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Organizational innovation efforts in multiple emerging market categories: Exploring the interplay of opportunity, ambiguity, and socio-cognitive contexts

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ABSTRACT

Industries with emerging market categories offer greater opportunities for firms to innovate. However, such opportunities are not a matter of "the more, the better." An increasing number of emerging market categories poses a dilemma. While more emerging market categories arguably bring about increasing growth opportunities, they can also generate greater ambiguity for incumbent firms, which may hinder their innovation efforts. This study attempts to address this dilemma by proposing that the number of emerging market categories in an industry will have an inverted U-shaped relationship with incumbent firms' innovation efforts. We further argue that this curvilinear relationship will be influenced by the socio-cognitive context of a firm's focal industry, in the sense that the degree of collective identity incoherence at the industry level will intensify the proposed inverted U-shaped relationship, whereas the prevalence of trade associations in the industry will depress this relationship. We test our hypotheses by examining research and development (R&D) investments of a sample of U.S. high-technology manufacturing firms and find support for our main prediction and the hypothesized effect of collective identity incoherence. We also find a surprising but intriguing moderating effect of trade associations.

> "It was never clear whether Kodak wanted to be a products company or a services company. Or a consumer company or a B2B company. The lack of a clear strategy for digital coupled with being in too many areas led to the current situation. The confusion was also visible in its M&A work. Acquisitions have been all over the place." (Hosanagar, 2012, interview clip[1])

The rise and fall of Eastman Kodak Company was one of the most telling business lessons in the 20th century. The decline of Kodak was not attributable to a lack of market opportunities or technical capabilities. To the contrary, a myriad of new opportunities emerged in the late 1980s and 90s, the critical period right before Kodak experienced its downfall. By 1999, the then-emergent digital imaging industry had at least four sub-market categories: digital cameras, home printing, online services, and min-labs. Acquiring, digitizing, storing, panting, manipulating, transmitting, retrieving, and projecting digital images had become easier, and options for each had increased. However, what is puzzling is that Kodak's research intensity did not increase during that period; rather, its research and development (R&D) spending (as a percentage of sales) decreased from its peak of 9.18% in 1985 to 5.60% in 2000 (Gavetti et al., 2003).

Part of Kodak's failure could be attributed to its loss of focus and being overwhelmed by too many choices in the newly emerged digital era, as alluded to by the interview quote above. In fact, Kodak was not alone in experiencing such a conundrum. The confusion and frustration facing industry incumbents like Kodak, paradoxically, often do not come from a lack of opportunities, but rather from having too many routes to choose from. Many industries around the world have experienced significant flux in the form of emerging technologies and accompanying changes in market dynamics, a phenomenon that has been termed as ``the fourth industrial revolution" and argued to have the potential to transform the organization of global value chains (Schwab, 2016). These changes offer significant innovation-related opportunities for industry incumbents, and yet also serve as sources of confusion and uncertainty.

This conundrum has also been reflected in the academic scholarship on industry dynamics, wherein some related streams in organizational economics— such as the industry life cycle perspective (Abernathy and Utterback, 1978; Klepper and Graddy, 1990) and technological change

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and evolution (Henderson and Clark, 1990; Tushman and Anderson, 1986)— suggest that firms enjoy greater innovation opportunities in emerging contexts than in maturing or declining ones. An emerging market category is defined as a newly formed or re-formed business sector that has shown evidence of or potential for significant growth due to recent changes in demand or technology (Porter, 1980) that awaits to be understood and developed by relevant stakeholders (Suarez et al., 2015: 442). However, emerging market categories can also generate significant challenges for firms. To incumbents, these new markets constitute unstructured settings that pose significant ambiguity (Santos and Eisenhardt, 2009: 644).

Ambiguous conditions occur when goals are vague, problematic, inconsistent, or unstable (March, 1978). Ambiguity not only increases search costs and uncertainty around the exploration of technological solutions and commercial possibilities, but also makes firms' attempts to predict the market difficult and prone to error (Suarez et al., 2015: 439), which in turn can hinder their willingness to invest in sustained innovation efforts. While the tension between opportunity and ambiguity may be present in any emerging context, such tension is particularly pronounced in industries that feature multiple emerging market categories. Although these industries afford firms greater opportunities for innovation, the existence of multiple market and technological trajectories may obfuscate organizational decision-making about which opportunities to invest in, as can be seen in the early days of the internet industry and in fields such as nanotechnology (Granqvist et al., 2013; Kaplan and Radin, 2011), as well as in many other industries that have undergone or are undergoing transformations.

In particular, we argue that the core issue here is not so much about the emergence of growth opportunities *per se*, but more about their multiplicity and the resultant ambiguity. As the number of new market categories increases, the ambiguous cues that they pose to incumbent firms typically do not grow in a linear fashion; instead, they tend to increase significantly due to the interactions of multiple moving parts. It thus seems that the same conditions— emergence and multiplicity— have the conflicting potential to both spur and curb a firm's efforts to innovate. The lack of clarity on this subject is also borne out by mixed empirical findings. For example, although some scholars have found that firms in emerging sectors such as industries related to biotechnology, nanotechnology, and information sciences showed a greater increase in innovativeness than conventional sectors (Park et al., 2005), others have found insignificant differences in innovation levels attained by firms in emerging versus mature contexts (McGahan and Silverman, 2001). We surmise that this inconclusiveness is partly so because the opportunities arising from technological advancement and market expansion on the one hand— and challenges associated due to ensuing ambiguity on the other—often coexist in emerging contexts, and their effects are therefore difficult to disentangle. Moreover, past research has not separated the condition of emergence from that of multiplicity (i.e. the presence of multiple new market categories), neither has it considered how the relative effects of opportunity and ambiguity may change as the number of emerging market categories increases. This inattention to the multiplicity of emergence is important to address, because rarely will there be only one emerging segment in an industry. Especially in today's world where ``interconnection" has become a new reality (Lagarde, 2013), a change in one part of the industry will often impact the dynamics of another, and it may be increasingly unrealistic to just consider the isolated effect of the emergence of a single market category. If, as we elaborate more in the theory development sections, the effect of the ``opportunity-ambiguity" dilemma embedded in emerging market categories on firms' innovation behavior changes in a nonlinear fashion as the number of emerging market categories goes up from one to many, then it should be both theoretically and empirically important to study the implications of such multiplicity.

In this paper, we unpack the opportunity-ambiguity dilemma generated by multiple emerging market categories and study how the socio-cognitive context of an industry influences incumbent firms' innovation efforts. Although the opportunity-ambiguity dilemma confronts both new entrants and incumbent firms (York and Lenox 2014), we focus on incumbent firms because we believe that this tension is particularly strong for them. On the one hand, incumbents are in a better position to innovate given their established structures, capabilities, and complementary assets (Teece, 1986; Tripsas, 1997); on the other hand, incumbents also tend to face greater internal and external constraints (Christensen, 1997; Hannan and Freeman, 1984; Tripsas and Gavetti, 2000), and the risks and stakes of betting on the ``wrong" direction are often greater for incumbent firms. In this paper, we seek to answer two interrelated questions: First, how does an increasing number of emerging market categories in an industry affect incumbent firms' innovation efforts, as manifested in their R&D intensity? Second, how do the socio-cognitive cues in a focal industry influence the relationship between an increasing number of emerging market categories and incumbent firms' innovation efforts?

In our attempt to address these questions, we start from the premise that organizational decision-makers are bounded rational (Cyert and March, 1963 [1992]). Therefore, although an increasing number of emerging market categories presumably offers enhanced growth opportunities, we argue that beyond a certain threshold level, the confluence of too many options can impede decision-making about the optimal direction to move towards, and firms either tend to become overly cautious and refrain from making major investment, or may divert resources from innovation to other types of activities, which both will result in reduced R&D investments. Building on insights that industries are socio-cognitive communities (Porac et al., 1989; White, 1981), and that firms will typically look for cognitive and normative cues in the face of ambiguity (DiMaggio and Powell, 1983), we then examine how two such cues, i.e. the coherence of collective industry identity (or the lack of it) and the prevalence of trade associations may moderate the relationship between the number of emerging market categories and firms' innovation efforts. Specifically, we investigate how the collective identity incoherence of new entrants into an industry may undermine the socio-cognitive stability of the industry (Lee et al., 2017; McKendrick et al., 2003) and how institutional actors such as industry associations (e.g. David et al., 2013; Greenwood et al., 2002; Ruef and Scott, 1998) might serve as a source of cognitive and normative stability for firms to guide their innovative efforts. We test our theory with a sample of U.S. manufacturing firms across multiple high-technology industries. This choice provides an advantage particularly in light of the extant literature on industry emergence, given that most empirical studies focus on a single emerging industry, and yet studies covering multiple industries are important for generalizing findings (Gustafsson et al., 2015: 16). In the ensuing sections, we first develop our conceptual framework and hypothesis, followed by a presentation of our methods and empirical findings. We subsequently discuss the theoretical, practical, and policy-related implications of our findings and explore grounds for future research.

1. Opportunity-ambiguity dilemma in emerging market categories

Research on technological discontinuities and industry life cycle has emphasized the relationship between emergence, industry growth, and firms' innovation-related efforts. Technological discontinuities produce an era of ferment, thereby providing firms with greater scope to try out alternative versions of a product or technology. Moreover, in emerging market categories, growing market demand also increases a firm's incentive to test out innovative ideas and solutions. This demand-side pull further incentivizes firms to innovate (e.g. Klepper, 1996; McGahan and Silverman, 2001).

In spite of offering greater growth opportunities, the emergence of new market categories often generates significant turbulence for industry incumbents (Lee and Paruchuri, 2008; Mitchell, 1989). The spawning of multiple technological problems and solutions, unclear linkages with products and services, and the absence of consensual criteria to evaluate and differentiate between competing offerings often generate significant ambiguity for firms (Benner and Tripsas, 2012; Rosa et al., 1999). In this study, we regard ambiguity as the existence of multiple alternative interpretations of a situation (Ellsberg, 1961; March and Olsen, 1975), or the lack of clarity of the meaning and implications of particular events or situation (Santos and Eisenhardt, 2009). In emerging contexts, ambiguity occurs because organizations typically have several promising technological and market trajectories to choose from, but the sheer number of such options makes it difficult to evaluate the promise of any one trajectory. Ambiguity, therefore, differs from more generic notions of environmental uncertainty (Milliken, 1987), wherein it is assumed that organizations lack the necessary probabilistic information to choose between options. Ambiguity, on the other hand, does not preclude the existence of information, but rather refers to a situation where the availability of information does not offer a resolution to the conflicts or state of confusion that might arise from multiple plausible interpretations of a given situation (Weick, 1995).

A socio-cognitive approach to innovation (Howells, 1995) suggests that ambiguity can particularly enervate a firm's intentions and abilities to engage in innovation-related activities. First, firms may interpret ambiguous signals as threatening, which in turn can drive them to behave rigidly and to minimize risk-taking (Staw et al., 1981). Second, ambiguity can muddle up the relationship between actions and performance, infusing randomness and thereby reducing a firm's ability to learn effectively about the environment (Lant and Mezias, 1992), thereby making it difficult for firms to conduct technological experimentation (Suarez et al., 2015). This may lead a firm to take recourse to superstitious learning, wherein the connections between actions and outcomes are often mis-specified, resulting in suboptimal decision-making (Levitt and March, 1988). Third, in ambiguous contexts, confusion and disinformation can impede meaningful communication among relevant stakeholders (Rosa and Porac, 2002), thereby preventing firms from committing to innovation efforts. Therefore, ambiguity emanating from emerging market categories can weaken a firm's motivation to explore effectively.

Together, the arguments above suggest an uneasy tension: although the presence of emerging market categories in an industry signals potential for future growth, these opportunities are often confounded with perceived ambiguity, which may suppress incumbent firms' decisions to invest in R&D activities. In fact, the relative strength of such positive and negative forces associated with emerging market categories is likely to change in a nonlinear fashion. We argue that the issue here is not so much about the emergence of market categories *per se*, but more so about the multiplicity of those emerging categories as well as the accompanying ambiguity that ensues in the industry. We elaborate these arguments below.

1.1. Innovation in multiple emerging categories

Insights from the tradition of cognitive psychology (Miller, 1956) and bounded rationality (Simon, 1991) suggest that as the number of new market categories increases in an industry, the perceived complexity and issues associated with heightened ambiguity will become more pronounced. Specifically, humans are only equipped with limited cognitive capability to absorb and process information (Miller, 1956). Going beyond these limits results in various negative cognitive and behavioral outcomes (Eppler and Mengis, 2004). For instance, examining cognitive overload in consumer behaviors, studies have shown that more is not always better. Known as the paradox of choice (Schwartz, 2005), excessive choices and information are associated with confusion, frustration, inaccurate judgments. The decision maker may be so paralyzed by the multitude of choices that they tend to delay their decisions, or not to make a decision at all (Greenleaf and Lehmann, 1995; Herbig and Kramer, 1994). Challenging the widely held assumption that more choices are better, psychological research has indicated the presence of ``choice overload hypothesis” which suggests that although multiple choices seem desirable initially, they eventually prove deleterious and demotivating for people making the choices. For instance, research has shown that people are more likely to purchase exotic gourmet jams or chocolates when offered a limited array of choices than when facing an excessive number of options (Iyengar and Lepper, 2000). Research on bounded rationality and firm performance also suggested that excessive information would overwhelm decision makers (Wagner et al., 1984) and cause cognitive distress (Keller, 2001).

Further, the information overload problem is more pronounced when decision makers do not yet have an available reference point, or well-conceived evaluation criterion (Chernev, 2003). In other words, when facing new and complex situations, decision makers without some ready-to-use evaluation criteria have greater difficulty in assessing available options and making decisions, because they have to overcome a double hurdle: that of understanding the complex information and coming up with a reference point (i.e., proper evaluation criteria) (Chernev, 2003). Consequently, decision makers are likely to receive more information than they can process, which may in turn lead to delayed decision-making or even refusal to interpret the information (Sinkula, 1994: 41).

Insights from this line of research have important implications for understanding firms’ decision-making in the context of emerging market categories. Scholars have found that, under high uncertainty, firms tend to simply wait to see how events unfold in order to avoid expensive strategic mistakes (Eisenhardt and Bourgeois, 1988; Bowman and Hurry, 1993). Drawing on arguments from cognitive psychology, we add onto this line of research by clarifying the underlying micro mechanisms that may have accounted for this ``wait-and-see” approach. Although purchasing gourmet jams or chocolates is different from decision making in R&D settings, we believe that there are some common underlying mechanisms. Moreover, the effects observed in the lab may be amplified in the context of R&D investments for a few reasons. First, choosing among an assortment of jams is a relatively straightforward decision, and there are more considerations and competing demands that may muddle the decision-making process in a corporate setting. Second, most organizations also have resource constraints, and face several trade-offs; in most situations, investing in one new technology or market category often implies sacrificing or taking resources away from another area. Such trade-offs among competing demands are often confounded with various agendas or even internal politics of a firm (Burgelman, 1983). Third, the stakes involved in R&D decisions are also much higher, as the consequences of betting on the wrong technology can be much more costly and irreversible than for instance, purchasing a gourmet jam not to one's liking. As a result, this process is often more complicated than a simple purchase decision studied in the lab setting. As suggested by research on ``status quo bias,” decision makers typically prefer to minimize uncertainty and stick with the status quo in important real decisions (Samuelson and Zeckhauser, 1988). Therefore, in contexts where the complexity of decision making is high, given the difficulty of predicting the future, firms may simply refrain from making any major decisions.

Arguments thus far suggest that while an increasing number of emerging market categories will generate more opportunities, it also poses greater ambiguity for firms when it comes to investing in new directions. In order to understand when the incidence of emerging market categories will generate either opportunity or ambiguity, we propose that when the number of emerging market categories in a firm's focal industry is low to moderate, the positive effect of opportunities is likely to dominate the negative effect of ambiguity on the firm's decision making. This is so because the cognitive load is still manageable, and thereby incumbent firms' decision-makers might be able to take advantage of opportunities while coping with the challenges associated with ambiguity with several mechanisms, including conducting local search (Cyert and March, 1963 [1992]) and establishing routines to facilitate change and innovation (Amburgey et al., 1993; Nelson and Winter, 1982). However, as the number of emerging market categories further increases, the cognitive overload and bounded rationality theses suggest that the disadvantages associated with perceived ambiguity may eventually outweigh the benefits of growth opportunities. Specifically, when factoring in the limitations of human cognitive faculties, the benefits of perceived opportunities may increase at a decreasing rate, because decision-makers might not be able to optimize and take full advantage of all the possible opportunities; on the other hand, the potential negative effects of ambiguity may intensify at an increasing rate, as the availability of excessive choices and accompanying information overload can become too much for them to handle effectively.

Furthermore, there are two additional reasons to conjecture the nonlinear effects of ambiguity. First, researchers have suggested that the same piece of ambiguous information often can be interpreted as an opportunity or a threat (Elliott and Archibald, 1989; Jackson and Dutton, 1988), and actors tend to be more sensitive to the ``threat" implications embedded in a message than to the ``opportunity" implications, even if the information itself is ambiguous and can go both ways (Jackson and Dutton, 1988; Staw et al., 1981). Insights from this line of research thus suggest that as the number of emerging market categories and the ensuing ambiguity increase, it is likely that the perceived opportunity will further decrease, and that the perceived potential negative consequences of making the wrong bets will go up, further impeding firms' decision-making in investing in R&D. Second, in the world of R&D, it is rarely the case that corporate executives will evaluate the perceived opportunities and costs of each emergent category independently; rather, given the interconnectivity among many incipient options (Lagarde, 2013; Schwab, 2016), the eventual decision often needs to be arrived in light of all the relevant choices and competing demands, further increasing the complexity of decision making. Consequently, as the number of new market categories in the environment goes up, the complexity of decision making may increase significantly.

In sum, we propose that there is likely to be a threshold effect when it comes to opportunities offered by emerging market categories: when too few, firms will not have sufficient room to innovate; when too much, firms may face a significant amount of confusion and may even become paralyzed in their decision making processes, suggesting a nonlinear relationship between multiple emerging market categories and firms' innovation effort in terms of R&D investment intensity. Hence our main proposition is:

Hypothesis 1. There will be an inverted-U-shaped relationship between the number of emerging market categories in an incumbent firm's focal industry and the firm's R&D intensity.

2. The influence of socio-cognitive cues

While the literatures on industry life cycle and evolutionary economics have highlighted the role of technological advancement as fundamental forces that drive innovation, scholars have also noted that it is important to examine the role of the broader socio-cognitive factors in facilitating or hindering innovation efforts during early phases of technological development and industry life cycle (Garud and Rappa, 1994; Grodal et al., 2015; Kaplan and Tripsas, 2008; Lounsbury, 2001; Sine et al., 2005; Van de Ven and Garud, 1993). The key underpinning of these realizations is the assumption that industries are social and institutional communities of shared meanings and structures of interaction (Porac et al., 1995; Geels, 2004). Furthermore, in technology-intensive industries such as the ones that we investigate in this study, the necessity to look at new technologies (and their related market opportunities) from a socio-cognitive lens becomes even more pertinent. We refer to Weick's (1990) framing of technology as ``equivoque" which suggests that technologies emerge at the intersections of several, often heterogeneous and competing pathways and thereby can be interpreted and understood in multiple ways, thus resulting in a lack of consensus about their subsequent trajectories. Furthermore, new technologies generate a significant amount of raw data, posing information-processing challenges for decision-makers (Garud and Rappa, 1994).

It obtains therefore that decision-makers will look for information cues from the broader industry context to enable them to interpret and understand the implications of developments in their industries that coincide with the emergence of new market categories. We highlight two such contextual cues that may influence the proposed curvilinear relationship between the number of emerging market categories and a firm's innovation efforts: the coherence of collective identity of the focal industry, and the presence of institutional actors such as industry associations.

2.1. Collective identity coherence of industries with emerging categories

We invoke the view of industries and markets as consensual meaning systems (Porac et al., 1989; White, 1981), often manifested as categories by which market players identify each other and assign codes for prescribed behaviors (Hsu and Hannan, 2005; Pólos et al., 2002). Collective identities of industries hinge upon such categories that specify industry participants' roles and expectations, as consensually held by both members in the industry and external audiences (Jensen, 2010; Navis and Glynn, 2010). Collective identity has therefore been conceived as the shared definition of a group that derives from members' common interests, experiences, solidarity, purpose, and outcomes (Taylor 1989; Wry et al. 2011). Scholars have found that incoherence in an industry's collective identity can generate challenges to its legitimacy and competitive uncertainty (Wry et al. 2011; Grodal 2018). The clarity of collective identity of an industry is associated with a prototype, i.e. the best representation of what it means to be a member or a participating firm of that industry (Mervis and Rosch, 1981; Navis and Glynn, 2011). Because such expectation of a typical category member constitutes an identity code that is agreed upon by industry members and understood by key external audiences (Polos et al., 2002; Navis and Glynn, 2010), the formation of a collective identity hinges on the coherence of the category's internal membership (Lee et al, 2019).

What factors might affect a focal industry's collective identity coherence? In emerging or dynamic contexts, the role of new entrants has been argued to be particularly critical in shaping or reshaping an industry's collective identity (Georgallis et al., 2018). For instance, the disk-array industry saw the entry of new players from disparate fields, having heterogeneous identities, thereby making it hard for incumbents to cohere around a stable collective identity (McKendrick and Carroll, 2001). Grodal (2018) argues that the entry of new actors with identities different from existing members in a field can significantly heighten competition for resources. Relatedly, Georgallis et al. (2018) note that the entry of new actors with incoherent identities that diverge significantly from incumbents can weaken the collective ability of an industry's members to offer a compelling rationale about their viability to external audiences.

While prior research has largely focused on how the diversity of new entrants may impact the coherence of collective identity of an industry, an important but understudied factor is the alignment between members' self-categorization and external audiences' perceptions (Glynn, 2008). Insights from cognitive psychology suggest that the self-proclaimed identity of a firm may not always align with what is recognized by external audiences (Eisenstadt et al., 2002; Swann and Ely, 1984), and identity discrepancies may arise thereby. At the aggregate level, when many new entrants into a category have such discrepancies between their own self-identification and external audiences' perceptions, those inconsistencies could result in threats to agreed-upon criteria in defining the prototype of the focal category (Rosa et al. 1999). As a result, it becomes more challenging for both category members and external audiences to delineate the boundaries and achieve shared interpretations of the category (Grodal, 2018; Lee et al., 2017).

Given these arguments, in this paper we highlight the impact of new entrants' identities on an industry's collective identity, especially the extent of (mis)alignment between new entrants' self-proclaimed identity affiliations and perceptions of important stakeholders. From an industry incumbent's perspective, in conditions of increasing discrepancies between new entrants' self-categorizations and how external audiences categorize them, the incumbent firm may have greater difficulty in identifying the new entrants' customers and competitors due to the lack of a meaningful reference group (Porac et al., 1989; Porac et al., 1995). The prevalence of such hard-to-categorize newcomers in an incumbent's industry may cause challenges for the incumbent to define the proper scope of its own business.

For example, as documented by Benner and Tripsas (2012), when the digital imaging industry first emerged, new entrants came from at least three types of backgrounds: photography, consumer electronics, and computing. Each of them conceptualized the digital imaging market in a different way, which created incoherence not only among industry participants, but also divergences between participating firms' self-perceptions and external audiences' perceptions. Along these lines, Tripsas (2009) found that although a digital photography firm selected the photography Standard Industry Classification (SIC) code for its own categorization, the firm mostly attracted computer peripherals analysts. Such discrepancies only exacerbated the confusion of incumbent firms such as Kodak, making it more difficult for Kodak to identify its core business in the changing landscape: should it be an imaging business? Computer peripherals business? Service business? Or something else?

We contend that the coherence of collective identity of a firm's focal industry—or the lack of it— can be a double-edged sword. Depending on the overall level of ambiguity in an industry, the coherence of collective identity may facilitate or hinder an incumbent firm's innovation efforts. When the number of emerging market categories is low to moderate, the lack of a coherent collective identity may actually suggest greater opportunities. As argued by some scholars (Lo et al., 2019; Pontikes and Barnett, 2015), the lack of clear category boundaries can sometimes be beneficial for participating firms, because such lenient market categories have more flexibility and allow for a wider range of fit. Therefore, such categories may create more growth opportunities and permit more space for innovative activities. In our context, when there are only a few clear emerging trajectories in an industry, a higher level of incoherence of an industry's collective identity caused by new entrants helps to relax pre-existing cognitive constraints for incumbent firms, allowing them to see opportunities outside the box more easily, which in turn makes the incumbents more likely to pursue ideas that may otherwise seem intractable.

However, when the number of emerging market categories within an industry is high, the lack of a coherent collective identity can exacerbate matters. New market or technology categories typically lack cognitive legitimacy and are poorly understood (Aldrich and Fiol, 1994; Hannan and Carroll, 1992; Hannan and Freeman, 1989; Sine et al., 2005); when an industry is populated by an increasing number of such emerging market categories, greater levels of collective identity incoherence among new entrants can make sensemaking and sensegiving processes more problematic (Stigliani and Elsbach 2018), further worsening the negative effect of ambiguity on incumbent firms' innovation efforts as theorized above.

To sum up our arguments, the collective identity of an industry is shaped by the interplay of how member firms, especially new entrants, perceive themselves and how external audiences perceive them, and that the coherence of such collective identity—or the lack of it—will moderate the proposed curvilinear effect of emerging market categories on incumbent firms' R&D investments. Although collective identity incoherence may signal more opportunities when the number of emerging categories is low to moderate, as the number of emerging categories continues to increase, greater levels of collective identity incoherence will make it more challenging for incumbent firms to interpret and process the ambiguous information emanating from the new market categories in the industry. We thus propose the following hypothesis:

Hypothesis 2. Collective identity incoherence of new entrants into an industry will reinforce (steepen) the hypothesized curvilinear relationship between the number of emerging market categories and incumbent firms' R&D intensity.

2.2. Institutional actors in industries with emerging categories

Institutional actors such as professional associations (Zhou, 1993) and trade associations (David et al., 2013; Sine et al., 2005) in an industry are instrumental in shaping its socio-cognitive environment (Rajwani et al., 2015). Although extant literature has traditionally regarded the influence of such institutional actors as normative forces (DiMaggio and Powell, 1983; Scott, 2001), we contend that their influences on industries are actually broader than what has been argued conventionally. Specially, trade associations in the industry[2] typically have multiple functions, including the development of industry standards, cultivating collective identity among members, certifying and accrediting worthy establishments or practices, and lobbying for favorable regulations, all of which are instrumental in legitimating and stabilizing an industry. In other words, these institutional actors shape the socio-cognitive environment of an industry through multiple mechanisms, including not only normative but also cognitive and regulative channels (Sine et al., 2005).

Just as the effect of collective identity coherence, the presence of trade associations in an industry may also be a double-edged sword when it comes to encouraging or hindering firms' innovation efforts. On the one hand, institutional actors such as trade associations are often dominated by elites and relatively conservative members (Selznick, 1949; Heinz and Laumann, 1982). Consequently, such collective actors often represent the interests of these risk-averse elites and tend to favor more established technologies (Sine et al., 2005), limiting firms' investment in and exploration of new technologies. On the other hand, however, because of their capacity to shape the norms and clarify boundaries of the focal industry, trade associations are particularly important in legitimating emerging market categories (Garud and Rappa, 1994; Hiatt and Park, 2013). They not only render legitimacy to new market ideas (Aldrich and Fiol, 1994), but also act as platforms where firms may identify potential collaborators and competitors and exchange ideas about the most viable ways to navigate the new market space, all contributing to mitigate issues associated with ambiguity (Lee et al., 2017).

The discussion thus far suggests that the moderating effect of trade associations is also contingent on the overall complexity of a firm's environment. When there are few emerging market categories, due to

[2] We use the terms trade associations and industry associations interchangeably in this paper.

the limited opportunities and ambiguity, the presence of trade associations may act as constraining forces, favoring existing technologies and limiting firms' innovation efforts. As documented by Sine et al. (2005), in the context of the independent-power sector, one of the most powerful collective representatives— the Independent Energy Producers Associations of California— was dominated by members who identified with more established approaches, and therefore favored the use of less-risky fossil-fuel technologies, narrowing the choices of firms in the independent-power sector.

However, with an increasing number of emerging market categories, the stabilizing power of associations becomes essential, in the sense that they not only help incumbents to identify promising opportunities, but also help clarify the boundaries of the newly emerged market categories, mitigating issues associated with high ambiguity. For instance, in the continuously evolving semiconductor industry, trade associations such as the Semiconductor Industry Association (SIA) and American Electronics Associations (AEA) have been argued to play an instrumental role in legitimating not only the entire semiconductor industry, but also the various emerging market categories within it (Saxenian, 1994), such as alternative energy, fuel cells, radio-frequency identification, lasers and holography, and micro-machines (Malonis and Selden, 2007). These associations issue awards, publish trade journals, and host conferences to endorse worthy ventures and nascent developments in the industry, and serve as platforms to connect actors from different segments within the broader semiconductor industry. Such activities help to clarify and legitimate the paths of different emerging trajectories.

In sum, we argue that trade associations, while constraining firms' innovation efforts when the number of emerging market categories is low, help mitigate some of the negative effects of ambiguity when the number of emerging market categories is high. Specifically, when the number of emerging market categories is low, the presence of trade associations will suppress the sense of opportunity for industry incumbents; conversely, their presence will serve to alleviate the deleterious effects of increased ambiguity as the number of emerging market categories increases. In other words, we expect that the presence of trade associations will suppress the inverted-U shaped relationship proposed in Hypothesis 1:

Hypothesis 3. The presence of trade associations in an industry will suppress (flatten out) the hypothesized curvilinear relationship between emerging market categories and incumbent firms' R&D intensity.

3. Data and methodology

3.1. Sample and data

We test our theory on the US manufacturing sector and focus on industries that are considered as "high technology". To identify these industries, we relied on the National Science Foundation's classification of high-technology industry (National Science Foundation, 2006). We then generated a random sample from the population of U.S. manufacturing firms listed in COMPUSTAT between the years 1997 and 2007[3]. Several considerations influenced our choice of research setting. First, the setting needs to reflect variations in emerging market categories as well as socio-cognitive contexts. Therefore, a setting that is comprised of multiple industries is crucial to test our arguments. Second, given our interest in a firm's innovation efforts, it is suitable that we focus on high-tech industries where innovation is critical for a firm's survival and performance. Third, confining our sample to high-tech industries offers comparability across firms, especially in terms of their reliance on R&D activities as a reflection of firms' innovation efforts. We employed multiple sources of data in this study: emerging industry information, company financials, association data, and initial public offering (IPO) data. We discuss these data sources in detail below.

In order to identify whether or not an industry has emerging market categories and how many such categories are present in it, we consulted the Encyclopedia of Emerging Industries (EEI hereafter) (Malonis and Selden, 1998, 1999, 2000, 2001, 2007), a comprehensive handbook on new market categories or segments that are emerging or fast growing[4]. Note that the EEI does not rely on official industrial classification systems in identifying emerging market categories; rather, it employs a pragmatic approach in classifying a new market. To be included, a focal market category does not have to be a legally regulated category or one with formal boundaries; instead, the kind of market categories that the EEI includes are ``specific industrial and business sectors, discrete types of business enterprises, and sometimes simply to describe a particular range of products or services," which are based on a collective understanding of how the competitive landscape is divided. This approach is also closely aligned with our socio-cognitive approach, in which the boundaries of a new market category are defined more by the collective schema of industry players than by regulatory regimes or the relabeling of existing niches. As a result, there need not to exist a perfect one-on-one mapping between the ``industries" as identified by the EEI and those as defined by established classification systems such as Standard Industrial Classification (SIC). The publishers of the EEI did offer a comprehensive concordance that allows one to easily match the industries identified in the EEI to the SIC system. Based on the EEI-SIC concordance, some SICs are associated with multiple emerging market categories. We adopted this EEI-SIC concordance to operationalize the number of emerging market categories in an industry by matching it to the respective industry SIC code.

We gathered company financial information from COMPUSTAT. Moreover, we obtained IPO data from the Kenney-Patton IPO database. The database consists of all *de novo* IPOs on the American stock exchange filed with the Securities and Exchange Commission (SEC) from 1990 to 2010 (Kenney and Patton, 2013). We identified the trade/industry associations within each industry from the Encyclopedia of Associations and all the associations we selected operate in manufacturing industries (i.e., SIC code of 20 to 39). Next, regional and local associations were excluded from the population because our focus was placed on national associations, given that such associations are much more likely to have the kind of stabilizing power that we theorize. Furthermore, given that our sample only consists of U.S. firms, we included only U.S.-based manufacturing associations.

To examine incumbent firms' innovation efforts in response to multiple emerging opportunities, we used a sample period from 1997 to 2007 with year 1996 included because of the lagged terms. Availability of yearly data reduced the final sample to 1278 firms, resulting in an unbalanced panel of 4704 firm-year observations.

[3] While these firm-level data are available for later years, we stopped data collection in 2007, because the publisher of the data source that we use to identify emerging market categories (Encyclopedia of Emerging Industries, or EEI— see below for more details) experienced a large-scale organizational and ownership change in 2007, and there were subsequent changes to the composition of the editorial team of EEI. The next (6th) edition of EEI was not published until 2011. We were concerned that these ownership and editorial changes may have systematically affected the way that data were collected, classified, and presented. To ensure the consistency and comparability of data across years, we decided to confine our study period between 1997 and 2007.

[4] The criteria that EEI used in identifying ``emergingness" include: growth, public attention, and innovativeness. In deciding on the list of emerging industries or business sectors to include, the EEI also consulted ``a wide assortment of variously ranked lists detailing the recent accomplishments of promising or well-established companies" and content experts (Malonis and Selden, 2007: X).

3.2. Dependent variable

Firm R&D intensity. Following prior studies (Chen and Miller, 2007; Cohen and Levinthal, 1990), we operationalized a firm's innovation effort as its R&D intensity, or the firm's annual R&D expenditure divided by sales, which captures a firm's commitment to and effort on innovation activities (Hoskisson and Hitt,1988). Because R&D intensity is left skewed, we followed prior work (e.g., Ho et al., 2004; Spithoven et al., 2012) and took the natural logarithm of the original value of R&D intensity plus one. More specifically, the measure was calculated as below:

$$R\&D\ Intensity_t = \ln\left(\frac{R\&D\ Expenditure_t}{Sales_t} + 1\right)$$

where t denotes a given year. To better establish causal inference, we also lagged all explanatory and control variables by one year.

3.3. Explanatory variables

3.3.1. Emerging market categories

This variable is a measure of the number of emerging market categories within a focal incumbent firm's industry, as identified by the EEI. For example, the photographic equipment and supply industry (SIC 3861) is identified with one emerging area (i.e., digital imaging), and the pharmaceutical preparations industry (SIC 2834) encompasses five emerging areas (i.e., anti-aging products and services, fertility medicine, nutritional supplants, superdrugs, and weight-loss programs). As there are only five editions of EEI available within our window of observation (Malonis and Selden, 1998, 1999, 2000, 2001, 2007), we only have data of emerging market categories for five years. To address this issue, we have interpolated the missing data for the intervening years.

3.3.2. Collective identity incoherence

This variable serves to test Hypothesis 2, which predicts the moderating effect of socio-cognitive cues from a firm's environment on emerging market categories. We used the incidence of identity mismatch as reflected in the categorization of SICs in a particular industry. Specifically, the variable was constructed as the number of *de novo* IPO firms that are assigned different SIC codes by the Security and Exchange Commission (SEC) from their self–identified SICs. For example, when Amazon.com went public, the self-assigned primary industry affiliation by Amazon.com was ``Information Retrieval Services" (SIC 7375), but the U.S. SEC assigned it a different SIC 2731 (i.e., ``Book Publishing"), in the official IPO record[5]. Hence, the more such new entrants into an industry, the less likely that the industry will maintain a coherent collective identity. This variable was updated yearly for each industry.

3.3.3. Industry associations

This variable was created to test Hypothesis 3, which predicts the moderating effect of an industry's institutional actors on the relationship between emerging market categories and firms' R&D intensity. The variable was constructed as the number of U.S. national industry associations at each four-digit SIC level in a firm's focal industry.

3.4. Control variables

There is a large body of literature describing a firm's incentives to innovate. To take into account the factors that might also affect a firm's reactions to perceived opportunities in the environment as manifested in innovation efforts, we included a number of firm-level as well as industry-level control variables.

Extant studies assert that *firm size* influences innovative activities, although empirical evidence of its effect has been inconclusive (Cohen and Levin, 1989). We believe that key decision makers in large versus small firms tend to perceive the environment and approach innovation differently, which may shape how industry-level category emergence affects firms' innovation efforts, and therefore should be an important factor to be controlled for. In this study, *firm size* was measured as the logarithm of a firm's annual sales. Prior literature suggests two possible effects of firm diversification on innovation. Again, the precise effects of diversification are mixed in the literature: some studies assert that firm diversification enhances innovation (Argyres and Silverman, 2004), while others suggest the opposite (Hoskisson and Johnson, 1992). The variable *firm diversification* was measured as the number of two-digit SIC categories in which the firm operates. The variable was calculated for each firm-year. We also controlled for a firm's *Slack* by computing the ratio of a firm's current assets to current liabilities. We controlled for *firm performance* by using a firm's ROA as a proxy. Considering that a firm's past R&D strategy may have a path-dependence effect on its subsequent R&D intensity, we also included a firm's lagged *firm R&D intensity* as one of our controls.

Besides these firm-level control variables, we also controlled for *industry growth* and used the number of de novo IPOs in an industry as a proxy to take into account the potential effect of the growth and the perceived hotness of industry, which may be empirically correlated with, but conceptually distinct from the number of emerging market categories within it. Lastly, given the high correlation between year dummies and industry-level variables, we do not include year dummies in our model, thus avoiding multicollinearity. However, the results hold with or without the inclusion of year dummies.

3.5. Analysis

We estimated our models using a General Linear Model (GLM) method. As data is not required to be forced into unnatural scales (Hastie and Tibshirani, 1990), GLM modeling technique, as the mathematical extension of linear modeling, can better accommodate nonlinearity and nonconstant variance structures. Given that our data are firm-year observations similar to pooled time series (i.e., independent variable contains interpolated values), GLM is appropriate since the technique allows one to specify any degree of interaction effects. More importantly, researchers can obtain standard errors allowing for intragroup correlation (Greene, 2012; McCullagh and Nelder, 1989). In so doing, within-firm variance can be effectively addressed. We used a Gaussian distribution with an identity link function and specified the models with maximum-likelihood function and standard errors allowing for intragroup correlation.

The basic estimation equation of our analysis is the following:

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 Z + \beta_4 XZ + \beta_5 X^2 Z + \beta_6 W$$

where Y is a firm's R&D intensity, X is the number of emerging market categories in the focal firm's industry, Z is the moderating variable on socio-cognitive cues, and W denotes a set of control variables.

4. Results

In Table 1[6], we report the descriptive statistics and correlations. In an unreported multicollinearity diagnostic, we assess the variance inflation factor (VIF) values. The mean VIF values for each model are below 4.00 and no VIF values across models exceed 10.00 (maximum VIF across models = 3.09 and mean VIF = 1.65), indicating that there is no serious multicollinearity problem (Greene, 2012).

Table 2 reports the regression analysis on the effect of emerging

[5] Please see the appendix for an example of such filings provided by Kenney and Patton (2013).

[6] For all tables and figures, the reported values and statistics are based on the transformed and lagged values in our formal regression analyses whenever applicable.

Table 1
Descriptive statistics and correlations

Variables		*M.*	*S.D.*	1	2	3	4	5	6	7	8	9
1	R&D intensity	0.503	0.913	1.000								
2	Emerging market categories	3.142	2.923	0.005	1.000							
3	Collective identity incoherence	0.322	0.200	0.008	–0.456	1.000						
4	Industry associations	9.905	9.822	0.101	0.175	0.056	1.000					
5	Firm size	–1.075	2.033	–0.353	0.062	–0.037	0.027	1.000				
6	Firm diversification	1.257	0.686	–0.151	–0.082	0.062	0.022	0.410	1.000			
7	Slack	5.269	6.363	0.280	0.017	–0.018	0.011	–0.262	–0.141	1.000		
8	Firm performance	–0.220	0.766	–0.279	0.018	0.017	–0.014	0.352	0.102	0.090	1.000	
9	Industry growth	4.647	5.071	0.095	0.324	–0.334	–0.079	–0.037	–0.063	0.059	0.002	1.000

Note: Correlations with absolute value of 0.036 or above are significant at the 0.05 level. $N = =4704$.

Table 2
GLM regressions of emerging market categories on firm R&D intensity

Variables	**Model 1** β (SE)	p-value	**Model 2** β (SE)	p-value	**Model 3** β (SE)	p-value	**Model 4** β (SE)	p-value
Emerging market categories			0.035(0.01)	.000***	–0.015(0.02)	.405	0.011(0.01)	.269
Emerging market categories^2			–0.004(0.00)	.000***	0.002(0.00)	.180	–0.001(0.00)	.564
Collective identity incoherence			0.087(0.03)	.001**	0.037(0.02)	.137		
Industry associations			0.003(0.00)	.000***			0.001(0.00)	.019*
Emerging market categories × Collective identity incoherence					0.201(0.06)	.000***		
Emerging market categories^2 × Collective identity incoherence					–0.025(0.01)	.000***		
Emerging market categories × Industry associations							0.002(0.00)	.015*
Emerging market categories^2 × Industry associations							–0.000(0.00)	.002**
Lagged DV	0.776(0.03)	.000***	0.765(0.03)	.000***	0.763(0.03)	.000***	0.765(0.03)	.000***
Firm size	–0.025(0.01)	.000***	–0.024(0.01)	.000***	–0.024(0.01)	.000***	–0.025(0.01)	.000***
Firm diversification	0.006(0.01)	.295	0.004(0.01)	.564	0.008(0.01)	.195	0.007(0.01)	.292
Slack	0.009(0.00)	.000***	0.009(0.00)	.000***	0.009(0.00)	.000***	0.009(0.00)	.000***
Firm performance	–0.002(0.03)	.941	–0.004(0.03)	.889	–0.006(0.03)	.858	–0.003(0.03)	.926
Industry growth	0.004(0.00)	.090	0.004(0.00)	.165	0.005(0.00)	.093	0.003(0.00)	.218
Constant	0.002(0.02)	.924	–0.079(0.02)	.001***	–0.056(0.02)	.013*	–0.033(0.02)	.070
–2 Log-likelihood	7354.17		7324.81		7320.66		7324.19	
Akaike's information criterion	7368.17		7346.81		7344.67		7348.19	
Bayesian information criterion	7413.36		7417.83		7422.14		7425.67	
N	4,704		4,704		4,704		4,704	

Note: *SE* denotes standard error.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

market categories on a firm's R&D intensity. Model 1 consists only of control variables, in which we take into account the factors that might affect a firm's innovation efforts as documented by the prior literature. Model 2 tests our opportunity-ambiguity argument, which characterizes the relationship between emerging market categories and a firm's innovation efforts. Models 3–4 investigate the effects of cues from a firm's socio-cognitive environment on the relationship between emerging market categories and R&D intensity. In particular, Model 3 introduces the variable collective identity incoherence and its interactions with emerging market categories. Model 4 includes the variable industry associations and its interactions with emerging market categories.

Hypothesis 1 predicts an inverted-U shaped relationship between emerging market categories and a firm's R&D intensity. Estimation results in Model 2 show that the coefficient of emerging market categories is positive ($\beta = 0.035$; $p < 0.001$) and the quadratic term of emerging market categories is negative ($\beta = =-0.004$; $p < 0.001$). The significance of both coefficients provides support to Hypothesis 1.

To further ensure the robustness of our hypothesized inverted U-shaped relationship, we conduct two additional assessments based on existing literature (Haans et al., 2016; Lind and Mehlum, 2010): whether the slopes are sufficiently steep at low and high ends of our data range; and whether the turning point of the inverted-U shaped curve is located within our data range. We assess the steepness of slopes at the ends of the data range based on recommendations by Haans et al. (2016). For the inverted-U shape curve to exist, the test must reject the null hypothesis that the slope at low values of emerging market categories decreases and the slope at high values of emerging market categories increases. Our results reject the null hypothesis at $p < 0.001$. Moreover, we also test the appropriateness of the inflection point. First, the turning point of the inverted-U shaped curve is approximately at 4.648 emerging market categories, which is close to the mean of emerging market categories at 3.142. Moreover, the 95 percent confidence interval of this turning point as computed by the Fieller method, is 0.208 as its lower bound and 0.221 as its upper bound. Therefore, the confidence interval indicates that the turning point falls within our data range since the minimum and maximum number of emerging market categories are 0 and 11 respectively.

Although our tests lend strong support for the hypothesized inverted-U shaped relationship between emerging market categories and firms' R&D intensity, to get a better sense of how the effect changes across different values of our independent variable, we consider the different marginal effects when the number of emerging market categories was fixed at several specific values. For example, when the number of emerging market categories is fixed at one (25th percentile), two (median), and five (75th percentile), its marginal effects are 0.0234, 0.0160, and –0.0063, respectively. This pattern indicates that the slope of the curve first increases at a decreasing rate, and then starts to decrease once the independent variable passes a certain threshold, lending further support for Hypothesis 1.

Recall that the dependent variable used in the regressions is (natural) log-transformed from the original value of R&D intensity. To evaluate the effect of our independent variable more meaningfully, we therefore calculated the corresponding changes in a firm's R&D intensity across a range of values of the independent variable. When all else is held constant at mean, as the number of emerging market categories increases from 0 to 1, there is a 3.14% increase in a focal firm's R&D intensity (i.e., 2.71828ˆ0.0309-1). As the number of emerging market categories continues to increase from 1 to 2, there is a 2.37% increase in R&D intensity (2.71828ˆ0.0234-1). By contrast, once the number of emerging market categories goes beyond the inflection point, we start to see increasing declines in the dependent variable. For example, when the number of emerging market categories increases from 5 to 6, we find a 0.63% decrease in a focal firm's R&D intensity (2.71828ˆ(–0.0063)-1). As the number of emerging market categories rises from 8 to 9, one sees a 2.83% decrease in R&D intensity (2.71828ˆ(–0.0287)-1).

Given that our outcome variable is R&D intensity, defined as a firm's R&D expenditure over its revenues, we also translated these numbers into dollar values to assess the monetary impact of our independent variable. Taking year 2001 (the mid-point of our sampled period) as an example, the average monetary value of R&D expenditure across all the sampled industries in that year is about $141.54 million. Given this, when all else are held constant at mean, as the number of emerging market categories increases from 0 to 1, there is about $4.44 million increase in a firm's annual R&D expenditure in 2001 (141.54 × 3.14%), which is not a trivial number. However, when the number of emerging market categories further increases from 8 to 9, we see a drop in a firm's annual R&D expenditure by about $4.01 million (141.54 × –2.83%).

In Hypothesis 2, we propose that the collective identity incoherence of new entrants will reinforce (i.e., steepen) the relationship between emerging market categories and a firm's R&D intensity when the number of emerging market categories is high. According to Haans et al. (2016), such a steepening effect for the inverted-U shaped relationship will be supported if the interaction between moderator and the squared term of the independent variable is negative and significant. As shown in Model 3 of Table 2, the coefficient of interaction between the squared term of emerging market categories and collective identity incoherence is negative and significant (β = =–0.025, $p < 0.001$), indicating that collective identity incoherence steepens the inverted-U shaped relationship as stated in Hypothesis 1. This finding is also consistent with Hypothesis 2 in which collective identity incoherence intensifies the negative effect of ambiguity associated with multiple emerging market categories. Moreover, when the number of emerging market categories is small, the moderating effect of collective identity incoherence on the relationship between emerging market categories and a firm's R&D intensity is positive and significant (β = =0.201, $p < 0.001$), indicating that a certain degree of collective identity incoherence may encourage R&D efforts when the level of ambiguity is low.

Finally, Hypothesis 3 contends that the prevalence of industry associations will flatten out the inverted U-shaped relationship between emerging market categories and a firm's R&D intensity. In Model 4, however, the negative and significant coefficient of interaction between the squared term of emerging market categories and industry associations does not support the argument in Hypothesis 3 (β = =–0.000, $p < 0.01$), according to which the prevalence of industry associations enhances the expectation from new opportunities while attenuating the negative effect of ambiguity. Interestingly, the results suggest a contradictory story that the prevalence of industry associations actually steepens instead of flattening out the inverted U-shaped relationship between emerging market categories and a firm's R&D intensity. We will return to this surprising finding of Hypothesis 3 in the post-hoc analysis section below.

To visualize the relationship between emerging market categories and R&D intensity (Hypothesis 1) as well as the moderating effects (Hypotheses 2 and 3), we plot the marginal effects of the independent variable across different values of both moderators, that is, when collective identity incoherence and industry associations are at the 25th, median, and 75th percentiles, respectively. We also overlay the raw data to allow visual inspections of the model fit, as shown in Figs. 1 and 2 below[7].

Both Figs. 1 and 2 suggest that there exists an inverted U-shaped relationship between emerging market categories and R&D intensity. Moreover, Fig. 1 indicates that such a relationship is steepened as the degree of collective identity incoherence increases from the 25th percentile, to the median value, and to the 75th percentile. This pattern lends support to Hypothesis 2. Contrary to Hypothesis 3, the primary inverted-U shaped relationship, as shown in Fig. 2, also steepens as the number of industry associations increases from the 25th percentile, to the median, and to the 75th percentile.

Specifically, as shown in Fig. 1, when the values of emerging market categories are below the turning point (around 4), there exists a positive relationship between emerging market categories and R&D intensity, regardless of the values of the moderator (collective identity incoherence). Yet, with increasing values of the moderator, the slope of the curve becomes steeper, indicating an increasing marginal effect of the independent variable. Taking the number of emerging market categories at one as an example, as the level of collective identity incoherence increases from 0.19 (25th percentile), to 0.22 (median), and to 0.41 (75th percentile), the slope of the curve (i.e. marginal effect) will increase from 0.0162, to 0.0195, and to 0.0442, respectively.

In contrast, Fig. 1 also indicates that when the values of emerging market categories go beyond the inflection point, there exists a general negative relationship between emerging market categories and R&D intensity, and that this relationship is intensified with the increasing values of the moderator. For example, when the number of emerging market categories is fixed at nine, as the level of the collective identity incoherence increases from 0.19 (25th percentile), to 0.22 (median), and to 0.41 (75th percentile), the slope of the curve is –0.0202, –0.0274, and –0.0812, respectively, revealing an increasingly negative marginal effect of the independent variable. Together, such patterns suggest that the moderator— collective identity incoherence— steepens the inverted U-shaped relationship between emerging market categories and R&D intensity.

Similarly, Fig. 2 shows that the slope of the curve is increasingly positive before the inflection point, while increasingly negative after the inflection point, this trend is intensified with the increasing values of industry associations. Based on our calculation, when there is one emerging market category in the industry, as the number of trade associations increases from 2 (25th percentile), to 10 (median), and to 13 (75th percentile), the slope would increase from 0.0110, to 0.0184, and to 0.0212, respectively, indicating an upward pattern of the marginal effects. In contrast, when the values of emerging market categories go beyond the turning point — again take nine as an example— the slope of the curve is –0.0063, –0.0306, and –0.0396, respectively, across the three levels of trade associations, indicating a downward trend of the marginal effects.

In summary, Figs. 1 and 2 support the inverted-U shaped relationship between the number of emerging market categories and incumbent firms' innovation efforts. They also show that the shape of the curve is moderated by the socio-cognitive cues conveyed in the focal industry. Overall, the results support our hypotheses 1 and 2, although we find significant yet unexpected results for Hypothesis 3.

In what follows, we first describe the additional robustness checks that we performed, and then report findings from a series of supplementary analyses in an attempt to further explore the surprising results of Hypothesis 3.

[7] We thank two anonymous reviewers for these graphing suggestions.

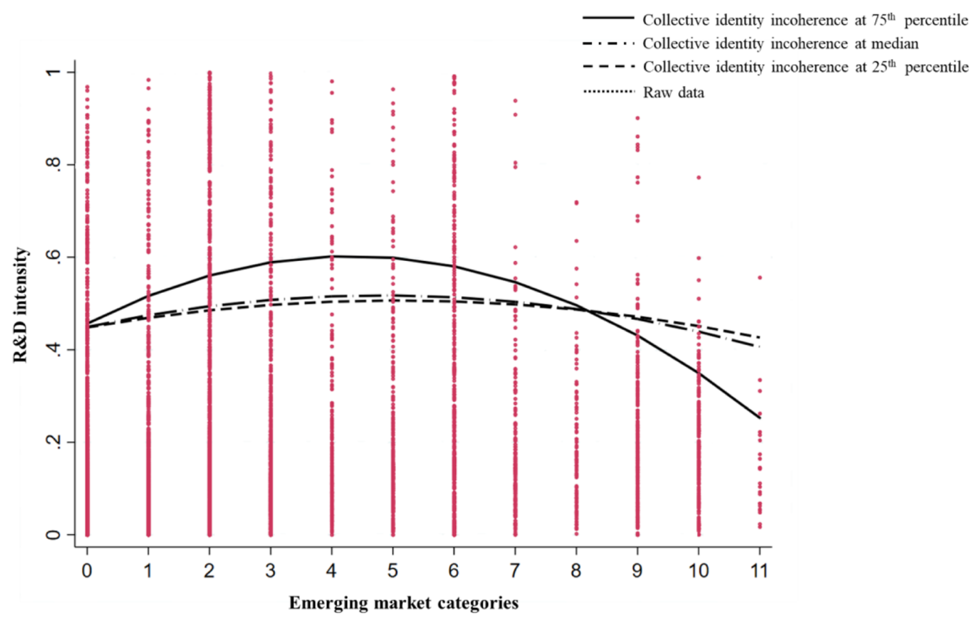

Fig. 1. Moderating effect of collective identity incoherence.

4.1. Robustness checks

To ensure the robustness of our findings, we conducted the same analyses with an alternative dependent variable and an alternative estimation method. Table 3 reports the results of the robustness checks.

4.1.1. Alternative measure of innovation efforts

In the existing models, we calculated R&D intensity based on the ratio of firm's annual R&D expenditure to sales. To see whether our results are robust to alternative measures, we also calculated R&D intensity based on the monetary value of R&D expenditure as an

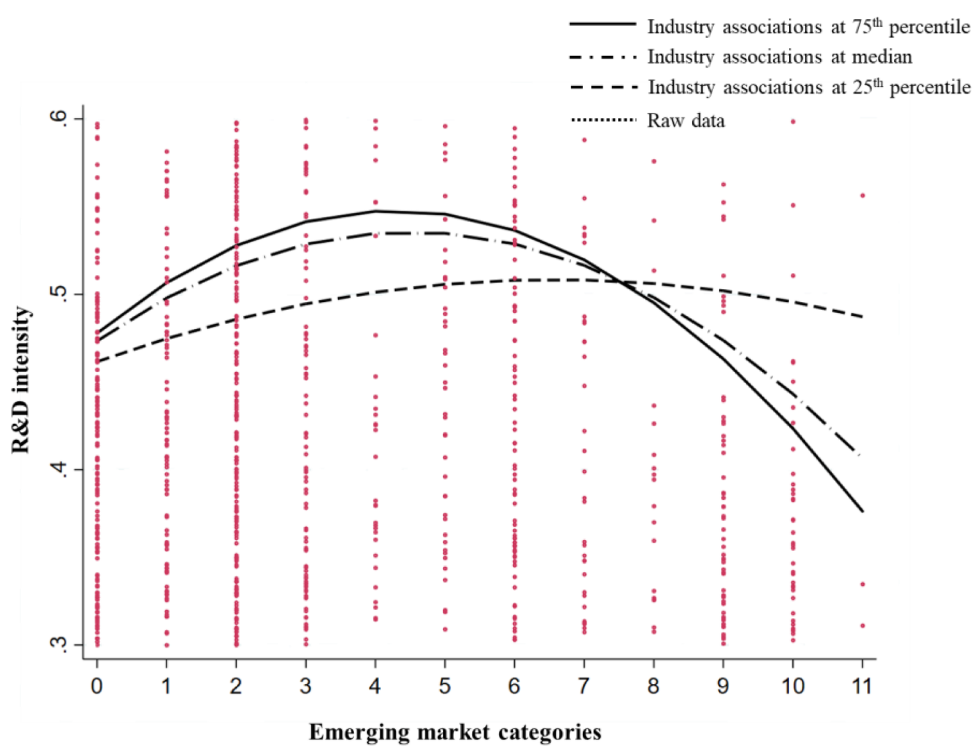

Fig. 2. Moderating effect of industry associations.

Table 3
Results of robustness checks.

Variables	**Model 1**				**Model 2**				**Model 3**			
	Alternative DV		*Alternative Model*		*Alternative DV*		*Alternative Model*		*Alternative DV*		*Alternative Model*	
	β (SE)	*p*-value	β (SE)	*p*-value	β (SE)	*p*-value	β (SE)	*p*-value	β (SE)	*p*-value	β (SE)	*p*-value
Emerging market categories	0.311(0.03)	.000***	0.027(0.02)	.087	0.115(0.06)	.052	0.033(0.04)	.363	0.145(0.04)	.000***	0.022(0.02)	.319
Emerging market categories^2	–0.026(0.00)	.000***	–0.002(0.00)	.164	0.004(0.01)	.576	–0.002(0.00)	.620	–0.005(0.00)	.283	–0.001(0.00)	.587
Collective identity incoherence	0.109(0.14)	.437	N/A		–0.037(0.16)	.816	N/A					
Industry associations	0.008(0.00)	.000***	0.001(0.00)	.114					–0.007(0.00)	.050*	0.001(0.00)	.524
Emerging market categories × Collective identity incoherence				.815(0.18)	0.000***	–.017(.12)	0.887					
Emerging market categories^2 × Collective identity incoherence			–0.125(0.02)	.000***	–0.002(0.01)	.875						
Emerging market categories × Industry associations								.016(.00)	0.000***	.000(.00)	0.647	
Emerging market categories^2 × Industry associations							–0.002(0.00)	.000***	–0.000(0.00)	.591		
Lagged DV	3.552(0.28)	.000***	0.430(0.05)	.000***	3.484(0.28)	.000***	0.430(0.05)	.000***	3.497(0.28)	.000***	0.430(0.05)	.000***
Firm size	0.782(0.02)	.000***	–0.059(0.03)	.033*	0.779(0.02)	.000***	–0.058(0.03)	.035*	0.775(0.02)	.000***	–0.059(0.03)	.033*
Firm diversification	–0.077(0.04)	.075	0.016(0.01)	.173	–0.052(0.04)	.222	0.017(0.01)	.168	–0.061(0.04)	.147	0.017(0.01)	.167
Slack	0.047(0.01)	.000***	0.011(0.00)	.000***	0.045(0.01)	.000***	0.011(0.00)	.000***	0.046(0.01)	.000***	0.011(0.00)	.000***
Firm performance	0.137(0.06)	.015*	0.070(0.07)	.294	0.132(0.06)	.017*	0.070(0.07)	.293	0.139(0.06)	.012*	0.070(0.07)	.294
Industry growth	0.022(0.00)	.000***	0.002(0.00)	.345	0.025(0.00)	.000***	0.002(0.00)	.392	0.022(0.00)	.000***	0.003(0.00)	.341
Constant	2.177(0.11)	.000***	0.082(0.07)	.217	2.234(0.11)	.000***	0.095(0.07)	.145	2.340(0.10)	.000***	0.087(0.07)	.199
–2 Log-likelihood	13,119.00		5,339.25		13,057.38		5,340.05		13,044.49		5,339.12	
Akaike's information criterion	13,141.00		5,357.25		13,081.38		5,360.05		13,068.49		5,361.12	
Bayesian information criterion	13,212.02		5,415.35		13,158.85		5,424.61		13,145.96		5,432.14	
N	4,704		4,704		4,704		4,704		4,704		4,704	

Note: *SE* denotes standard error.
*$p < .05$.
**$p < .01$.
***$p < .001$.

alternative dependent variable. Given the left-skewness in this variable, we transformed the values by taking the natural logarithm of one plus the original values. Next, we employed the same model specifications using the alternative dependent variable to test our hypotheses, and the pattern of results remained consistent with our main findings.

4.1.2. Alternative empirical strategy

To further test the robustness of our results, we also employed an alternative analytical strategy. Specifically, we re-ran all the analyses using panel data regression with firm fixed effect. Given that the industry affiliation of each firm is not time-varying, that our primary independent variable and the two moderators are all industry-level variables, and that there exist limited within-industry variations across the ten-year time frame during our observation period, such firm-fixed-effect models are arguably very conservative tests. Nonetheless, although the levels of statistical significance dropped in these fixed-effect models, the signs of the coefficients of our main independent variable are qualitatively consistent with those of the main analyses as reported in Table 2, partially supporting our results.

4.2. Post-hoc analysis

It is quite interesting that the moderating effect of the prevalence of trade associations is contradictory to what we have predicted in Hypothesis 3: instead of flattening out the inverted U-shaped relationship between emerging market categories and a firm's R&D intensity, it actually steepens this relationship. Upon further contemplation, such results, although unexpected, actually are quite in line with our central theoretical premise— that is, ``multiplicity" and the resultant ambiguity may hinder firms' decision-making and innovation efforts. We speculate that the stabilizing effect of trade associations theorized above may only hold when there exists a single, dominant trade association in an industry, and the nature of this effect may change qualitatively when their number increases from one to multiple. A single trade association will have greater power in consolidating multiple growth opportunities and reducing the cognitive ambiguity around emerging market categories because of its dominant influence. In contrast, the existence of more than one major trade associations may produce the opposite effect. The presence of multiple associations likely results in different power centers within the industry, each trying to gain superiority over the others, leading to greater institutional conflicts and heightened complexity. If that is the case, then the existence of multiple associations, instead of mitigating, may actually heighten cognitive fragmentation and instability in an industry, worsening the ambiguity accompanying multiple emerging market categories. In other words, the effect of having a single, dominant association in an industry may be qualitatively different from that of having multiple associations.

In fact, although no prior study to our knowledge has explicitly examined this proposition, some authors have alluded to the possibility that the presence of trade associations is not merely a matter of ``the more, the merrier." For example, Sine et al. (2005: 211) argued that ``these kinds of collective actors (such as industry associations) may variably affect the legitimacy of different forms of organizations." In other words, if multiple powerful associations coexist in an industry, and each endorses a particular form of organization, standards, or technology, it is likely that such endeavors will lead to institutional pluralism. On the one hand, institutional pluralism may spur innovation in a mature or stagnant industry (Lounsbury and Crumley, 2007); on the other hand, when an industry has already experienced high levels of ambiguity due to a large number of emerging market categories, institutional pluralism can further worsen the cognitive and normative burden on those incumbents under such circumstances. Indeed, scholars have acknowledged that pluralism typically creates the potential for fragmentation, incoherence, conflict, goal-ambiguity, and instability (Stryker, 2000; Heimer, 1999; also see Kraatz and Block, 2008). If this happens, then one would expect to see that the presence of multiple associations in an industry intensifies, rather than tames, the inverted-U shaped effect of emerging market categories on firms' innovative endeavors.

To examine this proposition, we split the sample into three groups: (1) industries without any national trade association; (2) industries with one national trade association; (3) industries with multiple national trade associations, and examined the effect of emerging market categories on R&D intensity in three sub-samples[8]. The results are shown in Table 4.

-As indicated in Model 1 of Table 4, in industries without any national trade associations, the coefficients of the linear and squared term of ``*emerging market categories*" are not statistically significant, although they exhibit the same pattern as we have found in our main analysis for Hypothesis 1 (see Model 2 of Table 2).

In contrast, Model 2 of Table 4 reveals that in industries with one national association, the coefficients of the linear and squared terms of *emerging market categories* are significantly negative and positive ($p < .05$), respectively. This suggests that when there is a single dominant trade association in an industry, the inverted-U relationship between emerging market categories and R&D intensity is reversed, just as we hypothesized in Hypothesis 3. That is, the presence of a dominant association may constrain the innovative efforts of firms when the number of emerging market categories is low, but when the number of emerging categories is high, such stabilizing power may help consolidate and clarify possible directions in the industry.

Model 3 shows that in industries with multiple trade associations, this moderating effect of associations is reversed. We see the same pattern as what we found in our main analysis for Hypothesis 1 (Model 2 of Table 2), indicating that the presence of multiple trade associations does not help alleviate the issues resulting from increasing incidence of multiple emerging market categories. Interestingly, in industries with multiple trade associations, the relationship between emerging market categories and R&D intensity exhibits the same pattern with that in industries without a major association, although the latter condition is not statistically significant. In other words, when it comes to resolving and mitigating increasing ambiguity in an industry, the presence of multiple trade associations seems to be just as unhelpful as the absence of such associations. To visualize these findings, we plot the relationships between emerging market categories and R&D intensity under the three conditions in Fig. 3.

As shown in Fig. 3, the effect of emerging market categories seems to be U-shaped when there is only one national trade association in an industry, and the positive effect kicks in only after the incidence of two emerging market categories. This indicates that firms tend to invest more in R&D activities as market opportunities go up when there is a single dominant association in the focal industry, suggesting that the presence of such an institutional actor may indeed be helpful for reducing cognitive confusion in the face of an increasing number of emerging market categories.

In contrast, when there are multiple trade associations in an industry, the effect of emerging market categories appears to follow an *inverted* U-shaped trajectory. That is, a firm's innovation efforts will initially increase and then drop as the number of emerging market

[8] We also employed an alternative approach to investigate the moderating effect of single vs. multiple trade associations. We developed a new binary variable ``multiple associations," which we coded as zero when there was only a single trade association in an industry, and one when there were multiple trade associations in an industry. Using this dummy variable as a moderating variable, we then re-tested Hypothesis 3 in the same way as we did for the main analysis. The results suggest that the presence of multiple trade associations indeed reinforces the inverted-U shaped relationship between emerging market categories and R&D intensity. We thank an anonymous reviewer for suggesting this alternative testing approach, which gives us further assurance for the differential effects of single vs. multiple trade associations. Full results from this additional supplementary analysis are available upon request.

Table 4
Effect of emerging market categories with zero, single, and multiple industry associations

Variables	Model 1 *No Industry Association* β (SE)	*p*-value	Model 2 *Single Industry Association* β (SE)	*p*-value	Model 3 *Multiple Industry Associations* β (SE)	*p*-value
Emerging market categories	0.039(0.03)	.139	−0.174(0.08)	.032*	0.035(0.01)	.000***
Emerging market categories^2	−0.004(0.00)	.104	0.058(0.03)	.040*	−0.004(0.00)	.000***
Lagged DV	0.753(0.09)	.000***	0.725(0.08)	.000***	0.769(0.03)	.000***
Firm size	−0.028(0.01)	.004**	−0.033(0.02)	.125	−0.026(0.01)	.001**
Firm diversification	0.013(0.01)	.052	0.017(0.01)	.185	0.005(0.01)	.531
Slack	0.001(0.01)	.860	0.003(0.01)	.564	0.010(0.00)	.000***
Firm performance	−0.011(0.03)	.714	−0.089(0.08)	.252	0.004(0.04)	.907
Industry growth	−0.008(0.01)	.173	−0.010(0.02)	.564	0.005(0.00)	.136
Constant	0.020(0.03)	.495	0.003(0.03)	.922	−0.021(0.02)	.336
−2 Log-likelihood	608.31		311.73		6241.14	
Akaike's information criterion	626.31		329.73		6259.14	
Bayesian information criterion	664.97		365.17		6315.28	
N	542		379		3,783	

Note: *SE* denotes standard error.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

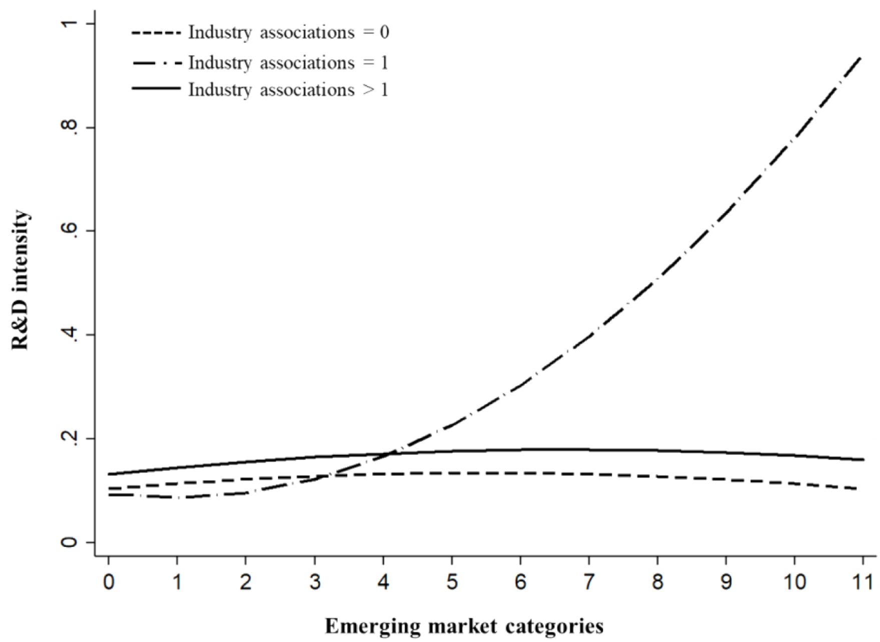

Fig. 3. Moderating effects of industry associations under three different scenarios.

categories increases beyond a threshold, which is consistent with the pattern that we find in our main analysis. This indicates that the existence of multiple trade associations in the industry is likely to lead to inconsistent norms and standards, further exacerbating the negative effects of ambiguity created by multiple emerging categories, thereby reducing incumbent firms' R&D intensity. The shape of this line is almost identical to the line representing the condition of zero trade association, again suggesting that the presence of multiple associations in an industry may lead to very similar outcomes to when there are no trade associations in the industry. Overall, our post-hoc analysis suggests that although the existence of a single dominant trade association indeed has a consolidating effect for an industry – thereby facilitating incumbent firms' innovation efforts, the presence of multiple associations may backfire and even heighten socio-cognitive fragmentation within an industry, exacerbating the problems associated with increasing incidence of emerging market categories. The effect of trade/industry associations on firms' innovation and their roles in consolidating industry development is therefore more complex than previous literature has suggested, and our investigations add interesting and nuanced insights into the collective understanding of the relationship between emerging market categories, industry associations, and incumbent firms' innovation efforts.

5. Discussion and conclusion

Emergence poses an interesting and important dilemma to firms' decision-makers. We frame this dilemma as the opportunity-ambiguity dilemma wherein we posit and find support for the argument that the incidence of emerging market categories does not always imply enhanced growth and innovative prospects for industry incumbents. When it comes to new market categories, several major streams of research in organizational economics —including the technological discontinuities and industry life cycle perspectives— have mostly focused on the bright side of emergence, emphasizing growth potentials and opportunities for innovation, while the negative effect of emergence on firms' innovation efforts is understudied. In this paper, we balance this view of emergence by investigating how emerging market categories may also affect firms' innovation strategies by generating ambiguity in the environment. More fundamentally, we believe that part of this unbalanced view in the existing literature is due to the inattention to the complexity and ambiguity inherent in many emerging contexts. Yet, a socio-cognitive view of innovation suggests that as the number of emerging market categories goes up, the cognitive burden that is imposed on firms will increase at an increasing rate, while the benefits of new opportunities will increase at a decreasing rate due to decision-makers' bounded rationality and cognitive limitations. As a result, when there are too many emerging market categories in an industry, firms may eventually decrease their R&D intensity. Our results support this core hypothesis. We also investigate the role of collective identity and institutional actors (i.e. trade associations) in influencing this basic tendency. In other words, whether market category emergence poses opportunity or ambiguity is not only driven by technological and market developments per se, but also by the socio-cognitive contexts in which they emerge. In particular, our results show that collective identity incoherence of new entrants and the presence of industry associations influence how firms act in industries experiencing the emergence of multiple possibilities.

5.1. Theoretical implications

By offering a richer, more balanced understanding of the relationship between market category emergence and a firm's innovation strategy, our study makes several theoretical contributions. First, we believe this paper has implications for several streams of innovation studies. The majority of industry life cycle literature has viewed innovation as a natural outcome accompanying the emerging stage of a market space, and the rates of innovation have been primarily attributed to economic factors such as opportunity and competition. A related literature on technological discontinuities has argued that radical or disruptive innovations typically come from new entrants or firms from outside of the focal industry (Christensen, 1997). This literature posits that incumbents are typically late to catch up or fail to respond at all because of the competence trap, which occurs when incumbents favor inferior routines that they have mastered over superior routines that they are unfamiliar with (Levitt and March 1988), or because of the innovator's dilemma, in which firms follow their mainstream customers too closely and as a result overlook inferior-performing but potentially disruptive new technologies that initially did not appeal to mainstream customers (Christensen, 1997). We acknowledge that all of these are important factors, but in this paper we consider an alternative explanation: incumbents may fail to act or react because of their cognitive limitations, especially in conditions of increasing complexity and ambiguity in their industry. Put differently, the ``blind spot" does not just come from incumbents' tendency to maintain the status quo, but also from a fundamental issue related to how humans process and respond to complex and equivocal information (Miller, 1956). In addition, by showing that the collective identity shaped by new entrants and the presence of institutional actors such as trade associations influence the effects of market category emergence, we further add to the literature on technological discontinuities and innovation studies by shifting our focus from the focal firm to the broader socio-cognitive environment in an industry. We explore how these factors act as ``cues" to either tighten or loosen the constraints posed by decision-makers' bounded rationality and cognitive limitations, thereby highlighting the ``relevance of the socio-cognitive approach to macro-level studies of technological change." (Howells, 1995:883)

Second, this study also contributes to recent scholarship on market and industry emergence (e.g. Forbes and Kirsch, 2011; Giarratana, 2004; Santos and Eisenhardt 2009; Sine and Lee 2009; Gustafsson et al., 2015). Studies on emergence have largely examined one emerging category at a time, rarely considering whether or how the multiplicity of emerging market categories may affect a firm's innovation efforts. Although recent studies have started to consider the implications of having multiple market categories in an emerging context (e.g. Suarez et al. 2015; Grodal et al., 2015), the consequences of having a diverse landscape with multiple emerging market categories within an industry are still not well understood. In this paper, we explicitly examine multiplicity and investigate how firms may cope with the opportunity-ambiguity dilemmas associated with this multiplicity that we highlight in this paper. We argue that the trajectory of each technology or market category is not independent of the other, and that the aggregate effect of such emerging categories may not be simply additive. Rather, when there is an increasing number of emerging market categories, the relationship between perceived opportunities, ambiguity, and firms' innovation efforts may change qualitatively. We believe that this finding offers a novel insight for understanding issues pertinent to market and industry emergence.

Finally, this paper also has implications for institutional effects on industry evolution (Geels, 2004). Institutions, by definition, are durable social structures (Scott, 2001: 49) that provide stability and meaning to social life and are resistant to change (Jepperson, 1991). One such stabilizing institutional force is collective institutional actors— such as trade associations. Yet, our finding of the unexpected moderating effect of industry associations suggests that although having a single dominant association in the field can indeed provide a certain degree of institutional stability, the presence of multiple collective actors actually reinforces the negative effects of ambiguity. This finding provides a more nuanced understanding of the role of institutional actors such as trade associations and how their presence influences the socio-cognitive context of the industry.

5.2. Practical and policy implications

Our study also has important practical implications for firms, R&D managers, and innovation policy makers. Although scholars have documented that in fast-paced environments, a ``wait-and-see" approach may result in eventual failure (Eisenhardt and Bourgeois, 1988), such strategic mistakes are still seen repetitively in the business literature, as evident by the well-documented notion of ``innovator's dilemma" (Christensen, 1997). In this paper, we propose another account for why incumbent firms often miss the windows of opportunity for innovation. The cognitive limitations- and bounded rationality-based view that we develop in this paper suggests that when emergence combines with multiplicity, firms are not likely to take advantage of all the possible opportunities that they face. On the contrary, they may either take a wait-and-see approach and become more conservative, or trade short-term growth objectives for long-term innovativeness. It is thus critical for firms to recognize this tendency and devise ways to mitigate the detrimental effects of ambiguity in emerging contexts. Such an observation is especially important in the present day, when ``the speed of current breakthroughs has no historical precedent," which ``is evolving at an exponential rather than a linear pace. Moreover, it is disrupting almost every industry in every country. And the breadth and depth of these changes herald the transformation of entire systems of production, management, and governance[9]."

By developing a socio-cognitive perspective to understand when and

[9] https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/.

why innovation levels vary across industries, our study also offers policy makers a way to understand how institutional levers such as trade association activity and new firm entry can influence strategic or innovative behavior of incumbent firms. An important insight derived from this study is that market categories—including both formal classification systems such as SIC and informal, consensus-based categories as those reported by EEI— have strong influences on firms' decision making. Although the kind of emerging categories referred in this paper is about the latter, we also stress the importance of official definitions and delineations of industry boundaries, because all the emerging market opportunities are conceptualized and empirically measured within industry boundaries of a focal firm. Therefore, regulatory agencies that have the authority to develop or assign such categories—such as the US Census Bureau, Office of Management and Budget, SEC, and equivalent agencies in other countries— should be particularly mindful about the role of such categories in anchoring firms' sensemaking. How they classify a business entity into one category or another may also affect the coherence of collective identity at the industry level and affect firms' innovation efforts in unintended ways, as shown in our analysis.

Another implication of this paper is that when dealing with emerging technologies or market categories, collective actors such as policy makers and industry associations may want to consider how to optimally ``manage" the mix of new entrants. Our study suggests that instead of viewing emerging market categories as proverbial "gold rushes" for all kinds of new firms to enter, it may be desirable to channel the flow of new entrants more strategically and encourage them to develop more coherent collective identities.

5.3. Limitations and suggestions for future research

There are some limitations of our study, which also open up several possibilities for deeper and richer explorations into the relationship between market category emergence and strategic behaviors of firms. First, although we empirically measure the presence of multiple emerging market categories in an industry, our study does not account for the precise nature of differences or similarities between each category and their inherent characteristics. Future research can specifically model the patterns of variation among the emerging market categories occurring in the industry in terms of rates of technological progression, market potential, complexity and ambiguity of the technologies, etc., and study the effects of such patterns on firms' behaviors.

Second, we do not consider a firm's strategic motives to be included in or excluded from a category. Yet, scholars have suggested that a firm may have an incentive to change its membership in a category for various reasons (Pontikes and Kim, 2017), such as impression management, avoiding certain regulations, or market diversification. For instance, one of our moderators— collective identity incoherence due to the misalignment between new entrants' self-categorization and the audience's perceptions— might have been a result of firms' strategic manipulation to avoid regulations. As an example, ride sharing services may categorize themselves as technology companies to evade utility regulations that traditional cab companies are subject to[10]. Although we believe that regardless of firms' underlying motives, such discrepancies—and the resultant collective identity incoherence— will shape the boundaries of the newly entered industry in unintended ways (c.f. Grodal, 2018), thereby affecting the perceived clarity of the industry and incumbent firms' innovation efforts, we also acknowledge that firms may have various motives to manipulate their categorization in one way or another. Future research may explore how firms can strategically position themselves in the category system when navigating newly emerged market categories.

While our study sheds light on how industry incumbents respond to market emergence in their respective industries, we utilize a somewhat coarse-grained operationalization of incumbents' strategic behavior: namely, R&D intensity. Future research would benefit from delving deeper into the precise nature of innovation or other activities that incumbents engage in to respond to emerging market categories. For instance, we do not know where exactly the R&D investment is targeted, and how firms may have redistributed their resources across different market categories. Moreover, are the patterns we observed in our data primarily attributed to organic innovation or changes in partnership or merger and acquisition activities? Do firms shift their resources from R&D to something else? If so, what are the alternative uses of such resources? Do firms alter their R&D activities from exploitation to exploration or vice-versa? Do incumbents change the focus of their knowledge search from internal sources to external arrangements such as licensing agreements and strategic alliances? Although data constraints and scope considerations of the current study have limited our ability to investigate these issues, future research along these lines will help in developing a broader conceptual understanding of how emergence affects the strategic choices made by managers.

We also acknowledge that our measure for the role of trade associations may not be ideal. While more fine-grained information such as membership or size of these organizations should offer more nuanced insights into the role of such institutional actors, such data were not easily available for most associations. Although, by only including national associations, we believe our measure has indirectly accounted for the size effect to some extent, future research may want to investigate whether different types of associations or associations that engage different types of members may have varying effects on incumbent firms' innovation efforts.

6. Conclusions

In this study we endeavor to resolve an important but relatively understudied dilemma posed by our collective understanding of industry dynamics and emergence. On the one hand, a dominant realization in the literature that has been borne out by a significant body of empirical work, is that emergence in industries spurs innovation and growth. On the other hand, emergence can pose significant socio-cognitive challenges for industry incumbents due to its inherent ambiguity. We have tackled this paradox in industries belonging to the high-tech U.S. manufacturing sector and have empirically assessed the effects of the multiplicity of emerging market categories in such industries on innovation-related strategic behaviors of incumbent firms. Our findings suggest a co-existence of both opportunity and ambiguity, and the relative prevalence of one over the other is largely driven by an increasing multiplicity of emerging market categories and the socio-cognitive context of an industry. We believe that the explicit emphasis on the effect of this multiplicity on the opportunity-ambiguity tension in emerging contexts contributes to our collective knowledge of the interplay between market emergence and innovation.

CRediT authorship contribution statement

Jade Y. Lo: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Supervision, Project administration. **Rajiv Nag:** Conceptualization, Resources, Writing - review & editing. **Lei Xu:** Methodology, Formal analysis, Writing - review & editing. **Shanti D Agung:** Formal analysis, Investigation, Resources, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[10] We thank an anonymous reviewer for this example.

Appendix

Using the Amazon Com IPO as an example, this appendix shows the source of the data found in this data base. Several pages of the Amazon Com Inc 424B prospectus are reproduced below, along with the first page of Amazon's S-1 registration statement, as downloaded directly from the SEC's EDGAR website. These pages show precisely where the variables assembled for this database were found in these IPO documents.

Amazon Com Inc
424B EDGAR Document

```
PRIVACY-ENHANCED MESSAGE-----
Proc-Type: 2001,MIC-CLEAR
Originator-Name: webmaster@www.sec.gov
Originator-Key-Asymmetric:
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 TWSM7vrzLADbmYQaionwg5sDW3P6oaM5D3tdezXMm7z1T+B+twIDAQAB
MIC-Info: RSA-MD5,RSA,
 JpitboD5ZynAPVJ5gntJTaIE01hnxiI8B0YKo6ly8bK+zh7aA+2f4W4YbJdpl0Tg
 fbzy4vOoU+oltyhbwWhueg==
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CONFORMED SUBMISSION TYPE:   424B1
PUBLIC DOCUMENT COUNT:       1
FILED AS OF DATE:            19970515
SROS:                   NONE          Date of filing

FILER:

        COMPANY DATA:
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                CENTRAL INDEX KEY:                   0001018724        identifier
                STANDARD INDUSTRIAL CLASSIFICATION:  BOOKS: PUBLISHING
OR PUBLISHING AND PRINTING [2731]  SEC assigned SIC
                IRS NUMBER:                          911646860
                STATE OF INCORPORATION:              DE
                FISCAL YEAR END:                     1231              State of
                                                                       incorporation
        FILING VALUES:
                FORM TYPE:              424B1
                SEC ACT:                1933 Act
                SEC FILE NUMBER:        333-23795
                FILM NUMBER:            97607381

        BUSINESS ADDRESS:
                STREET 1:               1516 SECOND AVE 4TH FLOOR
                STREET 2:               PO BOX 80387
                CITY:                   SEATTLE                      Firm
                STATE:                  WA                           address
                ZIP:                    98101
                BUSINESS PHONE:         2066222335
```

Amazon Com Inc
S-1 EDGAR Document

AS FILED WITH THE SECURITIES AND EXCHANGE COMMISSION ON MAY 14,
1997 REGISTRATION 333-23795

SECURITIES AND EXCHANGE
COMMISSION WASHINGTON, D.C.
20549

AMENDMENT NO. 5 TO

FORM S-1
REGISTRATION STATEMENT
UNDER
THE SECURITIES ACT OF
1933

AMAZON.COM, INC.
(Exact name of registrant as specified in its charter)

<TABLE>
Firm assigned
<S> SIC <C> <C>
DELAWARE 7375 91-1646860
(State or other (Primary Standard Industrial (I.R.S.
Employer jurisdiction of Classification
Code Number) Identification No.)
incorporation or
organization)
</TABLE>

1516 SECOND AVENUE, 4TH FLOOR
SEATTLE, WASHINGTON 98101
(206) 622-2335
(Address, including zip code, and telephone number, including area
code, of Registrant's principal executive offices)

JEFFREY P. BEZOS
PRESIDENT AND CHIEF EXECUTIVE
OFFICER
AMAZON.COM, INC.
1516 SECOND AVENUE, 4TH FLOOR
SEATTLE, WASHINGTON 98101
(206) 622-2335
(Name, address, including zip code, and telephone number,
including area code, of agent for service)

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