6-2009

Categories in Evaluation of Innovative Activities of Competing Firms

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ASAC 2009
Niagara Falls, Ontario

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CATEGORIES IN EVALUATION OF INNOVATIVE ACTIVIES OF COMPETING FIRMS[1]

I examine how the stock market evaluation of a firm's innovative activities is influenced by the categorization of the firm and its rivals. I find that innovations that blur the industry boundaries cause negative evaluation bias, but the competing innovations by outside-industry firms cause positive evaluation bias in firm valuation.

Introduction

The last decade has witnessed an explosion of research on the role of categorization in influencing firm behavior. As one of the clearest mechanisms of human thought, categorization is used to group objects based on some similarity among them (Rosch and Lloyd, 1978). When it is applied to organizations, researchers have explored how audiences of various types reward firms for conforming to categories and punish those that deviate (Zuckerman 1999; Hannan, Carroll, and Pólos 2003). Audiences are usually defined as collections of agents with control over material and symbolic resource that affect the success and failure of the firms (Hsu and Hannan, 2005). There is an isomorphism process that can be described as a two-stage process through which firms can gain legitimacy and audiences' resources (Zuckerman, 1999). In the first stage, a firm must gain the audience's attention by exhibiting certain common characteristics in its activities and offerings that may be readily compared to others. Activities and offerings that stand outside the field of comparison may be ignored by the audiences. This inattention by the audience constitutes the cost of illegitimacy (Zuckerman, 1999). Simply put, firms must first gain membership in a category to be recognized by the audience. In the second stage, legitimate firms that have already gain the membership in the first stage compete for the audience's resources by differentiating their offerings and demonstrating appeal within the category. By being different, a firm benefits because it faces less competition. But at the same time, firms are motivated to conform to a range of legitimate activities that are institutionalized in the category and are accepted by the audience as a cognitive consensus that describes legitimate practices and strategies that will lead to organizational success (DiMaggio and Powell, 1983; Suchman, 1995; Baum and Haveman, 1997; Deephouse, 1999). As such, one line of research suggests that a firm that spans market categories is difficult to be categorized and draws less attention from key audiences, and this inattention will reduce demand for the firm's offering and induce devaluation by audiences (e.g., Zuckerman 1999, 2000; Zuckerman and Kim, 2003). Another line of research has explored the tension that a firm faces in needing to both conform and stand out – the challenge of conforming to a category so as to be in the "consideration set" of an audience, while then differentiating from others so as to avoid direct competition for resources (Baum and Haveman, 1997; Deephouse, 1999; Phillips and Zuckerman, 2001; Hannan, Carroll and Pólos, 2003; Hsu 2006).

Yet the focus of extant research left at least three gaps unexplored. First, the primary attributes

[1] Special thanks to Brian Silverman, Terry Amburgey and Joel Baum, Anita McGahan, Mary Tripsas, You-Ta Chuang, Zilin He, Nan Jia, Tim Simcoe and Lizhi Ma.

used for categorization of firms in extant research have been similarity in product market space (for an exception see Benner, 2007a). How are attributes beyond product-market participation relevant to evaluation of a firm's conformance to, or deviation from, its category? Second, the extant research on categorical impact has not differentiated between economic penalties and social penalties for firms that defy the categorical imperatives. Is there evaluation bias generated by the categorization process? Third, it is unclear how audiences evaluate competitive threats that are generated by entities outside of the categories in which they place a firm. Although this is a logical extension of the logic of categorization – by definition, entities outside of the category are outside of the audience's consideration set, and therefore the audience may not consider the effect of such entities' actions on firms within the consideration set – the sociological literature on categorization has been largely silent on this issue.

In this paper I attempt to address the above issues and explore how categories influence the stock market valuation of a firm's technological innovations. Categories play important role in evaluating the value of a firm's innovative activities. On the one hand, stock markets value highly and welcome new technologies or patents (Pakes, 1985; Griliches, 1990; Brundell, Griffith and van Reenen, 1999). On the other hand, the information asymmetry between innovators and evaluators may induce the failure in financial markets for valuating innovating firms (Arrow, 1962). The intrinsic conundrum and huge information load required in evaluating the quality of uncertain organizational activities like innovation leads the evaluators to rely on categories to circumvent it (Zuckerman, 1999). I suggest that investors in the stock market will view the innovative efforts of a firm in technological space through the prism of the firm's categorization in product market space. This category-based valuation process however can create biased valuation. Specifically, investors will evaluate the innovative output of a firm by comparing its profile to the "norm" of its industrial category. Firms whose innovative output defies such comparison will be discounted by investors. I then argue that investors will recognize the threat of competing innovations when they come from within-industry rivals, but will be less likely to recognize such threats when they come from outside-industry rivals. I test these predictions in a multi-industry sample of nearly 500 large publicly traded U.S. firms in an unbalanced panel covering 1980 through 2000. I am interested in how the same independent variables influence firm stock market valuation and future cash flows in different directions. I find two instances of incorrect evaluation: 1) whereas the degree of category-mixing innovation is negatively valued by the stock market, future cash flows are not negatively affected by it; and 2) whereas the stock market valuation is not affected by competing innovations from outside-industry firms, future cash flows are negatively affected by such competition. These results offer support for my predictions.

Theories and Hypotheses Development

Financial markets in the United States represent a crucial audience for publicly traded firms. The availability of capital resources is critical for firms' long-term success and U.S. firms are particularly dependent on the U.S. securities market for financial resources (Benner, 2007a). Recent studies suggest that investors' attention could play an important role in determining asset prices. Important news or information is not reflected by prices until investors pay attention to it (Peng and Xiong, 2006). Investors' attention however is a scarce cognitive resource (Kahneman, 1973). Given the vast amount of information available and the inevitability of limited attention, investors have to be selective in information processing. Limited attention leads to category-learning behavior, that is, an investor tends to allocate attention along some categorical dimensions like markets or sectors (Peng and Xiong, 2006). In the financial markets, industry affiliation is the principal product category by which corporate equity shares are classified (Porac, Wade and Pollock, 1999; Barberis and Shleifer, 2003; Peng and Xiong, 2006; Mase, 2008). Categorization simplifies problems of choice and allows investors to process vast amounts of information efficiently (Barberis and Shleifer, 2003). Moreover, security analysts, as well as other business critics like the Wall Street Journal, are important intermediaries in the stock market, and they rely heavily on industrial categories to make stocks recommendations and forecasts. Their industry-based opinions and recommendations can significantly affect investors' appetite for a firm's shares. As a result, industrial categorization changes the salience of firms in different categories to the investors. When markets are segmented along categories, limited attention pushes investors, even the most informed ones like equity money managers, to focus on and trade only the subset of stocks of which they are aware (Merton, 1987). Similarly, security analysts usually develop expertises in one or two industries (e.g. Zuckerman, 1999, 2004). By focusing on some categories, investors are less attentive to other categories. It has been found that investors are unable to devote the attention needed to process potentially valuable information from other markets they are less aware in a timely manner (Hong, Torous, and Valkanov, 2007).

Technological innovation has been shown to be "value-relevant" in financial markets (Griliches, 1990; Hall, Jaffe & Trajtenberg 2005; McGahan & Silverman 2006) – that is, a firm's innovative output has a statistically significant impact on its stock market valuation – which indicates that a firm's innovation is a salient attribute to the financial market audience. Innovative investments and activities lead to creation of a stock of scientific knowledge. Firms can use this stock in many different ways to develop and license innovations, adopt more cost-efficient production techniques, introduce new products and processes and consequently increase their revenues and performance. Yet, the substantial information load required to understand innovations and considerable uncertainty inherent in how innovations can be used in pursuit of market opportunities and create value for the firm gives crucial importance for categories from which the audience can get clues.

In this paper, I suggest that investors and security analysts in the stock market will view the innovative efforts of a firm in technological space through the prism of the firm's industrial categorization in product market space. Investors may rely on technological norms or paradigms in an industry to facilitate the valuation. Such norms provide investors the expectations on "normal" technologies that will enable firms in an industry to offer "standard" products to the market and create value. It has long been discussed in the economics of technological change literature that technologies and innovations are industry-specific (e.g., Malerba, 2002; Castellacci, 2008). In each industry, there can be developed a technological paradigm or norm (Dosi, 1982, 1988). It defines a set of selected technological problems and "normal" problem-solving activities, which channels and circumscribes the set of opportunities and constraints for firms in an industry in their innovative activities. It also defines basic or average model of artifacts and systems in an industry that can be described in terms of some fundamental technological and economic characteristics (Anderson, 1991). This "average" specimen does not have to exist in reality, but are accepted and agreed upon by the customers. In the case of an airplane, technological norms can be reflected not only in terms of inputs and the production costs, but also salient technological features of the products that those firms in this industry provide for the market such as wing-load, take-off weight, speed, distance it can cover etc. (Cimoli and Dosi). Moreover, technological norms define appropriate business models that generate income stream in the industry. For example, traditional photographic industry used a razor/blade profit model (cf. Tripsas and Gavetti, 2000) that is based on the sales of film ("razor blade") and not on sales of cameras ("razor"). The technological paradigm in this industry was therefore concentrated on chemical technologies that are related to film.

Although the basic models of artifacts and systems in a paradigm can be progressively modified and improved over time, the technical progress displays strong patterns and invariance in term of the fundamental techno-economic characteristics of artifacts and the production process (Dosi, 1988). It is widely acknowledged that learning is local and cumulative. Local means that the exploration and development of new technologies is likely to occur in the neighborhood of the technologies already in use. Cumulative means that current technological development often builds upon past experiences of production and innovation and proceeds via sequences of specific problem-solving junctures. As described persuasively by Dosi (1982, 1988), one should be able to observe regularities and invariances in the pattern and trajectory of technological change that evolves. Therefore, technological norms in an industry may influence the expectation of audiences in the stock market on the innovative activities of firms in the industry.

Recombinant Innovation and Valuation

Innovation can be viewed as a process in which firms search for better solutions to a stream of technological problems (Nelson and Winter, 1982). Through search in the landscape of knowledge, a firm can create novel links between knowledge components (Fleming, 2001; Yayavaram and Ahuja, 2008). Although the paradigm may channel the search process in an industry, firms are motivated to search for novel solutions by exploring the recombination opportunities among diverse streams of technologies (Fleming, 2001; Sorenson, Rivkin and Fleming, 2006) or by searching into distant knowledge. Since different streams of technologies are generally associated with different industries (Dosi, 1982; Castellacci, 2008), such developed innovations can change the relative position of the firm vis-a-vis other firms in different industries and the degree to which the firm's technology profiles fit with the industry norms in technologies.

Although technologies are industry-specific as suggested by the analysis of technological norms, technological opportunities may reside in the recombination of technologies that are associated closely with different industries. The current development of smart phones, for example, is a result of recombining technologies from wireless communications, computers and softwares industries. Diverse streams of technologies can create valuable recombination opportunities for highly novel innovations (Fleming, 2001; Sorenson, Rivkin and Fleming, 2006). Recent studies on technological diversity and product diversification has shown that a firm can diversify into a new industry when it can apply its existing technologies into the new industry (Silverman, 1999; Miller, 2004). This implies the recombinant opportunities across industries and innovations that capitalize such cross-industry technological opportunities can create value for the firm. Moreover, by recombining features from established technological paradigms in different industries, producers can innovate in fairly structured and incremental fashion (Fleming, 2001; Haveman and Rao, 2006). Therefore, recombinant innovations may enable producers to improve on the established norms of technologies without incur high uncertainty and cost in technology development.

However, firms with innovations that are closely related to other industries may cause confusion in evaluation. They are more difficult to make sense of than category “purists” and as a result their innovative efforts are easy to be ignored or excluded from the consideration (e.g. Zuckerman, 1999). Moreover, the acceptance of technological norms in different industries by investors may lead to the perception that the value of a set of technologies is only meaningful if they are associated with a particular industry. Investors may be uncertain about how the technologies that are perceived to create value in another industry can create expected income stream in the focal industry of the firm. Such difficulty in evaluation is amplified by the fact that investors tend to focus only on stocks in limited number of industries so that they are not capable to understand technologies that are associated with industries they do not cover. In addition, recombinant innovations are more likely to generate interpretative discrepancy among investors and hinder them to reach consensus (Zuckerman, 2004; Hsu, 2006). Lack of attributes central to the audience's acceptance may cause the investors that have different preference to interpret information differently. Therefore, such innovations may cause the discrepancy between the increased performance and reduced evaluation in the stock market. In other words, negative valuation bias can occur for such kind of innovations:

Hypothesis 1 (H1): The more that a firm's innovation is recombine-across-industry, the higher the evaluation bias, i.e., the stock market value is less likely to reflect the value created by such innovation.

However, such categorical impact will vary for firms with differentiated organizational characteristics, such as the innovativeness of the firm. Innovativeness can serve as an effective quality signal for audiences. Continuous success in innovation can be viewed as evidence that the company is well managed, has sufficient technical capabilities, and has figured out and carved out a market niche for their innovations. Innovation portfolio can convey information about the lines of research a firm is conducting and how quickly the search is proceeding. It can also convey information about a firm's status in technological community. High status of a firm reduces the uncertainty about the quality of the firm's technologies (Podolny, 1993; Podolny and Stuart, 1995) and the legitimacy of their activities (Phillips and Zuckerman, 2001). However, I suggest that a highly innovative firm that is supposed to draw more attention from the audience will be severely undervalued when its innovations are recombinant across industrial boundaries. If such category-across innovation generates evaluation confusion among audiences and leads to ignorance from the audiences, highly innovative firms may be mistakenly ignored as other low innovative firms. Therefore, the highly innovation-intensive firms would suffer the most if their innovations cut across the industrial boundaries. This is like that the high quality entities will be penalized to a greater extent if they are indistinguishable from the low quality entities. Therefore, we can expect that

Hypothesis 2 (H2): The association between recombine-across-industry innovation and the negative bias in its stock market valuation is stronger for more innovation-intensive firms.

Competing Innovation and Valuation

How do categories influence the stock market's valuation of a firm when its innovative activities face technological competition from other firms? If categorization affects the evaluation of a firm's activities, it may also affect the evaluation of the firm's rivals and bring such categorical impact to bear on how the audience interprets the threats imposed by these rivals on the focal firm. Competition in technological space can be associated closely with competition in the product market (Podolny, Stuart and Hannan 1996) and consequently the categories in the product market, i.e., industries. However, the technological competition can also come from industry outsiders – firms outside the industry of a focal firm. If industry insiders and outsiders develop totally different technological trajectories, it is not necessary for the audience to evaluate the competition between them. But technological development is not cleanly limited by the industry categories as we have discussed in the cross-category innovation. Incumbent insiders can borrow useful components from technologies of firms in other industries, and firms can apply their technological capabilities in technologies that may be more associated with other industries (Silverman, 1999; Adner and Levinthal, 2002). Technological competition is therefore more likely due to rearrangements and recombination of elements from different technological fields and industries (Schumpeter, 1934; Nelson and Winter, 1982; Fleming, 2001). This causes firms in different industries to compete with each other for similar technological opportunities. Such common reliance on some types of resources in technological development increases the competitive intensity between firms which adversely affects each other's pursuit of market opportunities (Podolny *et al.*, 1996). Similar technologies may lead to similar functions of the products and tighten the competition in product markets. Working in the same technologies also increases the possibility that firms possessing these technologies may enter each other's product markets (Silverman, 1999; Miller, 2004). Therefore, as industry insiders, competing innovations from industry outsiders may negatively affect firm performance.

The paper suggests that the audiences in the stock market may evaluate the competing innovations from within and outside the industry differently. In the second stage of the categorization model (Zuckerman, 1999), audiences' attention is focused on the legitimate players that has conformed to the categorical imperatives in the first stage, and compete with each other to gain the access to common scarce resources held by the targeted audience. The audiences may develop rules-of-thumb on how firms react to each others' strategic moves in technologies development. For example, they may know how a new technologies developed by a core firm and by a niche player can have different impact on other firms in the industry (e.g., Podolny and Stuart, 1995). They may also have clues on whether the competition dynamics will be conditioned by the weak appropriation regimes in an industry (McGahan and Silverman, 2006). Therefore, the negative impact of competition within the category is more likely to be evaluated appropriately by the stock market. However, the competition from industry outsiders may be ignored by the stock market since they can be screened out in the first stage of the categorical model (Zuckerman, 1999). Even if the audiences in the stock market are aware of the technological competition from entities outside the industry, for several reasons I argue they are less likely to accurately recognize its impact on incumbents. First, audiences are uncertain about whether the technological competition can be translated to product market competition. It is common that same technologies can be shared by firms in different industries, but this does not necessarily indicate that these firms will compete in the product markets. Audiences rely on categories so that they can allocate their scarce attention to those objects that have least uncertainty and easier to be evaluate. Thus they are more likely to screen out the impact of those industry outsiders that increases the evaluation uncertainty. Second, audiences are uncertain about the strategic interactions between industry insiders and outsiders. How industry outsiders enter incumbents' markets and how incumbents will react is less predictable than the strategic interaction between incumbents. The consensus in evaluation of the competitive interactions is less likely to reach. Finally, this categorical impact can be amplified when investors or securities analysts are focused on a subset of industries and are less knowledgeable of firms beyond their coverage. If these audiences can analyze the information in all industries, they do not need to reply on categories to reduce information load in the first place. In sum, the competition from industry outsiders may be less captured by the stock market. Since the competition in the technological space is associated negatively with valuation of a firm, the less recognition of the competition from outside the industry may cause the stock market over-value a firm.

Hypothesis 3 (H3): Technological competition from outside-industry entities will be associated with a positive evaluation bias in the stock market valuation.

Finally, we can expect that such bias could be weaker if the firms are innovation-intensive. Although investors tend to rely on categorical information to avoid the information overload in analyzing the heterogeneous information of individual firms (Peng and Xiong, 2006), they may pay attention to the more idiosyncratic information on an individual firm if such attention is worthwhile. To attend to the most innovative and so that perceived competitively strong firms appears to be cost-efficient in attention allocation. Therefore, the stock market appears to be optimistic about and pay more attention to R&D intensive companies (Chan, *et al.*, 2001). As such, more attention will be devoted to these firms' competitive strategies and the market situation in which they are competing, and therefore more attention will be given to the rivals of these firms. As a result, more attention will reduce the influence of categories on the biased evaluation of competitive threats from inside or outside industry rivals. Therefore, we test:

Hypothesis 4: The association between outside-industry technological competition and positive evaluation bias in stock market valuation will be weaker for more innovation-intensive firms.

Data and Measurement

This study uses patents and patent citations to measure the degree to which a firm's innovative output deviates from that of firms with whom it is categorized. Patents have long been recognized as a rich data source for the study of knowledge creation and technological change (Griliches, 1990). A patent is a right awarded to inventors that enables them to exclude others from the unauthorized use of the disclosed invention for a predetermined period of time. The front page of a patent contains detailed information about the invention, the inventor, and the assignee. For the purposes of this study, three elements of information are particularly important: the patent class to which the patent is assigned (akin to a technology-based SIC class), the name of the organization to which the patent is assigned upon issue, and the technological antecedents of the invention (prior patents, also known as 'prior art', that are cited on a given patent). A patent is required to disclose all the 'prior art' citations that represent important technological building blocks for that patent. The inventor has a legal claim only to the aspects of the patent that do not overlap with the technological contents of the cited patents. Such patenting procedure is to assure each newly granted patent to be non-obvious, novel and useful judged by those trained in the current state-of-the-art of the relevant technological domains (Dahlin and Behrens, 2005). Using patents and their backward citations, I can construct a patent-citation network that tracks the search behaviors of firms and degree to which these behaviors conform to, or deviate from, those of similar firms. Although patent data have several limitations (see e.g., Podolny *et al.*, 1996; Fleming, 2001), their richness of detail and public accessibility make them particularly advantageous for identifying the location of firms' innovative efforts. In addition, there is reason to believe that patent information is salient to stock market analysts and investors. There is extensive media coverage of patent awards, patent infringement litigation, and patent licensing deals, reflecting the widely diffused public beliefs and interests in the value-relevance of patents. As such, firms tend to promote their innovative progress rather than conceal it and the stock market is found to react actively to the information on patenting activities (Pakes, 1985). Although patents are important non-financial indicators of an innovating firm's intangible assets, investors have great uncertainty and difficulty in assessing their value. Such uncertainty and difficulty can lead the audiences of a firm to rely on heuristics such as categorization, which in turn result in potential evaluation bias.

To study the discount and evaluation bias in stock market valuation of a firm's innovative activities, I use two sources to assemble the necessary data. The NBER Patent Data set provides information on patents and patent citations, and Compustat database provide information on firms' market valuation, cash flows and also on other firm characteristics that might affect market valuation or cash flows. I first extracted all public firms from the Compustat Database that have financial data on total assets, sales, earnings, capital expenditures and R&D expenditures between 1980 and 2000 and whose primary four-digit industry is between SIC2000 and SIC3999 (i.e., in the manufacturing sector). The original data have 38,750 firm-year observations for 4,605 firms. Firms that are included in the Compustat database are, by definition, large firms that are of sufficient interest to the investor community so that they are covered by Standard and Poor's. I then used the Compustat-NBER match files created by Hall and her colleagues[2] to link each of these firms to all patents assigned to it in the NBER Patent database (Hall, *et al.*, 2001; 2005). The NBER database comprises detailed information on almost 3 million U.S. patents granted by the U.S. Patent and Trademark Office during the period 1963-2002, and on all citations made to these patents between 1975 and 2002. Since the citation data start from 1975 while patent applications are truncated sharply after 2000 due to the lag between patent application and patent granting, I chose 1980 to 2000 as my observation window. Thus, my sample includes a firm-year observation for every firm that operates between 1980 and 2000, inclusive.

I then dropped observations for a variety of reasons. Since my theoretical predictions relate to firms that invest in innovation, I chose to exclude not only firms that do not report R&D expenditures, or report R&D expenditures of $0, but also firms whose rate of patenting fell below a threshold. In the results reported below, I excluded from the sample any firm that was granted fewer than 50 patents during the 1980-2000 observation window (consistent with Silverman 1999, 2002). I also excluded firms that appeared in Compustat for three or fewer years. Finally, since I use three-digit industry membership to categorize firms (consistent with Zuckerman 1999), I dropped several three-digit industries for which

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2 Available on Brownyn Hall's website: http://elsa.berkeley.edu/~bhhall/bhdata.html. The patents are matched to approximately 6,000 manufacturing corporations that appear in Compustat, either directly or through about 30,000 of their subsidiaries (as listed in *Who Owns Whom* as of 1989). Great efforts have been made to ensure the accuracy in the name matching (Hall *et al*., 2005: p20).

fewer than three firms are in the sample. There are 7,398 firm-year observations for 491 firms in the final sample. It represents nearly 11% of the Compustat firms in the original sample, and 19% of all firm-year observations during 1980-2000. These firms were granted 345,413 patents during this time frame, accounting for about 90% of all patents granted to all manufacturing firms in Compustat. The sample is clearly an unbalanced panel. Firms appear for a minimum of four firm-year observations and a maximum of 21 observations, with a mean of 17 observations. This can mitigate the survivor bias to a certain extent. The sample demonstrates a secular increase in the number of firms from 1980 through 1996, and then a drop in numbers afterwards. Patents exhibit a similar temporal pattern – there appears to be a strong increase in patents from the beginning of the 1980s, which may be a result of changes to patent regulations (Hall and Ziedonis, 2001). The declining number of patents toward the end of the sample period may be due to truncation associated with the time lag between a patent application and its granting decision; I correct for this by including year effects in the estimations below. The patenting trend displayed in this sample is consistent with that in the overall NBER patent database, as described in Hall, *et al.* (2005). The observations and patenting activities are also distributed unevenly across industries. The sample spans 14 two-digit (and 73 three-digit) SIC industries. SIC28 (chemical, biotechnology and pharmaceuticals), SIC35 (machinery and computer equipment), SIC36 (electrical and electronic components) and SIC38 (medical and scientific instruments) account for nearly 75% of observations in the sample and more than 85% of all the patents granted to the sample firms. This indicates the prominence of patenting activities in industries relying on technological knowledge. The average (median) assets of the sample firm is $3,914 (768) millions. The sample size range from as low as $1 million to as high as $284 billion. Therefore, the sample is representative of innovative firms with wide range of size.

Dependent Variables: $Ln(V/A)_{i,t}$ and $Earning_{i,t}$.

To measure the market valuation of a firm, the first dependent variable in my analysis is $Ln(V/A)_{i,t}$, which is defined as the natural logarithm of firm *i*'s market-value-to-book-value ratio in year *t*. Consistent with Miller (2004) and Chung & Pruitt (1994), I measure firm *i*'s market value (*V*) as of December 31 in year *t* as the product of the number of common shares outstanding and the stock price as of December 31, plus the liquidating value of the firm's outstanding preferred stock and the book value of its debt. The market value is then standardized by the total assets (*A*) of the firm. This variable is an approximation of Tobin's q, which requires strict assumptions about rates of depreciation and inflation to estimate the firm's replacement value as well as additional data that is less readily available for all firms (McGahan, 1999). In a sub-sample for which I can get values of Tobin's q using the method of McGahan (1999), my variable has high correlation of 97.92% with her measure of q. To measure the future cash flows of a firm, the second dependent variable in my analysis is firm $Earning_{i,t}$, which is defined as the net income standardized by the total assets of firm *i* in a given year. This variable is also called *ROA* or profitability of the firm. It indicates a firm's capabilities to generate sales and income streams.

Independent Variables: Recombine-across-category Innovations

Following Zuckerman and colleagues, I assume that a firm's association with an industry – specifically, an SIC code – represents its primary categorization in the eyes of stock market analysts and investors (Zuckerman 1999, 2000). Although there is discrepancies between the mental categories held by securities analysts and the self-claimed SIC code of the firm, they are highly correlated (Zuckerman, 1999, 2004). To measure the degree of categorical-blurring in a firm's innovative activities, I propose to use the technological proximity between a firm and those firms outside of its industry as a proxy. Firms whose innovations are spanning several industries are more likely to share technologies with firms outside of its home industry and move closer in technological space to firms in other industries. By definition technological proximity within the industry should be higher than across industries.

For each firm in my sample I construct annually updated patent pools – all patents that the firm applied for within the last five years. I then identify the primary patent class to which each patent was assigned, and aggregate across the firm's patent pool to generate a count of patents in each patent class. Following Silverman (1999, 2002), I use first four digits of IPC class (International Patent Classification, in format like A02B or G02H).[3] Altogether, the sample firms have patents in 547 IPC classes, although each firm is focused on only a subset of these classes and diversified firms generally cover broader. Thus, for each firm *i* I create a 547-element vector (F_i) to represent its position in technology space where each element represents the proportion of the firm's patent pool that was assigned to the relevant patent class (Jaffe 1986; Sampson 2004, 2007), and for any given firm most of the elements are 0. Then, I then compare firm *i*'s innovation profile to another firm's profile by calculating the angular separation or uncentered correlation of the vectors F_i and F_j in year *t* (Jaffe, 1986), which is defined as the dot product of two vectors divided by length of the two vectors: Fit ·Fjt /(|Fit||Fjt|). The proximity measure is unity for two firms whose position vectors are identical. It is zero for firms whose vectors are orthogonal (two firms apply for patents in totally different technical fields). The measure is bounded between 0 and 1 and it is closer to 1 the greater the proximity between two vectors. This measure is desirable because it is not influenced by the length of the vectors. One could argue that only the closest industry outsiders influence the perception of investors on a firm's innovation profiles. Therefore, I calculate the proximity outside of the industry ($ProxOut_{it}$) as the average value of the proximity measure between firm *i* and its closest 20 firms that do not share a three-digit SIC with firm *i*. I experimented with some sensitivity tests and found that the coefficients estimation is not very sensitive to the number of outsiders chosen in calculating this variable. Higher *ProxOut* indicates higher degree of category mixing in a firm's innovation profiles. I similarly obtain the proximity inside the industry ($ProxIn_{it}$), as the average value of the proximity measure between firm *i* and all other firms and all other firms within the same three-digit SIC as firm *i* respectively.

Independent Variables: Within- and outside-category Competition

I use patent citation data to measure the degree of technological competition or crowding around a firm's innovations. Since a backward citation link from one patent to another implies that the citing patent either builds up or is premised upon the technology of the cited antecedent patent, the knowledge embedded in prior patents can indicate the technological knowledge base of a firm. Because competition can be a result of common reliance on similar resources space (e.g., Hannan and Carroll, 1992; Baum and Haveman, 1997), I use the common reliance on technological antecedents to reflect the competition in technological space (Podolny, *et al.*, 1996; Stuart and Podolny, 1996). The calculation starts with the citation overlap between any two firms in each patent class. To calculate overlap in patent class is consistent with the idea that competition is more localized (e.g., Baum and Haveman, 1997). While proximity measure is based on the similarity in overall activities in technological areas, the competition measure is based on the common reliance on the same technological antecedents in a particular technological field. Formally, the citation overlap between firm *i* and firms *j* in a patent class in a particular year *t* is given by the number of reference patents co-cited by patents of both firms in the patent class in the past 5 years, divided by the number of reference patents cited by patents of firm *i* in the patent class in the past 5 years. The measure is asymmetric for two firms. The crowding in a patent class for firm

3 At the time the examiner assigns a patent to the U.S. Patent classes, she also assigns it to one or more IPCs. The IPC is maintained by an international agency, World Intellectual Property Organization (WIPO). Two classification schemes have different features (Lerner, 1994). For example, first four levels of the IPC classification are nested while the U.S. system in contrast uses a great deal of cross-references rather than hierarchical structures. The U.S. scheme is a library classification system designed for the sole purpose of facilitating searches for patent examiners and therefore any correlation with industrial activity is purely incidental (Thompson and Fox-Kean, 2005). To the contrary, the IPC system is industry and profession oriented and reflects the economic importance of new inventions. However, variables using two different classifications are highly correlated and the empirical results are quantitatively similar.

i can be obtained by summing up the co-citation ratios between the firm *i* and all other firms with patents in that class. Higher value indicates that the knowledge foundation of a firm's patents in a technical field is crowded by patents of other firms. This implies that the firm's technologies may have high redundancy with other firms' and therefore faces greater competitive pressure in trying to generate profits from those patents (Podolny *et al.*, 1996). I calculate a weighted average of the crowding measures in year *t* across all patent classes represented in firm *i*'s patent pool to construct a firm-level measure, Crowding with all other firms ($CrowdAll_{it}$). I then divide this measure into two components: Crowding within industry ($CrowdIn_{it}$), measured as the crowding measure between firm *i* and all other firms that overlap with any SICs of the focal firm, and Crowding outside industry ($CrowdOut_{it}$), measured as the competition measure between firm *i* and all other firms that do not overlap with any industries of the focal firm. Although its effects are not hypothesized, *CrowdIn* will be included in the regression models for the purpose of comparison with *CrowdOut*.

Moderator Variables: Patent Pool

I use the count of firm *i*'s patents applied over the last five years standardized by the total assets of the firm, $PatentPool_{it}$, as a crude measure of the firm's overall innovation production. Calculating the variable using past four years or six years, or use the patent granted rather than applied, does not change the empirical results. I use this variable to test the direct impact of innovations on firm earnings and market value and use the impact of its interaction with other independent variables to test hypotheses. I use innovation outputs *PatentPool* instead of inputs like R&D expenditures for the observability of the outputs for external audiences who may not know where the firm has invested its R&D money in. The value of this variable is highly skewed, but the exclusion of the extreme values of this variable does not change the results.

Control Variables

I also include several annually updated variables to control for firm-level characteristics that might affect a firm's market value and cash flows. Large firms are likely to have different abilities than small firms to take advantage of innovations. I control for this by including *Firm size*, measured as the natural log of the firm's total assets. Some firms are perceived by investors as "earnings" investments rather than "growth" investments, and this may affect stock market valuation (Benner, 2007a). Therefore, I include *Growth opportunities*, measured as the growth in the ratio of capital expenditure to sales, to account for the possible evaluation premium due to the high opportunities that come from firm's possession of new technologies (Zuckerman 1999). In addition, although our independent variables capture patented innovation output, I include *R&D intensity*, measured as R&D expenditure standardized by firm total assets in a year, to reflect a firm's innovative investment (Hall, 1993). A diversified firm is more likely to have technologies that span the industry boundaries. Therefore, I use a dummy variable *Diversified firm*, set equal to 1 if the firm have products in more than its primary three-digit SIC, and 0 otherwise. Finally, I include a dummy variable, *No Patents*, set equal to 1 if the firm had no patent applications in the past 5 years. This dummy variable can control for the possibility that the capital market treats differently those firms that have absolutely no innovative output in a given year (McGahan and Silverman, 2006).

Empirical Results

To test hypotheses on evaluation bias, I propose to use two kinds of models. The first kind is market valuation model, which estimates how categorical variables can influence a firm's stock market value. The second kind is earning model, which estimates how the same categorical variables can influence the future cash flows of a firm. The comparison between these two models will provide evidence on the evaluation bias. For the market valuation model, I follow the conventional approach in innovation studies (Griliches, 1981; Jaffe, 1986; Hall *et al.*, 2005). To reflect the firm heterogeneity and temporal effect, I specify a fairly general structure to incorporate firm fixed effects η_i and year fixed effects θ_t (Baltagi, 2001; Wooldridge, 2002). The valuation model *per se* may not provide convincing evidence on evaluation bias. For example, the firm value can be reduced by deviant innovation if deviation causes negative evaluation bias. However, this coefficient can also be interpreted as an accurate assessment that deviant innovation is of less value than non-deviant innovation. In other words, the reason that similar firms aren't investing in the areas that this firm invests in is that such investments are stupid and have low potential to create value for the firm. Similarly, crowding within the industry may have greater competitive impact on a firm's capability to generate future cash flows than crowding outside the industry, due to for example complementary assets, and the difference in their impact on firm value may just reflect this difference. In order to disentangle evaluation bias from shrewd assessment, I also look at earning models with the same independent variables. To reflect the future cash flows, I use the firm earning in *t+1* and other future period earning as the dependent variable. Since the market value is based on the expected future cash flows in a firm, the impact of independent variables on the market value should be consistent with the impact of the same independent variables on the future cash flows. The discrepancy of direction and magnitude between coefficients in the valuation model and the earning model will help us to detect evaluation bias.

Table 1 provides descriptive statistics and bivariate correlations for the variables. The mean of the dependent variable, *ln(V/A)*, is 0.460, and the mean of the market to book value (*V/A*) (approximation of Tobin's q) is 2.107. The number is similar to the Tobin's q found in McGahan (1999) and McGahan and Silverman (2006), but higher than the value found in studies like Miller (2004) and Hall *et al.* (2005). The two dependent variables have bell-shaped distributions although *ROA* has a relatively long left tail. The value range and correlations in variables of firm earning, firm size, R&D intensity and capital growth are comparable to the literatures (e.g., McGahan, 1999; Zuckerman, 1999; Gu, 2005). It shows that large firms tend to have low R&D intensity, less number of patents standardized by assets, and lower market to book value, which is consistent with prior studies (e.g., Miller, 2004). The number of patents in a five year window has the maximum value of 9,822 (Canon USA) and a distribution highly skewed to the left. Firms in the sample are R&D intensive and on average around 7% of their assets are devoted to R&D investment.

Table 1

Descriptive Statistics and Correlations

	Variables	Mean	S.D.	Min	Max	1	2	3	4	5
1	Ln(V)	0.460	0.646	-3.095	3.969	1.000				
2	Earning	0.071	0.155	-2.154	0.847	0.109	1.000			
3	Firm size	6.607	1.914	0.016	12.558	-0.344	0.203	1.000		
4	Growth opportunity	0.013	0.104	-0.131	6.287	0.096	-0.193	-0.088	1.000	
5	R&D intensity	0.069	0.088	0.001	2.052	0.375	-0.511	-0.320	0.166	1.000
6	No patents	0.035	0.184	0.000	1.000	0.033	0.010	-0.097	0.045	-0.025
7	Diversified firm	0.419	0.493	0.000	1.000	-0.264	0.053	0.467	-0.056	-0.255
8	Patent pool	0.185	0.462	0.000	10.073	0.213	-0.261	-0.389	0.065	0.339
9	Proximity within industry (ProxIn)	0.225	0.164	0.000	0.974	0.236	-0.107	0.147	0.088	0.337
10	Proximity outside industry (ProxOut)	0.072	0.041	0.000	0.385	0.029	0.009	-0.035	0.020	0.108
11	ProxIn X patent pool	0.044	0.120	0.000	2.069	0.275	-0.395	-0.319	0.135	0.540
12	ProxOut X patent pool	0.013	0.045	0.000	1.452	0.138	-0.158	-0.289	0.043	0.228
13	Crowding within industry (CrowdIn)	0.130	0.210	0.000	2.000	0.197	-0.038	-0.009	0.013	0.259
14	Crowding outside industry (CrowdOut)	0.145	0.168	0.000	1.818	0.096	-0.024	-0.043	-0.032	0.171
15	CrowdIn X patent pool	0.029	0.116	0.000	5.031	0.179	-0.264	-0.192	0.090	0.355
16	CrowdOut X patent pool	0.027	0.069	0.000	1.503	0.167	-0.192	-0.291	0.010	0.266

	Variables	6	7	8	9	10	11	12	13	14	15
7	Diversified firm	-0.079	1.000								
8	Patent pool	-0.076	-0.173	1.000							
9	Proximity within industry (ProxIn)	-0.257	-0.072	0.027	1.000						
10	Proximity outside industry (ProxOut)	-0.330	-0.106	-0.009	0.276	1.000					
11	ProxIn X patent pool	-0.069	-0.178	0.723	0.312	0.011	1.000				
12	ProxOut X patent pool	-0.056	-0.137	0.855	0.033	0.155	0.550	1.000			
13	Crowding within industry (CrowdIn)	-0.119	-0.168	0.049	0.462	0.252	0.176	0.039	1.000		
14	Crowding outside industry (CrowdOut)	-0.164	-0.208	0.001	0.181	0.477	0.004	0.067	0.486	1.000	
15	CrowdIn X patent pool	-0.048	-0.125	0.480	0.193	0.002	0.651	0.227	0.407	0.120	1.000
16	CrowdOut X patent pool	-0.075	-0.187	0.724	0.031	0.168	0.449	0.771	0.208	0.384	0.379

Table 2 reports the regression results for the valuation model. Model 1, 2 and 3 use the market value as the dependent variable. In the baseline model 1, we can find that *Firm profitability, R&D intensity*, and *PatentPool* are positively related to firm value, while *Firm size* is negatively related to firm value. This is consistent with the descriptive statistics and prior studies (e.g., Hall, 1993; Miller, 2006; Hall *et al.*, 2005). But the *No patent* dummy has a significant and positive efficient suggesting that the stock market tends to give higher value for firms without patenting in the past five years. The coefficients for these control variables are consistent across the more fully specified models discussed below. Model 2 includes key measures that distinguish between within-category and outside-category proximity and crowding. Model 3 adds the interaction between these independent variables and innovation level of a firm *PatentPool*. The detection of multicollinearity in all models shows that the highest VIF is 12.18 for *Firm size* and the second highest VIF is 8.66 for *PatentPool* and other variables have VIF less than 8. Since multicollinearity for the main variables is less than 10, it seems not imposing a serious estimation concern in the model except for that the standard errors of coefficients estimations might have been inflated (Greene, 2003).

Table 2

Valuation and Earning of Innovations

	Ln(V/A)_t	Ln(V/A)_t	Ln(V/A)_t	ROA_t+1	ROA_t+1	ROA2#	ROA2#
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	0.795	0.786	0.762	0.198	0.214	0.209	0.224
	[0.053]**	[0.058]**	[0.059]**	[0.019]**	[0.019]**	[0.014]**	[0.014]**
Firm size	-0.103	-0.107	-0.106	-0.024	-0.027	-0.027	-0.029
	[0.008]**	[0.009]**	[0.009]**	[0.003]**	[0.003]**	[0.002]**	[0.002]**
Growth opportunity	0	0	0	-0.008	0	-0.024	0
	[0.000]	[0.000]	[0.000]	[0.014]	[0.000]	[0.010]*	[0.000]+
Firm earning	1.405	1.396	1.4	0.313	0.312	0.196	0.191
	[0.041]**	[0.041]**	[0.041]**	[0.014]**	[0.014]**	[0.011]**	[0.011]**
R&D intensity	1.008	0.964	1.007	0.125	0.192	0.078	0.129
	[0.089]**	[0.089]**	[0.094]**	[0.030]**	[0.031]**	[0.022]**	[0.023]**
No patents	0.045	0.084	0.096	0.013	0.006	0.006	-0.001
	[0.027]+	[0.032]**	[0.032]**	[0.011]	[0.011]	[0.008]	[0.008]
Diversified firm	0.033	0.04	0.042	-0.003	-0.003	-0.007	-0.008
	[0.015]*	[0.015]**	[0.015]**	[0.005]	[0.005]	[0.004]*	[0.004]*
F test for firm fixed effect	18.612	17.805	17.53	4.037	4.078	7.841	8.036
F test for year fixed effect	33.942	32.355	32.22	10.863	11.328	12.795	13.839
Patent pool	0.114	0.112	0.186	-0.013	-0.046	-0.016	-0.047
	[0.014]**	[0.014]**	[0.033]**	[0.005]**	[0.011]**	[0.003]**	[0.008]**
Proximity within industry (ProxIn)		0.317	0.329	0.029	0.041	0.023	0.027
		[0.051]**	[0.053]**	[0.017]+	[0.017]*	[0.013]+	[0.013]*
ProxIn X patent pool			-0.095		-0.079		-0.032
			[0.088]		[0.030]**		[0.022]
Proximity outside industry (ProxOut)		-0.1	0.01	0.048	-0.027	0.017	-0.069
		[0.180]	[0.188]	[0.060]	[0.062]	[0.045]	[0.046]
ProxOut X patent pool			-0.792		0.406		0.467
			[0.320]*		[0.106]**		[0.079]**
Crowding within industry (CrowdIn)		-0.092	-0.071	-0.016	-0.007	-0.007	0.01
		[0.042]*	[0.044]	[0.014]	[0.015]	[0.011]	[0.011]
CrowdIn X patent pool			-0.157		-0.057		-0.099
			[0.081]+		[0.027]*		[0.020]**
Crowding outside industry (CrowdOut)		0.015	-0.019	-0.032	-0.054	-0.023	-0.035
		[0.046]	[0.050]	[0.015]*	[0.017]**	[0.011]*	[0.012]**
CrowdOut X patent pool			0.248		0.149		0.065
			[0.151]+		[0.050]**		[0.037]+
Observations	7398	7398	7398	7209	7209	7013	7013
R-squared	0.212	0.216	0.218	0.121	0.133	0.124	0.146
R_square within	0.212	0.216	0.218	0.121	0.133	0.124	0.146
R_square between	0.425	0.46	0.46	0.154	0.13	0.006	0.007

Number of firms: 491

Standard errors in brackets

+ significant at 10%

ROA2=(ROA_t+1+0.85*ROA_t+2)

In Model 3, the coefficient of *ProxOut* is insignificant although the negative sign is consistent with the prediction that category-mixing innovation induces confusion for audiences and reduces their evaluation of a firm. The coefficient of interaction term *ProxOutXPatentPool* is negative and significant, suggesting that the evaluational damage to the highly innovative firms is the most. This is consistent with the prediction of Hypothesis 2 and suggests that highly innovative firms are more likely to draw more attention from audiences if they have clear categorical affiliation and will lose more if their categorical affiliation is confusing in the eyes of audiences. Model 3 also distinguishes between within- and outside-category technology-based competition. Again, I find that within-category effects are different from outside-category effects. Specifically, the coefficient of *CrowdIn* is insignificant although the negative sign is consistent with the general competition arguments. The coefficient on *CrowdOut* is negative but not significant. However, the coefficient of interaction term *CrowdOutXPatentPool* is significantly positive. This seems to suggest that highly innovative firms can actually be valued favorably by the investors if their technologies are crowded by industry outsiders. One could also interpret this result as that the impact of outside-industry crowding becomes less negative compared to that of within-industry crowding when the firm is more innovative.

These results are also consistent with a compelling alternate hypothesis: perhaps technological proximity to firms in the same industry really is economically more valuable than proximity to firms in other industries, and perhaps the competitive effect of crowding from within-industry competitors really is stronger than the competitive effect of crowding from outside-industry firms. In this case, Models 2 and 3 would merely demonstrate that the stock market is accurately reflecting the economic realities associated with a firm's innovation efforts. To disentangle these alternate hypotheses, and thus to conclusively test my hypotheses, I estimated the effect of these same variables on firm *i*'s future cash flows. To the extent that these variables influence future cash flows in the same way that they influence stock market valuation, the alternate hypothesis would be supported (e.g., Baum and Silverman, 2004). To the extent that these variables influence future cash flows differently than they influence stock market valuation, ideally with sign difference, evaluation bias would appear to exist. I estimate the earnings model to assess the effect of deviation and crowding variables on future cash flows. In Model 4 and 5, I use the firm's net profits in year $t+1$, ROA_{t+1}, as dependent variable. In Model 6 and 7, I use the smoothed firm earning in year $t+1$ and $t+2$, $ROA_{t+1}+0.85ROA_{t+2}$, as dependent variable.

I also test the smoothed earning in year t+1 to t+3, $ROA_{t+1}+0.85ROA_{t+2}+0.72ROA_{t+3}$ and results are quantitatively similar but the sample size is reduced to 6511. I assume a 15% discount to reflect the reduced influence on present valuation of earnings far into the future. Models 4 and 6 incorporate the same independent variables as in Model 2, and Models 5 and 7 incorporates the same independent variables as in Model 3. Most of the control variables work in the same direction as in the market value model, except for the negative coefficient of *PatentPool*. This implies that the stock market may be overoptimistic toward innovation. Since all four models generate quantitatively similar estimations, I interpret the result in Model 4 and 5.

I find that *CrowdOut* has a negative and significant impact on future cash flows in Model 4 and 5, indicating a strong competition effect that is bigger than *CrowdIn*, whereas such negative impact was absent in market value Model 3. This sign difference in two models is the evidence of evaluation bias – the stock market does not anticipate the actual negative impact of *CrowdOut* on future cash flows. I interpret this result as support for Hypothesis 3. Moreover, the interaction term *CrowdOutXPatentPool* in Model 5 has a significant and positive effect on firm earnings, indicating that the negative effect of outside-industry competition on firm earnings is decreasing for more innovative firms. Combined with the positive impact we have found in Model 3 on market value, this seems to suggest that the evaluation bias on *CrowdOut* (negative for earning but insignificant for market value) becomes smaller for more innovative firms. This is consistent with the prediction of Hypothesis 4. In addition, I find another piece of evidence of evaluation bias in *ProxOutXPatentPool*, which is positive in the earning model but negative in the valuation model. This implies the existence of evaluation bias because the stock market gives lower valuation for firms whose innovations are proximate to industry outsiders even if such technological proximity is beneficial for firm future cash flows. The sign difference in *ProxOutXPatentPool* in Model 3 and 5 suggests that the evaluation bias is increasing with *PatentPool*, which is consistent with Hypothesis 2. But we do not find the evidence for Hypothesis 1 because the coefficients of *ProxOut* in both Model 3 and 5 are insignificant.

Discussion and Conclusion

Firms face dilemma in adapting to the environment that is composed of both economic and social imperatives. On the one hand, firms need to commit to innovative effort to adapt to the changing technologies. On the other hand, they must conform to the expectation of audiences who may not understand the changing technologies. However, how the firms' technological adaptation and its consequence are influenced by the institutionalization process in the firm-audience interface is still under-studied (Hargadon and Douglas, 2001; Berner, 2007a). The current study aims to explore the topic by examining whether the stock market appreciates the value-relevance of the firms' positions in the technological space that may be modified when firms innovate. The empirical analysis on firms' stock market value implies that the categorical effects that work to penalize the firms with innovations defying the industrial categorical imperatives on technologies will reward the firms with competition from firms outside the industry. The further analysis on firm's earnings indicates that the devaluation of category-mixing innovation and the over-valuation of outside-industry competition is actually a biased valuation, and such bias can depend on the innovativeness of a firm. The analyses confirm the intuition that categorization can help to circumvent the information asymmetry problem (e.g., Arrow, 1962) or information overload problem (e.g., Zuckerman, 1999; Barberis and Shleifer, 2003; Peng and Xiong, 2006) in the firm valuation process, it creates additional problem by focusing audience's attention within the category.

More work can be done to further our understanding of how innovative activities of firms lead to the industry convergence and how existing industry categories incorporate new elements in the technological development. Recent developments in institutional theory argue that a blending and hybrid form faces the least resistance from the existing institutionalized forms and facilitates the institutional change (e.g., Rao *et al.*, 2005; Haveman and Rao, 2006). But how do these recombinant innovations erode industry boundaries and influence the evaluation of external audiences? One possible direction is to study categorical overlap and legitimacy transfer between categories in the technological evolution through the blending of technological elements. Another possible way is to examine how the status of a firm in the technological field influences the institutional change (e.g., Rao *et al.*, 2005). The answer to these questions will have important implications for both researchers and the practitioners since the institutional force is as critical as the technical force and economic force when firms innovate.

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