This is the accepted manuscript of the following article: Arnaud Cudennec and Rodolphe Durand, 2023: Valuing Spanners: Why Category Nesting and Expertise Matter. AMJ, 66, 335–365, which has been published in final form at https://doi.org/10.5465/amj.2020.0042.

Valuing Spanners: Why Category Nesting and Expertise Matter

Arnaud Cudennec
The Hong Kong Polytechnic University
arnaud.cudennec@polyu.edu.hk

Rodolphe Durand
HEC Paris
durand@hec.fr

Acknowledgments
The authors thank Laszlo Tihanyi, Floor Rink, and the three anonymous reviewers for their constructive feedback and their guidance during the review process. They also thank Pitchbook for enabling data access. Also, for comments on earlier versions of this project, the authors thank participants at the AOM Annual Conference (2018), the EGOS Colloquium (2020) as well as at the research siminars of the Society & Organizations Institute from HEC Paris (2018), the Strategy, Organizations and Society international research workshop (2018), and the Northwestern-Kellogg MORS Ph.D. research workshop (2019). Special thanks are due to Romain Boulongne, Giada Di Stefano, Elisa Operti, and late Ned Smith for their support and valuable comments.

VALUING SPANNERS: WHY CATEGORY NESTING AND EXPERTISE MATTER

ABSTRACT

Organizations need to both differentiate themselves while conforming to their audiences' expectations. To meet this demand, organizations may span different categories. However, valuing spanners is challenging for audiences. We contend that spanners' valuation depends on category nesting, as the congruence of informational cues varies between basic categories and subcategories. Furthermore, we expect that more expert audiences find spanners to be more congruent (and hence, more valuable) at a subordinate level than at a basic level of categorization. We test our hypotheses using a mixed methods design in the context of venture capital investments. We analyze observational data on more than 29,000 venture capital deals and develop two experimental studies. Our findings support our hypotheses that subcategory-spanning lowers valuation, and that this effect is attenuated as investors' expertise increases. Our experimental studies further show that congruence is a causal mechanism explaining these effects. Our findings have important implications for research on organizational conformity and optimal distinctiveness, categorization in markets from an information processing perspective, and the impact of expertise on valuation.

A fundamental problem in management hinges on how favorably audiences value an organization's conformity to expectations. Organizations may present themselves to audiences as purists, clearly representative of a genre or a category; alternatively, they may combine multiple attributes belonging to a plurality of codes (Durand, Rao, & Monin, 2007; Goldberg, Hannan, & Kovacs, 2016). Valuing spanners, i.e. organizations that span categories, is challenging as well as determining whether they are worth more than purists. Indeed, not all spannings are equal as they depend on the type and characteristics of the spanned categories (Hannan et al, 2019; Wry, Lounsbury, & Jennings, 2014). At a micro-level, audience members process information (categorical attributes and cues) differently (Pontikes, 2012; Boulongne & Durand, 2021). At a macro-level, expectations change under the evolution of which attribute combinations become dominant, which reshuffles what spanning means and how for organizations to best balance conformity with differentiation (Zhao, Fisher, Lounsbury, & Miller, 2017; Taeuscher, Bouncken, & Pesch, 2020).

As a result, valuing spanners is a thorny issue, which explains why prior research resorted to necessary simplifying assumptions: assessing spanning at a given level within the layered category system that constitutes a market or assuming that all audience members similarly process and interpret information. In this paper, we tackle the challenge of explaining firm valuation[1] while relaxing these assumptions. We focus on how an audience (investors) differently value spanning firms depending on both whether they span categories at a basic or subordinate industrial sector level and how much investors' expertise varies.

Categories facilitate coordination among market players, i.e., producers, investors, clients, and intermediaries (Cattani, Porac, & Thomas, 2017). They structure markets by enabling comparisons between products or firms (Schneiberg & Berk, 2010). Categories represent "a meaningful consensus about some entities' features as shared by actors grouped together as an audience" (Durand & Paolella, 2013: 1100). Industrial sectors, but also artistic genres, political camps or scientific disciplines, are all examples of categories that audiences use to group together market players and, eventually, value them (Vergne, 2012; Vergne & Wry 2014). Categorical membership reduces informational uncertainty and investors value firms based on available informational cues, such as categorical features (Lee, Adbi & Singh, 2019; Wry et al., 2014; Zacharakis, 2010). As such, organizations need to carefully self-categorize, by affiliating with one or several market categories so that investors can identify and value them appropriately (Granqvist, Grodal & Woolley 2013, Glynn & Navis, 2013; Pontikes, 2018).

Many studies have provided evidence that conformity to existing categories improves identification and leads to higher valuation (e.g.: Hsu, Koçak, & Hannan, 2009, Leung & Sharkey, 2014). By contrast, spanning categories would generate unclear identities which are

[1] We use the term valuation to refer to the investors' assessment of a firm's economic value relative to other firms (Gompers, Gornall, Kaplan, & Strebulaev, 2020).

poorly understood, discarded and devalued, in various market settings, including movies, restaurants, wineries, and crowdfunding (for reviews, see Hannan, 2010; Kovács & Hannan, 2015; Wry & Vergne, 2014). Hence, the dominant view sees category membership as a disciplining cognitive and institutional mechanism that favors conformity to existing categories' features. For instance, a restaurant that respects the attributes of the "fast food" category is likely to be valued more highly than a "vegan fast food" restaurant, which is not yet an established category. The dominant view tends to limit evaluators' information processing to an evaluation of categorical similarity to pre-existing types. However, not all instances of category spanning are identical, and some may be more congruent than others (Rindova & Petkova, 2007; Wry et al., 2014). In particular, it is more challenging to find congruence among categories that are less discernable (Johnson & Mervis, 1997; Younkin & Kashkooli, 2020). Furthermore, from an information processing perspective, we know that valuation goes beyond evaluating similarity and that information processing capacity is limited for individuals who make valuation assessments (Pontikes, 2012; Simon, 1955; Turner & Makhija, 2012). Not all individuals possess the same stocks of knowledge about the category system, and their information processing capacity varies with their expertise (Althuizen & Sgourev, 2014; Boudreau et al., 2016). Therefore, drawing on an information-based perspective, we consider how investors might perceive congruence in the cues sent by category spanners. In doing so, we complement the existing perspective that is rooted in evaluating cues' similarity to preexisting category types.

So far, most studies have relied on single-level classification data, e.g., movie genres (Hsu et al., 2009), cuisine types (Durand, Rao, & Monin, 2007), or industrial nomenclatures (Ruef & Patterson, 2009; Sharkey, 2014). This perspective overlooks that categories are nested within each other: subcategories belong to basic categories, which in turn belong to superordinate categories (Boghossian & David, 2021; Hannan et al., 2019; Wry & Lounsbury, 2013). Ignoring the level of category nesting at which category spanning occurs implies that the information load is similar for spanning at a basic versus subordinate level, which is unrealistic. For instance, a category-spanning start-up may emphasize its affiliation with abstract basic categories (e.g., "finance," "information technology"), or it may emphasize its affiliation with subordinate categories (e.g., "microfinance," "credit risk") that more precisely capture its concrete activities within a basic category. Therefore, in relating category spanning to valuation, it is essential to account for category nesting so as to appreciate the level of information processing required, which supposedly grows as category nesting increases. Another consequence of failing to account for category nesting is that many organizations may have been miscategorized in prior studies, having been counted as specialists in a basic category when they actually span subcategories belonging to a basic category, hence favorably biasing the benefits of specialization.

Moreover, categories researchers have traditionally assumed that all audience members homogenously favor conformity to existing categories (Cattani, Porac, & Thomas, 2017; Fisher, 2020). However, when relying on an information processing perspective, we can relax the condition that all audience members homogeneously perceive categorical information, such as category spanning at subordinate and basic levels (Gehman & Grimes, 2017; Younkin & Kashkooli, 2020). Information processing is heterogenous across individuals (Joseph & Gaba, 2020; Turner & Mkhija, 2012), which has two important consequences when considering how investors value category-spanning firms. First, congruence may be less about conformity to pre-existing category attributes and more about compatibility across categorical cues provided by the firm. In this regard, a "vegan fast food" restaurant, while not offering meat-based burgers (and not conforming to "fast food" expectations) can still explain and legitimize how it combines kitchen ergonomics inspired by classical fast-food restaurants with vegan cuisine. Second, individuals form different interpretations of the same informational cue based on their expertise, i.e., an above-average level of domain-specific knowledge (Dane, 2010). In particular, venture capital (VC) investors are far from a homogenous audience (Pontikes, 2012); because they display unequal degrees of expertise in industrial categories (Mount, Baer, & Lupoli, 2021), they may diverge in the ways that they interpret given informational cues (Falchetti, Cattani, & Ferriani, 2021; Hochberg, Mazzeo, & McDevitt, 2015; Zacharakis, 2010).

Drawing on research on information processing, categories, and expertise, we contextualize the effect of an organization's category spanning on its valuation by conjointly analyzing the roles of category nesting, inter-category congruence, and audience members' expertise. We hypothesize that category spanning leads to lower valuation at lower levels of spanning. Indeed, assessing congruence across categories demands higher processing capacity for an average investor at a lower (versus higher) level of spanning because at deeper levels of nesting, the degree of specificity of categorical cues is higher while their level of distinctiveness is lower. We further reason that investors' expertise influences these relationships. In particular, expertise increases the probability that a valuator perceives subcategory cues as congruent, because experts better discriminate cues and their complementarity within their knowledge domains. Therefore, we expect expertise to attenuate the negative mediation of congruence on the relationship between subcategory spanning and valuation.

We tested these hypotheses using a mixed-methods approach. We collected and analyzed longitudinal data on actual VC investments (Study 1) and conducted a series of pre-registered experimental studies based on realistic vignettes in the setting of VC investments (Studies 2 and

3). In Study 1, we test the ecological validity of our hypotheses using more than 29,000 observations of VC deals worldwide from 1994 to 2017. In Study 2, we analyze data collected from a sample of undergraduate students from a large public research university in Hong Kong who were asked to value a start-up company. In Study 3, we replicate Study 2 with U.S. participants and manipulate congruence through a concurrent double randomization design to further test the causal effect of the mediation (Pirlott & MacKinnon, 2016). Our findings provide strong support for our hypotheses. Notably, the mediating effect of congruence on the relationship between subcategory spanning and valuation is more negative for non-experts.

Our study sheds light on three major questionings about whether organizations are better off by being conform to typical expectations or by combining features from different categories. First, at the macro-level, we contribute to explaining why certain strategic positionings lead to higher valuations than others. Beyond the characteristics of categories (their contrast, leniency, etc.), our findings invite scholars to consider category nesting and evaluators' information processing (Wry & Durand, 2020). Both are essential dimensions of an organization's positioning and whether it can reach optimal distinctiveness, i.e. the best possible position between imposed conformity and necessary distinction (Zhao et al., 2017; Zuckerman, 2016). Second, we join recent scholarly work in helping to explain how informational cues from distinct categories at different levels of category nesting (i.e. their specificity and distinctiveness) influence perceived congruence and determine a spanner's valuation (Boghossian & David, 2021; Younkin & Kashkooli, 2020). Our evidence that spanning penalties are not equal at subordinate or basic levels rebalances what spanning and specialization mean –subcategory spanners having been likely and unduly counted as purists at upper levels of categorization in prior studies. Third and finally, we show that individuals with lower expertise are less tolerant of subcategory-spanning than more expert individuals. Our findings complement the literature on the mechanisms and impacts of expertise on the valuation of innovations and deviations from prevailing standards (Althuizen & Sgourev, 2014; Boudreau et al., 2016).

THEORETICAL BACKGROUND

Category Spanning, Conformity, and Congruence

Prior research shows that category spanning negatively impacts an organization's market valuation (for reviews, see Hannan, 2010; Kovacs & Hannan, 2015). When organizations affiliate with multiple categories, they diminish their grade of membership in each category. A lower grade of membership impedes audience members' abilities to identify organizational features, thereby confusing their perceptions of the organization's identity (Hannan et al., 2019). Early psychological research showed that objects with a single categorical membership are more congruent with expectations and readily understandable than objects with fuzzy membership (Rosch & Mervis, 1975). As a result, scholars have argued and provided evidence that buyers and investors undervalue category spanning (Hsu, Koçak, & Hannan, 2009). For instance, using a natural experiment in the context of crowdfunding, Leung and Sharkey (2014) found that organizations with multiple labels are devalued relative to organizations that lack labels (see also Negro & Leung, 2013 in the context of wineries).

However, firms do not always conform to expectations. They introduce novelty, seeking to differentiate as they search for new clients or investors (Durand, Rao &, Monin, 2007; Taeuscher, Bouncken, & Pesch, 2020). While the dominant view on category spanning accounts for a variety of common situations in markets for consumption goods, it tends to ignore that firms may seek congruence with expectations, not only by blending into an existing category, but also by combining cues from compatible categories. Congruence is defined as a feeling of harmony between elements (Althuizen & Sgourev, 2014; Meyers-Levy & Tybout, 1989) and has been traditionally associated with the correspondence between an organization's identity cues and an existing category's features (Hannnan et al., 2007). For instance, Hargadon and Douglas (2001) documented how Edison adapted his novel lightbulb by using features that had little technical function but were congruent with those of the preexisting gas system (e.g., lampshades, burners, metered billing). We offer a view of congruence as an information processing effort rather than simply an evaluation of similarity to a prototype. This view helps to both preserve the actual theory and findings, and account for firms' innovativeness and observable attempts to span categories and combine categorical cues.

We draw on an information processing view of investors' decision-making (Zacharakis, 2010). First, individuals, including investors, have limited information processing capacity (Simon, 1955; Turner & Makhija, 2012). In situations of uncertainty, investors rely on any available informational cues when they value a start-up firm (Gompers, Gornall, Kaplan, & Strebulaev, 2020) and use cognitive shortcuts to estimate value (Wry et al., 2014; Wry & Durand, 2020). Second, firms strive to influence this information and categorization process to their advantage through the categorical cues they send. However, when category spanning occurs at lower level of nesting, information cues are less likely to become distinguishable (Rosch, 1978; Younkin & Kashkooli, 2020), making it harder to relate these cues together. Therefore, investors might fail to find congruence among the subcategories that a start-up firm spans. Finally, the ability to relate attributes and perceive congruence at lower levels of nesting depends on expertise (Boudreau et al., 2016; Johnson & Mervis, 1997; Mannucci & Yong, 2018). From this perspective, not all instances of spanning are equal—nor are all investors.

First, whereas category spanning traditionally has not been distinguished across levels, recent research points at the importance of category nesting. A nested category is a subordinate category that is included within a basic category through an "is-a" relationship and shares certain features with its basic category while adding some information (Hannan et al., 2019; Rosch, 1978). For instance, a musical artist can be identified with categories such as "country" or "rap," but also with more nested categories such as "outlaw country" or "conscious rap" (Younkin & Kashkooli, 2020). As such, spanning categories *within* a given domain is not equivalent to spanning categories *across* domains. Therefore, the notion that category spanning has several levels imposes different constraints on investors' information processing depending on the degree of category nesting. This realization has important consequences, not only for valuation, but also for the generalizability of prior findings that do not account for nesting, since a spanning organization at one level (a subordinate category) might be classified as a specialist at the highest level of taxonomy (basic category).

Second, the main mechanism explaining the valuation of category spanning is the perception of congruence (Althuizen & Sgourev, 2014; Meyers-Levy & Tybout, 1989). When a set of information is not congruent, it generates confusion and frustration and leads to lower valuations (Rindova & Petkova, 2007). When receiving complex information such as a combination of categorical cues, individuals try to integrate it within a structured knowledge domain (Vaghely & Julien, 2010; Wyer, 2012). The cognitive effort of this integration thus may vary based on category nesting, as the congruence of complex informational cues may differ at an upper or lower level of category spanning. Furthermore, individuals (including investors) vary in expertise, which in turn may affect their ability to make sense of category spanning, thereby influencing valuation.

Category Nesting and Expertise

Organizations strategically differentiate from others not only by positioning themselves relative to horizontally disposed categories, but also by affiliating with subordinate categories

(Boghossian & David, 2021; Gehman & Grimes, 2017; Younkin & Kashkooli, 2020). Schematically, categories represent different levels of inclusion in a chain where some categories are more basic, and others are subordinate to them. For instance, a microfinance company is a financial services company, but the reverse is not necessarily true. Two dimensions distinguish subordinate and basic categories: specificity and distinctiveness (Hannan et al., 2019; Rosch, 1978). Basic categories are less specific and more distinctive than subcategories (Murphy & Brownell, 1985; Rosch, 1978). For instance, "microfinance" or "credit risk" activities are more specific than "financial services" and are less distinct from one another than two basic categories like "financial services" and "information technology." We develop our arguments at the subordinate category level and compare the valuation of subordinate category-spanning (SubCS) firms with that of basic category-spanning (BCS) firms (see Figure 1).

- - - Insert Figure 1 about here - - -

In general, the usual assumption that everyone in an audience shares a common understanding about categorical information is simplifying, but acceptable. However, as soon as we introduce the layering of categories and adopt an information processing perspective, we need to relax the assumption of audience homogeneity (Boulongne, Cudennec, & Durand, 2019). Whereas categories would ideally produce homogenous mental representations across audience members (investors in our case), not everyone possesses the same knowledge in a categorical domain, and spanning at a nested level is not tantamount to spanning at a higher category level. Hence, investors' expertise must be isolated and studied in relation to category nesting and perceived congruence in order to more appropriately relate category spanning to firm valuation.

Expertise, defined as a "high level of domain-specific knowledge" (Johnson, 2013: 331), affects how individuals understand and use categories (Medin, Lynch, Coley, & Atran, 1997;

Murphy & Wright, 1984). Early cognitive research found that a major determinant of information processing differences across individuals is their level of expertise in the categorical domain (Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976). Still, the literature offers conflicting evidence regarding how expertise may impact the perception and valuation of category spanning.

Expertise enables relationships to be identified between various categorical features, which leads experts to favor category spanning within their expertise domain (Althuizen & Sgourev, 2014; Kovács & Hannan, 2010). In a field experiment in which individuals assessed entrepreneurial opportunities, Wood and Williams (2014) found that evaluators' expertise accentuates the positive relationship between perceived novelty and the attractiveness of the entrepreneurial opportunity. However, research also suggests an entrenched view, whereby greater expertise leads to experts significantly demoting category spanning in domains beyond their expertise (Lewandowsky, Little, & Kalish, 2007). For instance, Dane (2010) explained that whereas experts indeed identify complex cognitive relationships between various elements, they also fail to establish a single cognitive schema for information that crosses categorical boundaries and goes beyond their area of expertise. Such cognitive entrenchment is in turn likely to make experts less apt to accept bold innovative propositions. Supporting this view is a security and protection argument that suggests experts preserve their domain's purity and the benefits they derive from expertise by rejecting impure candidates that combine elements from their expertise domain with foreign components (Boulongne et al 2020; Coslor, Crawford & Leyshon, 2020). Hence, and interestingly, expertise is a touchstone that enables us to better understand how category spanning at different nested levels may impact investors' valuations.

HYPOTHESES DEVELOPMENT

As exposed above, subordinate and basic categories differ in their degrees of specificity and distinctiveness (Murphy & Brownell, 1985). How do those dimensions impact a category spanner's valuation? First, a high degree of specificity delivers precise and narrow informational cues. Therefore, for a firm, using cues from basic categories is less specific and speaks to a broader audience (of investors), whereas using cues from subordinate categories speaks to a narrower audience (Johnson & Mervis, 1997; Tanaka & Taylor, 1991). Basic categories deliver more general and abstract informational cues that are more easily processed, identified, understood, and positively valued by more people. Second, basic categories are more distinctive, i.e., they are less likely to resemble their neighbors, whereas there is often a greater resemblance between subcategories because they are nested within a higher-level category (Murphy & Brownell, 1985). Yet, a high resemblance between (sub)categories leads to informational overlaps which reduce the likelihood of being assessed positively. The high distinctiveness of basic categories makes it convenient for the average audience to identify their compatibility and potential points of convergence. In contrast, when a firm spans subordinate categories, investors must exert great effort to assimilate the subtle distinctions and apprehend the spanned subcategory features relative to the effort required to understand a firm that spans categories at a higher level (Murphy & Lassaline, 1997). Therefore, overall:

H1: Subordinate category spanning leads investors to provide a lower valuation of a firm relative to basic category spanning.

Perceived congruence between categorical cues is the mechanism through which the penalty imposed on a firm's valuation is greater at deeper levels of category nesting. Whereas classically, congruence equated to similarity with a category's expected features, from an information processing perspective, we reason that congruence depends on an impression of harmony between cues from different categories (Mandler, 1982; Meyers-Levy & Tybout, 1989), i.e., cues that "go well together" (Flecker & Quester, 2007: 989). By definition, at deeper levels of nesting, the degree of specificity of categorical cues is higher and the level of distinctiveness is lower (than at higher levels of nesting). As a result, more cognitive effort is required to understand feature combinations at the subordinate level. Because the subtle combinations of cues for nested categories are, on average, more difficult to comprehend than for basic categories (Gehman & Grimes, 2017; Rosch et al., 1976), subcategory spanners are likely to be perceived as having a lower level of congruence. At higher levels, processing appears to be less difficult, because associations between more easily identifiable features are less constrained by common membership in an existing category. Therefore, the likelihood of cognitively processing and understanding the harmony between features is lower at subordinate (versus higher) levels in the category system. Overall, the perceived congruence of subcategory spanning is expected to be lower than that of basic category spanning.

Congruence is associated with more positive assessments of spanners. For instance, in a series of experiments, van Rompay and Pruyn (2011) showed that high congruence between product features leads to better consumer evaluations. Likewise, when investors assess a start-up that spans multiple industrial categories, they need to perceive the combination of these informational cues as congruent in order to find it appealing (Zacharakis, 2010). In turn, displaying a lack of congruence generates frustration, resulting in a lower valuation (Althuizen & Sgourev, 2014; Rindova & Petkova, 2007).

As a result, perceived congruence across cues belonging to subcategories (versus basic categories) mediates the negative relationship between subcategory spanning and valuation because higher perceived congruence leads to higher valuation. Hence:

H2: Investors' perceptions of inter-category congruence mediate the negative effect of subordinate category spanning (versus basic category spanning) on firm valuation.

The Role of Expertise

The capacity to assimilate information about a feature combination put forward by a category spanner likely is not equal across audience members and affects how they value spanning at different category levels. As per H1 and H2, when compared with basic category spanners, subcategory spanners tend to be penalized due to a perception of lower inter-category congruence. However, congruence is neither an attribute that is inherent to an object nor a purely subjective impression. Individuals possess different stocks of knowledge and unequal capacities to discern and associate cues and features across categories; that is, they vary in expertise, which is likely to influence the extent to which category spanning across levels of nesting is perceived as congruent (Dane, 2010; Mannucci & Yong, 2018).

We theorized that the spanning of subcategories should be perceived as less congruent than the spanning of basic categories, because subcategories are more specific and less distinctive than basic categories. Yet, perceptions of specificity and distinctiveness depend upon audience members' expertise. First, to build their domain-specific knowledge, experts have encountered myriad members of their domain categories and stored in their memories highly diverse features and combinations corresponding to their knowledge domain (see Bilalić, McLeod, & Gobet, 2008 for a review). Therefore, as expertise grows so does the understanding of subcategories and their specificity (Johnson & Mervis, 1997; Tanaka & Taylor, 1991). Second, expertise leads to a greater ability to distinguish between subordinate categories. The ability to cognitively separate subordinate categories enables an expert to see how they relate together, thereby increasing the likelihood of finding congruence between them (Mannucci & Yong, 2018; Murphy & Wright, 1984). Hence, expertise enables investors to discern the subtle dividing lines between subcategories, to understand which features are distinct from those of the basic category to which they belong, and to estimate whether the feature combination across subcategories makes sense.

Regarding basic category spanning, although experts are likely to understand the low specificity of basic categories like non-experts do, they may find it more difficult to relate basic categories together. Expertise facilitates the assessment of congruence for subcategory spanners, as the combination of categorical cues belongs to their area of expertise. Yet, it hampers the assessment of congruence when categorical cues belong to domains beyond experts' knowledge domain (Dane, 2010). Accordingly, in a series of experiments, Moreau and colleagues (2001) found that while experts attribute a higher valuation to innovations that share continuity with their expertise domain, they offer poorer valuations than non-experts for discontinuous innovations (see also Oreg & Goldenberg, 2015). The authors concluded that expertise leads to accepting innovations as long as they relate to an expert's domain of expertise. An explanation for this phenomenon suggests that less expert evaluators better translate information across categories, as they are less constrained than more expert evaluators by structured cognitive schemas (Althuizen & Sgourev, 2014; Moreau, Lehmann, & Markman, 2001). Whereas evaluators with less expertise draw linkages between basic categories, evaluators with greater expertise are more entrenched in one knowledge domain and its corresponding subcategories. Therefore, expertise could decrease perceptions of congruence for basic category spanners. Interestingly, expertise is a touchstone that enables us to better distinguish the source and consequences of inter-category congruence across spanning levels. As such, expertise may have a contrasting moderation effect on the valuation of category-spanning firms at subordinate versus basic levels.

In sum, as their expertise increases, investors are more likely to find higher congruence in subcategory-spanning firms than in basic category-spanning firms. Therefore, we expect that expertise alleviates the negative effect of subcategory spanning (relative to basic category spanning) on inter-category congruence, and subsequently on valuation:

> *H3: Investors' expertise positively moderates the negative effect of a firm's subordinate category spanning (versus basic category spanning) on perceptions of congruence, which in turn positively impact a firm's valuation.*

OVERVIEW OF STUDIES

To test our hypotheses, we performed a correlational analysis of longitudinal data on approximately 29,000 VC deals worldwide (1994–2017) to establish whether the expected effects of our theory are present in actual organizational valuations (Study 1). We also performed two experimental studies (Studies 2 and 3). In Study 2, we replicated the findings from Study 1 and further investigated the mediating role of perceived congruence on the relationship between category spanning and valuation. In Study 3, we manipulated the mediator (congruence) to provide evidence of the causal effect of the mediation (Pirlott & McKinnon, 2016). Table 1 summarizes the design and the main findings of the studies.

- - - *Insert Table 1 about here* - - -

STUDY 1

Data and Sample

First, we tested our hypotheses with actual longitudinal data from VC deals inked between 1994 and 2017 worldwide. This is an ideal setting, as we were able to collect data on the valuations of organizations in diverse industry categories, as rated by professionals with varying levels of expertise. We collected data from Pitchbook, an official partner of the National Venture Capital Association (NVCA), the U.S. VC community's flagship trade association since 2016. Because we used five-year rolling windows ranging from $t-6$ to $t-1$ (where t is the year a deal was struck) to measure several independent variables, our analysis covers the period from 2000 to 2017. Consistent with the literature on VCs, we focused on lead investors (Nahata, 2008; Sorensen, 2007; Zhelyazkov & Tatarynowicz, 2020) who were the most involved in each deal and the most influential in defining the company's valuation. Based on data availability, our dataset contains 29,033 observations of funding deals that included 4,932 investors and 15,811 companies. Geographically, the deals involved companies headquartered mostly in North America (88.2%), followed by Europe (9.5%) and East Asia (1.4%).

Dependent variable: Valuation. The VC investment process has three main stages. In the first stage of pre-investment, investors screen the companies that have requested funding. The second stage involves the investment itself, when the company's valuation is determined to "reflect underlying or expected enterprise value" (Hsu, 2007: 727; Gompers, Kovner, & Lerner, 2009). The last stage of investment involves development and VC monitoring. Consistent with financial research, the company's valuation is the pre-money value (i.e., from the second stage), which is the value prior to receiving a capital infusion. Because the pre-money value is skewed to the right, we log-transformed the variable.

Independent Variables

Category membership. We relied on the Pitchbook industrial classification which comprises 41 basic categories and 218 subordinate categories. Companies are assigned to one primary basic category at a minimum (and potentially more basic categories) and one or more subcategories.[2] To test our hypotheses, we decomposed the population into three mutually exclusive cases (see Figure 1). Companies were considered to be in the subordinate category spanning (SubCS) condition when they were assigned to more than one subordinate category but only one basic category (30.7% of observations). Companies were considered to be in the basic category spanning (BCS) condition when they belonged to more than one basic category (46.3% of observations). Finally, companies were considered to be in the basic category membership

---

[2] The number of basic categories cannot not exceed the number of subordinate categories, as each basic category has at least one subordinate category.

(BCM) condition when they were assigned to only one basic category and one subordinate category (23.0% of observations).

Expertise. Following past research, an investor's expertise is a lead investor's past experience in the target company's primary basic industry (e.g., Mannucci & Yong, 2018; Sorensen, 2007). Hence, the lead investor's expertise in the target company's primary basic industry, *p*, in year *t* is calculated as:

$$Investor\ Expertise_{t,c} = \sum_{j=t-6}^{t-1} N_{j,c}$$

N_p indicates the number of investment rounds the lead investor has participated in by investing in companies in the same primary basic category *c* as the target company, during the five years preceding the deal year *t*. The average non-logged expertise score is 30.00 (*SD* = 55.86). We log-transformed the variable, as it is highly skewed to the right.

Control Variables

We used controls related to investors, deals, and companies. Specifically, following past studies, we used the following variables as controls: investor general experience, investor reputation, syndicate size, competitive intensity, category heat, investment stages (seed, early, late), round number, number of "slices" of novel activities, and the presence of a residual category (i.e., "other…"). See Appendix 1 for a detailed description of the control variables.

Analytical Approach

The dependent variable of our analyses is company valuation. However, as noted in the previous literature, pre-money value is available only for a minor number of observations due to confidentiality concerns (Claes & Vissa, 2020; Hsu, 2007). In our dataset, pre-money value is indicated for 33.2% of the observed deals (i.e., 29,033 out of 87,405 observations). Importantly, the absence of information on firm valuation might generate a sample selection issue that involves incidental truncation (Certo, Busenbark, Woo, & Semadeni, 2016; Wolfolds & Siegel, 2019).

To overcome this concern, we used a Heckman two-stage procedure to estimate our models. We set the binary variable, "valuation displayed," as a dependent variable in the selection stage and "valuation" as a second-stage dependent variable. First stages are not reported due to space constraints. The selection stages include the variables of *investor expertise*, all control variables, and the instrument *company description length*. The dataset contains keywords extracted from the companies' short description texts that are independent of the industrial categorization. Whereas companies with longer descriptions are more likely to have valuation data available, the number of keywords may not directly impact the valuation amount. Thus, we used this variable as an exclusion-restriction variable in the Heckman procedure (Certo et al., 2016). Unreported findings show a positive relationship between *company description length* and valuation ($p < .001$), which confirms the relevance of this variable as an exclusion-restriction (Certo et al., 2016; Wolfolds & Siegel, 2019). In Table 3, models 1–5, inverse Mills ratio (IMR) values are significantly related to the outcome of the second stage (i.e., *valuation*), which indicates a potential presence of omitted variable bias and thus the relevance of applying a Heckman specification.[3]

In the second stage, we included IMR as a predictor. The dependent variable for all models is *valuation*. Unreported results from the White and Cook and Weisberg tests indicate the presence of heteroskedasticity. Because the start-ups' valuations may be driven by unobserved heterogeneity among investors and companies, we used double clustering by investors and

[3] Also, the correlations between IMR values and the independent variables of interest are low, indicating that exclusion restrictions are strong (Certo et al., 2016).

companies. Our models include year fixed effects.[4] Across models, variance inflation factors range from 5.64 to 7.91, indicating that we can safely reject concerns about potential multicollinearity among the independent variables.

Results

Table 2 displays summary statistics and a correlation matrix. Table 3 presents the tests of our hypotheses using standardized betas. We began by testing our hypotheses using the full sample of VC deals across all industries (Table 3, Models 1, 2, and 3). Then, consistent with the settings of Studies 2 and 3, we tested our hypotheses using a subsample of deals in the finance and information technology (IT) industries (Model 4). Because investor expertise may play a role in start-up development and performance through rarely observable activities (e.g., networking and advising), investor expertise can have potential endogeneity effects on valuations across rounds (Nahata, 2008). To reduce this potential bias, we replicated our analyses using only company valuations at the time of the first round of investment for all industries (Model 5) and for finance and IT companies (Model 6).

Model 1 presents the effects of control variables. Unsurprisingly, *investor reputation, syndicate size*, category *heat* based on the number of companies in the category that received funding, investment *stage* and *round*, and *slice* (i.e., novel activities) significantly increase valuation. Model 2 introduces the *category membership* variable and Model 3 introduces the interaction with *investor expertise*. We compared SubCS firms with BCS firms to test H1. As expected, across the full models (3 to 6), SubCS firms received lower valuations than BCS firms, supporting H1. Another comparison reveals that SubCS firms also received lower valuations

---

[4] The results hold when we restrict the sample to start-ups headquartered in North America and Europe (i.e., 97.7% of the observations). When using the full sample, adding continent or country fixed effects does not change the directions of the main effects, but slightly reduces their statistical significance.

than BCM firms. This is to be expected, since investors tend to prefer pure membership (BCM) over category spanning. Across models, these effects are attenuated as investor expertise increases, which supports H3. For instance, Model 3 indicates that expertise positively moderates the effects of SubCS relative to BCS ($\beta = .04$, $p < .001$) or BCM ($\beta = .04$, $p < .001$) (see Figure 2)

- - - Insert Figure 2 about here - - -

In Model 4 for the subsample of companies operating only in finance and/or information technology, the results follow the same pattern as in Model 3. SubCS firms receive lower valuations than BCS ($\beta = -.07$, $p < .05$) and BCM ($\beta = -.07$, $p = .001$) companies, and investor expertise positively moderates these effects (versus BCS: $\beta = -.05$, $p < .01$; versus BCM: $\beta = -.08$, $p < .001$). These findings strongly support Hypotheses 1 and 3, although they do not reveal information about mediation as per H2, since no measure of congruence is available. Finally, models 5 and 6 are the full models at round 1, respectively, for companies in any industry, and for finance or information technology companies. Overall, the patterns and statistical significance of the relationships displayed in models 3 and 4 are replicated at round 1. These results lower the risk of potential endogeneity on the role of investor expertise on a company's performance and valuation across rounds.

- - - Insert Tables 2 and 3 about here - - -

Robustness Checks

We performed a series of robustness checks to investigate potential biases in our analyses.

Potential outliers. To minimize the potential influence of outliers on our results, we reran our models after winsorizing all continuous variables at the 99th percentile. The magnitude and statistical significance of the effects were unchanged, corroborating our findings.

Alternative measures of expertise. We tested the same models with expertise measured as specialization, i.e., the previously described non-logged measure of expertise divided by the total number of rounds in which the investor had participated within the six years prior to the focal deal in year *t*. Findings corroborate our results, as the relationships are the same, in the expected directions and at similar levels of statistical significance.

One could argue that another way of capturing investor expertise would be to track the degree to which the investor is successful in a given category. For each investor, we measured the number of successful exits, i.e., initial public offerings (IPOs) or mergers and acquisitions (M&As) (Gompers et al., 2009) for deals in which the investor played a leading role and that involved companies associated with the primary category of the target company within the six years prior to the focal deal in year *t*. We included this variable of *investor success in category* as a control in the six main models. The direction and significance levels of the hypothesized effects remain unchanged. *Investor success in category* is (unsurprisingly) highly correlated with *investor expertise* (r = .71), so including this variable as a control would run the risk of generating multicollinearity.

Alternative controls at the category level. In the main models, we controlled for category heat as a proxy for the appraisal of the category itself (Zhelyazkov & Tatarynowicz, 2020), which should impact a company's overall valuation. As robustness checks, we replaced this variable with a measure of category success i.e., the number of successful exits (IPOs or M&As) involving companies associated with the target company's primary category within the six years prior to the focal deal at year *t*. The results remain unchanged in terms of direction and significance levels. Furthermore, we reran the models, replacing category heat with category valuation (Kennedy, Lo, & Lounsbury, 2010), i.e., the average logged pre-money value of the companies associated with the target company's main category in *t*-1. Again, the hypothesized effects remain significant.

Controls at a subordinate level. Our models were measured using controls at a basic category level. As a robustness check, we reran the models using controls measured at a subordinate level, and all the hypothesized effects remained unchanged in terms of direction and significance level.

Discussion of Study 1

Study 1 provides a correlational analysis and primary ecological evidence of the expected effects. However, we cannot use this longitudinal dataset to evaluate whether the hypothesized mechanism (perceived inter-category congruence) explains them. Moreover, our measure of expertise is at the organizational level due to a lack of available data at the individual level. To improve internal validity and perform causal testing of our theory at the individual level, we developed two experiments (see Table 1), in line with previous research that used experiments with students or internauts to look at the individual-level mechanisms that impact the valuation of firms (e.g., Lee et al., 2019, Zunino, Dushnitsky, & van Praag, 2021).

STUDY 2

The objectives for Study 2 were to test causality in H1–H3 by examining whether SubCS leads to a lower valuation that BCS due to lower perceptions of congruence, and whether evaluator expertise positively moderates this relationship.

Design and Participants

Study 2 was a 3-cell quasi-experiment where we manipulated category membership (SubCS, BCS, BCM) and where we measured expertise. The preregistration document for this study is available on aspredicted.org at https://aspredicted.org/KVV_K2Q. To perform this experiment, we recruited a random online sample of undergraduate students from the paid participant pool of a large public research university in Hong Kong. In determining the sample size, we accounted for the limited size of the university's student population while expecting at least 50 participants per cell. We also anticipated a failed attention check rate of approximately 20% (Aguinis, Villamor, & Ramani, 2021). Thus, as preregistered, we recruited 360 students (i.e., 300*1.2).

Among the 360 participants who completed the survey, 53 failed to pass our instructions manipulation checks (IMC) and were excluded from the analyses. The final sample comprised 307 participants (slightly more than 51 participants per condition). On average, participants were 21.01 years old (*SD* = 1.93) and 72.31% were women. Participants were from Hong Kong (86.0%), Mainland China (12.4%), Taiwan (1.3%) and Macao (0.3%). The median duration for task completion was 383 seconds. The experiment was short and required few tasks, making it as reliable as an in-lab controlled experiment (Dandurand, Shultz, & Onishi, 2008).

Experimental manipulations

Participants were all told to imagine that they were junior investors in a VC firm who had been asked to evaluate a start-up's funding request and they all read the same short vignette introducing the start-up. Like previous research (e.g.: Lee et al., 2019; Leung & Sharkey, 2014), we manipulated the description of the start-up's category membership. Specifically, participants were randomly assigned to one start-up's category membership condition among three (subcategory spanning, basic category spanning, basic category membership).

Variables

Dependent variable: Valuation. Participants were asked the following question: "Would you recommend investing in the start-up?" (0 = not at all, 9 = strongly).[5] Participants' scores represent the *valuation* variable. Across conditions, *valuation* has a mean of 4.75 (*SD* = 1.62).

---

[5] Participants also were asked: "How appealing is the start-up?" (0 = not appealing at all, 9 = very appealing). The two items are highly correlated (*r* = .79, Cronbach's alpha = .88). In the following analysis, we use the first item of "Would you recommend investing in the start-up?" as a dependent variable but using the average of the two items leads to very similar findings.

Mediator: Congruence. We adapted items used by Fleck and Quester (2007) and Rifon, Choi, Trimble, and Li (2004) to measure perceived congruence.[6] We asked participants to indicate the extent of their agreement with the following six statements: "The industrial categories that the company uses... (a) go well together, (b) match together, (c) are compatible with each other, (d) are a good fit, (e) are congruent with each other, (f) are an appropriate combination" (0 = I completely disagree, 9 = I completely agree).[7] We averaged the scores for the six items to generate the variable of perceived congruence (Cronbach's alpha = .95). Across conditions, *congruence* has a mean of 5.52 (*SD* = 1.36).

Category membership treatment. Firms are exhibiting either subordinate category spanning (SubCS: microfinance, credit risk), basic category spanning (BCS: finance, information technology), or basic category membership (BCM: finance). All other features of the start-up profile were identical across conditions and applicable to any classification label, so they did not add any supplementary information. The start-up description was purposefully short (55 words) in an effort to maintain the attention of the participants. Figure 3 shows the start-up profile and the category membership treatment.

- - - Insert Figure 3 about here - - -

Expertise. We developed a 12-item questionnaire to measure participants' expertise, following established research (Mitchell & Dacin, 1996; Moreau et al., 2001; Park, Mothersbaugh, & Feick, 1994). Participants earned one point for each correct answer, and we used the total number of points as a finance expertise score (see Appendix 3 for details).

[6] To measure the perceived congruence between a sponsor and an event, Fleck and Quester (2007) asked the extent to which "The event and its sponsors go well together," "The sponsor firm is well matched with the event," and "In my opinion, this firm is very appropriate as a sponsor for this event." Rifon et al.'s (2004) scale of perceived congruence is composed of three items: compatible, good fit, and congruent.

[7] In the BCM condition, we asked whether "The industrial category that the company uses... (a) goes well with its business, (b) matches its business, (c) is compatible with its business, (d) is a good fit with its business, (e) is congruent with its business, (f) is appropriate to describe its business."

Participants whose scores were greater than or equal to the median were considered experts (following Althuizen, & Sgourev, 2014; Cowley & Mitchell, 2003; Kim, Hahn, & Yoon, 2015). In our data, the median was 5 out of 12 possible points, and the highest scoring participant achieved a score of 11. Overall, the sample comprised 155 non-experts (50.49%) and 152 experts (49.51%). Note that using a continuous or a trichotomous measure provides similar findings (see robustness checks).

Validity Check of Measurements

Category membership treatment. After the participants had evaluated the start-up, we asked them to indicate the extent of their agreement with the following statement: "[Category 1] and [category 2] is a conventional combination of industrial categories for a business" (0 = I completely disagree, 9 = I completely agree), as well as a second item where we replaced "conventional" by "frequent."[8] We averaged the items to construct the variable of perceived commonness. We performed an analysis of variance (ANOVA) test using category membership conditions as an independent variable and perceived commonness as a dependent variable. Across all participants, the effect was statistically significant ($F(2) = 9.65$, $p < .001$). We used *t*-test specifications to perform pairwise comparisons. SubCS ($M_{sub} = 5.22$, $SD = 1.05$, $n = 100$) was associated with lower perceived commonness than both BCM ($M_{bcm} = 6.00$, $SD = 1.45$, $n = 101$; $t(199) = 4.31$, $p < .001$) and BCS ($M_{bcs} = 5.63$, $SD = 1.20$, $n = 106$; $t(204) = 2.59$, $p = .010$).

Subjective expertise. Following the recommendations of the literature on expertise, we assessed the validity of our expertise measure by comparing it to subjective expertise, i.e. how participants self-assessed their knowledge in the finance industry (Alba & Hutchinson, 2000).[9]

[8] In the case of BCM, we asked whether they agreed that "'Finance' is a conventional (frequent) industrial category for a business".
[9] Adapting the items of Wallace and colleagues (2020) to the finance context, we asked participants "How much knowledge do you have about the finance industry, as compared to other people? (0 = very little, 9 = a lot), "In

The correlation between our objective (as above) and subjective measures of expertise reaches 0.24, which is consistent with levels found in the literature in non-product contexts (see the meta-analysis of Carlson, Vincent, Hardesty, & Bearden, 2009). Across participants, the self-assessed expertise variable has a mean of 3.62 (*SD* = 1.98). A two-tailed *t*-test indicates that experts as defined above have a higher self-assessed knowledge in finance than non-experts (M_{exp} = 4.10, *SD* = 1.89, *n* = 152; $M_{non-exp}$= 3.15, *SD* = 1.95, *n* = 155; *t*(305) = -4.31, *p* < .001). We provide summary and correlation tables in Appendix 2.

Hypothesis Testing

A Levene's test shows that we cannot reject the null of the homogeneity of variances across the three different conditions of category membership (*F(2)* = .61, *p* = .541), which allows the use of an ANCOVA. We run a 3-cell (category membership: SubCS, BCS, BCM) ANCOVA with expertise as a covariate. The overall model is statistically significant (*F(3)* = 3.30; *p* = .021). To test our hypotheses, we then compared the levels of valuation and congruence between SubCS and BCS firms for non-experts and experts. We also expected that, as in Study 1, the valuation of companies in the control condition (i.e., BCM) would not significantly diverge from that of companies in the BCS condition.

Using a linear regression with Hayes's (2017) PROCESS macro on SPSS, we tested the effect of SubCS (versus BCS) on valuation to test H1. We found that SubCS leads to a lower valuation than BCS (b = -.44, *p* = .047), which supports H1. Then, we tested the moderating effect of expertise on the effect of SubCS (versus BCS). The results show that expertise positively and significantly moderates the effect of SubCS (versus BCS) on valuation (b = .89, *p*

thinking about what I know about the finance industry, I feel that…" (0 = I know essentially nothing about it, 9 = I know essentially everything about it) and "How well informed are you about the finance industry?" (1 = completely uninformed, 7 = completely informed). Cronbach's alpha is .94.

= .042), which supports H3. When accounting for the interaction effect of expertise in the model, the effect of SubCS (versus BCS) becomes even stronger and more significant (b = -.88, p = .005), further supporting H1. These effects are robust when comparing SubCS to both BCS and BCM[10] (Figure 4) or when using a continuous or a trichotomous measure of expertise (see robustness checks).

- - - Insert Figure 4 about here - - -

Post-hoc power analysis. We ran a post-hoc power analysis using G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) on the interaction effect between expertise and SubCS (versus BCS) on valuation. The effect size (Cohen's f = .14 with a power of .50) could be interpreted as small-to-medium. All else being equal, to reach a power of .80 with an alpha of .05, we would have needed a sample of 97 students per condition. We used this post-hoc power analysis to determine our sample size in Study 3.

Mediation analysis. We conducted mediation analyses using Hayes's (2017) PROCESS macro in SPSS. When considering the entire sample of both non-experts and experts, congruence does not significantly mediate the effect of SubCS (versus BCS) on valuation. SubCS is associated with lower congruence, but this effect is not statistically significant (path a = -.24, p = .187). In turn, congruence predicts a higher valuation (path b = .56, p < .001) and while controlling for congruence, the effect of SubCS on valuation is only partially offset (path c = -.44, p = .047; path c' = -.29, p = .147). The indirect effect of congruence, however, lacks statistical significance (indirect effect = -.134; CI: [-.332, .068]; 10,000 bootstrapped samples).

Hypothesis 3 suggests that investor expertise influences the mediated effect of (sub)category

---

[10] When contrasting SubCS with both BCS and BCM, the interaction of expertise with the effect of SubCS (versus BCS and BCM grouped into one condition) is positive and significant (b = .80; p = .041) and the direct effect of SubCS (versus BCS and BCM grouped into one condition) is negative and significant (b = .66; p = .017).

spanning on valuation. We created two subsamples (experts and non-experts) and found that the mediation of congruence is significant for non-experts but not for experts. For non-experts, SubCS (versus BCS) leads to lower congruence (path a = -.51; p = .039) (Figure 5, Panel A). In turn, congruence is associated with higher valuation (path b = .70; p = .004), and the direct effect of SubCS on valuation is attenuated (path c = -88; p = .005; path c' = -.70; p =.022). The indirect effect of congruence is significant (indirect effect = -.180; CI: [-.437, -.004]; 10,000 bootstrapped samples). In contrast, the indirect effect is absent for experts (indirect effect = -.022; CI: [-.319, .382]; 10,000 bootstrapped samples). Detailed effects for experts are shown in Figure 5, Panel B. These findings provide evidence that, unlike experts, non-experts tend to demote SubCS as less congruent, supporting H3.

- - - Insert Figure 5 about here- - -

In unreported analyses, we ran a series of supplementary tests to evaluate the effects of different levels of expertise, socio-demographic characteristics, and different motivations of experts and non-experts. Measuring a mediation variable does not ensure that the causal effect of the mediator on the outcome will be fully captured (MacKinnon & Pirlott, 2015). A way to statistically address this issue is to run a model that uses potentially confounding variables as covariates (Hayes, 2017; MacKinnon & Pirlott, 2015). Hence, in a robustness check, we used categorical status or differences in categorical status as a covariate.

Robustness checks

We examined alternative measures and mechanisms to investigate potential biases in our analyses.

Expertise (alternative measures). While our main tests use a measure of expertise that was dichotomized at the median, we tested our results with (a) a continuous measure: when using the mean-centered continuous score of expertise as an independent variable (instead of a binary variable), the interaction of expertise on the effect of SubCS (versus BCS) is positive and marginally significant (b = .15, p = .083), and the effect of SubCS (versus BCS) is negative and significant (b = -.46, p = .034); and (b) a trichotomous measure: we divided the measure into 3 tiers and compared the individuals with an expertise score of 7 or above (N = 79, top 21.94%) with the ones who scored 3 or below (N = 129, bottom 35.83%). We then run our mediation analyses and we found that, in a similar way, for non-experts, the indirect effect of congruence is significant (indirect effect = -.353; CI: [-.677, -.061]), while it is not significant for experts (indirect effect = -.022; CI: [-.242, .528]).

Socio-demographic controls. Including the controls of age and/or gender changed neither the patterns nor the significance of the hypothesized effects.

Category status. We suspected that a possible source of variation in audience members' valuations could be their perceptions of the valence of each category. For instance, a person who positively appraises the category "microfinance" would potentially attribute a high valuation to subcategory-spanning firms that associate with microfinance and credit risk, regardless of whether they appreciate the form of subcategory spanning per se. To account for this explanation, we followed Sharkey (2014) by measuring category status. We asked participants to rate "How prestigious, respected, or esteemed do you think the following industries are?" (with possible answers ranging from 0 to 9). To build the variable of category status, we used the category status score in the BCM condition and the average of the two category status scores in the spanning conditions (SubCS or BCS). Including the category status variable changed neither the direction nor the significance of the hypothesized effects.

Another mechanism that might explain valuation differences across conditions could be differences in category status that would impact audience members' valuations (Zhao & Zhou, 2011). We thus measured the difference in status of the categories spanned and assigned a value of 0 in the BCM condition. Again, including this variable for status differences changed neither the direction nor the significance of the hypothesized effects.

Motivation. An alternative mechanism that could explain valuation differences is that non-experts may be less motivated and may put less effort into the valuation task. If this effect was not excluded, then it would confound the *ability* to process category spanning at basic and subordinate levels and the *motivation* to do so. To evaluate this possibility, we followed Lee and Arker (2004) and included the following four-part item to the end of the survey: "During the evaluation process, how involved were you while processing the information?" Participants were asked to indicate the extent to which they (a) were involved, (b) were interested, (c) had read it carefully, and (d) had paid a lot of attention (0 = not at all, 9 = very much). Controlling for motivation did not impact our findings. In sum, we can safely exclude the mechanism of motivation to perform the task.

Discussion of Study 2

The findings for Study 2 support for our hypotheses: SubCS firms receive lower valuations than BCS firms due to lower perceived congruence, and this effect is positively moderated by expertise. In contrast with experts, non-experts perceive SubCS firms as less congruent than BCS firms. A potential limitation of this study is that while our three conditions of category membership led to significantly different perceptions of commonness, as indicated in our manipulation checks, commonness was not captured by an objective measure. A more important limitation is that while Study 2 shows a positive correlation between our mediator (congruence) and our dependent variable (valuation), it does not fully show causality because the mediator was not manipulated (Pirlott & MacKinnon, 2016): Study 3's objective is to assess this causality.

STUDY 3

The objective of Study 3 was to test the causal effect of the mediation by using a manipulation-of-mediator design (Pirlott & MacKinnon, 2016; see also Jacoby & Sassenberg, 2011; Spencer, Zanna, & Fong, 2005). Specifically, we used a concurrent double-randomization design, which involves manipulating both the mediator and the independent variable (Pirlott & MacKinnon, 2016). We applied a treatment to congruence (*within-* versus *across-domain thinking*) that was likely to differentially influence the perceived congruence of BCS and SubCS firms and its effect on valuation.

Design and Sample

We used a 2 (category spanning: BCS, SubCS) × 2 (congruence: within-domain, across-domain) between-subjects design. The preregistration document is available at https://aspredicted.org/HNK_NYS. We recruited an online sample of U.S. participants on Prolific (Peer, Brandimarte, Samat, & Acquisti, 2017). Our goal was to collect 100 observations per condition, which is appropriate for mediation analysis with a desired power of 0.80 and an alpha of 0.05 when expecting small effect sizes (Fritz & McKinnon, 2007). Moreover, the post-hoc power analysis that we conducted in Study 2 confirmed that approximately 100 observations per cell should ensure sufficient statistical power. As in Study 2, we expected a failed attention check rate of approximately 20% (Aguinis et al., 2021); thus, we collected 480 observations (i.e., 4*100*1.2). After excluding participants who did not pass our IMCs, the final sample comprised 396 individuals. On average, participants were 42.48 years old (SD = 15.18) and 52.53% were women. The median duration of the experiment was 484 seconds.

Experimental manipulations

Participants were informed that the survey had two distinct parts: finding analogies and then evaluating a start-up company. Participants were randomly assigned first to an analogy-solving task (Goldwater & Jamrozik, 2019; Vendetti, Wu, & Holyoak, 2014) and second to a condition of category membership (either SubCS or BCS that are identical to those found in Study 2.)

Variables. We use the same variables of *valuation* and *perceived congruence* as well as *category membership* (BCS and SubCS) and *expertise* as in Study 2. Across all the conditions, valuation has a mean of 5.70 (SD = 1.80). Perceived congruence uses the same items as in Study 2 (Cronbach's alpha = 0.97) and it has a mean of 6.38 (SD = 1.64). Participants whose expertise scores were equal to or above the median (i.e., 5 out of 12 possible points) were classified as experts. Experts comprised 52.02% of the sample (n = 206) whereas non-experts comprised 47.98% of the sample (n = 190). Validity checks confirm that SubCS has a significantly lower perceived commonness than BCS (M_{subcs} = 5.72, SD = 1.90, n = 201; M_{bcs} = 6.19, SD = 1.99, n = 195; $t(394) = 2.42$, $p = .016$) and experts' subjective expertise in finance was significantly higher than that of non-experts (M_{exp} = 4.33, SD = 2.24, n = 206; $M_{non-exp}$ = 2.65, SD = 2.21, n = 190; $t(394) = -7.50$, $p < .001$).

Manipulated mediator*: *Congruence treatment. To manipulate perceived congruence, we built on recent research showing that when individuals are asked to cognitively bridge separate domains together, they are induced to rely on a relational thinking (Goldwater & Jamrozik, 2019; Vendetti et al., 2014). Relational thinking designates "inferential processes constrained by the relational roles that entities play rather than the specific features of those entities" (Gray & Holyoak 2020: 96). For instance, Vendetti and colleagues (2014) found that solving a series of across-domain analogies encouraged a relational thinking mindset, so that in a subsequent different experimental task, individuals were more likely to focus on relations between objects rather than on their features. In this study, in line with previous research, we reasoned that exposing individuals to an analogy-solving task would lead them to focus on how (sub)categories relate together rather than to focus on their specific features. In one condition, we encouraged participants to perceive congruence among subordinate categories within the same domain by asking them to solve analogies involving elements within the same domain. In the other condition, we encouraged participants to perceive congruence among basic categories (i.e., across different domains) by exposing them to analogies involving elements from two different domains.

Our congruence treatment consisted of asking participants to solve a series of eight verbal analogies. When reading "A is to B what C is to…", they were asked to find a possible solution "D." Participants were exposed either to a series of analogies *within* the same domain (e.g., "*Blindness* is to *sight* what *deafness* is to…?", with a possible correct answer being *hearing*) or to a series of analogies *across* different domains (e.g., "*Blindness* is to *sight* what *poverty* is to…?", with a possible correct answer being *money*). Participants were asked to write down the last term of the analogy. See Appendices 4a and 4b for more details on the procedure and materials we used for this treatment. This variable took a value of 1 if the participant was assigned to the *across-domain* condition and 0 if the participant was assigned to the *within-domain* condition.

We expected that participants who were asked to relate elements *across* different domains (*across-domain thinking*) would perceive BCS as more congruent and valuable than participants who were asked to relate elements *within* the same domain (*within-domain thinking*). Conversely, we expected participants subjected to *within-domain thinking* to perceive SubCS as more congruent and valuable than those subjected to *across-domain thinking.*

As a manipulation check, we tested the effect of our congruence treatment on our measure of perceived congruence (Pirlott & McKinnon, 2016). As expected, we found that participants exposed to *across-domain thinking* perceived a lower congruence in SubCS companies than those exposed to *within-domain thinking* (b = -.44, p = .056). However, congruence treatment does not affect significantly the perception of congruence when evaluating BCS companies (b = .04, p = .866).

Manipulated mediator and valuation. Our main test consists in analyzing the effect of the interaction between across-domain thinking (versus within-domain thinking) and SubCS (versus BCS) on valuation (Pirlott & McKinnon, 2016). A 2 (category membership: BCS, SubCS) x 2 (congruence treatment: within-domain, across-domain) factorial ANOVA indicates that the full model is significant ($F(3)$ = 4.76, p = .011). A linear regression shows that the interaction between SubCS (versus BCS) and across-domain thinking (versus within-domain thinking) is negative and statistically significant ($b_{subcs \times across}$ = -.98, p = .004)[11]. As Figure 6 shows graphically, our congruence treatment (within-domain versus across-domain thinking) significantly impacts the valuation of, respectively, SubCS and BCS firms.

- - - Insert Figure 6 about here- - -

A significant interaction between the main independent variable (category membership) and the manipulated mediation variable (congruence treatment) on the outcome of interest (valuation) provides evidence of the causal effect of our mediation variable on the outcome (Pirlott & McKinnon, 2016).

Supplementary analyses

Congruence treatment and mediation. As a supplementary analysis, we tested the mediation effect of perceived congruence on the relationship between our congruence treatment and valuation. We found that for SubCS companies, perceived congruence mediates the effect of

[11] This model includes the variables of age and perceived status of categories as controls. Without controls, results are robust (b = -.75, p = .039). Specifically, as expected, participants who were exposed to *across-domain* thinking provided significantly lower valuations of SubCS firms than participants who were exposed to *within-domain* thinking (b_{subcs} = -.66, p = .008). The valuation of BCS firms slightly increased under across-domain thinking relative to within-domain thinking, although the difference is not significant (b = .30, p = .178).

congruence treatment on valuation. When evaluating SubCS companies, participants exposed to *across-domain* thinking perceived lower congruence than those exposed to *within-domain* thinking (path a: = -.44, p = .056). In turn, perceived congruence is associated with higher valuation (path b = .44, p < .001). The direct effect of *across-domain* thinking on valuation (path c = -.66, p = .008) is alleviated when including perceived congruence as a covariate (path c' = -.46, p = .043), rendering the mediator marginally significant (indirect effect = -.193; CI: [-.424, .002]; 10,000 bootstrapped samples), as the confidence interval barely includes 0. In contrast, there is no significant mediation of perceived congruence when participants evaluate BCS companies. Figure 7 presents detailed findings.

- - - Insert Figure 7 about here- - -

***Congruence treatment, mediation and expertise*.** Results for Study 3 confirm that the mediation of congruence occurs at sub-level of classification but not at basic level. As per H3 and Study 2, we expected the effect of congruence to vary with expertise. As expertise increases, SubCS firms should be perceived as more congruent and more valuable when participants are exposed to within-domain thinking. Unreported findings show that for SubCS companies, perceived congruence mediates the effect of congruence treatment on valuation only for non-experts (path a = -.75, p = .037; path b = .43, p < .001; path c = -.52, p = .149; path c' = -.19, p = .563; indirect effect = -.325, CI: [-.726, -.029]). In contrast, there is no significant mediation of congruence for experts who evaluate SubCS companies (path a = -.17, p = .583; path b = .47, p < .001; path c = -.80, p = .026; path c' = -.72, p = .029; indirect effect = -.079, CI: [-.397, .188]). For non-experts evaluating SubCS companies, those exposed to across-domain thinking perceived subcategories as less congruent than those exposed to within-domain thinking. In turn, for both groups (experts and non-experts), perceived congruence significantly affected valuation.

Overall, the effect of congruence treatment on valuation occurs through the mediator variable (perceived congruence) for non-experts evaluating SubCS companies. This finding supports our hypothesis that the mediation of congruence varies with expertise. Unlike experts, non-experts penalize category-spanning at a nested level because they perceive low congruence among subcategories.

Discussion of Study 3

We found that manipulating perceptions of congruence with a treatment (within- versus across-domain thinking) impacts the valuation of SubCS companies, thereby providing evidence of the causal effect of the mediation (see Figure 6). Perceived congruence explains why category-spanning firms receive different valuations at the basic versus subordinate category levels. Additionally, as expected, the effect of the congruence treatment varies with audience members' expertise. We found that when non-experts evaluate SubCS companies, across-domain thinking leads to lower valuations than within-domain thinking, and that this effect occurs through perceived congruence. This finding is interesting, because it shows that whereas non-experts tend to devalue subcategory-spanning (Studies 1 and 2), a treatment that enhances perceived congruence is likely to change this trend. Enhancing within-domain relational thinking increases the non-experts' valuation of SubCS firms.

GENERAL DISCUSSION

In a series of three studies, we have examined whether category spanning leads to favorable valuations from investors when accounting for category nesting and investors' expertise. Adopting an information processing perspective, we expected a valuation penalty of category spanning at a subordinate level compared to spanning at a basic level. Moreover, we expected valuation penalties applied by non-experts to be higher than those applied by experts, because expertise should lead individuals to perceive higher congruence in subcategory spanning.

Overall, our results support this theory with some nuances.

Using mixed methods, across our three studies (see Table 1 for a summary), we found that subcategory spanners receive lower valuations than basic category spanners, but that this effect is alleviated as investors' expertise increases (Studies 1 and 2). Our results explain these effects by showing that subcategory spanning is perceived as less congruent than basic spanning by non-experts (Study 2) and that perceived congruence causally predicts higher valuations (Study 3). This paper makes three important contributions to management and organization studies.

Contributions

Conformity, valuation, and optimal distinctiveness. First, at a macro level, we contribute to research on conformity in markets, and in particular, to the question of optimal distinctiveness (Taeuscher, Bouncken, & Pesch, 2020; Zhao et al., 2017). A baseline tenet in management and organization studies is that organizations that stick to audiences' expectations fare better than those that deviate –since too large is deviation in negatively sanctioned. Yet, a host of studies argued and found that market players are more highly valued when paradoxically enough, they are both similar and different from their competitors. For instance, organizations may have a moderate level of differentiation on a given strategic axis (Deephouse, 1999) or by combining two or more dimensions of differentiation and conformity (Durand et al., 2007; Barlow, Verhaal, & Angus, 2019; Taeuscher et al., 2020; Bu, Zhao, Li & Li, 2022). Strict conformity may not accrue organizations the best returns as some degrees of differentiation allow them to reach an optimal distinctiveness (Zhao et al., 2017).

However, as Zhao and colleagues (2017: 103) express it "[a] firm's optimal distinctiveness rests on a constant interplay between managerial agency and stakeholder evaluation. This requires that managers explore and adapt to differences in evaluative frameworks across *different types of stakeholders*, and understand the malleable nature of their resources and capabilities under heterogeneous stakeholder expectations". Because organizations use categories to strategically position themselves in the market (Granqvist, Grodal, & Wooley, 2013; Pontikes, 2018), they may be willing to differentiate by playing with the degrees of specificity and distinctiveness that categorical nesting allows. Again, at deeper levels of nesting, the degree of specificity of categorical cues is higher and the level of distinctiveness is lower. From our results, organizations that self-categorize at a subordinate level and speak to an expert audience obtain higher valuations —while such positioning is discarded by a non-expert audience. Hence, modulating the level of category nesting is a way to seek differentiation while conforming to audience members' (e.g., investors') expectations.

Our findings thus contribute to scholarly work on organizational conformity and its benefits. More precisely, this paper enriches prior studies at the intersection of optimal distinctiveness and audience diversity (Fisher, 2020; Zhao et al., 2017) by offering a nuanced understanding of why more or less expert audiences see more or less positively impure (category) members, that is organizations that span categories at lower or upper levels of (industry) classifications.

Categorization and Information processing. Second, our approach tackles the categorization-valuation relationship building on an information processing perspective (Zacharakis, 2010). Beyond the classical chain linking reception, identification, and interpretation of (categorical) cues, we show that congruence between the categorical memberships that spanners display is the mechanism that leads to their higher valuation. However, the perceived congruence is on average lower at deeper levels of nesting, namely when a firm combines sub- (vs. basic) categories. Therefore, our paper provides evidence of the cognitive effort implied by the processing of disparate or congruent information displayed by category spanners and of its consequences on valuation. Information cues pose various challenges to valuators, particularly investors, depending on which categories are elicited and their nesting levels. Not only some combinations are more congruent than others at each (upper or lower) level of a category system but also not all audience members possess the same capabilities to appreciate the specificity and distinctiveness of the different categorical cues that a given spanner combines. Our paper provides evidence of both elements.

Therefore, categories have distinct informational content (e.g., specificity, distinctiveness), which market audiences, such as investors, interpret (Zacharakis, 2010). While the literature on market categories has studied the effect of important categorical attributes, such as contrast (Hannan et al., 2007), leniency (Pontikes, 2012) or distance (Kovács & Hannan, 2015), our paper responds to the call to examine how audience members heterogeneously make sense (or not) of informational cues (Durand, Granqvist, & Tyllstrom, 2017). Taking an information processing perspective allows researchers to systematically look conjointly at both sides of the market — producers (senders of informational cues) and audiences (receivers and valuators).

Moreover, our findings recalibrate the excessive emphasis on the supposed benefits earned by purist organizations. In the past, observing only one layer of category membership enabled researchers to discriminate between basic category membership and basic category spanning. For a host of these studies, the valuation of category membership relied on congruence expressed as an evaluation of similarity to pre-existing types (e.g., Hsu et al., 2009). Adopting an information processing approach, we have compared spanning at two levels of nesting and considered congruence as a meaningful correspondence among categorical cues across categories. This nuanced understanding of nesting and congruence helps revisit well-established findings about the benefits of (categorical) purism. Indeed, prior results on the benefits of pure categorical membership may have been inadvertently inflated because subcategory spanners may have been incorrectly classified as pure members of a higher-level category.

Expertise and valuation. We have made a third contribution by documenting how and why audience expertise plays a crucial role by modulating the extent of penalty for category spanners at both the subordinate and basic levels of category nesting. We have provided evidence that expertise impacts the valuation of category spanning differently depending on the level of category nesting: as investors' expertise increases, they find subordinate category spanning to be more congruent (Althuizen & Sgourev, 2014; Moreau et al., 2001). In what can be described as a magnifying glass effect, experts discern and use information about subcategories within their domain of expertise to render minor distinctions visible and congruent. As such, our findings address a debated problem in the literature on organizational valuation—that is, the conditions under which expertise leads to audience members rewarding (or conversely, penalizing) deviations from pre-existing categorical standards (Boudreau et al., 2016; Boulongne et al., 2019; Falchetti et al., 2021), a problem that has resulted in "mixed results" to this date (Zhou, Wang, Bavato, Tasselli, & Wu, 2019; see also Oreg & Goldenberg, 2015). Our findings suggest that experts are keener than non-experts to accept categorical deviations within their domain of knowledge, whereas experts do not see more congruence when evaluating categorical combinations that transverse different higher-level domains.

Practical Implications. We believe that our findings are relevant for practitioners. From our results, it appears that identifying with subcategories could be a rewarding strategy, but only if entrepreneurs speak to the right investors. Organizations, especially the younger ones, need to persuade investors to acquire resources and survive (Falchetti et al., 2021; Fisher, 2020). Yet, finding the right investors is an uncertain matching process (Claes & Vissa, 2020; Gompers et al. 2020). Showing distinctiveness goes hand-in-hand with combining categories (Hargadon &

Douglas 2001, Rao et al. 2005). What our paper shows it that a category-spanning organization should ensure that its target audiences find its combination of informational cues congruent. While market positioning is often viewed as a matter of distinction from categorical peers, this view is incomplete if one ignores audience members' expertise (Zuckerman, 2016; Durand et al., 2017; Boulongne et al., 2020). Practitioners that elaborate differentiation strategies should thus pay attention not only to the market structure and category nesting but also to their audiences' degree of expertise to maximize their valuation.

Limitations and Opportunities for Future Research

Our research has some limitations that open opportunities for future research. First, the layered structure of the industrial categories is simple. Because more category combinations are possible, replication is needed to test whether our findings hold when considering more complex category nesting associations and cue combinations. For instance, our experimental investigation does not account for spanning that occurs across subordinate categories that belong to *different* basic categories. Furthermore, categories vary in their degree of institutionalization and saliency over time (Ruef & Patterson, 2009). Paying attention to category nesting is even more important in this context because nascent categories are likely to emerge as subcategory. We leave this question for scholars to answer in future research.

Second, another fruitful area for further research would be to investigate whether our theory and empirical findings hold when accounting for highly normative categorical boundaries (Arjaliès & Durand, 2019, Douglas, 1966). Combining categories that lack congruence on moral and normative grounds may trigger sanctions (Ody-Brasier & Vermeulen, 2014, Phillips, Turco, & Zuckerman, 2013), but perhaps only from certain audiences' segments. For instance, expertise may be associated with higher interests and stakes in knowing and maintaining categorical boundaries (Coslor et al., 2020), which might impact the willingness of sanctioning category-spanning on moral and normative grounds.

Third, we focused on a particular type of audience: VC investors. However, entrepreneurs face other relevant audiences that are decisive for acquiring material or immaterial resources. For instance, entrepreneurs need to pitch their identities to the general public and consumers, crowdfunding users, generalist media, legal bodies, and so forth (Fisher, 2020; Martens, Jennings, & Jennings, 2007). In future research, scholars could examine other types of audiences that vary in expertise and how they perceive and value categorical combinations.

Another limitation exists regarding our measures of expertise. While our controlled experiments use an objective measure of expertise, future experimental research could either better ensure the exogeneity of this variable by comparing samples of “real-life” experts or by directly manipulating the level of expertise. Alternative mechanisms to expertise could also be further investigated. For instance, interest, conscientiousness, or intelligence may moderate the association between category spanning and audience’s valuation. Note also that factors complementary to congruence deserve further scrutiny such as flexibility or framing. For instance, experts demonstrate flexibility in activating different categorization processes (Boulongne & Durand, 2021) and find novel ideas more attractive when they are framed in concrete “how” terms, whereas non-experts prefer abstract “why” terms that emphasize broader objectives of the solution (Falchetti et al., 2021).

Finally, it is worth noting that our paper does not assume that, nor does it investigate whether experts make *better* decisions than non-experts. A large stream of research has focused on how expertise increases or decreases decision-making biases and performance (e.g.: Ericsson Charness, Feltovich, & Hoffman, 2006). An interesting area of further research could involve looking at whether more expert investors are making the most optimal choice in valuing (sub-) category-spanning firms.

Conclusion

In conclusion, our findings emphasize the importance of valuators' information processing abilities and capacity to find congruent informational cues proceeding from firms that span different categories at different levels of nesting. We invite a re-examination of existing evidence about firm valuation based on the assumption that spanning does not differ across category nesting levels or the degree of audience members' expertise. Our findings invite consideration of category membership as a tool for achieving both conformity and distinctiveness through the congruence of informational cues. Deviance, hybridity, or unconventionality as spanning cases need not be penalized –neither is organizational conformity a simple similarity attribute-ticking exercise. Hence, our paper paves the way for future studies on the influence of a category system's structure and audience members' heterogeneous abilities on firm valuations in markets.

REFERENCES

Aguinis, H., Villamor, I., & Ramani, R. S. 2021. MTurk research: Review and recommendations. ***Journal of Management***, 47(4): 823–837

Althuizen, N., & Sgourev S. 2014. Pièces de résistance? Core and casual consumers' Valuations of aesthetically incongruent artworks. ***Psychology & Marketing***, 31(8): 604–614

Arjaliès, D.-L., & Durand, R. 2019. Product categories as judgment devices: The moral awakening of the investment industry. ***Organization Science***, 30(5): 869-1123

Barlow M. A., Verhaal J. C., & Angus R. 2019. Optimal distinctiveness, strategic categorization, and product market entry on the Google Play app platform. ***Strategic Management Journal***, 40: 1219-1242

Bilalić, M., McLeod, P., & Gobet, F. 2008. Inflexibility of experts-Reality or myth? Quantifying the Einstellung effect in chess masters. ***Cognitive Psychology***, 56(2):73–102.

Boghossian D., & David R. J. 2021. Under the umbrella: Goal-derived category construction and product category nesting. ***Administrative Science Quarterly***, 66(4): 1084–1129

Boudreau, K. J., Guinan, E. C., Lakhani, K. R., & Riedl, C. 2016. Looking across and looking beyond the knowledge frontier: Intellectual distance, novelty, and resource allocation in science. ***Management Science,*** 62(10): 2765–2783.

Boulongne, R., Cudennec, A., & Durand, R. 2019. When do market intermediaries sanction categorial deviation? The role of expertise, identity and competition. ***Research in the Sociology of Organizations. Eds. Haack P., Sieweke J. and Wessel L. Issue on the "Microfoundations of Institutions"*** 65(A): 67-84

Bu, J., Zhao E.Y., Li K., & Li, J. 2021. Multilevel optimal distinctiveness: Examining the impact of within- and between-organization distinctiveness of product design on market performance. ***Strategic Management Journal***, Forthcoming.

Carlson, J. P., Vincent, L. H., Hardesty, D. M., & Bearden, W. O. 2009. Objective and subjective knowledge relationships: A quantitative analysis of consumer research findings. ***Journal of Consumer Research***, 35(5): 864–876.

Cattani, G., Porac, J. F., & Thomas, H. 2017. Categories and competition. ***Strategic Management Journal***, 38: 64–92.

Certo, S. T., Busenbark, J. R., Woo, H. S., & Semadeni, M. 2016. Sample selection bias and Heckman models in strategic management research. ***Strategic Management Journal***, 37: 2639–2657.

Claes K., & Vissa B. 2020. Does social similarity pay off? Homophily and venture capitalists' deal valuation, downside risk protection, and financial returns in India. ***Organization Science***, 31(3): 576–603

Coslor, E., Crawford, B., & Leyshon, A. 2020. Collectors, investors and speculators: gatekeeper use of audience categories in the art market. ***Organization Studies***, 41(7): 921–943

Cowley, E. & Mitchell, A.A. 2003. The moderating effect of product knowledge on the learning and organization of product information. ***Journal of Consumer Research***, 30: 443-454

Dandurand F., Shultz T. R., & Onishi K. H. 2008. Comparing online and lab methods in a problem-solving experiment. ***Behavior Research Methods***, 40: 428–434

Dane, E. 2010. Reconsidering the trade-off between expertise and flexibility: A cognitive entrenchment perspective. ***Academy of Management Review***, 35(4): 579–603.

Deephouse, D. L. 1999. To be different, or to be the same? It's a question (and theory) of strategic balance. ***Strategic Management Journal***, 20(2): 147-166.

Douglas, M. 1966. ***Purity and Danger: An analysis of concepts of pollution and taboo***. London: Routledge & Kegan Paul.

Durand, R., & Paolella, L. 2013. Category stretching: Reorienting research on categories in strategy, entrepreneurship, and organization theory. ***Journal of Management Studies***, 50(6): 1100–1123.

Durand, R., Rao H., & Monin, P. 2007. Code and conduct in French cuisine: Impact of code changes on external evaluations. ***Strategic Management Journal***, 28: 455-472

Durand R, Granqvist N, & Tyllstrom A. 2017. From categories to categorization: A social perspective on market categorization in ***"Categories, Categorization and Categorizing: Category Studies in Sociology, Organizations and Strategy at the Crossroads", Research in the Sociology of Organizations***, Emerald Publishing Limited, Volume 51: 1-30

Ericsson, K. A., Charness, N., Feltovich, P., & Hoffman, R. R. 2006. ***The Cambridge handbook of expertise and expert performance.*** Cambridge: Cambridge University Press.

Falchetti D., Cattani G., & Ferriani S. 2021. Start with "Why", but only if you have to: The strategic framing of novel ideas across different audiences. ***Strategic Management Journal***. Forthcoming.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. 2007. G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. ***Behavior Research Methods***, 39: 175-191.

Fleck N., & Quester P. 2007. Birds of a feather flock together... Definition, role and measure of congruence: an application to sponsorship, ***Psychology and Marketing***, 24(11): 975–1000.

Fisher, G. 2020. The complexities of new venture legitimacy. ***Organization Theory***,1(2): 1–25

Gehman, J., & Grimes, M. 2017. Hidden badge of honor: How contextual distinctiveness affects category promotion Among certified B Corporations. ***Academy of Management Journal***, 60: 2294–2320.

Glynn, M. A., & Navis, C. 2013. Categories, identities, and cultural classification: Moving beyond a model of categorical constraint. ***Journal of Management Studies***, 50(6): 1124–1137.

Goldberg, A., Hannan, M. T., & Kovács, B. 2016. What does it mean to span cultural boundaries? Variety and atypicality in cultural consumption. ***American Sociological Review***, 81(2): 215–241.

Goldwater, M.B., & Jamrozik, A. 2019. Can a relational mindset boost analogical retrieval? ***Cognitive Research: Principles and Implications***. 4(47): 1–16.

Gompers, P., Kovner, A., & Lerner, J. 2009. Specialization and success: Evidence from venture capital. ***Journal of Economics and Management Strategy***, 18(3): 817–844.

Gompers P. A., Gornall W., Kaplan S. N., & Strebulaev I. A. 2020. How do venture capitalists make decisions? ***Journal of Financial Economics,*** 135(1): 169–190

Granqvist, N., Grodal, S., & Woolley, J. L. 2013. Hedging your bets: Explaining executives' market labelling strategies in nanotechnology. ***Organization Science***, 24(2): 395–413.

Grayl, M. E. & Holyoak, K. J. 2020. Individual differences in relational reasoning. ***Memory & Cognition***, 48: 96–110

Green, A. E., Kraemer, D. J. M., Fugelsang, J. A., Gray, J. R., & Dunbar, K. N. 2010. Connecting long distance: Semantic distance in analogical reasoning modulates frontopolar cortex activity. ***Cerebral Cortex***, 10: 70-76.

Hannan, M. T. 2010. Partiality of memberships in categories and audiences. ***Annual Review of Sociology***, 36: 159–181.

Hannan, M. T., Pólos, L., & Carroll, G. R. 2007. ***Logics of Organization Theory***, Princeton University Press.

Hannan, M.T, Le Mens G. L., Hsu G., Kovács B., Negro G., Pólos L., Pontikes E., & Sharkey A. J. 2019. ***Concepts and Categories. Foundations for Sociological and Cultural Analysis***. Columbia University Press

Hargadon, A. B., & Douglas, W. 2001. When innovations meet institutions: Edison and the design of the electric light. ***Administrative Science Quarterly***. 46(3): 476–501.

Hayes, A. F. 2017***. Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach, 2nd ed.*** The Guilford Press, New York.

Hochberg Y. V., Mazzeo M. J., & McDevitt R. C. 2015. Specialization and competition in the venture capital industry, ***Review of Industrial Organization*** 46: 323-347.

Hsu, D. H. 2007. Experienced entrepreneurial founders, organizational capital, and venture capital funding. ***Research Policy***, 36(5): 722–741.

Hsu, G., Koçak, Ö., & Hannan, M. T. 2009. Multiple category memberships in markets: An integrative theory and two empirical tests. ***American Sociological Review***, 74(1):150-69.

Jacoby J, & Sassenberg K. 2011. Interactions not only tell us when, but can also tell us how: Testing process hypotheses by interaction. ***European Journal of Social Psychology***. 41(2): 180–190.

Johnson, K. E. 2013. Culture, expertise, and mental categories. ***In D. Reisberg (Ed.), The***

Oxford handbook of cognitive psychology, 330–345. Oxford: Oxford University press.

Johnson, K. E., & Mervis, C. B. 1997. Effects of varying levels of expertise on the basic level of categorization. ***Journal of Experimental Psychology: General***. 126(3): 248–277.

Joseph J., & Gaba V. 2020. Organizational structure, information processing, and decision-making: A retrospective and road map for research. ***Academy of Management Annals***. 14(1): 267–302.

Kennedy, M. T., Lo, Y.-C., & Lounsbury, M. 2010. Category currency: The changing value of conformity as a function of ongoing meaning construction. ***Hsu G, Negro G, Koçak Ö, eds. Categories in Markets: Origins and Evolution, Research in the Sociology of Organizations***, 31: 369–397.

Kim J. S., Hahn M., & Yoon Y. 2015. The moderating role of personal need for structure on the evaluation of incrementally new products versus really new products. ***Psychology and Marketing***, 32(2): 144–161.

Kovács, B., & Hannan, M. T. 2015. Conceptual spaces and the consequences of category spanning. ***Sociological Science***, 2: 252–286.

Lee A.Y. & J.L. Aaker 2004. Bringing the Frame Into Focus: The Influence of Regulatory Fit on Processing Fluency and Persuasion. ***Journal of Personality and Social Psychology***, Vol. 86, No. 2, 205–218

Lee M., Adbi A., & Singh J. 2019. Categorical cognition and outcome efficiency in impact investing decisions. ***Strategic Management Journal***, 41(1): 86–107.

Leung, M. D., & Sharkey, A. J. 2014. Out of sight, out of mind? Evidence of perceptual factors in the multiple- category discount. ***Organization Science***, 25(1): 171–184.

Lewandowsky, S., Little, D., & Kalish, M. L. 2007. Knowledge and expertise. In F. T. Durso (Ed.), ***Handbook of applied cognition*** (2nd ed.): 83–109. Chichester, UK: Wiley.

MacKinnon D. P, & Pirlott A. G. 2015. Statistical approaches for enhancing causal interpretation of the M to Y relation in mediation analysis. ***Personality and Social Psychology Review***. 19(1): 30–43.

Mannucci, P. V., & Yong, K. 2018. The differential impact of knowledge depth and knowledge breadth on creativity over individual careers. ***Academy of Management Journal***, 61(5): 1741–1763.

Martens, M. L., Jennings, J. E., & Jennings, P. D. 2007. Do the stories they tell get them the money they need? The role of entrepreneurial narratives in resource acquisition. ***Academy of Management Journal***, 50(5): 1107–1132.

Medin, D. L., Lynch E. B., Coley J. D., & Atran S. 1997. Categorization and reasoning among tree experts: Do all roads lead to Rome? ***Cognitive Psychology***, 32(1): 49–96.

Meyers-Levy, J., & Tybout, A.M. 1989. Schema congruity as a basis for product evaluation. ***Journal of Consumer Research***, 16(1): 39–54.

Mitchell, A. A. & Dacin P. A. 1996. The assessment of alternative measures of consumer expertise. ***Joumal of Consumer Research***, 23: 219-39.

Moreau, C. P., Lehmann, D. R., & Markman, A. B. 2001. Entrenched knowledge structures and consumer response to new products. ***Journal of Marketing***, 38: 14–29.

Mount, M. P., Baer, M., & Lupoli, M. J. 2021. Quantum leaps or baby steps? Expertise distance, construal level, and the propensity to invest in novel technological ideas ***Strategic Management Journal***, 42(8): 1490—1515.

Murphy, G. L., & Brownell, H. H. 1985. Category differentiation in object recognition: Typicality constraints on the basic category advantage. ***Journal of Experimental***

Psychology: Learning, Memory and Cognition, 11(1): 70-84.
Murphy, G. L., & Lassaline, M. E. 1997. Hierarchical structure in concepts and the basic level of categorization. ***In: K. Lamberts & D. Shanks (Eds), Knowledge, concepts and categories***: 93–131. London: UCL Press.
Murphy, G. L., & Wright, J. C. 1984. Changes in conceptual structure with expertise: Differences between real-world experts and novices. ***Journal of Experimental Psychology: Learning, Memory, and Cognition***, 10(1): 144–155.
Nahata R., 2008. Venture capital reputation and investment performance. ***Journal of Financial Economics***, 90(2): 127–151.
Negro, G., & Leung, M. D. 2013. "Actual" and perceptual effects of category spanning. ***Organization Science,*** 24(3): 684–696.
Ody-Brasier, A., & Vermeulen, F. 2014. The price you pay: price-setting as a response to norm violation in the market for Champagne grapes. ***Administrative Science Quarterly***, 59(1): 109–144.
Oreg S., & J. Goldenberg. 2015. ***Resistance to innovation: Its sources and manifestations***. Chicago, IL: The University of Chicago Press.
Paolella L., & Durand R. 2016. Category spanning, evaluation, and performance: Revised theory and test on the corporate law market. ***Academy of Management Journal***, 59(1): 330–351.
Park, C. W., Mothersbaugh, D. L., & Feick, L. 1994. Consumer knowledge assessment. ***Journal of Consumer Research***, 21(1): 71–82.
Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. 2017. Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. ***Journal of Experimental Social Psychology***, 70: 153–163.
Phillips, D. J., Turco, C. J., & Zuckerman, E. W. 2013. Betrayal as market barrier: Identity-based limits to diversification among high-status corporate law firms. ***American Journal of Sociology,*** 118(4): 1023–54.
Pirlott, A. G., & MacKinnon, D. P. 2016. Design approaches to experimental mediation. ***Journal of Experimental Social Psychology***, 66: 29–38.
Pontikes, E. G. 2012. Two sides of the same coin: How ambiguous classification affects multiple audiences' evaluations. ***Administrative Science Quarterly***, 57(1): 81–118.
Pontikes, E. G. 2018. Category strategy for firm advantage. ***Strategy Science***, 3: 620–631
Rao, H., Monin, P., & Durand, R. 2005. Border crossing: Bricolage and the erosion of categorical boundaries in French gastronomy. ***American Sociological Review***, 70(6): 968–991.
Rifon, N. J., Choi, S. M., Trimble, C., & Li, H. 2004. Congruence effects in sponsorship: The mediating role of sponsor credibility and consumer attributions of sponsor motive. ***Journal of Advertising***, 33(1): 29–42.
Rindova, V. P., & Petkova, A. P. 2007. When is a new thing a good thing? Technological change, product form design, and perceptions of value for product innovations. ***Organization Science***, 18(2): 217–232
Rosch, E. 1978. Principles of categorization. ***In Rosch E., & Lloyd B. B. Eds Cognition and categorization***: 28-49, London: Palgrave Macmillan UK.
Rosch, E., & Mervis, C. B. 1975. Family resemblances: Studies in the internal structure of categories. ***Cognitive Psychology***, 7(4): 573–605.
Rosch, E., Mervis, C. B., Gray, W., Johnson, D., & Boyes-Braem, P. 1976. Basic objects in natural categories. ***Cognitive Psychology***, 8(3): 382–439

Ruef, M., & Patterson, K. 2009. Credit and classification: The impact of industry boundaries in nineteenth-century America. ***Administrative Science Quarterly***, 54, 486-520.

Sharkey, A. J. 2014. Categories and organizational status: The role of industry status in the response to organizational deviance. ***American Journal of Sociology*** 119: 1380–1433.

Schneiberg, M., & Berk, G. 2010. From categorical imperative to learning by categories: Cost accounting and new categorical practices in American manufacturing, 1900–1930. ***Categories in Markets: Origins and Evolution. Research in the Sociology of Organizations***, Vol. 31 (Emerald Group Publishing, Ltd., Bingley, UK), 255–292.

Sharkey, A. J. 2014. Categories and organizational status: The role of industry status in the response to organizational deviance. ***American Journal of Sociology*** 119: 1380–1433.

Simon, H. A. 1955. A behavioral model of rational choice. ***The Quarterly Journal of Economics***, 69(1): 99–118.

Sorensen, M. 2007. How smart is smart money? A two-sided matching model of venture capital. ***Journal of Finance***, 62(6): 2725–2762.

Spencer, S. J., Zanna, M. P., & Fong, G. T. 2005. Establishing a causal chain: Why experiments are often more effective than mediational analyses in examining psychological processes. ***Journal of Personality and Social Psychology***. 89: 845–851.

Taeuscher, K., Bouncken, R. B., & Pesch, R. 2020. Gaining legitimacy by being different: Optimal distinctiveness in crowdfunding platforms. ***Academy of Management Journal***, 61(1): 149–179.

Tanaka, J.W., & Taylor, M. 1991. Object categories and expertise: Is the basic level in the eye of the beholder? ***Cognitive Psychology***, 23(3): 457–482.

Turner K. L. & Makhija M.V. 2012. The role of individuals in the information processing perspective. ***Strategic Management Journal***. 33(6): 661–680.

Vaghely I.P., & Julien P.-A. 2010. Are opportunities recognized or constructed? An information perspective on entrepreneurial opportunity identification. ***Journal of Business Venturing*** 25(1): 73–86.

Van Rompay T., & Pruyn. A. 2011. When visual product features speak the same language: Effects of shape-typeface congruence on brand perception and price expectations. ***Journal of product innovation management***, 28 (4): 599-610.

Vendetti, M. S., Wu, A., & Holyoak, K. J. 2014. Far-out thinking: Generating solutions to distant analogies promotes relational thinking. ***Psychological Science***, 25(4): 928-933.

Vergne, J.-P., & Wry, T. 2014. Categorizing categorization research: Review, integration, and future directions. ***Journal of Management Studies***, 51(1), 56–94.

Vergne, J.-P. 2012. Stigmatized categories and public disapproval of organizations: a mixed-methods study of the global arms industry 1996-2007. ***Academy of Management Journal***, 55(5): 1027–1052.

Wallace, L. E., Patton, K. M., Luttrell, A., Sawicki, V., Fabrigar, L. R., Teeny, J., … & Wegener, D. T. 2020. Perceived knowledge moderates the relation between subjective ambivalence and the "impact" of attitudes: An attitude strength perspective. ***Personality and Social Psychology Bulletin***, 46(5): 709–722.

Wolfolds S. E., & Siegel J. 2019. Misaccounting for endogeneity: The peril of relying on the Heckman two-step method without a valid instrument. ***Strategic Management Journal***. 40(3): 432–462.

Wood, M. S., & Williams, D. W. 2014. Opportunity evaluation as rule-based decision making. ***Journal of Management Studies***, 51(4): 573–602.

Wry, T., & Durand R. 2020. Reasoning with heuristics: a new approach to categories theory and the evaluation of hybrids, in ***M.L. Besharov and B.C. Mitzineck (eds.), Organizational hybridity: Perspectives, processes, promises***, 69: 73–91. London: Emerald Publishing.

Wry, T., & Lounsbury, M. 2013. Contextualizing the categorical imperative: Category linkages, technology focus, and resource acquisition in nanotechnology entrepreneurship. ***Journal of Business Venturing***, 28(1): 117–133.

Wry, T., Lounsbury, M., & Jennings, P. D. 2014. Hybrid vigor: Securing venture capital by spanning categories in nanotechnology. ***Academy of Management Journal***, 57(5): 1309–1333.

Wyer R. S. 2012. The role of knowledge accessibility in cognition and behavior implications for consumer information processing. ***Handbook of consumer psychology / edited by Curtis P. Haugtvedt, Paul M. Herr and Frank R. Kardes.***

Younkin, P., & Kashkooli, K. 2020. Stay true to your roots? Category distance, hierarchy, and the performance of new entrants in the music industry. ***Organization Science***, 31(3): 604–627.

Zacharakis A. 2010. Venture capitalists decision making. An information processing perspective. ***In Douglas J. Cumming. Venture Capital: Investment Strategies, Structures, and Policie***s, John Wiley & Sons, Inc.

Zhao W., & Zhou X. 2011. Status inconsistency and product valuation in the California wine market. ***Organization Science***, 22(6): 1435–1448

Zhao, E. Y., Fisher, G., Lounsbury, M., & Miller, D. 2017. Optimal distinctiveness: Broadening the interface between institutional theory and strategic management. ***Strategic Management Journal,*** 38(1): 93–113.

Zhelyazkov P. I., & Tatarynowicz A. 2020. Marriage of Unequals? Investment quality heterogeneity, market heat, and the formation of status-asymmetric ties in the venture capital industry. ***Academy of Management Journal***, 64(2): 509–536.

Zhou, J., Wang, X. M., Bavato, D., Tasselli, S., & Wu, J. 2019. Understanding the receiving side of creativity: A multidisciplinary review and implications for management research. ***Journal of Management***, 45(6): 2570–2595.

Zuckerman, E. W. 2016. Optimal distinctiveness revisited: An integrative framework for understanding the balance between differentiation and conformity in individual and organizational identities. ***In Pratt M. G., Schultz M., Ashforth B. E., & Ravasi D. (Eds), The Oxford Handbook of Organizational Identity***, 183-199. Oxford, UK

Zunino D., Dushnitsky G., & van Praag M. 2021. How do investors evaluate past entrepreneurial failure? Unpacking failure due to lack of skill versus bad luck. ***Academy of Management Journal***. Forthcoming.

TABLE 1: Summary of Studies

	Method & Sample	Conditions	Main Results
Study 1	**Observational** 29,033 VC deals <u>Scope</u> - Cross industries - Finance and IT	Category membership: SubCS, BCS, BCM Expertise (continuous)	*SubCS* companies have a lower valuation than *BCS* (**H1 supported**). *Investor's expertise* positively moderates the effect of SubCS (versus BCS) on valuation (**H3 supported**). Effects are replicated for companies in Finance and IT (consistently with the following experiments).
Study 2	**Experimental** 307 undergraduate students <u>Scope</u> - Finance and IT **Pre-registered**	Treatment of category membership: SubCS, BCS, BCM Measure of expertise: non-experts, experts	<u>Replication with causal test</u> *SubCS* companies have a lower valuation than *BCS* (**H1 supported**). *Investor's expertise* positively moderates the effect of SubCS (versus BCS) on valuation (**H3 supported**). <u>Mediation analyses</u> Congruence mediates the effects of SubCS (v. BCS) on valuation but only for the non-experts (**H2** partially supported, **H3**)
Study 3	**Experimental** 396 online participants (Prolific) <u>Scope</u> - Finance and IT **Pre-registered**	Treatment of category membership: SubCS, BCS Treatment of congruence: within- versus across-domain thinking	<u>Causal test of mediation: manipulation-of-mediation design</u> As expected, *SubCS* companies have a higher valuation under the *congruence treatment* for SubCS (*within-domain* thinking). *(Perceived) congruence* mediates the effect of the *congruence treatment* (*within-domain* thinking) on the valuation of SubCS companies. In sum, *(perceived) congruence* is a mediator that causally impacts the outcome of interest (valuation).

Note: SubCS = subordinate category spanning, BCS = basic category spanning, BCM = basic category membership

TABLE 2 Summary and Correlation Tables (Study 1)

		Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	**Valuation**	16.53	1.54	7.48	25.46	1.00													
2	**Subordinate Category Spanning (SubCS)**	0.31	0.46	0.00	1.00	0.00	1.00												
3	**Basic Category Spanning (BCS)**	0.46	0.50	0.00	1.00	0.01	-0.62	1.00											
4	**Basic Category Membership (BCM)**	0.23	0.42	0.00	1.00	-0.01	-0.36	-0.51	1.00										
5	**Investor expertise**	2.23	1.62	0.00	6.57	0.16	0.20	-0.21	0.03	1.00									
6	**Investor general experience**	3.44	1.62	0.00	7.26	0.18	-0.05	0.04	0.00	0.56	1.00								
7	**Investor reputation**	0.00	0.02	0.00	0.25	0.14	0.00	-0.01	0.01	0.26	0.35	1.00							
8	**Syndicate size**	1.06	0.76	0.00	4.41	0.29	0.01	0.02	-0.03	0.22	0.26	0.08	1.00						
9	**Competitive intensity**	3.77	1.50	0.00	5.88	0.10	0.25	-0.22	-0.01	0.56	0.00	0.02	0.13	1.00					
10	**Category heat**	0.86	0.36	0.02	1.92	0.05	0.00	0.08	-0.09	-0.01	0.05	0.00	0.09	-0.01	1.00				
11	**Stage (1:Seed, 2:Early, 3:Late)**	2.19	0.65	1.00	3.00	0.50	0.01	-0.04	0.03	0.00	0.05	0.06	0.05	-0.07	-0.07	1.00			
12	**Round number**	2.90	1.99	1.00	29.00	0.48	0.00	0.02	-0.02	0.05	0.06	0.02	0.18	0.03	0.10	0.53	1.00		
13	**Slices**	1.13	0.92	0.00	7.00	0.08	0.03	0.10	-0.14	0.08	0.01	0.01	0.08	0.17	0.08	-0.03	0.06	1.00	
14	**Residual category**	0.05	0.22	0.00	1.00	-0.02	-0.14	0.21	-0.10	-0.11	-0.01	-0.02	-0.02	-0.15	0.04	-0.02	0.00	-0.02	1.00

TABLE 3 Category Membership, Investor Expertise and Start-up Valuations (Study 1)

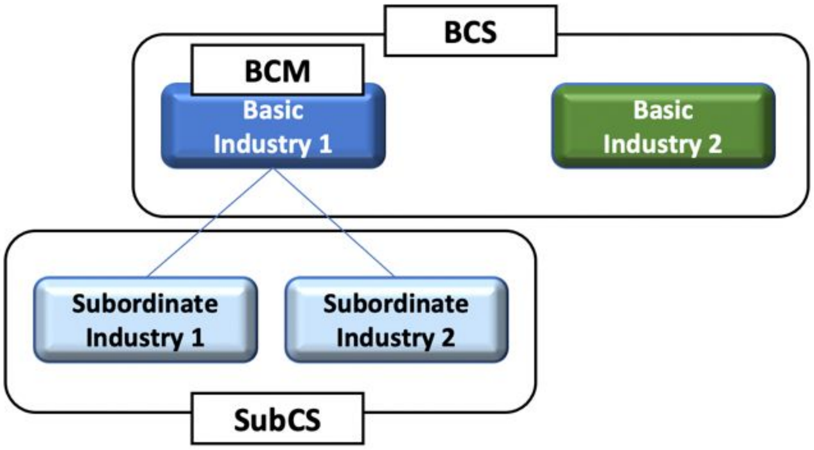
	(1)	(2)	(3)	(4)	(5)	(6)
	All industries			Finance & IT	All industries	Finance & IT[a]
	All rounds				Round 1	
Subordinate Category Spanning (SubCS) *versus* Basic Category Spanning (BCS) — **H1**		-.03***	-.06***	-.07*	-.06*	-.08*
		(.001)	(.000)	(.013)	(.013)	(.021)
Subordinate Category Spanning (SubCS) *versus* Basic Category Membership (BCM)		-.01	-.04***	-.07***	-.06**	.-11***
		(.352)	(.001)	(.001)	(.010)	(.006)
Expertise × SubCS (*v.* BCS) — **H3**			.04***	.05**	.05**	.10**
			(.000)	(.001)	(.008)	(.001)
Expertise × SubCS (*v.* BCM)			.04***	.08***	.05*	.11**
			(.000)	(.000)	(.014)	(.003)
Investor expertise	.06*	.07**	.10***	.12*	.10*	.20**
	(.018)	(.009)	(.000)	(.023)	(.033)	(.010)
Investor general experience	.01	.01	.01	.00	.02	-.01
	(.739)	(.814)	(.843)	(.959)	(.653)	(.915)
Investor reputation	.06**	.06**	.06**	.06**	.06**	.08***
	(.004)	(.004)	(.004)	(.007)	(.001)	(.000)
Syndicate size	.12***	.12***	.12***	.10***	.09**	.09*
	(.000)	(.000)	(.000)	(.000)	(.001)	(.033)
Competitive intensity	-.05	-.04	-.04	-.07	-.03	.03
	(.276)	(.343)	(.358)	(.391)	(.743)	(.820)
Category heat	.04***	.04***	.04***	.08***	.04***	.14***
	(.000)	(.000)	(.000)	(.000)	(.001)	(.000)
Stage(1:Seed,2:Early,3:Late)	.35***	.35***	.35***	.39***	.28***	.35***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Round number	.21***	.21***	.21***	.18***		
	(.000)	(.000)	(.000)	(.000)		
Slices	.03***	.03***	.03***	.03*	.04**	.03†
	(.000)	(.000)	(.000)	(.032)	(.001)	(.086)
Residual category	.00	.00	.00	.02	.02	.09**
	(.659)	(.852)	(.796)	(.395)	(.151)	(.004)
IMR	-.16***	-.16***	-.16***	-.19***	-.21***	-.15***
	(.000)	(.000)	(.000)	(.018)	(.007)	(.201)
Observations	29,033	29,033	29,033	9,970	7,730	2,778
R-squared	.418	.418	.419	.454	.195	.241

Note: Effects are robust normalized beta coefficients (β). P-values are in parentheses (p). IMR is the result of a Heckman two-step model that contains *investor expertise*, all the control variables as well as the instrument of *company description length* in the selection stage.

[a]As our experiments use two basic categories, from Finance and information technology (IT) industries, we replicated the general models with these categories only. The subsample "Finance & IT" includes four basic categories related to Finance and six basic categories related to Information Technology.

*** $p < .001$ ** $p < .01$ * $p < .05$ † $p < .1$

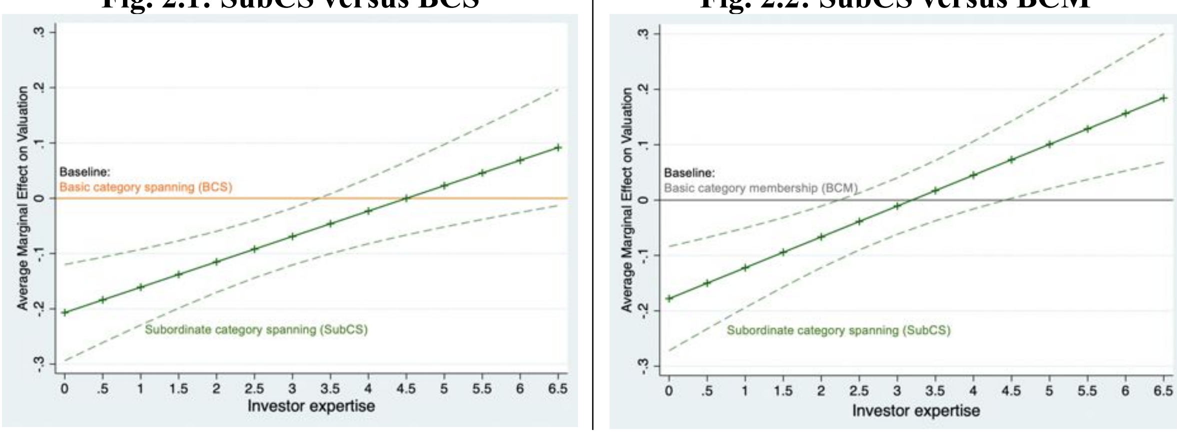
FIGURE 1. Category Membership Conditions across Studies



Note: Three conditions of category membership are used across the studies: subordinate category spanning (SubCS), basic category spanning (BCS), and basic category membership (BCM).

FIGURE 2. Effects of Category Membership by Investor Expertise on Valuation (Study 1)

Fig. 2.1: SubCS versus BCS **Fig. 2.2: SubCS versus BCM**



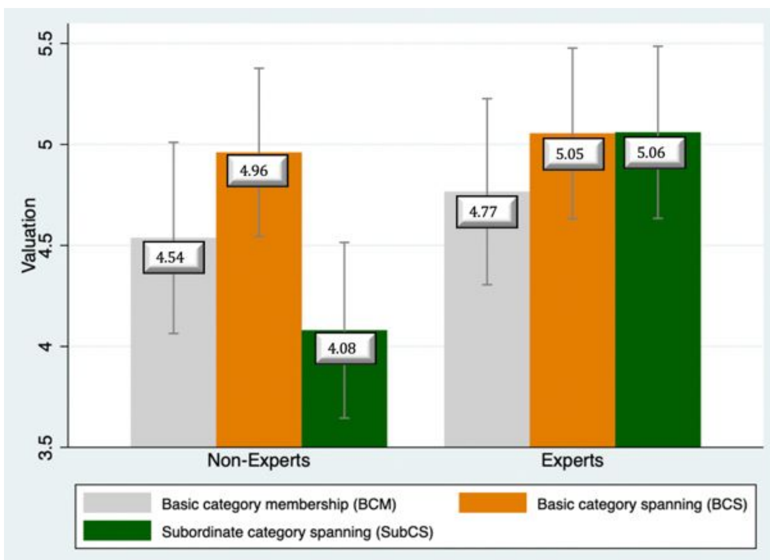
Note: Based on Model 3, the graph shows the average marginal effect of subordinate category spanning (SubCS, green line) as compared with basic category spanning (BCS, orange line, Fig.2.1.) and with basic category membership (BCM, grey line, Fig.2.2.) on *valuation* across levels of *investor expertise*. Dashed lines represent the 95% confidence intervals. The higher the investor expertise, the higher the valuation of SubCS as compared to BCS — which supports H3 — and as compared to BCM (control condition).

FIGURE 3: Start-up Profile and Treatment Conditions (Studies 2 and 3)

Novus
Business Description **Industry: *[Classification]***   In 2017, Jane D. and Marc A. founded ‘’Novus’’, a company that operates in the businesses of microfinance, credit risk, and information technology. Novus offers a service of microfinance that allows small-sized entrepreneurs getting small loans directly through mobile transactions. The company's revenues stem from the loan rates and a commission on the entrepreneurs’ profits.

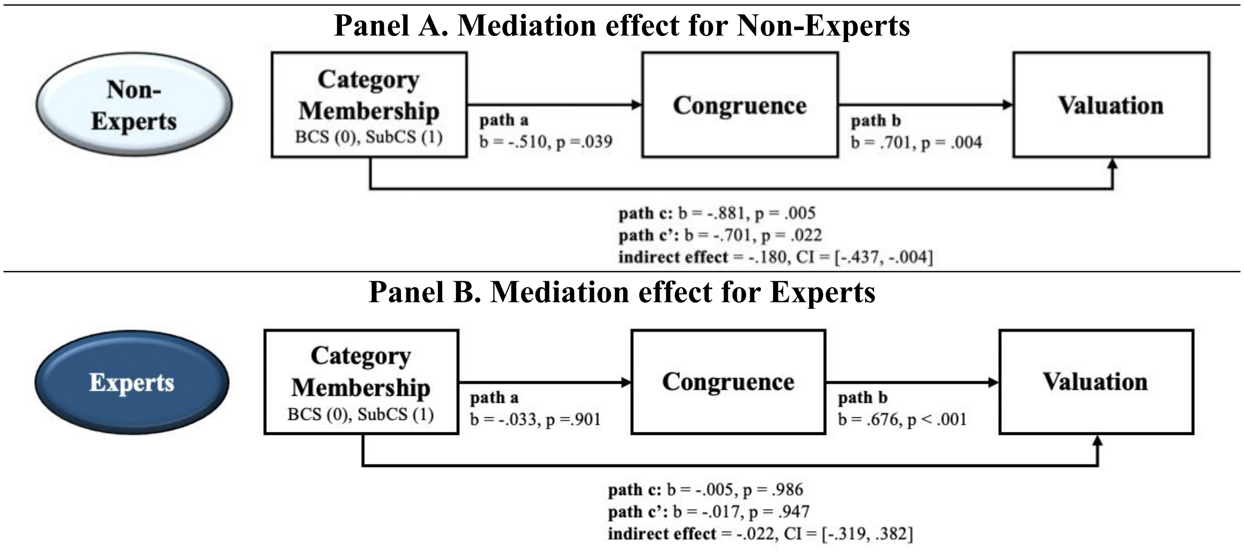
Note: The manipulation consists of replacing “[Classification]” with either “Microfinance, Credit Risk” (subordinate category spanning, SubCS), “Finance” (basic category membership, BCM), or “Finance, Information Technology” (basic category spanning, BCS). In Study 3, the conditions are either BCS or SubCS.

FIGURE 4. Effect of Category Membership by Expertise on Valuation (Study 2)



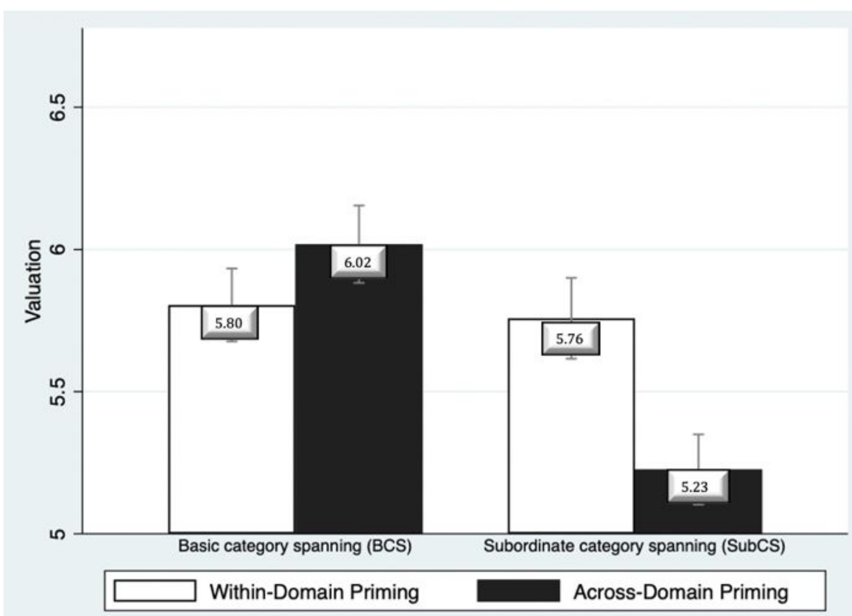
Note: The test for H3 is shown graphically. H3 is supported because there is a positive effect of the interaction between expertise and SubCS (versus BCS) on valuation ($b_{subcs\ (v.\ bcs) \times exp} = .89, p = .042$). The mean of valuation in SubCS condition is lower than in BCS condition for Non-Experts whereas there is no significant different between SubCS and BCS among Experts *** $p < .001$, † $p < .1$

FIGURE 5. Mediation with Congruence (Study 2)



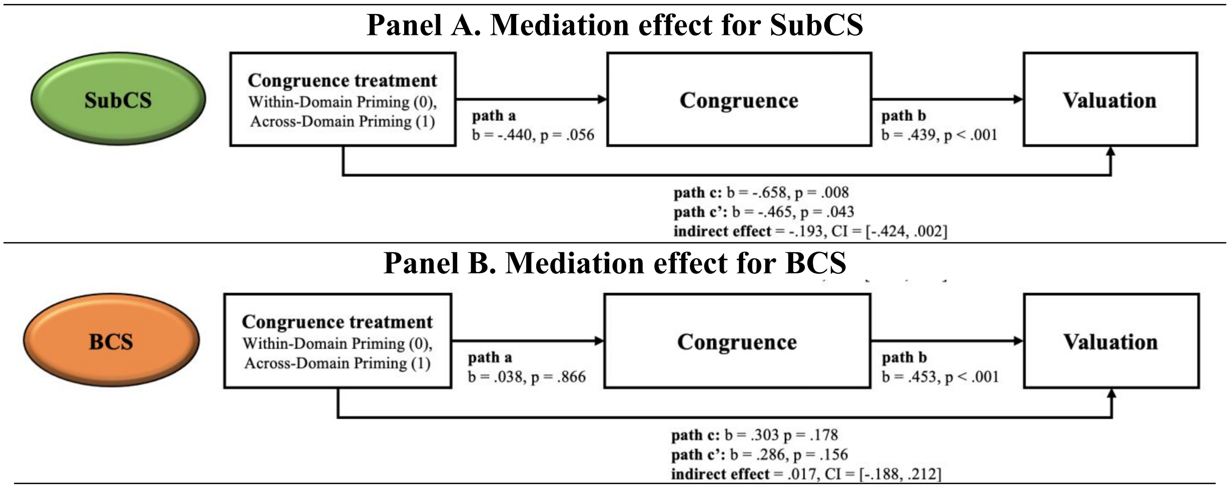
Note: BCS = basic category spanning, SubCS = subordinate category spanning.
Panel A presents the mediation effects of congruence of the relationship between category membership and valuation for Non-Experts. The indirect effect is significant for Non-Experts (effect = -.180, CI: [-.437, -.004], 10,000 bootstrap samples).
Panel B presents the mediation effects of congruence of the relationship between category membership and valuation for Experts. The indirect effect is not significant for Experts (effect = -.022, CI: [-.319, .382], 10,000 bootstrap samples)

FIGURE 6. Effect of Congruence Treatment by Category Membership on Valuation (Study 3)



Note: As expected, the valuation of SubCS is higher under within-domain thinking than under across-domain thinking (b=-.66, p=.008). While we expected that the (perceived) congruence of BCS would be lower under within-domain thinking than under across-domain thinking, the difference is not significant (b=.30, p=.178).

FIGURE 7. Mediation with Congruence (Study 3 – supplementary analysis)



Note: BCS = basic category spanning, SubCS = subordinate category spanning.
Panel A presents the mediation effects of congruence of the relationship between congruence treatment and valuation for the subordinate category-spanning (SubCS) companies. The indirect effect is marginally significant for SubCS (effect = -193, CI: [-.424, .002], 10,000 bootstrap samples).
Panel B presents the mediation effects of congruence for the basic category-spanning (BCS) companies. The indirect effect is not significant for BCS (effect = .017, CI: [-.188, .212], 10,000 bootstrap samples)

APPENDIX 1: Description of Study 1 Control Variables

No.	Variable Name	Measure	Expected Relationship with DV (valuation)	Logged
1	Investor general experience	Difference between the total number of investments made by an investor between $t-6$ and $t-1$ and the investor's expertise in the focal deal	Positive	Yes
2	Investor Reputation	Investor's share of cumulated initial public offering (IPO) capitalization between $t-6$ and $t-1$	Positive	Yes
3	Syndicate size	Number of investors that participated in a funding deal	Positive	Yes
4	Competitive intensity	Number of investors in the company's basic category, same quarter and country	Positive	Yes
5	Category heat	Ratio between the number of deals in t (i.e. the deal's year) that involve companies associated with the primary category of the target company and the average number of deals that involve companies associated with the primary category from t-6 to t-1	Positive	No
6	Investment stage	Variable takes 1 if the deal is at seed stage, 2 at early stage and 3 at late stage	Positive	No
7	Round number	Number of the deal's round	Positive	No
8	"Slice" innovative categories	Number of cross-classification segments that denote novel, trendy activities (e.g., machine learning, big data, virtual reality) to which the company affiliates	Positive	No
9	Residual category	Variable takes 1 if the company is associated with at least one category that starts with "other" (e.g., "other financial services"), and 0 otherwise	Negative	No

Notes: We incremented by 1 every logged variable to avoid generating missing values due to zeros.

APPENDIX 2: Summary and Correlation Tables (Studies 2 and 3)

Summary and Correlation Tables, Study 2

	Variable	Role	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10
1	Valuation	DV	4.75	1.62	0.00	8.00	1.00									
2	Congruence	Mediator	5.52	1.36	0.67	9.00	0.47	1.00								
3	Category Membership (0= BCS, 1=SubCS)	Main IV	2.00	0.81	1.00	3.00	-0.02	-0.12	1.00							
4	Expertise (0 = Non-Experts, 1 = Experts)	Main IV	1.50	0.50	1.00	2.00	0.14	0.18	0.03	1.00						
5	Subjective expertise	Manip. check	3.62	1.98	0.00	8.00	0.29	0.21	0.07	0.24	1.00					
6	Perceived commonness	Manip. check	5.62	1.28	2.00	9.00	0.40	0.55	-0.24	0.07	0.14	1.00				
7	Perceived status	Suppl. analysis	5.59	1.84	0.00	9.00	0.22	0.22	-0.02	0.14	0.23	0.24	1.00			
8	Age	Sample description	21.01	1.93	18.00	28.00	0.02	-0.02	-0.01	0.10	0.11	-0.01	-0.06	1.00		
9	Gender (0= Male, 1= Female)	Sample description	0.72	0.45	0.00	1.00	-0.03	-0.05	0.09	-0.13	-0.14	-0.06	-0.08	-0.11	1.00	
10	Motivation	Suppl. analysis	6.48	1.48	1.00	9.00	0.00	0.13	-0.02	0.20	0.11	0.22	0.28	-0.04	0.05	1.00

Summary and Correlation Tables, Study 3

	Variable	Role	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1	Valuation	DV	5.70	1.80	0.00	9.00	1.00										
2	Congruence	Mediator	6.38	1.64	0.83	9.00	0.50	1.00									
3	Congruence Treatment (0= Within-domain, 1= Across-domain)	Main IV	0.54	0.50	0.00	1.00	-0.04	-0.05	1.00								
4	Category Membership (0= BCS, 1=SubCS)	Main IV	0.51	0.50	0.00	1.00	-0.12	-0.05	-0.03	1.00							
5	Expertise (0 = Non-Experts, 1 = Experts)	Suppl. analysis	0.52	0.50	0.00	1.00	0.07	0.12	0.00	0.01	1.00						
6	Subjective expertise	Manip. check	3.53	2.38	0.00	9.00	0.24	0.27	0.02	0.03	0.35	1.00					
7	Perceived commonness	Manip. check	5.93	1.77	0.50	9.00	0.34	0.61	-0.03	-0.07	0.06	0.23	1.00				
8	Perceived status	Control	5.23	2.38	0.00	9.00	0.35	0.27	-0.03	-0.22	0.13	0.35	0.31	1.00			
9	Age	Control	42.48	15.18	18.00	79.00	-0.16	-0.09	-0.04	0.02	0.14	0.02	-0.10	-0.02	1.00		
10	Gender (0= Male, 1= Female)	Sample description	0.53	0.50	0.00	1.00	-0.11	-0.13	0.10	0.04	-0.21	-0.35	-0.09	-0.20	0.01	1.00	
11	Motivation	Suppl. analysis	7.62	1.38	0.00	9.00	0.25	0.33	-0.06	-0.02	0.13	0.24	0.26	0.23	0.16	-0.08	1.00

APPENDIX 3: Test of Knowledge in the Domain of Finance (Studies 2 and 3)

N°	Questions	Correct Answers
1	Both commercial banking and investment banking consist of supplying short-term loans to individuals and small businesses.	False
2	Private equity is the amount of money that households have available	False
3	A takeover bid consists of making an offer to shareholders to buy the target company's shares in order to gain control of the business	True
4	Venture capitalists are also designated as start-up entrepreneurs	False
5	Grameen Bank is known for its activity in microfinance	True
6	A leveraged buyout (LBO) is a derivative product designed to transfer the credit exposure of fixed income products between two or more parties	False
7	The "primary market" is the market where a company issues stock or bonds for the first time and sells those securities directly to investors	True
8	Hedge funds are risk-averse funds that provide long-term secured funding to start-up companies	False
9	A swap is a derivative contract	True
10	A "bancassurance" company operates in both banking and insurance	True
11	"FinTech" is the nickname of quantitative financial analysts	False
12	A "yield" refers to the liquidation by an entrepreneur of all his or her stocks	False

Note: These definitions are adapted from the website Investopedia (www.investopedia.com), a world's leading source of financial content that provides dictionaries as well as news and advices in financial services.

APPENDIX 4a: Procedure for the Congruence Treatment (Study 3)

In this appendix, we provide more details about the procedure that we used in Study 3 for the congruence treatment. Participants were randomly assigned to either the "within-domain" condition or the "across-domain" condition and were asked to solve a series of eight analogies. After reading a problem like "A is to B what C is to…?", they had to write down a possible term "D." They were told in advance that a response would appear on the screen after 10 seconds to help them complete the task. They were also told that they could write down "?" if they had no idea about a possible response. After the solution was displayed, they could write down the solution of their choice and decide to go to the next page. They were encouraged to follow their intuition and to respond quickly. A timer was displayed for each analogy problem, which gave them forewarning as to when the solution would appear (i.e., after 10 seconds). In doing so, we also aimed to avoid creating unnecessary stress for participants. After completing the series of analogies, participants moved to the second part of the experiment.

APPENDIX 4b: Materials for the Congruence Treatment (Study 3)

N°	Analogy tasks *"A is to B what C is to…"*	Possible answer *"D"*
	Within-Domain Thinking	
1	Answer is to Riddle what Solution is to…	Problem
2	Basketball is to Hoop what Soccer Ball is to…	Goal
3	Eraser is to Pencil what Whiteout is to…	Pen
4	Burger is to Bun what Sub is to…	Roll
5	Blindness is to Sight what Deafness is to…	Hearing
6	Blizzard is to Snowflake what Monsoon is to…	Raindrop
7	Landscaper is to Lawn what Gardener is to…	Garden
8	Watermelon is to Rind what Orange is to…	Peel
	Across-Domain Thinking	
1	Answer is to Riddle what Key is to…	Lock
2	Basketball is to Hoop what Traveler is to…	Destination
3	Eraser is to Pencil what Amnesia is to…	Memory
4	Burger is to Bun what Book is to…	Cover
5	Blindness is to Sight what Poverty is to…	Money
6	Blizzard is to Snowflake what Army is to…	Soldier
7	Landscaper is to Lawn what Stylist is to…	Hair
8	Watermelon is to Rind what Cigarette is to…	Butt

Note: As in previous research (Goldwater & Jamrozik, 2019; Vendetti et al., 2014), we used materials on analogies developed by Green et al. (2010), who used 40 within-domain and 40 across-domain analogies. In order to keep the experiment short and the level of fatigue low, we provided only eight analogies to solve (either *within* or *across*). We chose analogies with the lowest difference of rated difficulty in the within- and across-domain conditions, as reported by participants in Green et al.'s (2010) study. Average rated difficulty scores for the eight within-domain analogies and the eight across-domain analogies that we chose were 3.51 and 3.38 out of 7, respectively, making them comparable in terms of difficulty.

Arnaud Cudennec (arnaud.cudennec@polyu.edu.hk) is an assistant professor of management at The Hong Kong Polytechnic University. He received his Ph.D. from HEC Paris. His research primarily focuses on the determinants of valuation in markets, including categorization processes, expertise, and social institutions.

Rodolphe Durand (durand@hec.fr) is the Joly Family Professor of Purposeful Leadership at HEC-Paris and the founder and academic director of the Society and Organizations Institute. Rodolphe's primary research interests concern the normative and cognitive dimensions of firms' performance, especially the consequences for firms of identifying and coping with major environmental and social challenges.