these producer actions is set of market niches in which firms compete and which customers see as distinct ways of creating a particular product (Polos, Hannan, & Carroll, 2000; Porac, Thomas, Wilson, Paton, & Kanfer, 1995). For example, Scottish knitwear manufacturers occupy a niche based on location (Scotland), style (classic), and quality (high) (Porac et al., 1995; Porac et al., 1989).

Thus categorizers make their choices based on their own beliefs about how to view a set of objects, but also based on their understanding of how other categorizers view the same set of objects.   White's observation that producers attempt to array themselves into different niches based their own resource endowments and their views of the outputs of other producers suggests that the key to competitive survival is differentiation: choose a niche, or in this case a scheme, that is very different from others, which carves out a unique space where others cannot compete.   This assures access to a unique stream of resources, which will lead to user attention and survival. Choosing a position highly similar to rivals means competition for scarce resources.

In markets for classification, this suggests that categorizers that change their schemes in an attempt to become more similar to other categorizers are likely to perform worse than if they attempt to differentiate themselves. In general, changing to a new scheme is risky. Poorer performance may ensue because a change in a scheme requires a categorizer to recalibrate its prior classifications. Doing so can be difficult, and can result in changed evaluations as categorizers attempt the translation. For example, when a

stock market analyst changes firms, it can be difficult to figure out how to translate his prior ratings to the new system. Dan Reingold remarked that changing companies meant "a lot of work to do getting ready…. I didn't intend any dramatic ratings changes, but I still had to write new reports and explain my reasoning on every stock I covered" (Reingold, 2006). Although this represents the experience of one analyst changing companies, an entire brokerage firm changing schemes would require extreme amounts of effort to translate the ratings, as well as difficulties and changes understanding and adapting to the new system.

The change process can be difficult for any kind of a scheme change. Yet difficulties are likely to be exacerbated when the new scheme is highly similar to other schemes. A change to a differentiated scheme offers an ability to attract users through advertising a new way of seeing. Choosing a differentiation strategy in general requires education of customers (Baum et al., 1997), since it is unlikely that customers will have a well-formed notion of how a differentiated product (in this case, classification scheme) works. Such education efforts may attract customer attention and interest. In addition, changing to a scheme that is less like others allows categorizers to capture a unique space in ways of seeing. Conversely, changing to a scheme more similar to others in the industry could signal to users that the categorizer "got it wrong" the first time and is trying to imitate other, more successful categorizers. It also forces the categorizer to compete for the use of labels that already have well defined conceptions due to their common usage; this forces the categorizer to adopt to those conceptions.

In addition, as a categorizer chooses a scheme that is more similar to all other schemes in a differentiated industry, it risks confusing users, who do not know how to

interpret the combination of categories. For example, equity research categories often

divide into groups using labels that are a call for action ("buy" or "sell") and labels that

are descriptive ("market performer" or "market underperformer"). A brokerage firm that

attempts to become more similar to all firms will need to incorporate categories from

both descriptive and action labels. Such a scheme can be difficult for investors to

interpret, as it loses internal coherence.

This prior discussion suggests the following hypothesis:

H4: The interaction between new schemes and similarity is negative:

categorizers that change their scheme to a more similar scheme gain fewer

customer accounts than those who do not.

4.4 Classification Schemes and Legitimacy

The prior hypothesis discussed how similarity might affect the user response to

the categorizer's classification scheme. However, it is worth considering the implications

for categorizers who share the exact same scheme as other categorizers.

The prevalence of a particular organizational choice or activity often suggests that

the choice is legitimate, or seen as proper and desirable by an important audience

(Suchman, 1995). While innovative organizational choices are seen as improving some

technical aspect of the adopting organization, as these choices diffuse throughout an

organizational population, they become expected behavior (Fligstein, 1985; Westphal,

1997; Westphal & Zajac, 1994). As other adopters choose the same activity, they do so

not for technical reasons, but because adoption offers the organization legitimacy. That

is, by adopting the same actions as others, the firm gains the approval of important

audiences and thus access to valuable resources. Thus, organizations adopt poison pills

or multidivisional forms because it is seen as adherence to a particular value orientation,

not because it is necessarily more efficient (Fligstein, 1985). Firms adopt long term

incentive plans to appear to adhere to the principal of maximizing shareholder value, but

the more organizations that have adopted them, the less likely the firms are to implement

them (Westphal et al., 1994). Underlying the notion of adoption is the larger issue of

prevalence or frequency: doing the same thing that many others in the same field do

gives organizations legitimacy (Ruef & Scott, 1998).

Categorizers using the same scheme as others appear to be following cognitive

norms, or rules about what types of structures or practices are allowed in the industry

(Ruef et al., 1998). That is, there are strongly held beliefs about how categorizers should

behave. They must be unbiased and fairly represent the objects that they categorize (Hsu,

2006b; Lounsbury et al., 2004). Having a frequently used scheme suggests that the

categorizer is following structural norms of how classification schemes should look.

Users may further assume that such a scheme is likely to be used in an appropriate way.

The choice of a frequently used scheme suggests to users that the categorizer conforms to

a standard way of seeing the classified objects, and that it will fairly and objectively

evaluate them. Hence, critics, a subset of categorizers that confer value on objects

through sorting them, gravitate to quality schemas that are well-structured, since they are

better able to justify their critical skills in using well-known schemas (Hsu, 2006b).

Legitimacy is important for categorizers in general because classification schemes

are most often deployed in markets where objects are not easily understood by potential

customers (users). Thus, user uncertainty exists at two levels. First, users have

uncertainty about the categorized objects themselves. Second, users have uncertainty about the classification scheme providers as well. Because the objects are difficult to understand, users may have difficulty interpreting ex ante whether or not the categorizer is performing its job accurately and fairly.   Choosing a categorizer that uses the same scheme as other categorizers can reduce some of this uncertainty, because by picking a legitimate organization, users feel assured that the categorizer is following industry norms for classification.

Thus, a categorizer choosing a frequently used classification scheme is likely to gain more users because it is perceived as legitimate. This suggests the following hypothesis:

H5: The greater the frequency of the classification scheme, the greater the increase in customer accounts.

However, while the scheme itself may be seen as more legitimate when more categorizers use it, and thus may capture more users, increased frequency of the scheme also means increased competition. When categorizers have exactly the same scheme, they are no longer competing on a particular vision of the world as defined by scheme selection. Instead, the focus of customer attention changes. Since users need not compare categorizer by the difference in their schemes, they can instead turn their attention to the categorizer's use of the scheme. Thus, categorizers with the same scheme compete on their ability to place objects within the scheme and provide valuable information. Although users may be drawn to a scheme that is familiar and legitimate within an industry, users should be drawn most strongly to those firms that are also best

performing—that is, the ones that give the most useful information and the most accurate or timely placement of objects.[6] This suggests that quality moderates the relationship of legitimacy.

> **H6:** High performing categorizers that use frequently used schemes will gain more customer accounts than lower performing categorizers using frequently used schemes.

4.5 Alternative Explanations

There are a number of alternative explanations for why a user might choose to join or leave a particular categorizer. For example, merger activity may bring users from two firms together, increasing users but not through the choice of the users. Second, users may choose a particular categorizer because it has high status in the industry. Finally, users may choose a categorizer because of other strategic efforts not related to the classification scheme, such as price or service. I will control for these alternative explanations as much as possible in my analyses.

4.6 Summary

This chapter suggests that classification schemes can have an impact on performance, specifically altering the number of users that a categorizer has as clients. Classification schemes provide information, sorting the world for users, but they are also

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[6] I specifically focus on quality in this section rather than status. This is because when users are examining categorizers that share the exact same scheme, they are likely to be comparing firms based on actual information about which scheme is used. Choosing a categorizer based on legitimacy of the scheme suggests a decision process in which multiple schemes are available to users for examination and for which the scheme is a deciding factor. Thus, information about the scheme is being gathered and use of the scheme can be compared directly across categorizers. On the other hand, choosing a categorizer based on status need not involve an understanding or observation of the scheme itself. I test for an effect of status rather than quality as a robustness check in the next chapters.

tools for categorizers to attract business and show their skills at processing information. For this reason, both overly clear and overly ambiguous classification schemes may draw fewer customers than those that are moderately ambiguous.

However, it is not enough to look at only the configuration of an individual scheme. Multiple classification schemes usually exist for categorizing a set of objects. A particular categorizer's scheme is thus compared to other categorizers' schemes. Categorizers choose their schemes by looking at the choices of other categorizers, and molding their scheme in response. Strategic changes to look more similar to many other schemes are likely to reduce the number of users that become clients of the categorizer, as highly similar schemes are likely to be confusing, and changes may be seen as a sign the categorizer is not as competent as the one it is imitating. This is true because, when multiple different styles of classification schemes exist, being similar to all of them results in a disconnected scheme. On the other hand, having the exact same scheme as several other categorizers can be helpful, especially if the categorizer is highly skilled. Using the same scheme creates legitimacy, but shifts the locus of competition from the scheme to the ability to use it.

CHAPTER 5

MEASURES AND METHODS

5.1 Introduction

The prior theoretical discussion and hypotheses develop two dependent variables, the degree of ambiguity and the change in user accounts of the categorizer. In this chapter, I explain my planned analyses. I begin with an extended discussion of my context. I then discuss the measures and methods for each study. Finally, I discuss the sources of my data.

5.2 Industry Context

I use the equity rating systems from United States broker-dealers from 1993-1999 as a setting in which to test my theory.   Equity rating systems are the set of categories that divide equities of publicly traded corporations based on their potential future performance. Thus, they are classification systems based on quality. Many include both horizontal and vertical categories. The categories within each rating system designate positive, neutral, and negative opinions of the researchers, ostensibly based on the expected future performance of the equities themselves.

Equity rating systems are part of the larger genre of equity research. Equity research can be divided into buy-side and sell-side research (Kessler, 2004; Reingold, 2006). Buy-side research is performed by large investment companies, such as mutual

funds or hedge funds. These companies then buy equities, based on their research. They make profits by purchasing investments that increase in value. Sell-side equity research is performed by a wide variety of companies, from independent research organizations to full service financial institutions and investment banks. For independent research organizations, the reports issued by their analysts form the sole activity of the organization. True broker-dealers primarily serve as places for institutional investors and individuals to buy and sell stocks. They often provide advising services for individual investors in the form of portfolio management services. (Institutional investors often do this in-house.) Their revenues come largely from commissions from buying and selling securities. Banks also act as broker-dealers. Banks offer a wide range of services for individuals, institutional investors, and firms. They receive a large portion of their revenue from fee for service activities such as underwriting debt and equity offerings and supporting mergers and acquisitions (Eccles & Crane, 1998; Mizruchi & Stearns, 2001).

Equity research occurs as a service for the clients of all of these firms. In theory, equity research is designed to help investors understand the performance of equities bought and sold on any of the major stock exchanges (Agrawal & Chen, 2005; Branson & Pagach, 2005; Clement, 1999; Kesner, Shapiro, & Sharma, 1994; McNichols et al., 1997; Reingold, 2006). The role of the analyst was created to help clients better process information. Analysts specialize by industry, and often bring strong industry experience and knowledge to their position. As a result, their understanding is valuable to individual investors, who may not understand complex financial and strategic statements, and institutional investors, who own stocks in many different industries and may not be able to understand the nuances of all industries. Investors use equity research in the hopes that

it will help them buy and sell equities profitably. Equity analysts develop their research

based on relationships with the companies they cover, analysis of the market, and

proprietary financial modeling. Equity analysts are barred from basing their reports on

anything other than public knowledge—that is, analysts cannot make recommendations

or forecasts based on insider information (Kessler, 2004; Reingold, 2006).

The result of equity research is the research report, issued quarterly, with updates

as needed based on new information from the firm. These research reports have three

parts: an analysis, an earnings forecast, and a rating. The analysis is a description by the

analyst of what the firm has accomplished and the analyst's opinion what the firm and its

market is likely to accomplish in the future. The earnings forecast, often called the

estimate, is a prediction for the firm's earnings in the short term (often a prediction is also

made for a longer horizon). The rating is a categorization of the firm, ostensibly based on

its predicted performance, that is a "summary judgment" of the other elements (personal

interview).

Analysts carefully choose the firms that they cover. No broker-dealer covers all

possible equities/firms in a particular industry. The average firm is covered by only five

to seven analysts (Zuckerman, 1999), even though there are hundreds of analyst firms.

Analysts focus on firms that fit neatly into a particular industry (Zuckerman, 1999;

Zuckerman et al., 2003b). They also prefer industries that have a fair number of firms

(O'Brien & Bhushan, 1990). The profitability of the industry for their clients also plays a

role—as one director of research explained, "We don't cover airlines. They simply aren't

profitable investments for our clients." And analysts may prefer firms for which they

already have favorable views (O'Brien et al., 2005). These firms are usually strong

performers, because high (or increasing) performance is easier to forecast and rate than reduced performance.

Analysts at broker-dealers that provide underwriting services face a complicated role. On the one hand, their duty is to properly describe the organizations as they see them. This service is provided for the investors, who pay commissions to the broker-dealer to buy and sell securities on their behalf. On the other hand, analysts are part of a larger organization which derives a great deal of revenue from its underwriting business. Underwriting occurs when banks assume the risk of an equity or bond issue. Simplistically, underwriting banks, in groups, purchase the shares from the selling firm and then resell them for an increased price. That spread is profit for the organization. In order to encourage investors to purchase the public offering, the equities being underwritten need to be evaluated positively, as this enhances the willingness of investors to pay for the new issue. Analysts, because of their focus on a large number of equities within a specific industry, understand the landscape of competition within that industry. As a result, their insight can be very useful for investment clients. This dual role often creates pressure for the analyst to issue a positive rating (O'Brien et al., 2005; Sieland, 2003).

Little has been studied about the actual descriptive analysis that appears on the research report. Instead, much more is known about how earnings forecasts are made and how ratings are given. The reliability of these parts of the report is very important. Clients care that the forecasts are accurate, since they base decisions of material impact on them. Individual equities rated by broker-dealers also care about the forecasts and ratings. While the increase to a firm's share price from a positive rating is minimal, the

decrease to the firm's share price from a negative rating can be almost 10%, an effect that lingers for almost six months (Womack, 1996).

Earnings forecasts are ostensibly based on the prior performance of the firm as well as the current market conditions. This also depends on the skill of the analyst. Highly ranked analysts outperform their peers in the ability to correctly forecast earnings (Stickel, 1992). However, analysts themselves care about the forecasts because it determines their job prospects. Analysts lose jobs for poor performance (Mikhail et al., 1999), but they also have higher turnover when they make wild predictions, especially if they are new (Hong, Kubik, & Solomon, 2000). As a result, earnings forecasts tend to be clustered because analysts make predictions based on what they think others will predict (Bajari & Krainer, 2004). Furthermore, individual analysts report that they often create these earnings forecasts after discussing their estimate with company management. That is, analysts who have close relationships with a company will often call up that company to check to see if they are "in the ballpark" for the earnings estimate (Reingold, 2006).

Ratings also are also ostensibly based on the potential performance of the company but may instead be the result of analyst issues. The rating that an equity analyst gives is supposed to be a summary judgment on the equity of the firm. That is, equities expected to perform well in the short term should be rated highly, while those with poor performance should receive low ratings. However, analysts know that both companies and investors care a great deal about the ratings of an individual equity. Companies who receive lower than expected ratings usually complain angrily to the equity research group that gave the rating. They retaliate against individual analysts, refusing to talk to them or answer their questions. When the rater is an investment bank, firms will threaten to

remove their business (and may in fact remove it). In at least one case, an analyst was fired after a firm complained about its rating (Reingold, 2006; Sieland, 2003). Institutional clients may also dislike low ratings. Institutional investors typically hold large blocks of stock and cannot easily sell it. A lowered rating creates a problem for an institutional investor that holds a great deal of the stock. The investor cannot sell, yet questions arise as to why it continues to hold a poor performer. As a result of these pressures, analysts carefully consider what rating they supply.

Individual analysts cannot create their own rating systems. The rating system is created by the director of research and other senior staff members. Although they may not create it, all analysts at a brokerage firm use the same rating system. In the 1990s, brokerage firms were able to create whatever rating system they chose. As a result, systems ranged from one category (only equities recommended as a buy) to more than twenty separate categories. The individual categories within classification scheme were not specified either. Some firms focused on ordinal rating systems, dividing their ratings into a series of equal intervals. Other firms created rating systems which were more horizontal in nature, dividing positive ratings into multiple categories based on the type of stock rather than the expected performance. And other firms include hybrid types, including both horizontal and ordinal ratings.

In my sample I include sell-side research only. Buy-side research is performed by private companies and is accessible to the public. Within sell-side research, I include data on independent research firms, broker-dealers, and investment banks. This is important because, as mentioned earlier, each of these types of organizations has different

audiences, which I believe to influence the ambiguity of the rating system. By focusing

solely on one type of research provider, I would limit the generalizability of my findings.

5.3 Sample

My sample is an unbalanced panel of all of the firms based in the United States

issuing ratings on publicly traded firms in the US that released ratings to IBES/Thomson

Research between the years 1993 and 2000. I focus on the years between 1993 and 2000

partially because of data availability, but also because a series of scandals (several related

to the collapse of Enron) at high profile investment banks in 2000-2001 roiled the

industry, resulting in the Global Research Settlement, a set of fines and regulations for

equity research in general. Before 2001, brokerage firms were free to use any rating

system they chose, without explanation. The new rules allow firms to use any system

they wish, but the full system must be described and accompanied by written

explanations on the research report itself. This may have affected the types of systems

that firms use. By restricting my setting to before 2001, I can measure the effect of

brokerage firms[7] acting without restraints from legal regulations directly related to the

rating system itself.

Although my data begin in 1993, there is no indication that left censoring is an

issue in my analysis. Left censoring would be a concern to the extent that the factors that

affect ambiguity prior to 1993 significantly differ from those that affect ambiguity during

the sample period. If that is the case, results may be incorrect. In my specific sample,

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[7] I use the term "broker-dealer" or "brokerage firm" here for ease of description. Brokerage implies that a firm sells securities. Technically, this does not describe all of the firms which perform equity research. Research-only firms do not sell securities, and investment banks work both as brokerages and also in other areas. However, for the sake of parsimony, and because most people call them brokerages, I use these terms.

left censoring would be a concern if 1993-2000 represented a unique time in equity research. The close links between equity research and underwriting business began to permeate brokerage firms in the late 1980s. During this time, underwriting activity and new issues began to grow, and analysts at some firms began to pay careful attention to their firm's underwriting clients when making their reports (Kessler, 2004; Reingold, 2006). By 1990, an article in the Wall Street Journal listed eleven popular category labels for stocks, noting that these categories allowed "considerable wiggle room" for making recommendations (Schultz, 1990). What were later described as "excesses" in behavior among analysts began to occur in the late 1990s (Kessler, 2004). Although I measure the schemes of the firms beginning in 1993, I was able to capture firm underwriting activity and status for the prior 3 years, which means my information about the industry begins in 1990. Thus, beginning my sample in this time actually captures brokerage firm activity before the strong push to underwrite permeated almost every firm, but still situates it in the middle of a period of common activities for equity research.

Focusing on these years yields approximately 1229 observations on 230 broker-dealers. The firms vary widely in net capital. In the 1999 data, the largest firm was a diversified financial services organization with over $1 billion in assets, while the smallest one was an individual research provider with less than $500,000 in assets. The sample includes both public and private firms performing a wide range of services, from boutique research firms to full service investment banks. Although there were over 9515 broker-dealers registered with the SEC in 1987 alone, this number includes many individuals buying or selling stock for a few clients. In fact, 261 of the firms in the industry accounted for nearly 80% of the revenue of the industry (SIA Factbook 2002).

My sample ranges from large, publicly traded firms to a few private individuals running an independent firm, just as in the industry itself.

Some large firms have chosen not to reveal their information to Thomson Research. I was able to examine these firms through their public SEC filings, and they do not differ in demographic characteristics from the other firms that did choose to release their information. In addition, some of these firms were covered by an alternate data source, which allowed me to compare schemes between those that revealed information and those that did not.[8] The two data sources differed largely by which small regional firms they chose to include, although both included many smaller firms.

With this original sample, I also gathered customer data information from the SIA Industry Yearbook. Many firms chose not to list information in this directory, or, if they did, did not include customer segment data. The firms that did not release information tended to be smaller, regional firms—larger publicly traded firms almost always released information. In general, smaller firms comprise less than 20% of the revenue of the industry. Some smaller firms did release information, and in other aspects, such as status or underwriting activity, the non-sharing smaller firms did not appear to be different from similar size firms that did share information.

5.4 Variable definitions and Operationalization: Study 1

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[8] This alternate data source was the original provider of my data. They pulled my access to the data after a major client of theirs expressed concern that the firm was releasing their proprietary information to day traders and other subscribers. This concern is shared by most large firms in the industry; they wish to directly reveal their research only to their subscribers, not to the general public or to subscribers of "Consensus Ratings" services which combine the ratings of many firms into a single rating. Thomson is one such service.

5.4.1 Equation

The general form of the equation for predicting the ambiguity score follows the

form:

$$\text{Prob}(y=j)= F\left(\mu_j - \sum_{k=1}^{K} \beta_k x_k\right) - F\left(\mu_{j-1} - \sum_{k=1}^{K} \beta_k x_k\right)$$

where j represents the 1 to 7 ambiguity scales, and $\sum \beta_k x_k$ captures the predictor variables.

The μ and β for each equation are computed with an ordered probit function (Liao, 1994).

5.4.2 Detailed Description of Measures

<u>Dependent Variable</u>

The dependent variable of my study is the ambiguity in the rating system.[9] This

is a measure of perception by a potential user or categorizer. In statistics, ambiguity has

long been a concern in rating scale construction. The ability of individuals to discern

between scaled values varies considerably with the labels that are used. For example, a

leading statistical guide suggests that a non-ambiguous rating system should focus on the

traits of clarity, relevance, precision, variety, and uniqueness(Guilford, 1954).[10] Clarity

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[9] It is important to discuss exactly how I arrived at the classification scheme that was created. Due to data limitations and the withdrawal of data by my original data provider, I was forced to construct the classification scheme by observing what the firm actually used. In some sense, it could be argued that focusing on the categories that were used is more appropriate than the categories created, since users only see categories that are used, and never see categories that are not used. However, it is certainly possible that categorizers have more categories that they do not use. In terms of creating a classification scheme, it is not clear that the addition of other categories would necessarily clarify categories that were actually used, and thus that appear in my scheme. In fact, it is likely to make the schemes more ambiguous. The only exception to this is firms who used only one category. On a practical note, dropping these firms from the sample does not change the results of any of the hypotheses. Acquiring data including firm names, necessary to match to wider broker characteristics, required signing extraordinarily strict confidentiality agreements with two data providers. While I cannot share direct evidence, I am reasonably confident that using the constructed categories does not materially affect my results.

[10] Both authors discuss the importance of objectivity in creating a scale and suggest that rating schemes should not place value judgments on the individual categories. However, the rating scheme here is developed precisely to determine value, and thus must be subjective. Therefore, I leave out this trait as it is not relevant to the current study.

suggests that the scheme uses "short statements, in simple, unambiguous terminology" ((Guilford, 1954) p. 293). Relevance means that each category named should be consistent with its future contents (that is, one shouldn't name a category "bad" if all the objects within it are valuable stocks that should be purchased). Precision suggests that the category should refer to a very precise point upon the scale. Variety means that the same words should not be repeated throughout the scheme. Uniqueness means that the category labels should not be general if at all possible (not "excellent," "superior," "average," "poor"" (Guilford, 1954) p. 293).

In my study, ambiguity is something that is created by categorizers that can be interpreted in many ways by the users of the scheme. Since the categorizers are the ones who create the scheme, it was important to measure the ambiguity of the scheme using their experiences, and not that of users, who might ascribe meaning or perceive clarity in a scheme that was designed to be ambiguous. Therefore, I focused on finding coders who had experience in equity research and financial institutions to capture the perspective of the categorizer, not the perspective of the users or objects. I was able to find two finance MBA students who had worked for financial institutions in investment banking and equity research.

To measure the ambiguity of the rating system, I had the two MBA students score each rating system on a 1 to 7 scale, with 7 being a completely ambiguous system, while 1 was a completely unambiguous system. I gave them specific guidelines about how to approach the coding. After defining ambiguity, and emphasizing that it measured overlapping categories and not "good" or "bad" behavior, I asked them to rate the systems given their understanding of the clarity of the language used and their experience

in the finance industry. They were instructed to measure the degree to which they felt a single equity could be correctly placed in multiple categories. The students practiced on approximately 20 rating systems, after which we discussed their ratings and clarified any questions they had. The students worked independently to code each of the classification schemes in a large subset of the data. Their intra-class correlation on 618 additional schemes was .81, well within the acceptable range. I then divided the remaining schemes between the two of them. As a result, the dependent variable used in my analysis contains ratings from each rater. Sample rating systems and their coding are listed in Appendix A. Using the MBA students represents a conservative test; having worked in the industry they are more likely to be familiar with the terms used, and thus less likely to find ambiguity within them.

In addition, I also had an untrained undergraduate research assistant code the schemes as well. His intra-class correlation was only .53 with the MBA students. However, using his codings versus the codings of the MBA students produced similar results. This suggests to me that the coding scheme is robust.

Independent Variables

Conflict of Interest: Broker-dealers that provide underwriting services face a well known conflict of interest. On the one hand, their duty is to properly describe the organizations as they see them through their equity research. This service is provided for the investors, who pay commissions to the broker-dealer to buy and sell securities on their behalf. On the other hand, these organizations typically derive a great deal of revenue from their underwriting business, and so maintaining strong relationships with

underwriting clients (and thus companies covered by equity research) is very important.

Slighted clients often change underwriters or refuse to give additional business if they

feel they are presented in an unfavorable light. Some companies have actively retaliated

against individual analysts, attempting to get them fired or shutting them out of

conference calls (Kessler, 2004; Reingold, 2006). In fact, among the analysts I

interviewed, dealing with intense and sometimes abusive pressure from the companies

they covered was a major theme. The inherent conflict of interest combined with the

strong pressure of the companies themselves often creates pressure for favorable

classification (O'Brien et al., 2005; Sieland, 2003).

Using SDC's Venture Xpert, a database of all new issues in the stock market, I

measured the level of conflict of interest by examining the amount of underwriting

activity (venture capital and non-venture capital backed IPOs as well as equity issues for

established organizations) that was issued in the prior year. I chose the issue date

because firms often work on underwriting projects for much longer than a single year.

Projects issued in the prior year may have been started three years before the offering is

completed. The first underwriting variable is the raw count of new issues.

In addition, I developed a second variable to take into account the level of

underwriting of a given firm relative to the total possible amount of equities it covered.

A large brokerage firm underwriting many equities relative to the number it covers faces

a similar level of conflict of interest as a small firm facing only a few. I then mean

centered the variable. I used the potential for conflict of interest because of the difficulty

predicting the future performance of a covered equity. Many equities that have been

performing well may face a downgrade due to strategic changes or unforeseen

macroeconomic events. Therefore, any underwriting activity by the brokerage firm represents a conflict of interest. I divided the raw conflict variable by the total number of equities to get this number. I then mean centered the variable and shifted it by .2 to remove any negative values. Since the measure of status (see below) contains negative values when mean centered, a negative status and negative underwriting variable will multiply to be positive, which does not accurately represent the data.

Status I follow Phillips and Zuckerman (2001) and Rao et al (2001) in using *Institutional Investor* magazine's annual ratings as a measure of status of an individual brokerage firm. *Institutional Investor* surveys institutional investors to find the best individual according to such dimensions as performance and responsiveness. The actual performance accuracy of a particular firm is extremely difficult to calculate for the average observer: each analyst covers between 5 and 20 firms, issuing ratings several times each year, and there may be more than 100 analysts in a particular firm. The top three analysts are listed in numerical order and called "All-Star Analysts." The *II* Analyst rankings are a good measure of status because they are not perfectly correlated to an equity analyst's performance. This is evidenced by a comparison of the *Institutional Investor* rankings to performance indicators constructed by Starmine, a company that specifically measures the analysts' accuracy in predicting stock performance. (Starmine ratings only began in 2001, which is too late for my sample.) The best performing companies and analysts frequently differ from the ones listed by *Institutional Investor*. Thus, the *II* rankings are a measure of perceived quality and prestige. This was confirmed in an interview with the head of an equity research department of a large investment bank. In addition, conversations with industry veterans suggest that analysts

themselves lobby for their *II* rankings, and that they prefer these over other rankings or performance metrics that may exist. Some analysts have been compensated based on their *II* status. While quality of information may get individual analysts noticed, it is extremely rare for new firms to appear on the *II* magazine rolls.

Because status is sticky (Podolny, 1993), I constructed a measure of the brokerage firm's status by counting the total number of *Institutional Investor* all-star analysts the firm had in the prior three years. I then took the average of this number. Brokerage status is highly skewed, since most brokers have a status of zero. As a result, following Rao et al, I took the log of the averaged status variable. Using a one year lag rather than the average generates similar results. I then mean-centered the status variable.

Status & Conflict: To create the interaction term in Hypothesis 2, I multiplied the status variable with the conflict variable.

Control Variables

Path Dependence It may be that ambiguity is not a conscious choice for a brokerage firm, but rather is the result of the firm simply doing what it has always done, that is, because of path dependence. To control for this, I lagged the dependent variable (ambiguity measure). Doing so reduces the sample size by 234 observations.

Size Larger firms may be able to make choices that smaller firms cannot because they have more resources. To the extent that an economic advantage may influence the composition of the rating system, I controlled for the size of the firm by using the number of analysts the firm employed in a given year. Because the number was highly skewed, I took the natural log. Using the number of analysts also allowed me to include research-

only firms, which because they are not brokers, need not publicly file information about their finances.

Experience It is possible that newer brokerage firms may choose more ambiguous schemes unintentionally because they do not have skill in developing rating systems.   I used the firm's founding date to control for this. The founding date was determined by examining the NASD web site, company web sites, news reports, and SIA directories.

Total Categories Ambiguity may increase as the number of categories increases because of limits to human processing. Studies of rating scales indicate, for example, that the ability of raters to process the difference between individual categories diminishes as the number of categories increases (Guilford, 1954; Spector, 1991). In addition, in the setting of equity research, since there are only three types of ratings, positive, neutral, and negative, increasing numbers of categories means increasing amounts of categories measuring the same type of rating (i.e. several positive rating categories), increasing the likelihood of overlap or confusion.

Variability in the firm's equity coverage A brokerage firm's rating system might simply be reflecting coverage of a wide range of equities. If the world of the firm is highly ambiguous, then the firm may be unable to clarify it through its rating system. To capture this variability in the equities that a firm covers, I summed the number of industries that the firm covered using industry sector data from IBES. Firms dealing with a wide range of industries may create more ambiguous systems than firms that focus on a particular industry.

Mean Beta I included a control to capture the volatility in the brokerage firm's equities. It may be that firms covering highly volatile industries on average create more ambiguous schemes to deal with the volatility. I used the average beta of the firm's stock portfolio to capture this.

Variance of Betas I also included a measure to capture high variance in the betas of the firm's equity coverage. This was calculated as the variance of all betas in the firm's stock portfolio.

Percentage of Unique Equities I also created a measure that captured the number of unique equities that each firm covered. Some brokerage firms specialize in covering equities that no other firms cover. This might influence the type of rating system they create. I used the total number of unique equities divided by the total number of equities covered to control for this.

Workload The workload of the analysts may have an influence on the type of schemes that the company creates. Covering many stocks requires a large amount of work from a single analyst, and it may make them unable to devote enough time to carefully analyze each firm. When equity analysts have many stocks to cover, they may need a clearer scheme with fewer rules in order to be able to classify them. Conversely, having many stocks to cover could encourage research departments to create ambiguous rating systems if such systems might hide poor performance. I divided the total number of equities by the total number of analysts to determine the average number of equities that a given analyst would cover.

Amount of Ambiguity of Other Categorizers Firm decisions may also be influenced by the behavior of other firms. If many other firms have ambiguous

classification schemes, a brokerage firm might also choose to have a more ambiguous scheme. I created a lagged measure of the average ambiguity of high status brokerage firms, since these firms' activities are visible to all brokerage firms.

Year I controlled for the year because of the time period of my sample using year dummies. During the late 1990s, a great deal of investment activity and growth occurred, which might influence the kinds of schemes being created.

5.4.3 Method

Because my dependent variable is an ordinal rating from 1 to 7, with each integer representing an increase in value over the last, I used an ordered probit (Long, 1997). OLS assumes that the dependent variable can range from positive to negative infinity, and is thus an inappropriate method to use. Ordered probit models estimate the probability of an outcome given a set of independent variables and a series of cut points (Liao, 1994; Long, 1997). In addition, ordered probit models assume that the error is normally distributed, unlike the ordered logit model, which assumes a logistic distribution.

In addition, since my sample contains multiple observations per firm, I used clustering by firm to deal with the lack of independence between observations. In addition, I used robust standard errors.

5.5 Variable Definitions and Operationalization: Study 2

5.5.1 Sample Changes

I started, as before, with the unbalanced panel of all of the firms based in the

United States issuing ratings on publicly traded firms in the US that released ratings to

IBES/Thomson Research between the years 1993 and 2000. To obtain information on

customer accounts, I used the SIA Industry Directory. The Securities Industry

Association is an industry trade group of broker-dealers in the United States. Many firms

in the directory are willing to reveal detailed information about their customer accounts,

offices, and registered representatives (salespeople). However, not all of the firms in the

original 230 broker-dealers are listed in the SIA, and, in addition, several of the firms

who had a directory listing did not reveal detailed information. As a result, my sample

decreases to approximately 700 observations on 130 firms. The remaining 130 firms

mimic the size distribution of the original sample, with firms ranging from less than $1

million to over $1 billion in net capital. The chief difference between the two samples is

that I lose research-only firms. These firms are private, and typically serve only

institutional investors. Because they do not sell securities, they do not need to file X-

17A-5 forms with the SEC, and most release essentially no information. While this is not

ideal, there remain several small firms in the sample that focus only on institutional

clients. Although these remaining firms receive revenue from brokerage commissions

rather than subscription revenue, they have essentially the same goal as the research-only

firms: to provide information solely for sophisticated investors.

In addition, I also lose many small firms that chose to reveal no information about

their customer accounts. Examining the X-17A-5 forms of many of these firms indicates

that they are similar in net capital, but the forms do not reveal systematic differences

between the two, and their classification schemes do not appear to be different. It is

possible that these smaller firms may be materially different from those that chose to
reveal information. However, in terms of their impact on the industry, they account for
very little of the overall revenues of brokerage firms.

In two instances, large firms that had recently merged did not reveal customer
account information during the year of the merger, but reappeared in the next year. I was
able to measure differences in the classification scheme for these firms during that time,
and added a dummy variable in general to account for merger activity for this and other
firms.

5.5.2 Equation

The general structure of the equation for the measure of the change of customer
accounts follows the form

$$y_{it} = \alpha + \beta x_{it} + \eta_i + \varepsilon_{it}$$

where α is the intercept, β is the coefficient for the explanatory variables, η
represents a fixed effect unique to each firm, and ε is the individual error term for
observation in a given time period.

5.5.3 Measures

<u>Dependent Variable</u>

I wanted to capture the arrival or departure of customers as a way of capturing
response to the classification scheme. Revenue measures may be influenced by the
number of trades given to a single customer. However, measuring the raw customer
accounts, rather than the revenue, captures customers choosing or departing from a

particular firm. In addition, many firms in the industry obtain revenue from multiple streams, including investment revenue and advising activities. These numbers are typically included in measures of firm revenue. Focusing on brokerage customer accounts allows me to focus on the success of the brokerage portion of the firm's business rather than confounding it with other activities. Developing an account with a particular brokerage firm allows a customer access to the firm's research, and in some cases, to the analysts who provide it. Thus, increasing numbers of customers represent a positive response to the firm's activities. Conversely, declining customers send a signal to the firm that they are not properly serving these customers. I measure the change in customer accounts as the number of customers of firm j in year t-1 subtracted from the number of customer accounts of firm j in year t.

Independent Variables

Ambiguity This is measured as before, using the 2 coders and the 1 to 7 point scale. I lagged this variable.

Ambiguity^2 I created the quadratic term by multiplying the ambiguity variable times itself.

Similarity I measured the similarity of the scheme by calculating the average pairwise Jaccard score for each brokerage firm in a given year (Hsu, 2006a; Ruef, 1997). Jaccard scores capture the pairwise similarity of objects when not sharing attributes of a third object does not mean that the first two are similar to each other. Jaccard scores are measured as intersection over union of a given set of words. For example, the Jaccard score of two schemes, "Buy, Hold, Sell" and "Strong Buy, Buy, Sell" is 2/4. A detailed

description, including a visual representation, is included in Appendix B. For each

brokerage firm in a given year, I first calculated the pairwise score for each firm relative

to all others in the same year. I then averaged these scores together to get a firm's total

average pairwise similarity. This measure captures the extent to which the scheme uses

similar categories as all other schemes in the marketplace.

Strategic Change This variable was created by interacting the variable New with

the change in similarity variable (both detailed below), to capture the increase or decrease

in similarity of a new scheme relative to other schemes.

New This variable is coded 1 if the categories used by the firm in a given year are

different than the combination of categories used by the firm in the prior year.

Change in similarity I measured this as the difference in the average pairwise

similarity of the firm in a given year versus its average pairwise similarity in the

prior year.

Legitimacy The extent to which a scheme is widely used by other brokerage

firms measures how widely accepted the scheme is. Widely used schemes are often

considered industry standards, and may be the first choice for new entrants. In addition,

schemes used by many firms means that many customers are experienced with such

schemes. I measured the frequency of usage of the scheme by counting the number of

firms that used the exact scheme as the focal firm. I lagged this variable.

Quality I used the Wall Street Journal's analyst ratings to determine the quality of

the brokerage firm, that is, how well they used the scheme and analysts that they had.

The Wall Street Journal, during the period from 1992 to 2000, used both forecast

accuracy and stock picking accuracy to determine the best performing brokerage firms. I

used the total number of Wall Street Journal ranked analysts that the firm had in the prior year to measure the firm's quality in the prior year. Because this number is highly skewed, I took the natural log.

This measure differs from the status measure described earlier and used as a control because it specifically measures performance.[11] As a result, many firms with strong analyst performance make the WSJ list but do not make the list of *Institutional Investor* magazine, which is created by survey and seen as a popularity contest by analysts in the industry. In conversations with analysts and investment bankers, the WSJ rankings rarely came up, but the *II* ones routinely were mentioned. As expected by theory, status and quality are highly correlated, but not excessively so.

Legitimacy*Quality To measure the extent to which customer migrate to high quality firms that use the same schemes as others, I interacted the legitimacy and quality variables.

Control Variables

Firm Controls

Age Newer firms may lack experience, and as a result, may gain or lose large amounts of customers. As a result, I controlled for firm age. I used the founding date of the firm.

Coverage The number of industries that a firm covers may affect its classification scheme. Firms covering large numbers of firms may change their schemes more

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[11] Measurement varied by year, but for most years, the top stock picks of individual analysts were included and checked for accuracy. For some years, firms were graded by an examination of all of their top stock picks, which were then sorted into individual analyst performance. Either method would create slightly different results, but in the end, the choices and forecasts of the analysts was the basis for their ranking, rather than the response or nomination by institutional investors.

frequently because they need a scheme that allows them to deal with multiple industries.
I used the sum of the industries to control for this.

Workload I calculated the average number of stocks covered by the analysts at the firm by dividing the total number of equities covered by the total number of reporting analysts at the firm. To the extent that the workload of an individual analyst might impact the quality of the research, and thus the customer response, controlling for workload is important.

Underwriting Underwriting activity may encourage new customer accounts as firms wanting underwriting services choose a single brokerage firm to handle multiple accounts. I used the total amount of underwriting issues for the firm in the prior year.

I also included a measure to account for the percentage of underwriting of the firm in a given year, calculated as the total amount of underwriting divided by the total number of equities covered.

Focus Institutional investors and retail investors may have different preferences and may act differently in choosing a brokerage firm. As a result, I controlled for the firm's client focus. I created a dummy variable. Institutional Investors was coded 1 if more than 75% of the firm's registered representatives (salespeople) were institutional focused.

Status I used the same status measure as in the prior section.

Change in quality Customers may flock to firms that have increased their abilities in stock picking and earnings forecasts. Conversely, customers may leave firms who

decline in these areas. To control for this, I used the difference in quality between time 1 and time 0.

Controls related to the classification scheme

Total Categories Research on human processing shows that humans have difficulty distinguishing between categories as the amount of them increases. Firms with higher numbers of categories may cause customers to leave because customers do not understand the schemes. I used the sum of the number of categories to control for the size of the classification scheme.

Frequency of changes Frequently changing schemes may confuse customers, causing them to leave. Thus, for each firm-year, I counted the total number of changes that had occurred in the prior years of the sample. This number was set to zero the first year of the sample.

Length of time of prior scheme Customers may prefer firms with stable classification schemes. To control for this, I included a variable to take into account the length of time the prior year's scheme had lasted.

5.5.4 Method

My dependent variable measures change, and can theoretically range from negative to positive infinity. Although some economists argue that mathematically, an equation with change as the dependent variable should also only contain variables measuring change in the independent variables, others argue that, based on theoretical predictions, predicting change through levels rather than change is acceptable (Allison, 1990). Allison (1990) further notes that, in cases where change is the dependent variable,

the lagged term should not be included in the equation because it is captured in the dependent variable. Because firms appear in multiple years, my data are not independent across observations. I fit both ordinary least squares with firm clustering and fixed effects models. Because fixed effects models separate variance across firms and within the same firm, I focus on these results in my discussion.

5.6 Data Sources

My data come from several sources. A summary of the data sources is listed in Appendix C. I received information on the rating systems from IBES/Thomson using the btext field of the broker recommendations file. IBES also was the source of the industry coverage data and information on the analysts. Information about the financial details, size, age, and customer makeup were determined by examining the directories of the Securities Industry Association Yearbook. It was confirmed, when possible, through X-17A-5 statements, a brokerage firm annual report that contains balance sheet information on all registered broker-dealers in the United States, required by the SEC. I also used the NASD online broker history and web sources to confirm founding dates and headquarters location. Information about the underwriting activity of a brokerage firm was gathered using SDC Platinum. Information about the brokerage firm's coverage universe was collected from IBES (Thomson Financial) and linked to CRSP data using firm CUSIPs (for equities covered by a given brokerage firm) to get information on firm betas. This data was also used to get the percentage of unique stocks covered by individual brokerage firms.

In addition to the archival data I gathered, I also conducted informal interviews with a dozen individuals who worked in a variety of roles in the brokerage industry. Included in the group was the head of the legal department of a large investment bank, *Institutional Investor* ranked analysts, the head of a research department of a major financial institution, investment bankers, and two institutional investors. The interviews lasted between fifteen minutes to over an hour and a half. Interviewees were asked open ended questions about their experience in the industry as well as the history and evolution of equity research as a whole. I also asked specific questions about different aspects of my dissertation.

CHAPTER 6

RESULTS

This chapter presents the results of the hypotheses discussed in chapters 3 and 4. Given the two dependent variables, ambiguity and performance, I will discuss each separately for ease of communication.

6.1 Descriptive Statistics, Ambiguity

The data collection resulted in 1229 observations on 230 brokerage firms. The average length of time in the sample was approximately 4 years. The mean ambiguity of the firms in each year are summarized in Figure 6.1. In general, ambiguity is increasing during the time period of the sample, starting at an average of 3.59 in 1993 to a high of 4.497 in 2000. Underwriting levels are summarized in Figure 6.2. The amount of underwriting activity (new issues) of the firms in the sample increases over time, peaking in 1998, and then falling in 1999, but climbing again in 2000. This is similar to the maximum levels of underwriting. The highest amount of underwriting by a single firm was 490 new issues in 1998.

Table 6.1 provides descriptive statistics and correlations for the data. The use of the lagged dependent variable resulted in the loss of 243 observations from the 1229 in the original sample. Several variables are worth noting. The average ambiguity score in the sample is 4.077, with a standard deviation of 1.7. The average number of categories

is 3.699; with a maximum of sixteen unique categories. The average amount of underwriting is approximately 32 new issues, with a maximum of 423. The mean of the status variable is zero. This variable was mean-centered. Since the vast majority of firms have a status score of zero, mean centering the data lowered the value of the mean and created negative values for status for many firms.

Most of the correlations presented in Table 6.1 are unremarkable. Not surprisingly, the lagged dependent variable is highly correlated with the dependent variable. Other variables are not highly correlated with the dependent variable. A few variables are highly correlated. Various rules of thumb suggest there is a concern for multicollinearity when correlations are high. Different sources suggest levels ranging .6 from .75. First, size and coverage are correlated at .77. This suggests possible multicollinearity. Both variables are controls. Transforming the variables reduces this correlation, but does not substantively change the results. Neither does removing either variable. Therefore, I leave both variables in the equation. Not surprisingly, underwriting is correlated with size at a level of .61. Again, transformations reduce this correlation, but do not alter the results. For ease of interpretation, I use the raw underwriting numbers. Similarly, status is highly correlated with size, but has little effect on the results.

More concerning is the relatively high correlation between status and underwriting. Various rules of thumb suggest there is a concern for multicollinearity when correlations are high. Different sources suggest levels ranging .6 or .75. At .54 it is high. Again, I used transformations on both of these variables in an attempt to reduce the correlation. Doing so reduced the correlation to .48, but did not alter the results. The

correlations between the interactions are also high. Much of this is due to the fact that the vast majority of observations for status are zero. Ideally, this measure should be expanded to include more information about status across all firms. Doing so would require collecting more data which is not clearly available for the time period under examination. It also suggests that an additional way to capture the status of a firm may be to use an indicator variable suggesting high status or no status. The results of this are discussed below.

6.2 Results, Dependent Variable Ambiguity

The results of the models are presented in Table 6.2. Several control variables are worth discussing. First, the lagged dependent variable is significant and positive, suggesting that prior ambiguous classification schemes increases the probability of an ambiguous classification scheme in the current period. Total categories is also positive and significant. Size, however, is negative and significant. Relative ambiguity is positive and significant, suggesting increasing probabilities of ambiguous classification schemes as other firms have ambiguous schemes as well. In several of the models, the variance of the beta score is significant and positive, suggesting that firms covering a wide variety of industries (firms that cover equities with widely different betas) have higher probabilities of ambiguous schemes than others.

Hypothesis one suggested that high levels of underwriting activity would lead to increased ambiguity in the classification scheme. This hypothesis is supported using the raw count of underwriting activity. The standardized coefficient (bStdX) for underwriting is .1333, suggesting that an increase of one standard deviation in the amount

of underwriting increases the probability by .1333. I also graphed the range of

probabilities for values of underwriting activity in Figure 6.3. The effects are quite

striking. As underwriting activity increases, the probability of receiving a 1, 2, 3, or 4

rating declines, while the probability of receiving a 5, 6, or 7 increases. The

measurement of underwriting activity using a percentage measurement is not significant.

Hypothesis two suggested that the interaction between status and underwriting

was positive. The interaction is significant at the .10 level using the raw count of

underwriting and is significant at the .01 level using the percentage measurement.

However, interpreting the coefficient of an interaction effect in an ordered probit cannot

be reliably done using significance levels (Ai & Norton, 2002). Instead, a graphical

approach is better. The method suggested by Ai and Norton, using the inteff command in

STATA, does not support clustering in the data. As a result, I offer two alternatives.

First, I show a graphical version of all predicted probabilities. In Figure 6.4, the

predicted probabilities as the interaction between status and underwriting increases from -

135, the lowest value, representing a firm with no status and no underwriting, to 1250,

representing a high status firm with high levels of underwriting. The probabilities are

vastly different. For the no status/no underwriting firm, the probability of having a rating

system rated a 6 is approximately .11, while it is close to .37 for a high status firm with

high levels of underwriting. The probability of a no status/no underwriting firm of

having a rating system coded as a 7 is close to zero, while it is .10 for a high status firm

with high levels of underwriting. In Figure 6.5, I graph the probabilities for the ratio of

underwriting. The probabilities look similar. (The graph in 6.5 is misleading because

there are only two values less than -1 in the data. Removing these outliers does not affect

the results of the hypotheses.) In addition, in Table 6.3, I show the results of using

ordinary least squares to predict the level of ambiguity. Using OLS is technically

incorrect, as the assumptions of OLS require that the dependent variable range from

negative to positive infinity. Clearly, the 1 to 7 levels of ambiguity do not fit this

assumption, and so predictions using OLS may not be in the range of the data. However,

interaction effects in OLS are easily interpretable. I divided the variable conprior by 100

to make the coefficient clearer. The interaction is significant at the .05 level (one-tailed

test). The effect is significant and positive. It suggests that given a one unit change in

the status variable, the slope of the dependent variable is predicted to increase by 0.0813.

Stated another way, when status is zero, the effect of underwriting on ambiguity is 0.035

(Jaccard & Turrisi, 2003).

Using OLS also has the benefit of being able to use variance inflation factors to

examine multicollinearity. The VIFs for the variables of concern, status, underwriting,

and size. The VIF for size is high, at 5.16. Removing it from the equation decreases the

p-value of the interaction, but does not change the direction of the effect. I also

substituted a variable for registered representatives (salespeople) to capture size. Doing

so drastically reduced the number of observations, since registered representative data

was not available for many firms. This substitution decreased the correlations, and

increased the p-value of the interaction.

In addition, I created a dummy variable for status, coded as 1 if the firm had been

ranked by *Institutional Investor* magazine, and 0 otherwise. Using this measure rather

than the raw status score in the interaction does not significantly alter the p-value of the

interaction, but it does reduce the high correlation between the main effect for status and the interaction.

I did a series of additional analyses to examine the robustness of my results. In equity research, other researchers have suggested the presence of a U shaped curve between status and ratings (Phillips et al., 2001). While I gave a rationale for why I felt a U shaped relationship between status and ambiguity was unlikely, I nonetheless tested for such a relationship. This effect was not significant. I also created a quadratic term for underwriting; it was not significant.

I reran the models using ordered logit specifications rather than ordered probit. The results remained the same. There were a few firms which had relatively high ratios of underwriting to equities covered. I removed these firms from the sample. When this occurs, the potential underwriting variable loses significance, but the raw measure of total underwriting maintains its significance.

To create my dependent variable, I used a mix of the ratings from both MBA coders. In addition, I had both MBA coders code the entire dataset and reran the models using each coder separately, getting similar results to using the mixed dependent variable. I also wanted to see if financial background affected the ambiguity score given to the rating systems. An undergraduate with no financial expertise also coded the rating systems after being given guidelines about what constituted an ambiguous classification scheme. His inter-rater reliability with the combined skilled coders' ratings was much lower, only .51. Careful inspection of the data indicated agreement between all three coders at the extremes of the rating system; however, the middle ratings differed between the unskilled and skilled coders. The coefficients from an ordered probit using the

unskilled coder are in the same direction as those of the skilled coders, although weaker. In addition, I created a variable that used only the lowest ambiguity measure of all raters. I also averaged the scores of all coders together and ran both a tobit model and OLS. The results were robust to all specifications.

Concerned that my definition of ambiguity might be biased in favor of finding ambiguity, I also recoded the dependent variable to consider the possibility that some classification schemes were nuanced, rather than ambiguous. For example, some rating systems include five balanced categories, two positive, one neutral, and two negative. Most raters gave such a scheme an ambiguity score of 3. However, for some, this might be seen as a very nuanced world, rather than a slightly ambiguous one. I added an additional variable that counted the total number of expanded categories that the scheme used. For example, a scheme that included "strong buy, buy, speculative buy, hold, sell" would be coded '2' for the two expanded categories (strong buy and speculative buy) that could be providing nuance to the classification scheme. My results were robust to this additional variable. I also added a variable measuring whether the scheme was vertical or not. A vertical scheme involves an implicit order from best to worst. This variable was strongly significant and negative, suggesting that vertical schemes were rated as less ambiguous than other schemes. When this variable was added, alone or in combination with the expanded categories variable, the results remained robust.

In addition, the graphs suggested that there might be a difference between ambiguity ratings of 5, 6, or 7 versus ratings of 1, 2, 3, or 4. Thus, I considered the possibility that ambiguity acts in a dichotomous fashion, rather than on a continuum. I recoded all schemes rated 4 or below as a zero, for unambiguous, and all schemes greater

than or equal to 5 as a 1, or ambiguous. I then reran the models using a probit model.
The results are slightly less significant but the coefficients are very similar.

In addition, there is a potential concern of simultaneity bias with the total
categories variable. Total categories may be determined in tandem with the ambiguity of
the classification scheme. In such a case, it may not be appropriate to treat the two as
independent. I made several attempts to deal with this. First, I lagged the total categories
variable and reran the models. The results are slightly less significant, but the
coefficients are similar. Next, I used the total categories variable as the dependent
variable instead of ambiguity. None of the hypothesized effects were significant;
however, the measures for size and relative ambiguity were significant.[12]

In sum, the models presented above are robust to multiple alternative
specifications, both in terms of choices with made with the dependent variable as well as
the form of the interaction.

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[12] I did also experiment with simultaneous equations (Three stage least squares, or 3SLS) in an attempt to
deal with the potential for simultaneity bias. Statistical techniques for using simultaneous equations with
limited dependent variables, such as the ambiguity rating scale, do not currently exist. Therefore, I was
forced to make an assumption that the dependent variable ranged between negative and positive infinity.
3SLS is useful when the number of equations matches the number of endogenous or simultaneous variables.
This fits the case here because there are two equations, and total categories and ambiguity are the two
variables in question. I specified two equations: I used lagged total categories and all other variables to
predict total categories. I then used all variables except for lagged total categories to predict ambiguity.
The coefficients and significance levels remained similar for the ambiguity equation. This method cannot
be seen as a reliable examination due to the limitations of my dependent variable, but does offer some
evidence that the original model is robust to alternative specifications.

6.3 Descriptive Statistics, Performance

The sample size for the final four hypotheses is reduced from the sample for the first set of hypotheses. This occurs for several reasons. First, using fixed effects requires at least two observations per firm. Firms with only one observation were dropped. In addition, information on customer accounts was available only for the subset of firms that released information in their profile in the SIA directory. Thus, the model contains 520 observations for which data was available.

The descriptive statistics for the performance variables as well as the correlations are presented in Table 6.4. A few variables are worth further discussion. The average similarity of classification scheme is .439, with a low value of .415 in 1998 and a high of .46 in 1994. Thus, the level of similarity is generally stable over the time period. However, despite this similarity, there is a high level of change in the system. The mean for new schemes is .582, suggesting that a firm uses a new combination of categories than in the prior year 58% of the time. The average scheme is shared by only 3.3 other categorizers. Thus, the market for brokerage rating systems is extremely dynamic during this time.

In the correlations, a few variables raise the concern for multicollinearity. Size is highly correlated with a number of variables, including total categories, status, quality, and the frequency*quality interaction. Removing it from the models does not affect the results of the hypotheses. Substituting other size measures, such as total salespeople, does not change the results.

Of greater concern is the high correlation between the components of the strategic change variable of .90. To address this issue, I mean centered the similarity variable.

This barely reduced the correlation; other transformations were equally unsuccessful. All results were unaffected. Examining the variance inflation factors on the correlation data, using a cutoff of 5 reveals that the interaction term and change in similarity variable for the main effect have a VIF of 6.03 and 5.68, repectively. The high correlation and high VIF for this variable is not unexpected because of the nature of the way the variable is constructed. Since the interaction term is a difference variable interacted with a binary variable which represents almost a perfect split in the data, the resulting data will closely follow the original variables. In this case, the interaction has the effect of changing all of the difference scores to zero for firms that did not change their schemes, while the values for firms that did change their schemes are unchanged.

6.4 Results, Dependent Variable Performance

Table 6.5 captures the results of a fixed effects regression using the dependent variable change in customer accounts. Model 1 shows the results of the control variables. Models 2 through 8 show the results of the hypothesized variables.

In general, several control variables are worth discussing. First, having a retail focus appears to increase the number of customer accounts that a firm has. This is not surprising; retail-focused firms may have more customers simply because each individual customer has a lower account volume than an institutional investor. Thus, more retail customers are needed to achieve revenues for a firm. Next, underwriting activity also significantly influences change in customer accounts: the more underwriting of new issues that a firm does, the greater the change in customers accounts. However, the relative volume of underwriting activity to coverage did not seem to affect the dependent

variable. Interestingly, quality appears to have a negative affect on customer accounts, although it is not significant. Worried that this might be due to any correlation with status, I removed the status variable from the equation. The quality variable remained negative. Merger and takeover activity did not have a statistically significant affect on customer accounts, suggesting that joining two firms was not a significant driver of a change in customer accounts. Also, size has a negative effect on the change in customer accounts, but this effect is not significant.

Hypothesis three suggested that ambiguity followed an inverted U shape. The main effect of ambiguity is shown in Model 2 of Table 6.5 It is positive, though not significant on its own. The U-shaped hypothesis is supported in models 3 and 8. In both models, the main effect is positive, while the squared term is negative, suggesting a U shaped relationship. The squared term is significant at the .10 level in model 3 of Table 6.5, while the main effect is not significant. In model 8, both main effect and squared term are significant at the .05 level. The inflection point is graphed in Figure 6.6. This shows that having a scheme rated a 1 or a 7 attracted fewer customers than having a scheme rated 4 or 5. Given that the mean of the ambiguity scores is close to 4, this suggests that firms with an average level of ambiguity relative to others do better than firms adopting an extreme position. In real numbers, this suggests that firms choosing a scheme that is rated a 1 gain approximately 12,234 customers, holding all other variables constant. Firms choosing a 4-rated scheme have a change in customers of 30,312, holding all other variables constant. Firms with a highly ambiguous scheme (rated a 7) have an increase of 20,454 customers, holding all other variables constant.

Hypothesis four suggested that firms that chose to change their scheme to be more similar to others would do poorly compared to those that did not. Model 4 of Table 6.5 shows the main effects without the interaction. The coefficient for new schemes is significant and negative, suggesting that having a new scheme reduces the number of customer accounts. The coefficient for change in similarity is positive and significant, suggesting that changes in a firm's similarity score increase the number of customer accounts. This does not mean that action by the firm necessarily drives these increases, since similarity can change either by the firm's own actions or by the actions of other firms. The interaction effect distinguishes between the two.

Hypothesis four predicted a negative coefficient for the interaction. This hypothesis is supported in models 5 and 8 of Table 6.5. In model 5, the interaction is significant and negative at the .01 level, and remains so in model 8. In numerical terms, the effect of a 1 unit increase in the change of similarity when the scheme is not new is 178,322 customer accounts. However, it is important to note that the similarity variable, as measured by the Jaccard score, varies between zero and 1. A value of one is extremely unlikely, particularly as the number of firms in a given years increases. In general, the interpretation of the interaction effect is difficult to conceptualize, and so the graph in Figure 6.8 shows the interaction in detail. One line represent a change in similarity when a firm has also changed its scheme (where New = 1 and change in similarity is calculated as $Similarity_t$- $Similarity_{t-1}$), suggesting a strategic change. The other represents a change in similarity caused by the changes of other firms (where New = 0 rather than 1). Examining the line for strategic change reveals that firms that changed their schemes to become much more similar to other schemes lost customers, as evidenced by the negative

slope of the line. However, firms that changed to new schemes from the ones they had

before that were highly dissimilar to other firms actually gained customers, as evidenced

by the positive values of customer accounts at low levels of similarity. Implementing

such a strategy would be difficult: a firm must not only change its scheme, but must also

rely on other firms not changing their schemes in a similar way. This suggests that

strategic change in general does not yield benefits to firms.

Examining the line for changes in similarity due to changes in other firms (where

New = 0) reveals an opposite effect. Firms that did not change their schemes, but instead

became more similar due to the scheme choices of others, often gained customers, as

shown by the positive slope of the line. At the extreme, however, as a brokerage firm's

similarity changed drastically as a result of the actions of other firms, the actual level of

customer accounts is negative.

Hypothesis five suggested that using a frequently used scheme increases customer

accounts. The effect of the variable for frequency is positive and significant in Model 6

in Table 6.5, giving support to hypothesis five. An additional firm using the same

scheme as the focal firm increases the focal firm's customer accounts by approximately

1300.

Hypothesis six suggested that this effect would be increased as the firm's quality

increased. The effect of the interaction between quality and frequency is positive and

significant at the .01 level in both models 7 and 8 in Table 6.5. When quality is zero,

using a frequently used scheme gains a firm 2419 customer accounts. Or, conversely,

when no other firms have the same scheme, being high quality loses a firm 12064

customer accounts. A graph of the interaction effect is in Figure 6.7. The table shows

the change in customer accounts at low levels of quality, at mean quality, and at high quality for differing frequencies. While all firms benefit from using a scheme that matches others, high quality firms have the most to gain from using the same scheme as other firms. In fact, high quality firms appear to suffer when they use a scheme that no one else uses.

It is important to discuss the implications of Hypotheses 4, 5, and 6 in the industry context. Overall, the results suggest that the industry operates in niches of different schemes. Hypothesis four argues that becoming more similar to other firms lowers the change in customer accounts. A scheme that is similar to all other schemes is likely to have categories that match the two dominant paradigms of schemes, categories of action and categories of description. All schemes with high similarity scores included at least one category of each. On the other hand, a frequently used scheme is not necessarily highly similar to many other schemes. The most frequently used schemes (Buy, hold, sell; strong buy, buy, hold, sell) were consistent in their categories of action. Thus, though these schemes were identical to each other, they were not similar across all other firms.

I used several alternative specifications to check the robustness of my results. My dependent variable is a change score. I also ran models predicting the raw customer accounts variable, using a lagged customer accounts variable as a control. The results remained similar. In addition, I ran the models using ordinary least squares and clustering rather than using the fixed effects models. Clustering does not allow distinctions of within versus across firm variance. All of the hypothesized results remained significant. The only change of note was in the raw similarity variable, which

became positive and insignificant. In general, this points to an opportunity for further

investigation on the raw similarity variable and how similarity might influence customer

accounts.

CHAPTER 7

CONCLUSION

This dissertation makes contributions in several areas. It extends the literature on classification by highlighting the role of the categorizer in the resultant schemes that are created. It also brings into focus competition among categorizers, showing how competition shapes categorizer performance. This dissertation had two aims: first, to provide an alternative explanation for why classification schemes are created, and second, to show that classification schemes have a material impact for those who create them. I shall discuss each in turn.

7.1 Contributions to Theory on Classification

I first argued that classification schemes may be created for other purposes rather than traditionally argued clarity purposes. Certainly other authors have pointed out that classification systems are used in ways that benefit those that create them (Bowker et al., 2000; Douglas, 1986; Douglas et al., 1992). This is evident in racial classification, for example, where distinctions are drawn between different races in order to privilege one race above another, and in art, where elites create divisions of art in order to dominate cultural resources (Bowker et al., 2000; DiMaggio, 1987). This chapter argues for a slightly different possibility. Rather than suggesting that it is through control of sharp boundaries across categories that powerful actors exert control, I suggested that elites can reap benefits from creating weak or overlapping boundaries—that is, through creating

ambiguous classification schemes. This is possible because of how users perceive both ambiguity and categorizers. Humans are predisposed to try to make sense of ambiguous encounters (DiMaggio, 1997). As a result, they may perceive an ambiguous system but will attempt to develop an interpretation of it that makes sense to them.

While the predisposition of users to attempt to interpret ambiguity in a favorable way may make it seem like something that many categorizers would choose, in fact not all of them do. Favorable incentives, such as a conflict of interest, which may make an ambiguous classification system extremely lucrative, may result in the creation of such a scheme. However, those most likely to create ambiguous classification schemes are those with both the incentive to do so and the influential social position to buffer their choices. Such firms can create ambiguous systems because users appreciate the status of the categorizer even if they do not completely understand what it is that the categorizer does. Since actors in general like to be affiliated with higher status others, users may be willing to remain with them simply for the affiliation. Furthermore, the categorizers' powerful market position gives them the resources to withstand any negative repercussions of such activity. Having an ambiguous classification scheme benefits these categorizers because it allows them to have several options for classifying a particular object.

Having established that classification schemes are strategically created in certain circumstances, I then turned to examine the implication of these classification schemes on firm performance. Prior research has frequently argued the benefits of classification for categorized objects, highlighting the importance of category placement (Ruef et al., 2007; Zuckerman, 1999). Yet the impact for the categorizer of the choice of a particular

scheme had not been examined.   The choice of the classification scheme matters in a tangible way to categorizers—both in terms of which categories are chosen, but also in terms of how the categorizer positions its scheme relative to others. My findings bring into focus the competition among categorizers, pointing out that this may shape the kinds of classification schemes used. Classification schemes rarely exist in isolation: restaurant guides, product guides, rating systems and directories abound. Categorizers can compete on at least three dimensions: placement of objects, information shared, or the configuration of the scheme. When categorizers are mentioned in the press and in research, the focus has generally been contained to descriptive differences about the first two dimensions. I show that the third dimension deserves attention as well.

Ambiguity captures the relationships of categories within a single scheme. My results suggest that while categorizers may choose ambiguity as a strategy for their own benefits, it works to a point. Too much ambiguity results in fewer customers than those who choose moderate levels. Too little ambiguity also results in fewer customers. This may be due to the fact that uncertain markets are difficult to clearly categorize in the first place; focusing on clarity may constrain the ability to use the scheme.

The relationship of categories within the scheme is not the only determinant of firm performance. I showed that frequency also played a role. Categorizers who chose the exact same scheme benefited from doing so. However, they gained the most customers when they were also higher in quality, measured as their ability to use the scheme. This is because choosing the same scheme shifts the locus of competition from type of scheme to use of the scheme.

Finally, I examined how changes in the similarity of the categorizer's classification scheme relative to others affected the resultant customer accounts. Categorizers that changed their scheme to be more similar to other categorizers declined in performance, while categorizers who had others move to be more similar in their scheme increased their performance.

Overall, the second part of the dissertation suggests that meaning creation is a competitive behavior, not just an act of comprehension. Categorizers jockey for position by carefully choosing and shifting the categories they use; this has implications for their performance, but also broadly for understanding of the categories. Increased usage of categories increases performance, but it also pushes toward standardization of meaning, as more and more firms share similar schemes.

In addition, this dissertation points to the need to consider the classification scheme in its entirety. Prior research has highlighted actions within a single category, such as survival, identity formation, and success (Kennedy, 2005; Rao et al., 2005; Ruef et al., 2007; Zuckerman, 1999; Zuckerman et al., 2003a). This dissertation complements a focus on individual categories by juxtaposing different categories within a scheme against each other and across different categorizers. As a result, it adds to a growing body of research considering multiple classification schemes (Benjamin et al., 1999; Rao et al., 2007). Prior authors have examined whether the coverage decisions and resultant ratings have converged across multiple schemes. They have often faced the task of attempting to make different classification systems commensurable. I examined why these systems might be similar or different in the first place. I suggested that it is not

simply an empirical difficulty that multiple systems differ; rather, these systems are carefully designed.

7.2 Implications for Strategy

Overall, this dissertation argues that cultural aspects shape and inform firm strategy and vice versa. I first argued that strategic action shapes the creation of classification schemes. Before, strategic action had been largely examined in the maintenance and use of classification schemes. The creation of a classification scheme is an attempt to create meaning out of a set of objects and is thus a profoundly cultural act. Categorizers add the element of strategy to this act. Yet classification schemes also impact performance. It is well established that classification schemes convey information and shape markets; I argued that they also have an impact on categorizer (and thus firm) performance.

7.3 Directions for Future Research

In this dissertation, I highlighted the role of the categorizer in scheme creation. Further research on categorizer choices abound. For example, mergers among categorizers require the creation of a single system for the combined company. Researchers could examine whether a particular scheme dominates, or whether schemes are blended together. New entrants also face the choice of creating a scheme. Investigations into their choices may uncover new insights into how competition shapes classification.

In addition, there are opportunities to examine how classification schemes do or do not converge over time. In my particular setting, schemes diverged until a rule change by the SEC required full disclosure of the classification scheme, at which point most firms adopted the same, three part scheme. Legal requirements certainly shape scheme convergence, but other factors may also contribute to the proliferation of unique schemes, or, conversely, the convergence of schemes to a few recognizable types.

Finally, I considered the schemes in absence of the categorized objects. Yet the choice of the scheme obviously has an impact on what is categorized and how. How does the configuration of the classification scheme affect how categories are used?

FIGURES

FIGURE 2.1

A Series of "Chairs" Assembled through Prototypical Association

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[13] In order of appearance, the chairs are: Restaurant Chair #26, Hotel Banquet Chair (www.restaurant-services.com); Chair, 1890 (pencil) by Vincent Van Gogh (www.vangoghgallery.com); Alphabet Chair, 2003, by Sarah Peters (www.sarahpeterssscultpure.com); and Wave chair by Paola Lenti (www.paolalenti.com)

FIGURE 6.1

Ambiguity Scores Summarized by Year
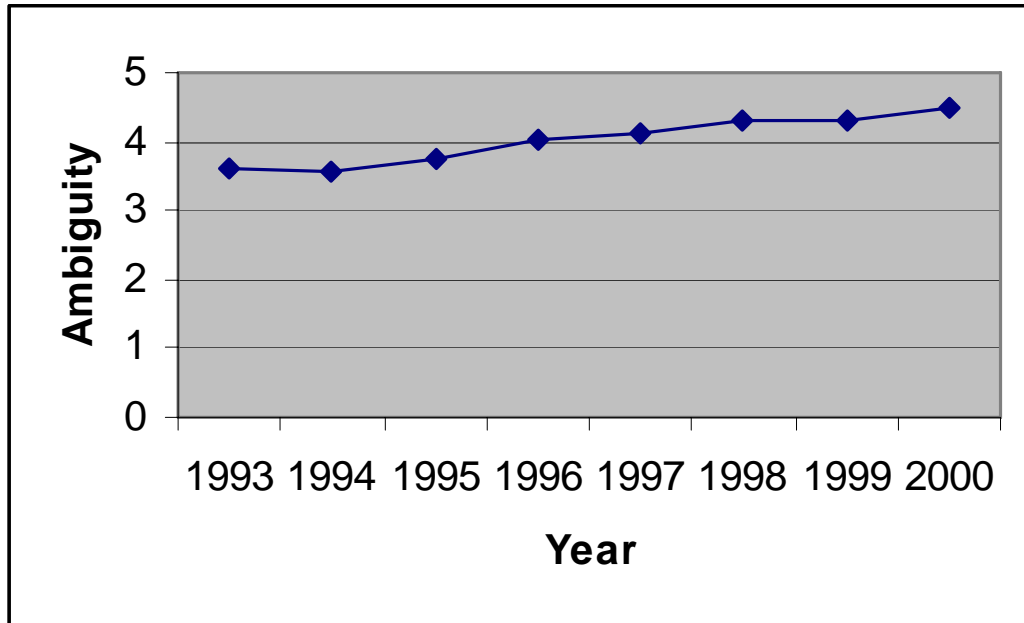
FIGURE 6.2

Underwriting Activity 1993-2000
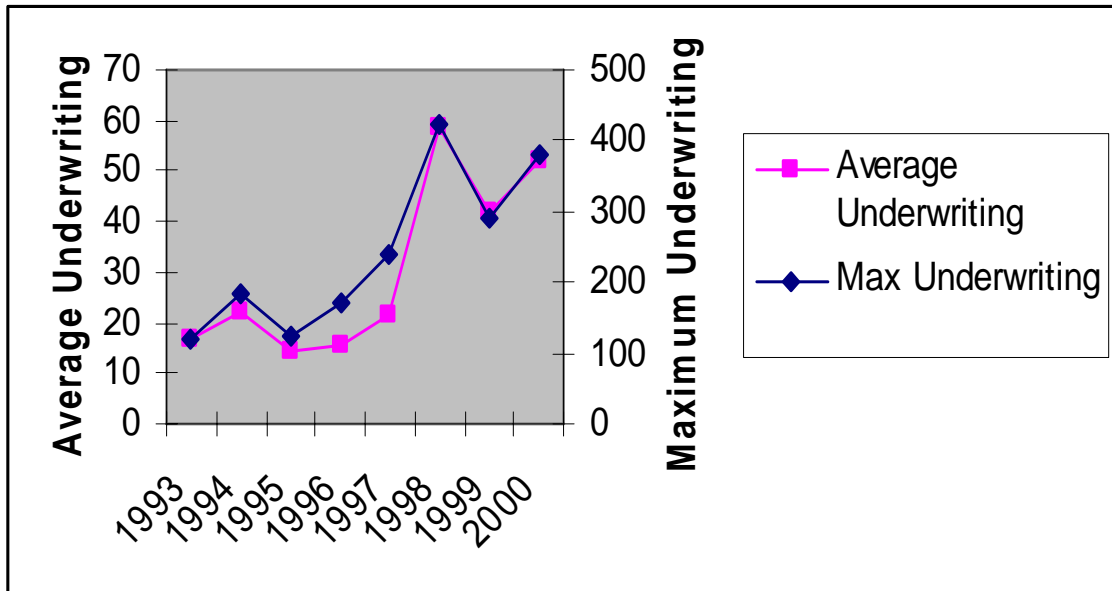
FIGURE 6.3

Predicted Probabilities for Changing Values of Underwriting (Count)
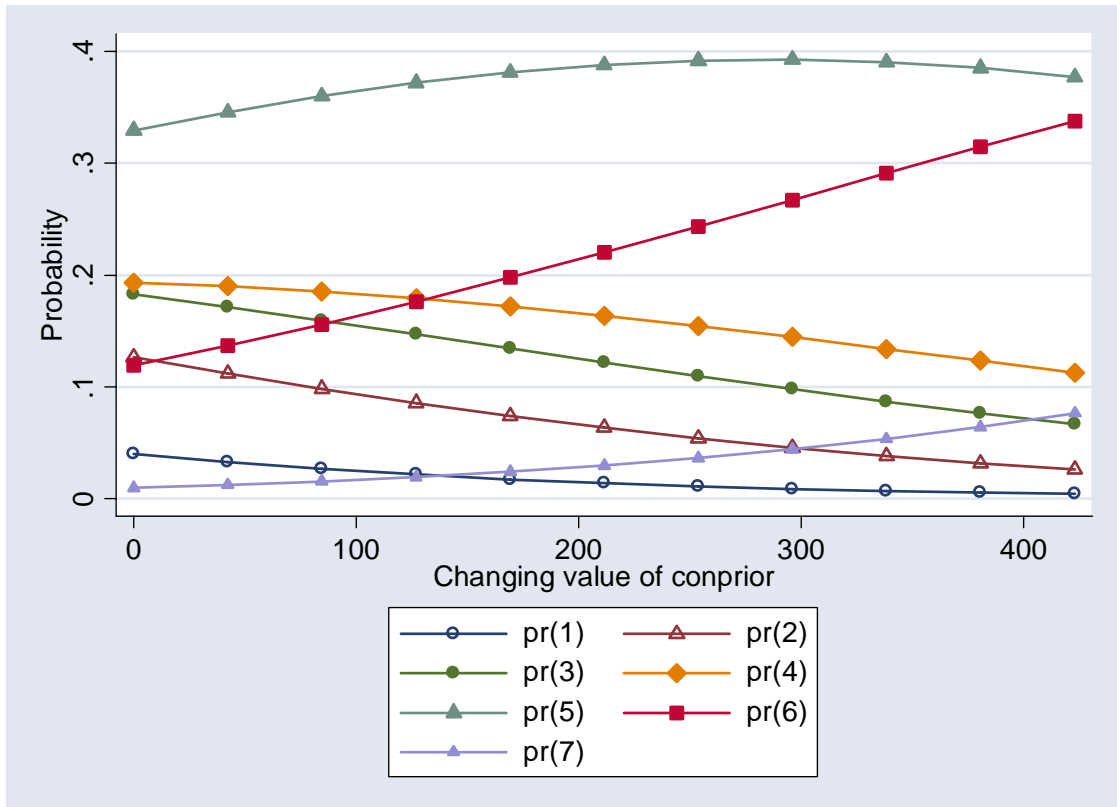
FIGURE 6.4

Predicted Probabilities for Changing Values of the Interaction between Status and

Conflict of Interest (Count)
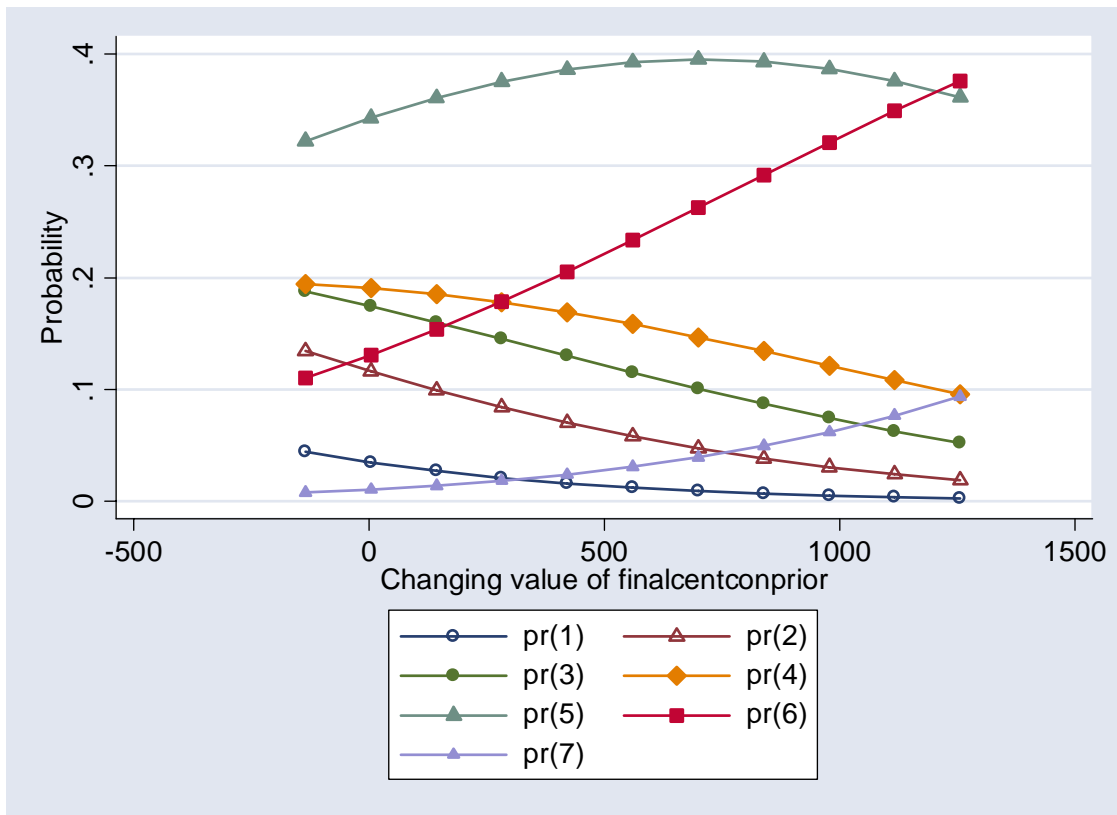
FIGURE 6.5

Predicted Probabilities for Changing Values of the Interaction between Status and

Conflict of Interest (Ratio Measure)
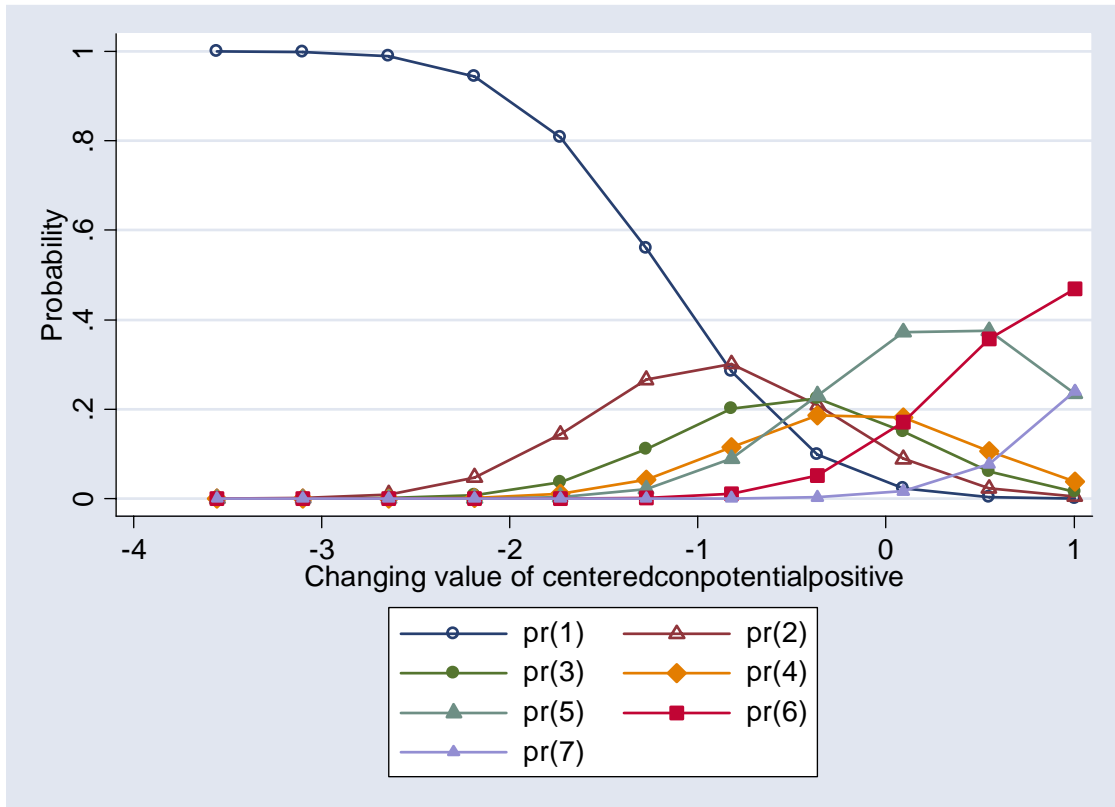
FIGURE 6.6

The Effect of Ambiguity on Customer Accounts (holding other variables constant)
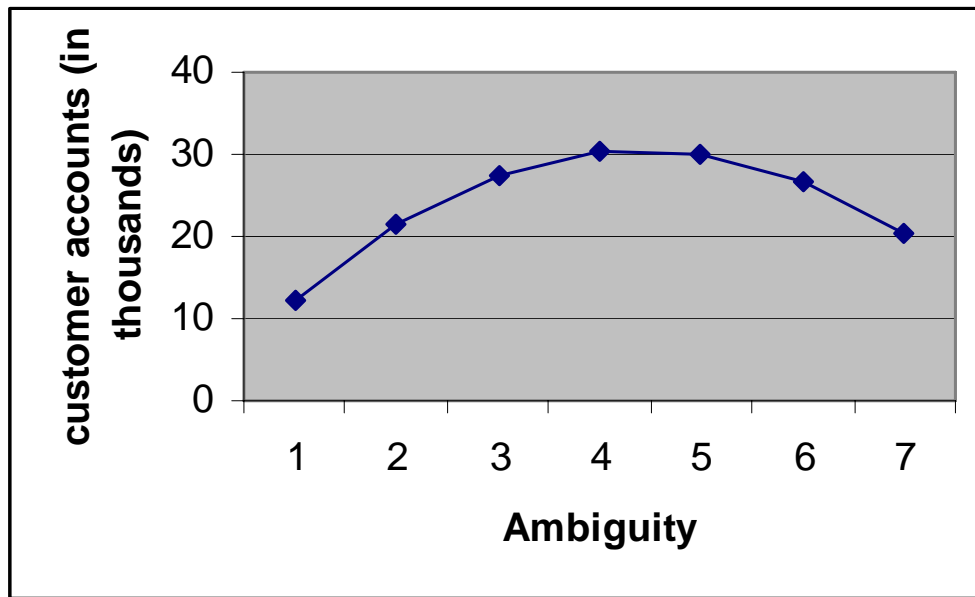
FIGURE 6.7

Graph of the Interaction between Frequency and Quality
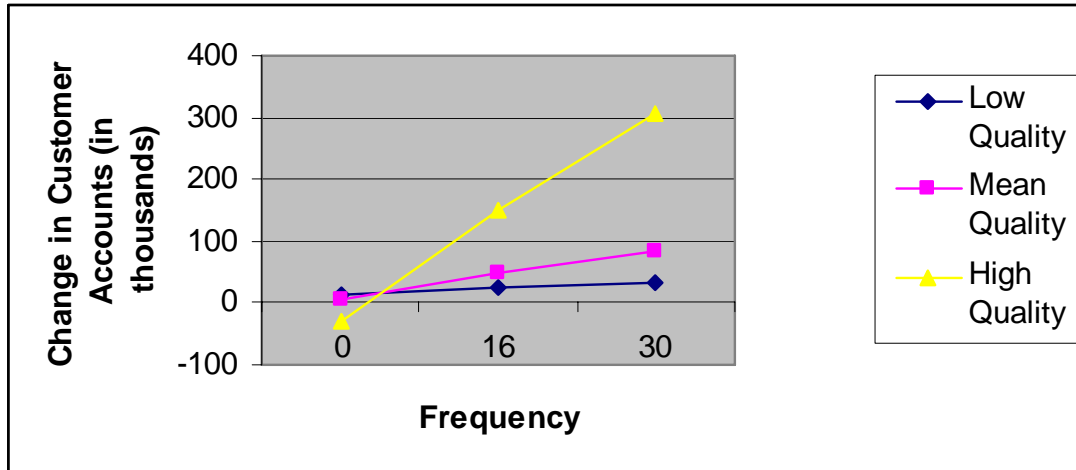
FIGURE 6.8

Graph of the Interaction between Similarity and New Schemes
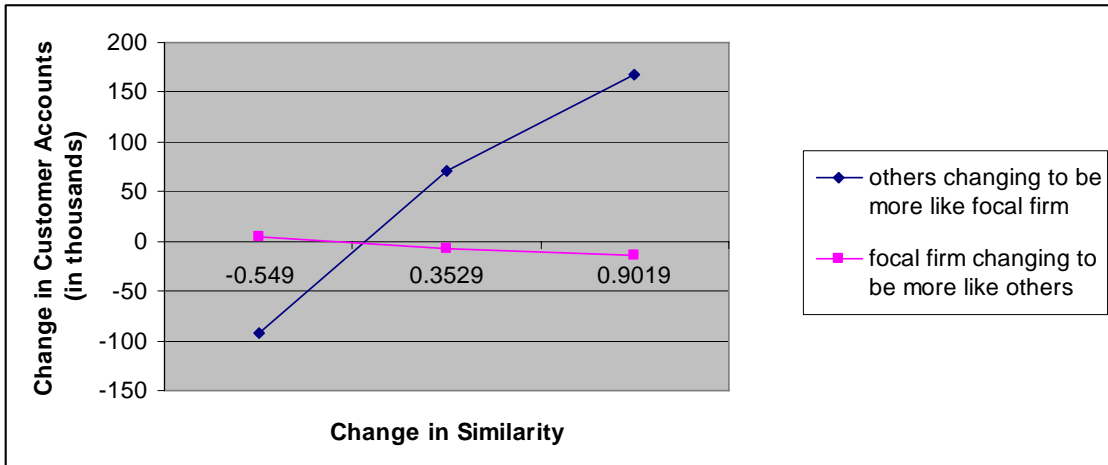
TABLES

TABLE 6.1

Descriptive Statistics and Correlations

	Mean	S.D.	Min	Max	Ambiguity	Lagged Ambiguity	Total Categ.	Experience	Workload	Size	Coverage
Ambiguity	4.077	1.764	1.000	7.000	1.00						
Lagged Ambiguity	3.974	1.796	1.000	7.000	0.68	1.00					
Total Categories	3.699	1.680	1.000	16.000	0.19	0.23	1.00				
Experience	1950.090	43.776	1799.000	1998.000	0.06	0.06	-0.32	1.00			
Workload	11.160	9.436	0.500	118.000	-0.05	-0.02	0.05	-0.03	1.00		
Size	2.394	1.135	0.000	5.645	-0.10	-0.08	0.47	-0.42	-0.12	1.00	
Coverage	3.143	0.882	0.000	4.710	-0.12	-0.09	0.42	-0.41	0.15	0.77	1.00
Rel. Ambiguity	4.250	0.433	3.770	4.895	0.14	0.13	0.05	0.07	-0.13	0.02	-0.14
Mean Beta	0.824	0.289	-0.286	2.236	-0.04	-0.05	-0.03	0.02	-0.05	0.10	-0.05
Variance of Betas	0.298	0.132	0.000	1.815	-0.05	-0.06	0.03	-0.01	0.00	0.22	0.22
Percent Unique Firms	0.055	0.102	0.000	1.000	0.05	0.05	-0.07	0.08	-0.05	-0.22	-0.17
Underwriting (levels)	32.286	58.148	0.000	423.000	0.08	0.09	0.30	-0.28	-0.02	0.61	0.41
Status	0.000	0.874	-0.319	3.718	0.07	0.08	0.32	-0.30	0.04	0.55	0.41
Status*Underwriting (levels)	27.489	135.642	-135.133	1442.322	0.15	0.15	0.28	-0.20	0.02	0.41	0.30
Percent Underwriting	0.200	0.490	0.007	11.132	0.12	0.11	0.08	-0.03	-0.15	-0.07	-0.16
Status*Percent Underwriting	-0.011	0.254	-3.556	5.018	0.04	0.04	0.10	-0.24	0.09	0.30	0.29

TABLE 6.1, continued

	Rel. Ambiguity	Mean Beta	Var. of Beta	Percent Unique	Underwriting (levels)	Status	Status* Underwriting (levels)	Percent Underwriting	Status* % Underwriting
Ambiguity									
Lagged Ambiguity									
Total Categories									
Experience									
Workload									
Size									
Coverage									
Rel. Ambiguity	1.00								
Mean Beta	-0.34	1.00							
Variance of Betas	-0.19	0.39	1.00						
Percent Unique Firms	0.06	-0.07	-0.05	1.00					
Underwriting (levels)	0.16	0.11	0.06	-0.12	1.00				
Status	-0.06	0.12	0.07	-0.14	0.54	1.00			
Status*Underwriting (levels)	0.03	0.06	0.02	-0.09	0.63	0.80	1.00		
Percent Underwriting	0.13	0.15	-0.06	0.05	0.19	-0.03	-0.02	1.00	
Status*Percent Underwriting	-0.08	-0.01	0.05	-0.11	0.32	0.54	0.56	-0.36	1.00

TABLE 6.2

Results of Ordered Probit, Dependent Variable: Ambiguity

	(1)	(2)	(3)	(4)	(5)
Lag. Ambiguity	0.503	0.496	0.495	0.491	0.490
	(0.042)**	(0.042)**	(0.042)**	(0.042)**	(0.042)**
Total Categories	0.238	0.246	0.240	0.245	0.241
	(0.046)**	(0.046)**	(0.046)**	(0.047)**	(0.047)**
Experience	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Workload	-0.004	-0.006	-0.006	-0.007	-0.007
	(0.003)	(0.003)+	(0.003)+	(0.003)*	(0.003)*
Size	-0.095	-0.181	-0.189	-0.231	-0.211
	(0.052)+	(0.065)**	(0.057)**	(0.068)**	(0.070)**
Coverage	-0.092	-0.082	-0.077	-0.073	-0.074
	(0.070)	(0.069)	(0.070)	(0.070)	(0.070)
Rel. Ambiguity	0.367	0.304	0.398	0.355	0.354
	(0.120)**	(0.129)*	(0.121)**	(0.130)**	(0.131)**
Mean beta	-0.123	-0.155	-0.195	-0.206	-0.184
	(0.179)	(0.183)	(0.182)	(0.185)	(0.185)
Variance of betas	0.492	0.524	0.677	0.674	0.658
	(0.392)	(0.390)	(0.388)+	(0.388)+	(0.388)+
% unique firms	0.032	0.039	0.049	0.051	0.041
	(0.309)	(0.310)	(0.311)	(0.312)	(0.311)
Underwriting		0.002		0.001	0.001
		(0.001)**		(0.001)	(0.001)
Status			0.195	0.170	0.074
			(0.064)**	(0.064)**	(0.095)
Interaction					0.001
					(0.001)+
Observations	986	986	986	986	986
Robust standard errors in parentheses					
+ significant at 10%; * significant at 5%; ** significant at 1%					
One tailed tests on all hypothesized variables; two-tailed tests on all other variables					
Year variables omitted					

TABLE 6.2, continued

	(6)	(7)	(8)
Lagged Ambiguity	0.512	0.494	0.487
	(0.042)**	(0.042)**	(0.041)**
Total Categories	0.238	0.240	0.242
	(0.047)**	(0.047)**	(0.047)**
Experience	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)
Workload	-0.003	-0.005	-0.006
	(0.003)	(0.003)+	(0.003)+
Size	-0.100	-0.187	-0.191
	(0.054)+	(0.057)**	(0.057)**
Coverage	-0.078	-0.073	-0.076
	(0.069)	(0.070)	(0.071)
Rel. Ambiguity	0.346	0.367	0.343
	(0.135)*	(0.129)**	(0.130)**
Mean Beta	-0.122	-0.234	-0.213
	(0.197)	(0.191)	(0.191)
Variance of Betas	0.457	0.714	0.675
	(0.410)	(0.392)+	(0.393)+
Percent Unique	-0.098	0.046	0.043
	(0.310)	(0.310)	(0.311)
Underwriting Ratio	0.247	0.147	0.609
	(0.234)	(0.142)	(0.247)*
Status		0.195	-0.031
		(0.064)**	(0.106)
Ratio*Status Interaction			1.579
			(0.642)*
Observations	967	986	986
Robust standard errors in parentheses			
+ significant at 10%; * significant at 5%; ** significant at 1%			
One tailed tests on all hypothesized variables; two-tailed tests on all other variables			
Year variables omitted			

TABLE 6.3

Results of Ordinary Least Squares, Dependent Variable: Ambiguity

Lag Ambiguity	0.594
	(0.037)**
Total Categories	0.160
	(0.036)**
Experience	0.001
	(0.001)
Workload	-0.005
	(0.004)
Size	-0.190
	(0.081)*
Coverage	-0.078
	(0.090)
Rel. Ambiguity	0.466
	(0.156)**
Mean Beta	-0.210
	(0.220)
Variance of Betas	0.808
	(0.455)+
Percent Unique	0.013
	(0.394)
Underwriting (/100)	0.035
	(0.115)
Status	0.031
	(0.108)
Underwriting*Status interaction	0.081
	(0.049)+
Constant	-1.709
	(2.724)
Observations	986
R-squared	0.49
Robust standard errors in parentheses	
+ significant at 10%; * significant at 5%; ** significant at 1%	
Year variables omitted.	

TABLE 6.4

Descriptive Statistics and Correlations

	Mean	S.D.	Min	Max	Change in cust acct	Size	Cover.	Wkload	Total Categ.	Status	Quality	Change Quality	Retail Focus
Change in Cust. Accts	5.612	35.522	-159.400	497.200	1.00								
Size	2.449	1.085	0.000	5.645	0.22	1.00							
Coverage	3.234	0.817	0.000	4.710	0.12	0.76	1.00						
Workload	11.714	9.503	0.500	118.000	-0.00	-0.16	0.10	1.00					
Total Categories	3.737	1.671	1.000	16.000	0.04	0.43	0.38	0.01	1.00				
Status	0.028	0.870	-0.275	3.768	0.28	0.54	0.40	0.03	0.35	1.00			
Quality	0.036	1.002	-0.630	3.033	0.22	0.67	0.48	0.03	0.35	0.65	1.00		
Change in Quality	0.015	0.584	-2.890	2.773	-0.01	0.00	0.00	-0.01	0.02	-0.01	-0.28	1.00	
Retail Focus	0.551	0.498	0.000	1.000	0.03	-0.18	-0.05	0.01	-0.18	-0.16	-0.07	-0.02	1.00
Underwriting	32.286	58.148	0.000	423.000	0.25	0.61	0.42	-0.02	0.28	0.54	0.65	0.01	-0.00
Underwriting focus	0.193	0.490	0.000	11.125	-0.01	-0.04	-0.11	-0.14	0.13	-0.04	0.03	0.02	0.04
Merger	0.025	0.157	0.000	1.000	0.01	0.17	0.13	-0.02	0.05	0.01	0.08	0.06	-0.06
Ambiguity	3.974	1.796	1.000	7.000	0.02	-0.08	-0.08	-0.01	0.22	0.10	-0.01	0.03	-0.05
Similarity	0.439	0.158	0.033	1.000	0.00	-0.20	-0.14	-0.03	-0.03	-0.00	-0.10	0.01	0.05
New scheme	0.582	0.493	0.000	1.000	-0.08	-0.08	-0.06	-0.03	0.02	-0.04	-0.08	-0.03	-0.00
Change in Similarity	-0.007	0.096	-0.557	0.345	0.09	-0.05	-0.03	-0.00	-0.04	-0.05	-0.05	-0.05	0.12
Strategic Change	-0.005	0.087	-0.557	0.345	0.02	-0.01	0.01	-0.00	0.03	-0.02	-0.03	-0.02	0.08
Frequency	3.311	3.435	0.000	16.000	0.02	-0.29	-0.31	-0.03	-0.41	-0.11	-0.15	-0.01	0.10
Frequency * Quality	-0.410	3.772	-10.088	27.816	0.24	0.52	0.41	0.05	0.24	0.39	0.68	-0.24	-0.12

TABLE 6.4, Continued

Retail Focus										
Underwriting	1.00									
Underwriting focus	0.19	1.00								
Merger	0.18	0.01	1.00							
Ambiguity	0.09	0.11	0.01	1.00						
Similarity	-0.11	-0.02	-0.02	0.11	1.00					
New scheme	-0.09	0.05	0.05	0.11	0.01	1.00				
Change in Similarity	-0.00	-0.01	-0.01	-0.07	-0.37	-0.03	1.00			
Strategic Change	0.01	-0.01	-0.00	-0.09	-0.32	-0.06	0.90	1.00		
Frequency	-0.15	0.02	-0.03	-0.11	0.47	-0.07	-0.08	-0.12	1.00	
Frequency * Quality	0.41	-0.01	0.08	-0.14	-0.11	-0.06	-0.08	-0.05	-0.29	1.00

TABLE 6.5

Results of Fixed Effects Regression, Dependent Variable: Change in Customer Accounts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prior Changes	-3.016	-3.024	-2.214	-6.718	-6.830	-3.665	-4.382	-7.285
	(4.367)	(4.372)	(4.407)	(4.747)	(4.639)	(4.380)	(4.323)	(4.588)
Length Lasted	-2.191	-2.037	-1.431	-3.218	-3.579	-2.818	-3.466	-3.492
	(2.890)	(2.916)	(2.946)	(2.943)	(2.877)	(2.914)	(2.879)	(2.869)
Size	-4.497	-4.628	-4.616	-3.446	-3.970	-4.171	-4.170	-5.341
	(11.773)	(11.790)	(11.776)	(11.736)	(11.469)	(11.754)	(11.587)	(11.145)
Coverage	5.321	5.379	4.664	5.334	5.770	3.623	3.634	5.039
	(11.809)	(11.822)	(11.820)	(11.747)	(11.480)	(11.840)	(11.671)	(11.271)
Workload	-0.116	-0.125	-0.150	-0.065	0.135	-0.060	-0.059	0.192
	(0.699)	(0.700)	(0.699)	(0.700)	(0.686)	(0.698)	(0.688)	(0.666)
Total Categories	-1.329	-1.345	-0.937	-1.162	-0.951	-0.087	-0.622	1.477
	(2.177)	(2.180)	(2.197)	(2.165)	(2.116)	(2.319)	(2.292)	(2.273)
Status	-0.979	-0.953	-1.138	-0.928	1.280	-0.159	0.555	1.341
	(6.792)	(6.800)	(6.793)	(6.776)	(6.642)	(6.801)	(6.707)	(6.490)
Quality	-2.537	-2.541	-2.493	-1.987	-3.028	-2.579	-11.039	-12.064
	(4.639)	(4.644)	(4.638)	(4.631)	(4.532)	(4.631)	(5.181)*	(4.984)*
Change in Qual.	-1.689	-1.783	-1.593	-1.267	-1.523	-1.545	-1.061	-0.761
	(3.475)	(3.486)	(3.485)	(3.493)	(3.414)	(3.470)	(3.424)	(3.324)
Retail focus	25.447	25.621	26.564	25.336	28.729	24.590	24.278	30.404
	(10.492)*	(10.511)*	(10.521)*	(10.654)*	(10.441)**	(10.488)*	(10.339)*	(10.153)**
Underwriting	0.127	0.126	0.133	0.113	0.105	0.119	0.100	0.082
	(0.059)*	(0.059)*	(0.059)*	(0.058)+	(0.057)+	(0.059)*	(0.058)+	(0.056)
Und. Focus	-7.749	-7.765	-10.156	-4.906	-2.829	-8.073	-7.641	-6.773
	(12.215)	(12.228)	(12.337)	(12.166)	(11.898)	(12.195)	(12.022)	(11.671)
Merger	6.286	6.290	6.040	6.981	4.800	6.392	4.182	2.009
	(12.396)	(12.409)	(12.396)	(12.322)	(12.052)	(12.374)	(12.214)	(11.686)
Ambiguity		0.668	9.138					13.786
		(1.562)	(6.359)					(6.222)*
Ambiguity^2			-1.150					-1.552
			(0.837)+					(0.814)*
Frequency						1.357	1.220	2.419
						(0.886)+	(0.874)	(0.921)**
Qual*Freq							2.737	2.876
							(0.793)**	(0.775)**
Similarity								-67.421
								(31.025)*
New				-7.572	-8.868			-9.811
				(4.130)*	(4.047)*			(3.989)*
Change in Sim.				40.754	208.376			178.322
				(17.227)*	(42.392)**			(45.305)**
Strat. Change					-200.384			-191.578
					(46.510)**			(45.372)**
Constant	1.800	-1.002	-15.645	12.781	12.538	1.709	11.056	10.738
	(33.956)	(34.619)	(36.183)	(35.323)	(34.518)	(33.895)	(33.522)	(36.238)
Observations	522	522	522	520	520	522	522	520
Number of firms	127	127	127	127	127	127	127	127
R-squared	0.05	0.05	0.06	0.08	0.12	0.06	0.09	0.19
Prob > F	0.33	0.38	0.34	0.08	0.00	0.27	0.03	0.00
Standard errors in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%								
One-tailed tests for hypothesized variables, two tailed tests for all others. Year variables omitted.								

APPENDICES

APPENDIX A

Sample Classification Schemes & Ratings

Rating System	Numerical Rating
Buy, Sell	1
Buy, Hold, Sell	1
Outperform, Sector Perform, Underperform	1
Strong Buy, Buy, Hold, Sell	2
Buy, Accumulate, Hold, Switch, Sell	3
Strong Buy, Buy, Speculative Buy, Trading Buy, Accumulate, Hold, Watch	5
Accumulate, Buy	5
Top pick/average risk, top pick/above average risk, top pick/speculate, outperform/average risk, outperform/above average risk, outperform/speculate, sector perform/average risk, sector perform/above average risk, sector perform/speculate, underperform/average risk, underperform/above average, underperform/speculate	7
Strong buy, buy, speculative buy, trading buy, accumulate, hold, neutral, avoid, underperform, lighten, sell	7

Calculation of the Average Pairwise Jaccard Score

The Jaccard score measures the intersection over union of two sets of objects (Hsu, 2006a; Ruef, 1997). It is useful when the absence of overlapping objects between two sets does not necessarily make a set similar to another. To calculate the Jaccard score, each scheme was compared to the other schemes present in the same year. The scores were put in a scheme by scheme matrix, and then averaged across rows to get the average pairwise Jaccard score. This was repeated with each year in the data. I also created Jaccard scores looking at firms of the same kind (retail or institutional focused, hybrid focused) as well as all firms for which I had scheme data in a given year. The different measures were highly correlate (.93, .95, and .98). A smaller, stylized example of the coding is detailed below.

For a single Jaccard coefficient:

Scheme 1: Buy, Hold, Sell

Scheme 2: Strong Buy, Buy, Hold, Sell

Jaccard coefficient = (Buy, Hold, Sell)/(Strong Buy, Buy, Hold, Sell) = ¾ = .75

Scheme	Buy, Hold, Sell	Strong Buy, Buy, Hold, Sell	Marketperform, Outperform, Underperform	Marketperform, Strong Buy, Buy, Neutral, Sell	Average Score
Buy, Hold, Sell		¾ (.75)	0/3 (0)	2/5 (.4)	.3833
Strong Buy, Buy, Hold, Sell	¾ (.75)		0/4 (0)	3/6 (.5)	.4167
Marketperform, Outperform, Underperform	0/3 (0)	0/4 (0)		1/7 (.1428)	.0476
Marketperform, Strong Buy, Buy, Neutral, Sell	2/5 (.4)	3/6 (.5)	1/7 (.1428)		.3476

APPENDIX C

List of Data Sources

Thomson/IBES

X-17A-5 forms (SEC, Thomson One Banker)

SDC Platinum

NASD web site

Securities Industry Association Yearbook

CRSP database

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