

**STRATEGIC CATEGORIZATION, CATEGORY BUNDLE,  
AND TYPECASTING**

**THREE ESSAYS ON PRODUCT CATEGORIZATION**

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## **Abstract**

Categories are social agreements about the meanings of labels applied to products. Categories serve as the basis for market interaction: audiences use categories to make sense of the products offered to them, producers apply product categories in marketing activities to reach their target customers, and market intermediaries refer to prototypical categories in assessing the quality of products. As a widely used sociocognitive concept, categorization has accrued prominence in research and practice, with researchers investigating the social and economic impacts of categorization and practitioners probing superior categorization strategies that optimize their economic returns. However, current strategic management and organization theory research has achieved limited success in expounding on how organizations strategically manipulate category labels to acquire excess returns and how audiences process categorical information in assessing the products to which they are exposed.

This dissertation joins the ongoing dialogue on categorization and contributes to the literature by offering three essays that respectively address three understudied questions. First, how do producers manipulate the categorical perception of the audiences for their offerings? Second, how do audiences handle the interconnected relationships between categories when they classify products in the market? Last, how do the market identities imposed on market candidates persistently affect their career development?

I chose the feature film industry in North America (Canada and the U.S.) as the empirical setting for my dissertation, since a dominant category system, *film genres*, significantly affects the market success of all film market participants. The genre labels associated with a film shape moviegoers' consumption decisions, and the categorical perception of moviegoers of an actor/actress has considerable impacts on the actor's/actress's career advancement. Using a gigantic database of feature film projects that were exhibited in theaters in the U.S. and Canada from 1990 to 2015, I construct three unique datasets that are respectively used to test my hypotheses and answer my research questions at the film, genre, and actor levels. I summarize my key findings as follows.

Chapter 2 investigates the strategic categorization behaviors of film studios. The unit of analysis is film projects. In this chapter, I found that studios shape audience perceptions of the genres of their films by manipulating the composition of film crews via cognition-, capability-, and newness-based channels. I also demonstrate that the manipulation of a film crew will ultimately affect the box office of a film.

Chapter 3 explores a common phenomenon, the clustering of certain categories, in some product markets. I define the categories that co-appear frequently as a "category bundle" in this paper and examine the extent to which the co-appearance of categories will affect a category's usage in products. I found that the market is aware of category bundles since a category that has a high fitness

in bundles is more likely to appear in the description of a product. The unit of analysis in this chapter is the genre.

Chapter 4 concerns the application of market categories in the labor market. Built upon the consensus in the category literature that categories are mutual understandings among market participants regarding the grouping of products, I strive to answer a classic question in labor market research: how does the market identity of a job market candidate (i.e., being a specialist or generalist) affect their long-term career development? I found that the perception of external audiences of the focal candidate in terms of their market categories is the reason why specialist actors/actresses enjoy persistent advantages in the labor market. The unit of analysis in this chapter is the individual.

## **Dedication**

*To the loving memory of my father.*

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# **1 Introduction**

## **1.1 Research questions**

A category is a set of entities in which intragroup members share certain attributes that are not possessed by members outside the group. Categories are ubiquitous in society: they include the genres in films and pop music, cuisine styles in restaurants, tags on online auction platforms, and geographic locations in winemaking. As a socially constructed idea to simplify the classification of entities, a category “serves as a basis for interaction between producers, buyers, and external audiences (Vergne and Wry, 2014: p.68)”. In the product market, product categories facilitate the understanding of audiences of the products by grouping goods with similar attributes. In the labor market, categories allow employers to quickly estimate the capabilities and qualifications of job market candidates. Due to its significance in organizational and social life, strategy and organization theory scholars have made substantial efforts in investigating the antecedents and implications of categorization, which refers to the process through which an organization or individual receives category labels from the market.

Various contexts and different research questions have been probed by previous studies. Zuckerman (1999) investigated the penalties when organizations

attempt to straddle categories in the stock market; Negro, Hannan, and Rao (2011) explored the conditions under which producers defect from their current category in the Italian winemaking industry; and Merluzzi and Phillips (2016) discussed the contingencies in which job market candidates with less diversified category labels in their profiles will be discounted in the labor market. The topics covered in category research include the stock market (Zuckerman, 1999, 2004), feature films (Hsu, 2006; Hsu, Negro, and Perretti, 2012), open source software (Alexy and George, 2013), and the labor market (Leung, 2014; Zuckerman et al., 2003).

Despite the burgeoning literature devoted to topics in category research, our understanding of categories is limited to the penalties imposed when subjects (organizations or individuals) cross category boundaries and centers on how audiences shape the categorization process by devaluing subjects that deviate from the pre-existing prototypical categories (Durand and Boulongne, 2017; Hsu, Hannan, and Koçak, 2009; Jones, Maoret, Massa, and Svejenova, 2012, Zuckerman, 1999). A more recent stream of research has embraced a goal-based approach, arguing that audiences evaluate subjects based on the goals audiences pursue rather than the comparison of subjects and prototypes (Durand and Paoletta, 2013; Paoletta and Durand, 2016). Nevertheless, both the goal-based and prototype-based approaches to categorization frame categorization as an

audience-centric process, emphasizing the passive roles of producers in the categorization of their products. What are the roles of producers in the product categorization process? To what extent and in what way do producers determine the category labels attached to their products? These are the questions I strive to answer in Chapter 2. Incorporating the emerging strategic categorization literature (Barlow, Verhaal, and Angus, 2019; Pontikes and Kim, 2017), I argue that producers are strategic about categorization. Specifically, I attempt to contribute to the current literature by (1) comprehensively reviewing the mechanisms through which producers shift the perceptions of audiences on the category labels of a product and (2) examining whether the strategic categorization of producers has economic impacts on their products. The key research questions are the following:

*Research questions for Chapter 2: Are categories passively received from audiences or actively manipulated by producers? Regarding producers, how do they shape the category memberships of products to optimize their economic gains?*

While Chapter 2 addresses the question regarding the antecedents of a product's category membership by emphasizing producers' role in the categorization process, it concerns, at the product level, how producers pool categories together in their products without asking why those categories are simultaneously chosen in the first place. To take a simple example, while it is

important to know how a film studio combines romance and comedy elements to create a romantic comedy, it is also rewarding to know why it is romance and comedy, rather than romance and thriller, that often co-appear in film projects. In Chapter 3, I offer a novel explanation for the co-appearance of categories in a product by incorporating the interconnectedness of a category system into the framework. I review the types of connections that a category can build with other categories and examine how different types of connections exert heterogeneous impacts on the usage of a category for a product. The research question for Chapter 3 is the following:

Research Question for Chapter 3: *At the category level, does the interconnected feature of a category system affect the audiences' usage of category labels?*

Answering the research question in Chapter 3 complements the questions that I proposed in Chapter 2 (how are categories determined).

The other implication of Chapter 3 is that it also offers a novel interpretation of a paradox in category research. On the one hand, previous research suggests that products that span categories will be punished by audiences with less economic gains and more negative ratings (Zuckerman, 1999; Hsu et al., 2009). On the other hand, category spanning is widely seen in our social lives (e.g., multigenre films, fusion restaurants, etc.). Following the theoretical arguments in Chapter 3,

category spanning might simply be an embodiment of the correlated structure of categories. As long as interconnected categories are needed to describe a product, category spanning will appear in product descriptions regardless of the underappreciated evaluation of audiences. In other words, category spanning becomes a self-organizing process that is independent of the manipulation of market participants (i.e., producers, consumers, and critics).

While Chapters 2 and 3 are theory-driven pieces that investigate the antecedents of category membership at the product and category levels, Chapter 4 addresses an application of categories in the labor market research. There is a long-standing puzzle in the career advancement research: is attaining a specialist identity or generalist identity more advantageous to a job market candidate? As the identity of a job market candidate is measured by the market categories associated with the focal candidate (e.g., Leung, 2014; Zuckerman et al., 2003), the specialist-generalist trade-off can be rephrased in a “category literature language”: is category spanning beneficial to job market candidates? Organization scholars have provided conflicting views on the roles of category spanning (specialist or generalist) in job market candidates’ careers (Ferguson and Hasan, 2013). A typical argument is that specialists will enjoy additional hiring opportunities in the early stage of their careers, but the return will decrease as they climb the career

ladder (Zuckerman et al., 2003; Ferguson and Hasan, 2013). If this is the case, in a perfectly competitive market, the ratio of specialists should decrease among job candidates with longer tenures. I fact-checked this prediction in the feature film labor market, in which actors and actresses freely compete for casting opportunities, and found an anomaly: the ratios of specialists are highly stable among actors/actresses across different career stages, suggesting that job specialization is pervasive even though the asserted specialist advantage should have long gone (see Figure 4-1 in Chapter 4). Motivated by the contradiction between the theory and phenomenon I observed, I raise the following questions:

*Research Questions for Chapter 4: What enables the persistent specialism in a labor market, and how does the underlying contingency prevent specialist gains from dissipating? In “category” language, under which conditions do the category labels attached to individuals persistently affect the career advancement of job market candidates?*

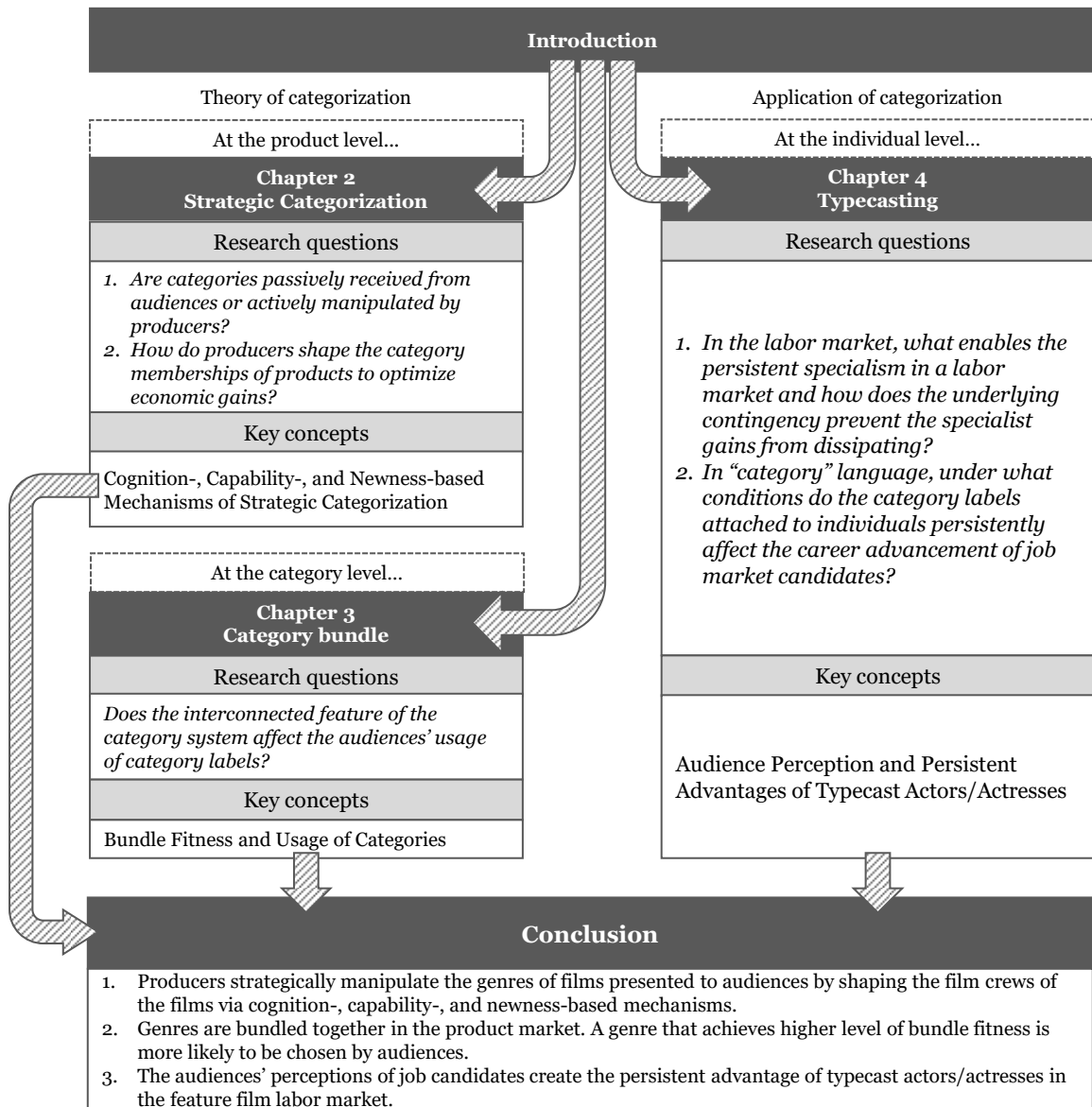
I argue that the insights from category research can resolve the puzzle of the prevalence of job specialization and the shrinking specialist advantage predicted by the career advancement literature. Categories are mutual understandings among market participants on the grouping of products, which incorporate producers, market intermediaries, and audiences. Among all market participants, audiences (consumers) play an important role in the categorization of products:



they can grant legitimacy to or withhold legitimacy from products (Bower, 2015a), and they can also use the material and symbolic resources they control to determine the fate of a product (Hsu and Hannan, 2005). Feature films are a typical setting in which audiences (moviegoers) are nontrivial determinants of the market success of products. Nevertheless, though we have thoroughly examined the dominant position of audiences in determining the box office of a film, we do not know to what extent audiences shape the hiring decisions of film studios. In Chapter 4, I argue that the audience perception of actors is a scope condition of the specialist advantage. Since the perceptions of audiences are incorporated into studios' hiring decisions, the recruitment of actors/actresses becomes a dual-matching process. Studios not only conduct skill-based matching tests (e.g., are the skills and talent of the job candidate sufficient to take the role?) but also conduct perception-based matching tests (e.g., is the public image of the job candidate compatible with the role characterized in the film?). In the dual-matching framework of feature film hiring decisions, the relatively settled audience perceptions are the reason why some actors/actresses enjoy persistent specialist advantages in the market.

## **1.2 Roadmap**

The overarching theme of my dissertation is to deepen our understanding of the antecedents and implications of the categorization process. Under a common theme, the three chapters address different elements of the objective pursued in the dissertation at three levels of analysis. Figure 1-1 illustrates the roadmap of the dissertation and the positions of each chapter in the dissertation.



**Figure 1-1:** Structure of the dissertation

### 1.3 Empirical context

The empirical context for this dissertation is the feature film industry in the United States and Canada. Feature films are a critical cultural industry in North America in terms of economic significance and social impact (Basuroy, Desai and

Talukdar, 2006). On the economics side, the North American feature film industry sold 1.4 billion tickets and received \$80.8 billion in revenue in 2012 (Statista, 2018; The U.S. Census Bureau, 2015). Regarding the social impact, feature films deeply affect the knowledge, attitudes, opinions, and behavior of individuals (McDonald, 2004). In addition to its extensive influence in society, the film industry is particularly suitable for my research because it has an institutionalized category system, *genres*, which structures the filmmaking and exhibition processes. Genres partition the demand side of the industry into varied niches. Films classified in the same genre are perceived as similar in terms of their structural components such as plots, characters, settings, themes, and style (Hsu, 2006; Schatz, 1981) and are intended to attract moviegoers with similar tastes. Genres also split the supply side of feature films into different segments since different genres, such as romance, action, and thriller, require film crews with different skillsets. Last, detailed, transparent film records are available for the North American feature film industry, making an extensive analysis of the antecedents and implications of categorization possible for this dissertation.

Since Chapters 2 through 4 analyze the categorization process at different levels, I constructed three datasets at the product, category, and individual levels to address the questions regarding different levels of analysis. In Chapter 2, the

dataset includes 2,404 feature films produced in the US and Canada from 2000 to 2015. In Chapter 3, my dataset is the genre-entry decisions of 6,159 films. Because we consider 20 genres for each film, the final dataset incorporates 123,180 (6,159 \* 20) genre-entry decisions. In Chapter 4, the dataset comprises the casting records of 21,914 actors and actresses from 1990 to 2015. Actors/actresses enter my research sample once they have stayed in the industry for five years, and I record their career advancement until (1) December 31, 2015, (2) they are reported deceased, or (3) it has been ten years since their last job, whichever comes earlier. The final sample includes 176,324 individual-year observations. I utilize multiple sources to build my datasets. Most data were retrieved from the Internet Movie Database (IMDb), The Movie Database (TMDb), and Rotten Tomatoes. Some variables are based on the Academy Awards Database, Springfield! Springfield! ([www.springfieldspringfield.co.uk](http://www.springfieldspringfield.co.uk)), and Box Office Mojo. The Data and Method sections in each chapter have detailed explanations of how I built my samples.

## **2 Toward a Strategic Perspective on Categorization**

### **2.1 Abstract**

Existing research emphasizes the exogeneity of categorization, arguing that penalties will arise when organizations attempt to straddle categories. However, category spanners are widely observed in modern society, implying that unidentified mechanisms may trigger organizations to cross category boundaries. I argue that product categorization is endogenous to organizations to some extent, and organizational agents play an important role in shaping the categories the focal organization perceived by audiences. Using large data from online film databases, I study the categorization of feature films in North America. I find that the team- and personal-level attributes of a film crew, via cognition-, capability-, and newness-based channels, affect the genre labels the focal film will receive from audiences. In addition, the extent to which the film crew interferes in the categorization process ultimately affects the box office of the focal film. My research advances category research by framing categorization as a producer-centric process.

Keywords: category; category spanning; strategic categorization; producer-centric view

## **2.2 Introduction**

Product categories play important roles in economic life (Durand and Paoletta, 2013). Moviegoers rely on genres to make sense of the films they are going to watch; sommeliers estimate the value of wine by its place of origin or grape variety; and gourmets judge the quality of food by the cuisine style it belongs to. Categories are the cognitive consensus among producers, intermediaries and customers regarding the grouping of products (Durand and Khaire, 2017). Once a product is categorized, its attributes and characteristics are anticipated, and audiences can evaluate the quality of an offering by comparing it to other equivalent members of that category. In this regard, categories benefit both producers and audiences by assisting the former in targeting suitable niches and facilitating the audience's understanding of products.

Whereas a category helps audiences make sense of the products offered to them, the mismatch between categories and products can distort audiences' perception of products. Specifically, products claiming memberships in multiple categorical domains may receive less positive evaluations from audiences (Hsu, Hannan, and Koçak, 2009; Zuckerman, 1999). On the producer side, multiple categories restrict the producer's ability to effectively target customers in either market (Hsu et al., 2009; Negro and Leung, 2013); on the audience side, audiences

find products that span categories confusing and less appealing than products that are specialized and fall under a single category (Leung and Sharkey, 2014). Emphasizing the negative impacts of categorization arising when the actual product offered by producers deviates from the prototype suggested by current category system, this stream of research is built upon the neo-institutional tradition of organizations that concerns the homogeneity of modern organizations (DiMaggio and Powell, 1983) and the decoupling between actual offerings and legitimate prototypes in modern society (Meyer and Rowan, 1977).

However, the adverse effects of multiple categories, which is referred to as “the categorical imperative” (Zuckerman, 1999: p.1398), requires more careful scrutiny because products that span categories do in fact exist. Among the Top 10 box office in North America in 2016, all movies bear at least three genre tags, and one movie was even labelled with six genre tags<sup>1</sup>. Scholars have recently attempted to reconcile the so-called categorical imperatives with the fact that category-spanning products are ubiquitous, emphasizing that category spanning brings benefits to producers and audiences under certain circumstances (Paolella and Durand, 2016; Wry, Lounsbury, and Jennings, 2014). Moreover, acknowledging

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<sup>1</sup>Box office data are from Box Office Mojo ([www.boxofficemojo.com](http://www.boxofficemojo.com)); genre information come from IMDb.



the potential benefits of category spanning, scholars further argue that producers may be strategic about category spanning (Durand and Khaire, 2017; Pontikes and Kim, 2017; Vergne and Wry, 2014). In other words, producers may intentionally pursue membership in multiple categories, as long as the benefits from category spanning surpass the potential losses that result. The question is, which type of producers span categories for strategic purposes and to what extent does the strategic categorization of products shift its performance.

A re-evaluation of category spanning requires a review of its properties. The first question that needs to be asked is whether a category is merely an exogenous product feature that truly reflects the product's position in a class of similar products, or a strategically manipulated tool whereby producers attempt to favorably position their product? Previous research demonstrating categorical imperatives has emphasized the impersonal, informational nature of categories (e.g., Hsu et al., 2009; Leung and Sharkey, 2014; Negro, Hannan, and Fassiotto, 2015; Negro and Leung, 2013; Zuckerman, 1999). However, if products that span multiple categories have systematic differences in performance relative to rival products, rational decision makers will select the category labels that maximizes their market returns. In this sense, category is endogenously determined. Recent research has started to inquire as to the strategic nature of the categorization

process (e.g., Durand and Paoella, 2013; Negro, Hannan, and Rao, 2011; Pontikes and Kim, 2017). My research seeks to contribute to this dialogue by redirecting researchers' attention to the effects of organizational agents in strategic categorization.

The second question that needs to be asked in order to re-evaluate category spanning is if categorization is intentional and strategic, will it have implications on a product's economic and social outcomes? Previous research has discussed the economic effects of category spanning thoroughly (e.g., Hsu, 2006; Hsu, et al., 2009; Negro, Hannan, and Rao, 2010a; Paoella and Durand, 2016; Ruef & Patterson, 2009; Zhao, Ishihara, and Lounsbury, 2013; Zuckerman, 1999, etc.). However, these studies were based on the inherent assumption that categories are given. By considering that category spanning can be both the impersonal embodiment of product features and the outcomes of intentional strategies schemed by organizational agency (Durand and Khaire, 2017), I suggest that previous research might be biased, especially in the contexts in which producers can decide what and how audiences, such as market intermediaries and customers, get access to and evaluate the products.

In this paper, I probe the strategic nature of product categories. I argue that other than given, "natural" features of products, organizational agents also play an

important role in determining the extent to which a focal product is attached to multiple category labels by third parties. A review of North American (the U.S. and Canada) feature film industry reveals that the key members of a film crew, namely producers, directors, and casts, dominate the categorizing work in the filmmaking. Moreover, my empirical analysis suggests that these key members affect audiences' perception of films via cognition-, capability-, and newness-based channels. In sum, the significant impacts of crew members on audiences' perception of the genre(s) of a film (operationalized as genre width, the extent to which a film is labelled by multiple genres) indicate that organizational agents intentionally and strategically manage the categories of their products. In addition, I employ a structural model to further investigate the indirect outcomes of strategic categorization. I find that the categorizing work of organizational agents (filmmakers) will ultimately affect a film's box office by shifting audience perception of genre width via cognition-, and capability-based mechanisms. Moreover, by acknowledging the categorizing work of organizational agents and employing a control function approach, I find that studies investigating "the categorical imperative" may yield biased results without considering the strategic nature of categories. This finding reveals that category spanning is endogenously determined by filmmakers.

The contributions of this paper are twofold. First, I provide a strategic perspective on product categorization decisions. Contrary to prior research that argues that categories are passively received, I argue that categories can also be actively enacted by strategists. I offer both *ex ante* evidence (that the characteristics of film crew members are closely related to the perceived genre width of a focal film) and *ex post* testimony (that the extent to which a film crew manipulates a film's perceived genre labels influences film's box office) of strategic categorization. Second, this study contributes to the nascent strategic categorization research by exploring the roles of organizational agents in category spanning. A growing body of literature has acknowledged that categorization can be motivated by strategic considerations (e.g., Durand and Khaire, 2017; Hsu and Grodal, 2015; Pontikes and Kim, 2017; Rhee, 2014; Wry and Castor, 2017). In this vein, current research focuses on how categorical-level exogenous factors, such as status differences and similarity between categories, trigger an organization's manipulation of categories (e.g., Pontikes and Kim, 2017; Wry and Castor, 2017). The role of organizational agency, which takes into account both the incentive and discretion to modify the perceived categories of an organization's products, however, is neglected (Durand and Khaire, 2017). The empirical findings suggest that previous research has downplayed the importance of organizational agents in

categorization. By acknowledging that organizational agents may participate in categorizing work for cognition-, capability-, and newness-based purposes, this paper depicts a more inclusive and complete picture of strategic categorization.

In the next section, I briefly review the literature on categories, categorization, and strategic aspects of categorization. Subsequently, I describe the research context, the modern North American feature film industries (2000-2015) and formulate hypotheses. A description of data, variables, and identification strategy follows. I then present the results. I conclude by discussing the main implications of my findings and future directions for research.

### **2.3 Strategic categorization**

Categories and categorization process in markets are thriving topics that have occupied a crucial place in theories of organizations over the past decade (Negro, Koçak, and Hsu, 2010b; Vergne and Wry, 2014). A foundational assumption in category research is that categorization is a socially-constructed partitioning process enabled by producers, intermediaries, and consumers (Negro et al., 2010b; Vergne and Wry, 2014). People use categories to organize and interpret objects. If objects (organizations or products) fall into different categorical groups through this socially constructed process, they should differ (at

least cognitively) in the eyes of audiences in terms of organizational or product attributes. As a result, categories should not be mixed or compounded. Organizations straddling categories by mixing elements of multiple categories will be devalued or overlooked by audiences (Hsu et al., 2009; Zuckerman, 1999). The penalties from category spanning, referred to as the “categorical imperative” (Zuckerman, 1999), have found empirical support in studies examining the stock market (Zuckerman, 1999), online platforms (Kovács and Hannan, 2010; Hsu et al., 2009; Leung and Sharkey, 2014), wine production (Negro et al., 2010a, 2011), and feature film industry (Hsu et al., 2009; Zhao et al., 2013; Zuckerman et al., 2003).

Though the categorization process is jointly shaped by producers and audiences, the categorical imperative adopts an “audience-centric” view where the penalties for spanning hinge on the perception of audiences (Wry et al., 2014: p.1311) For example, in the stock market, securities analysts determine whether listed companies “cross the line” or not (Zuckerman, 1999); in winemaking, sommeliers rate the quality of wines (Negro et al., 2010a); and in the film industry, critics and audiences label genres for films (Hsu, 2006; Hsu et al., 2009; Zhao et al., 2013). In this line of research, categories are seen as pre-defined norms and rules imposed on organizations, and the initiatives of producers that cause them

to span categories are underappreciated (Negro et al., 2010b; Pontikes and Kim, 2017). This audience-centric view of categorization is deeply rooted in the neo-institutional and ecological tradition of organizational research in which a category is thought to be taken for granted, controlled by the perception of audiences, and considered a tool to coordinate organization-environment relationships (Durand and Paoletta, 2013; Negro et al., 2010; also see Vergne and Wry, 2014 for a detailed review). In fact, most category researchers embracing the audience-centric view have deep ecological backgrounds (e.g., Hannan, Hsu, Negro, Zuckerman, etc.) or actively apply a neo-institutional perspective in their work (e.g., Hsu et al., 2009; Negro et al., 2010b; Zuckerman, 1999).

Are producers merely passive receivers or active players in the categorization process? Recent empirical studies have started to shift our thinking from the former view to the latter. In a study on winemaking, Negro and colleagues (2011) find that Italian winemakers choose to defect from or stick to their current category based on their belief of the strength of their own and other categories. Although wine critics categorize and rate wine, vintners do have room to decide whether they defect or not (Negro et al., 2011). The similar scenario in which agents self-select the category labels they affiliate with is also seen in patent applications (Wry and Castor, 2017), software categorization (Pontikes and Kim, 2017), and

impact investing (Quinn and Munir, 2017). Along with the empirical evidence, a “producer-centric” view emphasizing the pro-active role of producers in categorization is emerging (Durand and Khaire, 2017; Durand and Paoletta, 2013; Rhee, 2014; Vergne and Wry, 2014;). According to this view, producers will actively manage their category labels to maximize economic or social benefits (Durand and Khaire, 2017). The categorization process is hence not merely ascribed and given, but also agentic and strategic (Durand and Khaire, 2017). That said, the producer-centric view has not reached a consensus on how organizational agents engage in the strategic categorization process. Two “versions” of the producer-centric view that differ in how much agents “strategize” the categorization process are being debated.

### **2.3.1 An organizational agent approach to strategic categorization**

The first version of producer-centric view suggests that the strategic roles of organizational agents are limited to detecting the external environment and choosing category labels that are in tune with public opinion. For example, scientists in nanotechnology field tend to mimic the high-status scientists’ actions by replicating their category spanning decision in patent applications (Wry and Castor, 2017); ammunition manufacturers expand into less controversial industries to dilute the negative impression of their stigmatized home category



(Vergne, 2012). In this stream of research, an organizational agent acts as a “steward” who monitors fluctuations in the external environment that may adversely or favorably affect his or her home category. In accordance to these fluctuations, the category labels of the organization are adjusted to maintain the cognitive consistencies between categories and anticipated and expected social norms (Meyer and Rowan, 1977). Similar to the exogenous perspective on categorization, this stream stems directly from institutional theory and organizational ecology (Durand and Paoletta, 2013; Negro et al., 2010b). Studies in this stream widely examine the impacts of environmental variables on organizations’ category spanning decisions (e.g., Chae, 2016 examine community-level antecedents of category spanning; Negro et al., 2011; Pontikes and Kim, 2017, and Wry and Castor, 2017 examine category-system level factors). The effects of organizational agents in this stream are trivial. The only “strategizing” work that organizational agents do is that they transfer environmental pressure onto organizations and, with little discretion, choose the category labels that match the external environment.

Nevertheless, a growing body of literature, which I refer as the second version of producer-centric view, has purported a more proactive role of organizational agents in categorization process. From this perspective,

organizational agents not only transmit the external pressure onto organizations and promote harmony between external expectation and organizational categories, but directly affect the categorization process with their resources and power (Rhee, 2014; Waguespack and Sorenson, 2011). Under certain circumstances, agents even counter the existing categorization scheme, reinterpreting the meaning of existing categories and creating new categories (Durand and Khaire, 2017; Ruef and Patterson, 2009). Drawing on the cognitive psychology and organizational identity literature (Vergne and Wry, 2014), this stream emphasizes the importance of individual-level traits, such as perception and mental models, in categorization research (see Porac, Thomas, and Baden-Fuller, 1989; Cattani, Porac, and Thomas, 2017, etc.). Compared to previous perspectives on strategic categorization, this perspective integrates the proactive features of organizational agents into the analysis, creating a more comprehensive theoretical framework. Table 2-1 lists the various perspectives on the categorization process. The intention of this comparison is not to question the validity of any perspective; indeed, each perspective has gained empirical support in various contexts. The purpose, rather, is to provide a map through which we can navigate the context-specific categorizing systems and categorization processes in different settings. In the next section, I review the filmmaking process in North

American feature film industry and attempt to highlight the forces driving categorization in this setting. My analysis shows that categorization in the filmmaking setting is to a large extent a producer-driven process. Although third parties (e.g., audiences and critics) still decide the categories to which a film belongs, their perception of the focal film is deeply affected by the strategizing of filmmakers who decide which niche market to target and how clear category boundaries the focal film should have. The second version of producer-centric view is hence needed to complement our understanding of product categorization (Vergne and Wry, 2014).

**Table 2-1:** Perspectives on categorization

	Audience-centric view of categorization (categorical imperative)	Producer-centric view of categorization (version 1)	Producer-centric view of categorization (version 2)
Core argument	Category is exogenous to organizations	Category is both exogenous and endogenous to organizations; environmental factors drive the categorization of organization through the moderation of organizational agents.	Category is both exogenous and endogenous to organizations; external environment and organizational agents jointly shape the categorization of organizations.
Role of audiences	Evaluating the offering of organizations	Evaluating the offering of organizations	Evaluating the offering of organizations
Role of organizational agents	Complying with external environment by accepting the category labels bestowed by social norms	Transmitting the external pressure into organizations	Not only transmitting the external pressure into organizations but also manipulating the categorizing process. In some cases even revamping current classification system by creating new categories
Theoretical underpinnings	Organizational ecology and institutional theory	Organizational ecology and institutional theory	Cognitive and social psychology
Empirical evidence	Hsu et al., (2009); Zuckerman (1999)	Castor and Wry (2017); Pontikes and Kim (2017)	Perretti and Negro (2007); Waguespack and Sorenson (2011)

## **2.4 Research setting: North American Feature Film Industry**

The film industry in North America is one of the most critical cultural industries in terms of its economic significance and social impacts (Basuroy, Desai and Talukdar, 2006). In 2012 the U.S. film industry had created 1.4 billion admissions and a revenue of \$80.8 billion (Statista, 2018; The U.S. Census Bureau, 2015). More than two-thirds (71%) of the U.S and Canadian population went to the cinema at least once a year, and youth population (18-24) went to the movies an average of 6.5 times a year in 2016 (MPAA, 2017). Attracting a wide range of audiences on a frequent basis, feature films deeply affect the knowledge, attitudes, opinions, and behavior of individuals (McDonald, 2004).

Compared to the value chains of most manufacturing industries, whose technological complexity and low visibility make their production processes a “black box” for customers, filmmaking is relatively transparent to outsiders. Star directors, casts, and producers attract massive media attention, making the filmmaking process somewhat traceable for external researchers. Generally, filmmaking can be divided into six major stages: acquisition and development, pre-production, principal photography, post-production, distribution, and exhibition (Wasko, 2008, also see Figure 2-1). Various film crew members

participate across the six stages. Some crew members, such as producers and directors, take part in multiple stages from development through post-production, making their position dominant in the filmmaking process; other ancillary members, such as line-producers and writers, have only limited influence since they only take charge in certain stages.

The acquisition and development stage starts with a concept. Concepts usually come from the writers. Directors and producers may also come up with ideas, but it is the writers who contribute the most ideas to the script market. Nevertheless, the writers have little clout in filmmaking (Wasko, 2008). Once they sell their ideas to a producer through agents, they have little influence on the development of ideas and scripts. On the other side of the process, producers play a leading role in filmmaking since they guide the film through development, pre-production, principal photography, and post-production (Wasko, 2008). Represented by their production companies, producers circulate the scripts they purchased to major studios, seeking production pacts with studios. Studios, propped up by their conglomerate parents (e.g., Walt Disney, Time Warner, 21st Century Fox, Comcast, Sony, and Viacom), are important financiers of a film project. Studio executives read the script and decide whether to reject the idea or provide a development deal.

It should be noted that studios also have in-house writers and producers, and the whole development stage can happen within the studio hierarchy. Of all films released by the members of the Motion Picture Association of North America (MPAA), more than half of the films were in-house productions (Wasko, 2008: p.48). That being said, this does not contradict my assertion that producers hold sway in filmmaking. When studios organize in-house film projects and release the films, the in-house team is identified as both distributor and producer in my data.

Further evidence of the influence producers have in filmmaking is that they are responsible for hiring the director and main cast during the development stage (Wasko, 2008: p.51)<sup>2</sup>. Producers also hire writers to rewrite, revise, and polish the script. The newly hired directors and stars will also offer suggestions on the script. The polishing process ensures that the characters in the script match the casting style of the main cast and the script is compatible with the director's shooting style. Often the script is changed and reworked so many times that the writers "don't even recognize their original work" (Wasko, 2008, p.60).

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<sup>2</sup> Sometimes agents will circulate a package deal, which includes the script prepared by their client writers and major actors/actresses for which they represent, to producers. The approval of such deal means producers do not need to look for casts in the development stage. Nevertheless, such deal will be approved only if producers believe that the potential casts match the characters in the script.

The end of the development stage is often a major hurdle facing film projects, with films being stuck in development hell if they are not green-lit. If a film project receives a green light from a studio executive, it will move into pre-production stage; if it fails to do so, it will not likely be developed. Less than 15% of the film projects get green-lit (Taylor, 1999 quote from Wasko, 2008). Most projects that have received the green light will be completed, as a great deal of money has already been invested in the project (Wasko, 2008). Once a film project starts its pre-production stage, a large proportion of the creative part of filmmaking, such as writing shooting scripts, drawing storyboards, and designing scenes, have been completed. The firm crew now focuses their attention on administrative decisions such as creating the shooting schedule and finding filming locations.

After pre-production, a film enters the most important and costly part of the filmmaking process—principal photography (Wasko, 2008). The director will take over much of the producer’s role in this stage. As the core figure of the film crew, directors coordinate the technical and artistic teams and ensure that the film crew sticks to the shooting plan set in the pre-production stage. Financiers, who are studio representatives for blockbusters and other investors for indie films, may pay a visit from time to time (they are called “The Suits”), but, in general, it is the

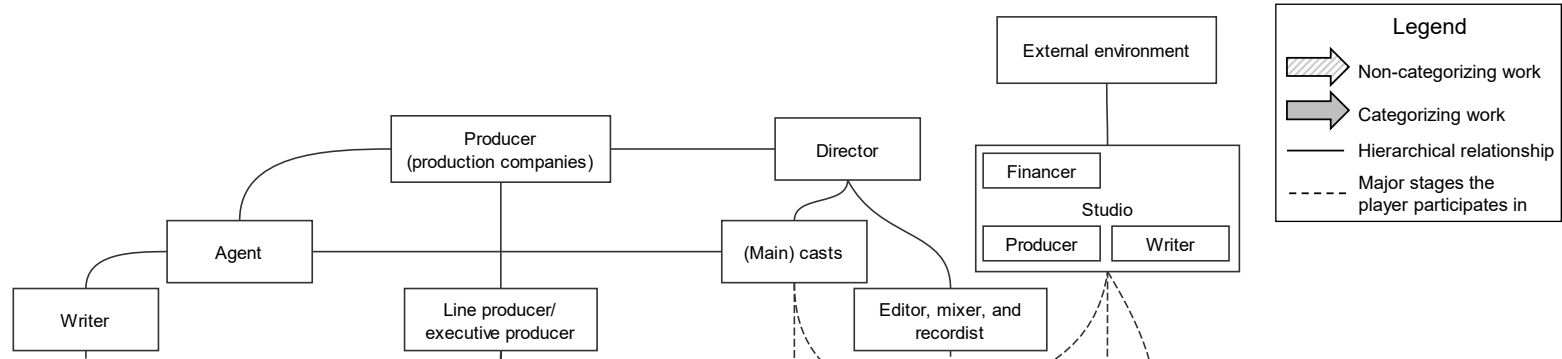


director who maintains control throughout photography (Silver, 1975, quote from Perretti and Negro, 2007). Principal photography is often seen as the “most glamorous and/or creative part of the manufacture of the film commodity (Wasko, 2008, p.59)”. The spark of creativity, nevertheless, relies on director's deep understanding of the screenplay and effective cooperation between the casts.

Post-production starts after shooting concludes. During this stage, other elements of the film, including scoring, mixing, dialog, music, sound effects, and special effects, are added (Wasko, 2008, p.59). Editors undertake most of these jobs under the supervision of directors. It should be noted that in the modern Hollywood film industry, producers, studios, and financiers often reserve the final cut privilege, unless the directors are extremely established and bankable (Wasko, 2008). When post-production finishes, studios take over the project and start the distribution and marketing process. Distribution and marketing have become one of the most important aspects of contemporary Hollywood film industry, with marketing costs accounting for one-third of the total cost a major studio spends on a film project (Wasko, 2008, p.63). Directors and casts still participate in the marketing of films, although their primary duties on the film have been completed. They may take part in the road shows organized by distributors, attend film festivals, or create multiple versions of trailers, all of which affect the audiences’

decision to go to cinema and their prior perceptions of the film. Figure 2-1 summarizes the hierarchy of film crew, the timeline of filmmaking, and the major players who participate in categorizing and non-categorizing work in North American film industry.

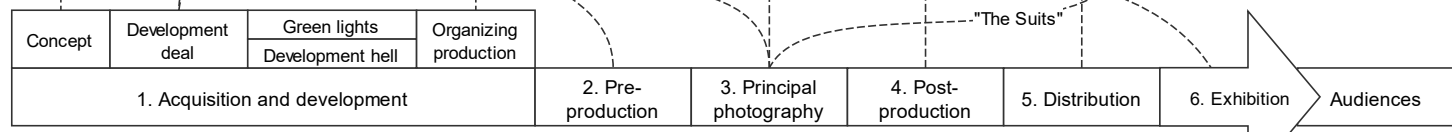
**Hierarchy**



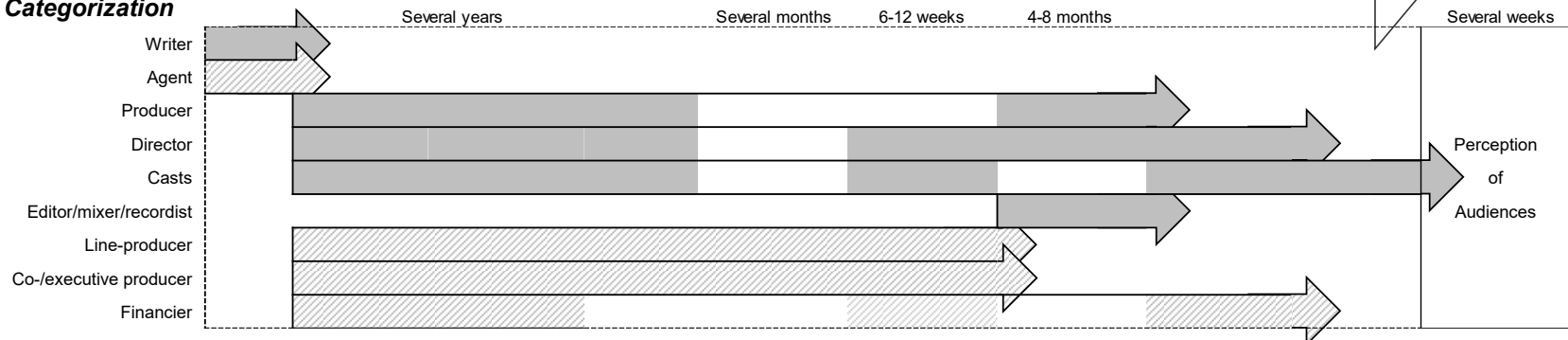
**Legend**

- Non-categorizing work
- Categorizing work
- Hierarchical relationship
- Major stages the player participates in

**Timeline**



**Categorization**



**Figure 2-1:** Filmmaking in North America: Hierarchy, Timeline, and Categorization

### **2.4.1 Categorizing work in filmmaking**

There are multiple categorical dimensions in feature films, such as genre, country, technical specs, and ratings. Genre is the most important of these dimensions. It is the tacit “contract”, or consensus, between filmmakers and audiences resulting from their repeated social interaction (Schatz, 1981). Early audiences evaluate the offerings of filmmakers and label the offerings, and films classified under the same genre are perceived as similar in terms of structural components such as plot, character, setting, thematics, style, and so on (Hsu, 2006; Schatz, 1981). When films are released in theatres, the mass audiences will browse all available offerings in the market and go to the movies whose genre labels match their preferences. In general, the genre of a film affects which types of audiences will watch it. Genre is one of the most widely explored categorical systems in previous category research (e.g., Hsu, 2006; Hsu et al., 2009, Zhao et al., 2013, Zuckerman et al., 2003). Following previous scholars, I focus on the categorization of films in terms of genre labels in this paper.

Although multiple film crew members participate in filmmaking (see Figure 2-1), not all members contribute equally to shaping the perceptions of audiences regarding genre labels the film is associated with. Some crew members’ work is irrelevant to the categorization of the focal film. For example, agents primarily

focus on the matchmaking between their clients (writer and casts) and producer (Zuckerman et al., 2003). Line-producer, co-producer, executive producer, mostly handle the daily operations of filmmaking, and they seldom contribute to the artistic component of a film. When they take a few creative responsibilities, they do so under the supervision of producers. The real categorizing work is done by the producer, who acts as the head of the film crew, and members of the film crew with a creative role. The categorization process starts when the producer buys the script from the writer. The original script stipulates important boundary conditions for the film crew to work with, and it likely informs subsequent steps in the production process and the potential audiences it will attract. Using professional knowledge and prior experience, the producer estimates the market potential of the script and considers how the script be polished. If the producer believes that the script will have better box office revenues if developed into a blockbuster that contains multiple genre factors, a reasonable decision is to hire corresponding directors and casts who have related knowledge and experience to deal with such a project. Likewise, when the producer anticipates that audiences are looking for stylized films (e.g., cult films), then directors and casts who have wide acceptance in that niche market may be hired to ensure that the film will match audiences perception of a certain genre. Anyhow, producers are at the helm of the categorizing work in

filmmaking, especially in the acquisition and development stage when other film crew members such as director and casts are not ready yet.

The director and leading casts, who are respectively at the head and main players of the creative stream of a film crew, also play important roles in shaping the perception of audiences. The director dominates the principal photography and post-production stages. During the filming, the director controls the artistic, dramatic, and technical aspects of the film, and his or her professional knowledge, experience, taste, and even intuition, will set the tone of the final product and vastly shape the overall perception that audiences have of it. A mismatch between the director's specialization and the requirements of a project may confuse audiences. Ang Lee, with three Academy Awards, is skilled at creating cultural and emotional conflicts in films and presenting such conflicts in sophisticated narratives. His style and philosophy of filmmaking made him a major success in *Sense and Sensibility*, but also resulted in a less favorable version of *Hulk*. In the post-production stage, the director also supervises other film crew staff that have creative responsibilities. Although the editing work of other staff (e.g., editors, mixers, recordists, and projectionists) deeply shape the artistic and aesthetic styles of films through mixing, music, sound effects, and special effects, among others, they perform their work in consultation with the director, based on his or her

conception of the finished product. Some credible directors, such as Akira Kurosawa and the Coen Brothers, even edit their own films. In sum, directors undertake more categorizing work during the principal photography and post-production stages (see Figure 2-1 for details).

The distinctive roles of the cast in film categorization are based on their unique position in film crew: they are the interface through which audiences know the film. Casts are the only film crew members who still have the ability to shape audiences' perception of films during the exhibition stage of the films. Their identities and stereotypes, such as action heroes (e.g., Jackie Chan, Jason Statham, Arnold Schwarzenegger, etc.), comedians (e.g., Jim Carrey and Robin Williams), or dramatic film actors (e.g., Leonardo DiCaprio, Jodie Foster, Kate Winslet, etc.) deeply affect how audiences recognize and evaluate films (Zuckerman et al., 2003). The identity spillover of the cast could be even more pronounced when the cast enjoys high status (McDonald, 2008). Furthermore, the leading actors and actresses also participate in multiple stages of filmmaking as early as the development of a film (Wasko, 2008). Their in-depth involvement in a film project makes their contribution in categorizing the film non-negligible.

My analysis of filmmaking in North America reveals that “genre-giving” is never a purely exogenous, passive process in which a film is “indexed” by audiences

based upon its fit with current classifications (Negro et al., 2010b). Categorizing work starts long before a film is released. Core members of the film crew (producer, director, and casts), based on their own understanding of the film and by applying their skills, shape the storyline, narrative, structure, artistic and aesthetic style of the film during the filmmaking process (Schatz, 1981). These elements together come together to create the feature film that is presented to audiences, who then categorize the focal film in the exhibition stage. Put differently, filmmakers set the tone of categorization, and audiences categorize films based on the result of production they are exposed to in the cinema.

Although this study emphasizes the initiative of organizational agents (producer, director, and casts) in film categorization, it does not deny the possibility that other exogenous factors also affect how audiences categorize feature films. An important channel through which the external environment drives the categorization of film projects is via film studios. As I mentioned earlier, film studios usually reserve the final cut privilege in modern Hollywood (Wasko, 2008). Their role in filmmaking is purely commercially-oriented: by removing controversial content and reinforcing the plot that is welcome by the market, studios produce films with bankable genres in the market. To tease out the effects



of external environment on film categorization, I control for studio-level variables and environmental-level factors in the analysis.

As opposed to previous research, which views categorization from an audience-centric perspective and assumes it only occurs during the exhibition of a film (e.g., Hsu et al., 2009; Zhao et al., 2013), this article advocates a producer-centric perspective, arguing that the categorization process starts as early as the development stage and is promoted by multiple organizational agents. But how does the film crew shape audiences' perception of the categories of a feature film and what benefits does this perception-shifting work bring to the organization? Returning to the definition of a category upon which the entire field of category research was built, I propose the cognition-, capability-, and newness-based mechanisms that drive audiences' perception of the focal film and investigate their performance implications.

## **2.5 Hypotheses and corollaries**

### **2.5.1 Cognition and capability-based mechanisms**

I begin my analysis by focusing on the cognition- and capability-based rationales affecting the perceived genres of the films. A category is the shared understanding among all market players about the collective identities of producers' products (Khaire and Wadhvani, 2010; Vergne and Wry, 2014). It is,

by definition, a socially-constructed cognitive consensus of how social space is partitioned (Gaertner et al., 1989, 1993, 2000; Negro et al., 2010b). To make audiences perceive the focal product falls under the categories intended by the producer, the focal product should be cognitively consistent with audiences' conception of those categories. Such cognitive consistency can be achieved by presenting in cues, hints and symbols in the offering, or embracing myths and rituals that evoke audiences' memories of the prototypical products belonging to those categories (Meyer and Rowan, 1977). For example, to stimulate audiences' recognition of the focal film as a Western-Romance, filmmakers might include romance elements such as wedding, kissing scenes, and emotional conflicts, as well as common western symbols, such as desolate landscape, cowboys, and gunfights, in the storyline. Incongruent cues, as confirmed in social psychological experiments (Gaertner et al., 1989, 1993, 2000), will lead to mismatched cognitive processes of audiences and biased evaluations of the focal product.

While audiences' categorization of products will be facilitated by sufficient cognitive cues, this assistance will be useful only if the products presented to audiences possess features that truly support their (implied) categorical claim. This argument is particularly pronounced in a category emergence research (e.g., Hsu and Grodal, 2015; Khaire and Wadhvani, 2010), in which researchers found

that the legitimacy of a new category is conditional on the fact that the new product possesses some new attributes that are not part of the current category system (Durand and Khaire, 2017). For example, a new artwork category called “modern Indian art” emerged in the auction market in the last decades of the 20th century. An important reason why collectors, auction houses, and critics created this category is that they realized that some Indian artworks have some unique aesthetic features that make them difficult to be classified in current categories (Khaire and Wadhvani, 2010). As another example, the popularity of the “light” cigarette category in the U.S. coincided with tobacco producers’ manipulation of nicotine and tar levels in their products. Category membership will be perceived by audiences in the manner intended by audiences only if they possess features that align with perceptions of that category.

The same rationale also applies in the filmmaking context. To make the focal film be perceived in part of the genres that the producer intended to target, filmmakers should build a film crew that are both capable of filming in those genres and cognitively suitable to do so. Genres are the sub-fields in feature film production. Film crews with particular skills sets are suited for different genres, such as romance, western, and thriller. For a film project planning to attract audiences in a single niche (e.g. horror), the best strategy is to fill positions with

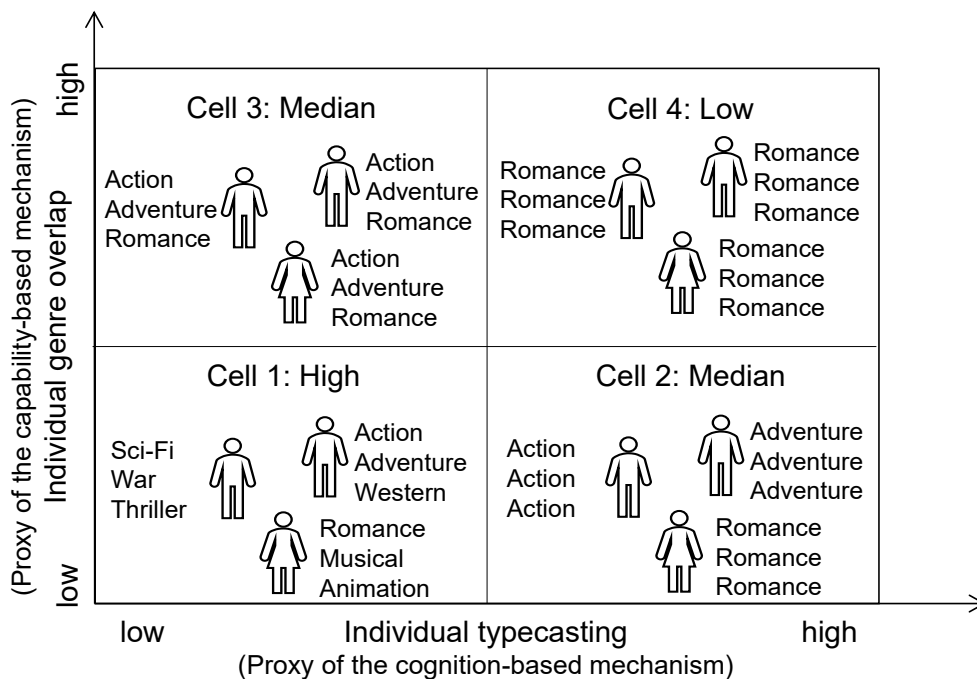
crew members specialized in horror film production. Adequate experience of crew members in the targeted genre not only ensure that the film crew is competent in filming horror films, but also send clear message to the audiences that the film crew is creating a film that personifies that genre. Similarly, for a film aiming at a wide audience, it is preferable to hire a film crew with diversified skills in multiple genres. The diversity of a film crew's prior experience serves as both a guarantee that the film crew can handle a multi-genre production and a signal of what audiences preferring to watch blockbusters with multiple elements can expect from the final product. This argument leads to the first hypothesis regarding the effects of film crew diversity on the film's perceived genre width.

*Hypothesis 1: The level of diversity of a film crew's prior experience with respect to different genres is positively associated with audiences' perception of the genre width of the focal film.*

#### *2.5.1.1 Decomposing the effects of film crew diversity*

Hypothesis 1 examines the cognition- and capability-based explanations of the driving forces of firm categorization. Nevertheless, this hypothesis is limited in two respects: first, it discusses the antecedents of audience perception at the film crew level, while individual-level effects (e.g., high-profile casts and directors) are assumed as nonnegligible in the feature film industry (Basuroy, Chatterjee, and Ravid, 2003); second, by treating film crew diversity as both a signal of cognitive

consistency and embodiment of filmmakers' competence, the empirical test cannot tell us which mechanism dominates audience perception. To redress the gap, I decompose film crew diversity into two individual-level components, typecasting of crew members and overlap of experience between crew members, in Figure 2-2. Typecasting refers to the process by which a film crew member is repeatedly identified with a specific character or particular type of film. It is a longitudinal summary of a filmmaker's career path. In a study of the feature-film labor market, Zuckerman et al. (2003) found that typecasting is independent of the sorting process driven by actors' underlying skill differences. In addition, they found that typecasting actually reflects the general belief (or preconception) in the market that the focal actors can (only) act well in the categories in which they are associated (Zuckerman et al., 2003). The typecasting of the whole film crew, in this sense, approximates the cognition among general audiences of the extent to which the film crew can effectively create certain types of films. The second indicator, overlap of experience between crew members, compares the filming experience among crew members. Because the overlap of experience between crew members directly affects the breadth of knowledge the film crew has (Vasudeva and Anand, 2011), it approximates the capacity a film crew has to create multi-genre films.



**Figure 2-2:** Decomposing the effects of film crew diversity

Figure 2-2 illustrates the relationships among the typecasting of crew members (proxy of cognition-based mechanism), the overlap of experience between crew members (proxy of capability-based mechanism), and diversity of a film crew’s prior experience. To simplify my analysis, I assume that each film crew contains three members and each member participated in the production of three single-genre movies before they joined the current film crew. The exact number doesn’t matter since it does not change my results. The crew members can be either producer, director, or cast. As shown in the figure, low levels of typecasting of crew

members and experience overlap between members (Cell 1) will yield the highest level of film crew diversity; high levels of typecasting and experience overlap between crew members (Cell 4) will yield the lowest level of film crew diversity. Besides the extreme values, a group of typecasting members who specialize in different genres (Cell 2), and a combination of “jack-of-all-trade” members who have the same profile (Cell 3), will yield the median level of film crew diversity. Additionally, holding genre overlap between crew members constant, typecasting of individual members is negatively associated with the diversity of film crew’s genre experience (diversity decreases when film crew moves from Cell 1 to Cell 2 and from Cell 3 to Cell 4). Holding typecasting of individual members constant, genre overlap between crew members is also negatively associated with the diversity of film crew’s genre experience (diversity decreases when film crew shifts from Cell 1 to Cell 3 and from Cell 2 to Cell 4). Relating these results to Hypothesis 1, we can deduce the following reasoning:

*Corollary 1 (cognition-based mechanism): The typecasting of a film crew member is negatively associated with audiences’ perception of the genre width of the focal film.*

*Corollary 2 (capability-based mechanism): The overlap of prior experience between crew members with respect to different genres is negatively associated with audiences’ perception of the genre width of the focal film.*

### **2.5.2 Newness-based mechanism**

While the cognition- and capability-based mechanisms consider the perceptible outcome of hiring experienced filmmakers, the third mechanism, newness-based mechanism, concerns the perceptible outcome of hiring film crew members who possess little industry experience. Although newcomers do not have robust identities and proven track records, they are often more proactive (Ng and Feldman, 2010). Reflected in a firm's daily operations, newcomers are more likely to pursue uncertain, radical innovations, while old-timers tend to exploit the old certainties and gain stable revenues (Barker III and Mueller, 2002; Hambrick, 1984; March, 1991). Empirical studies in the feature film context validate the aforementioned argument. Miller and Shamsie (2001) found that executives from major Hollywood studios tend to pursue more product line experimentation during the early stage of their tenure. Production line experimentation entails the studio releasing films in genres that they have not produced previously. When executive tenure increases, a studio's product line experimentation declines (Miller and Shamsie, 2001). Another, more direct piece of evidence is provided by Perretti and Negro (2007), who found that a film crew with high incidence of new members are more likely to introduce new genres or new combinations of existing genres into their productions.



The proactiveness of newcomers vis-à-vis old-timers derives from their subtle differences in knowledge bases (March, 1991; Simon, 1991). Old-timers on average know more (March, 1991; Perretti and Negro, 2007). Besides possessing greater professional knowledge, old-timers have mastered the routines and conventional practices of their organization and the industry, while newcomers do not yet possess the tacit knowledge of the workplace. The proportion of old-timers and newcomers within an organization, as a result, determines the knowledge base and behavioral patterns of the organization (March, 1991; Simon, 1991). Organizations led by old-timers have the discretion to either use well-established practices or develop new solutions when they confront problems (March, 1991), while organizations dominated by newcomers do not have routines or conventions to rely on. In other words, old-timers are more likely to “exploit” their knowledge base (perform “local search”); newcomers have to “explore” extensively (perform “distant search”, see Katila and Ahuja, 2002; March, 1991). Because distant search (exploration) involves discovering new possibilities using alternative methods (Afuah and Tucci, 2012; March, 1991), newcomers who perform distant search are more likely to be perceived as proactive and innovative.

The proactivity of a new film crew and the distant search it performs will ultimately affect the perception of audiences. As the film crew attempts to explore

new approaches of presenting a story to audiences, it may, either accidentally or on purpose, avoid the images, symbols and cues that are routine in previous works of the same kind, and instead, adopt novel elements that are consistent with the theme of the focal film whilst not common in previous films. As a result, new crew members are more likely to create a film in which multiple motifs, narratives, and cinematic techniques are blended together. Therefore, I hypothesize the following:

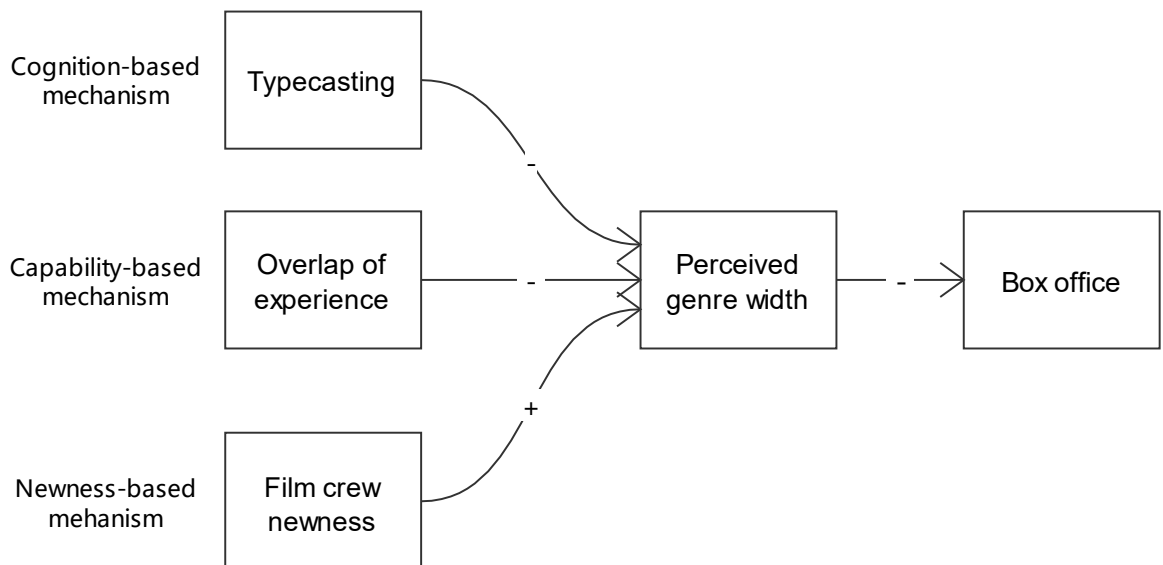
*Hypothesis 2: The level of newness of a film crew is positively associated with audiences' perception of the genre width of the focal film.*

Hypothesis 2 argues that newcomers are more likely to produce a film that has wide genre width. But do all new members have the same weighting in promoting the perceptive diversity of the focal project? As discussed earlier, producers play a leading role in filmmaking by guiding the film through development, pre-production, principal photography, and post-production (Wasko, 2008). Possessing greater administrative power, the producer's intention of creating a new and complex production is more likely to be implemented than that of other crew members such as the director and cast. Thus I hypothesize the following:

*Corollary 3: The relationship between newness of a film crew and perceived genre width is stronger for a film crew that possesses a new producer.*

### 2.5.3 Indirect effects of strategic categorization

I have discussed the cognition-, capability-, and newness-based mechanisms through which filmmakers affect the genre perception of audiences. Yet manipulating audience perception is not the ultimate objective of filmmakers. As strategic categorization involves substantial resource commitment (e.g., hiring specific actors and directors, form a specific film crew, etc.), filmmakers will not be motivated to participate in strategic categorization unless they can expect equivalent returns. Naturally, the next question is to what extent can filmmakers affect a film's box office via strategic categorization. In other words, I am particularly interested in the causal link between film crew characteristics to a film's box office via audiences' genre perception (see Figure 2-3).



**Figure 2-3:** Indirect effects of organizational agents on a film's box office

Previous research has provided abundant empirical evidence on the second stage of the causal link I am interested in—the relationship between category spanning and a product's economic and social performances (Hsu et al., 2009; Zuckerman, 1999; Zuckerman et al., 2003). The negative relationship between category spanning and economic returns holds even if countervailing moderators are considered (see Kovács and Hannan, 2010; Negro et al., 2010a; Ruef and Patterson, 2009), various measurements of category spanning are used (category coherence in Barbosu, 2016; count measurement in Hsu, 2006; and fuzzy categories first employed by Kovács and Hannan, 2010), and rigorous causality identification tools are applied (natural experiment in Leung and Sharkey, 2014; field experiment in Bowers, 2015).

Returning to the first stage of the causal link, if the relationship between film crew characteristics and genre width is strong enough, the impacts of filmmakers beyond shifting audiences' perception on a film should be observed. By manipulating the genres perceived by audiences, filmmakers may further influence the profitability of the film. Thus:

*Hypothesis 3: The strategic categorization of filmmakers, through cognition-, capability-, and newness-based mechanisms, will*

*ultimately affect the box office of the focal film. Put differently, filmmakers indirectly affect the box office of the focal film through shifting audiences' perception of film genres.*

Figure 2-3 visualizes the relationships I describe in Hypothesis 3. Since the causal link will exist only if there are strong relationships between film crew characteristics and genre width, as well as between genre width and box office, the mediating relationship proposed in Hypothesis 3 also serves as an *ex post* test of the existence of strategic categorization, namely the causality between film crew characteristics and genre width perceived by audiences. In addition, perceived genre width, which was exogenous in previous studies, is not strictly exogenous in my theoretical framework since I theorize that it is affected by internal filmmakers in the feature film setting. This yields the following corollary:

*Corollary 4: As internal players (filmmakers) can manipulate the genres perceived by external players (audiences), the perceived genre width becomes endogenous to a film's box office.*

Corollary 4 suggests that research that does not consider the strategic nature of filmmakers may yield biased results when evaluating the categorical imperative in the feature film context.

## **2.6 Data, variable, and identification strategy**

I collected data covering all feature films produced in the US and Canada between 2000 and 2015 from Internet Movie Database (IMDb). IMDb is the

largest online movie database covering as many as 384,768 feature films as of November 21, 2017. It provides exhaustive information needed for this study including film name, release date, box office, genre(s), audience rating, MPAA rating, director, cast(s), producer(s), distributor, budget, and opening screens. I also collected award information from Academy Awards Database and additional genre information from The Movie Database (TMDb). TMDb is a competitor and non-commercial version of IMDb with a vibrant online community. It provides API support for users to retrieve its film data. I used its information on film genres and constructed genre-related variables by matching the information from both IMDb and TMDb.

I chose 2000 as the starting year because both databases have more detailed information on movies released over the last two decades. There are 9,317 feature films theatrically released between January 1, 2000 and December 31, 2015<sup>3</sup>. Films with incomplete information on the variables I used were dropped. Overall, the number of observations in my models ranges from 1,744 to 2,404, accounting for 18.7% to 25.8% of theatrical films released during this period. The sample size varies since different sets of explanatory variables were controlled in different

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<sup>3</sup> The number of movies released is collected from Box Office Mojo ([www.boxofficemojo.com/yearly](http://www.boxofficemojo.com/yearly)).

estimations. I use two identification strategies to separately conduct ex ante and ex post analysis of strategic categorization. A detailed description follows.

### **2.6.1 Ex ante analysis of strategic categorization**

#### *2.6.1.1 Dependent variable*

Following previous literature Hsu et al., 2009; Kovács and Hannan, 2010; Paoletta and Durand, 2016; Zhao et al., 2013I use an index of concentration to operationalize the dependent variable, perceived genre width of the focal film. The index is constructed in four steps. First, I gather information on film genres from IMDb and TMDb. IMDb uses 22 genres to categorize a film, while TMDb employs 19 genre labels. I use only genres that are recognized by both sources, which are 18 in number. They are *Action, Adventure, Animation, Comedy, Crime, Documentary, Drama, Family, Fantasy, History, Horror, Musical, Mystery, Romance, Sci-Fi, Thriller, War, and Western*. Genres are assigned by engaged external audiences (audiences or critics). Since a film can have a multiplicity of various artistic and narrative features, audiences do not always provide a consistent classification of a film. Their divergence in terms of genres film reflects the film's grade of membership (or degree of typicality) in different categories (Kovács and Hanna, 2010), which is captured in the following formula:

$$\text{GoM}_{ig} = \begin{cases} 0, & (\text{if } i \text{ does not have genre } g) \\ 0.5, & (\text{if } i \text{ has genre } g \text{ in either IMDb or TMDb}), \\ 1, & (\text{if } i \text{ has genre } g \text{ in both IMDb and TMDb}) \end{cases}$$

where  $i$  is the focal film I consider,  $g$  is one of the 18 candidate genres. A film can have a full membership (GoM = 1), half membership (GoM = 0.5), or no membership (GoM = 0) in a certain genre.

After I measure the grade of membership of a film for a certain genre, the third step is to measure the comparative saliency of that genre in its genre profile. It is measured using the following equation:

$$\mu_{ig} = \frac{\text{GoM}_{ig}}{\sum_{k \in G} \text{GoM}_{kg}},$$

where  $\mu$  represents the comparative saliency of genre  $g$  on film  $i$ , the denominator is the sum of the GoM a film gets in a set of 18 genres ( $G$ ), and the numerator is the typicality of a film in genre  $i$ . The more genre labels assigned to a film, the less comparative saliency of any genres in that film. For example, if a film is assigned to five genres, say, romance, action, western, science-fiction, and thriller, it becomes hard for audiences to believe that this film resembles the “prototypical” romance film that they watched before. The last step is to calculate the genre width of a film by summing up the square of comparative saliency of each genre, using the following equation:

$$\text{Width}_i = 1 - \sum_{g \in G} \mu_{ig}^2,$$



where the range of  $\text{Width}_i$  is  $[0, 1)$ . The larger the value of width, the more genre labels a film claims membership in. Note this variable also acts as a mediator in the box office equation.

### 2.6.1.2 Independent variables

The first key independent variable is film crew diversity. The review of the filmmaking process recognizes three types of film crew members that are essential to a film's categories: producer(s), director(s), and cast. I consider all members that are titled as "producer" or "director" and the first four names that are credited as "cast" in the film credits. I employ a similar approach that I used in the genre width compilation to calculate film crew diversity. The first step is to measure the prior experience of crew member  $j$  in genre  $g$ :

$$\text{GoM}_{jg} = \sum_{t \in [T, T-5]} \text{GoM}_{jgt},$$

where  $\text{GoM}_{jg}$  denotes the accumulated grade of membership in genre  $g$  of all film projects crew member  $j$  was employed in during previous five years. I only consider the crew member's experience in the recent five years (1825 days before the theatrical release of the focal film) because the prior experience a crew member gains may become obsolete as time goes by (Hoang and Rothaermel, 2005). After I obtain prior experience at the individual level, the second step is to aggregate the experience of all crew members in a certain genre together and calculate the

expertise of the film crew regarding that genre. This is achieved by summing up all crew members' previous experience in genre  $g$  and dividing it by crew members' experience in all 18 genres. I do so using the following equation:

$$\varphi_{cg} = \frac{\sum_{j \in C} \text{GoM}_{jg}}{\sum_{j \in C} \sum_{g \in G} \text{GoM}_{jg}}.$$

There are  $j$  crew members belonging to film crew  $c$  in this formula.  $\varphi$  represents a film crew  $c$ 's expertise in genre  $g$ . The larger the value, the more specialized the film crew is in this genre. Finally, I calculate the level of diversity of a film crew's experience with respect to different genres using the following equation:

$$\text{Diversity}_c = 1 - \sum_{g \in G} \varphi_{cg}^2,$$

where the range of  $\text{Diversity}_c$  is  $[0, 1)$ . The larger the value of diversity, the more diversified experience the film crew has.

Film crew diversity can be decomposed into two individual-level variables: typecasting of individual crew members and overlap of prior experience between crew members. Because we already know the GoM of a crew member in each genre, the typecasting of that crew member during the past five years is given by:

$$\text{Typecast}_j = \sum_{g \in G} \left( \frac{\text{GoM}_{jg}}{\sum_{g \in G} \text{GoM}_{jg}} \right)^2,$$

where the maximum value of  $\text{Typecast}_j$  is 1, which means the focal crew member only worked in one genre in the past five years. Lower values represent a more

diversified genre experience for the crew member. When I consider the average typecast level of all crew members in the film crew, I take the average of producer's, director's, and casts' typecasting variables.

The third key independent variable is the overlap of experience between crew members. To account for this overlap, the overlap in the of GoM profiles of the individual crew members needs to be calculated. The overlap of experience between two crew members can be calculated using an extended Jaccard similarity formula (Strehl and Ghosh, 2000):

$$\text{Overlap}_{j_1 j_2} = \frac{\mathbf{GoM}_{j_1}^T \mathbf{GoM}_{j_2}}{\|\mathbf{GoM}_{j_1}\|^2 + \|\mathbf{GoM}_{j_2}\|^2 - \mathbf{GoM}_{j_1}^T \mathbf{GoM}_{j_2}},$$

where  $\mathbf{GoM}_{j_i}$  is a vector of 18 elements measuring the grade of membership of crew member  $j_i$  in each genre in the past five years;  $\|\mathbf{GoM}_{j_1}\|^2$  is the Euclidean norm of this vector. The extended Jaccard similarity index is suitable as an overlap measurement for two reasons. Firstly, it can be used to compare two continuous non-negative vectors, while the original Jaccard similarity index can only compare two binary vectors (see applications in Paoletta and Durand, 2016 and Pontikes and Kim, 2017). Secondly, it ignores the zero-zero matches that may inflate the similarity between two individuals. This is a useful attribute since most of the crew members in my dataset only have experience in a small fraction of all available genres in the past five years. When I consider the level of overlap in the film crew,

I take the average of the pairwise overlaps among producer(s), director(s), and cast:

$$\text{Overlap}_c = (\text{Overlap}_{pr,dr} + \text{Overlap}_{pr,ar} + \text{Overlap}_{dr,ar})/3.$$

The last independent variable is a counting variable measuring the newness of the film crew, ranging from zero to three. It takes the value of zero when none of the producers, directors, and cast are newcomers and the value of three when none of them have participated in feature film production in previous years. When I compare the effects of new producer, director, and casts, we replace the count-based variable with three dummies taking the value of one when the focal producer/director/cast is a newcomer and zero otherwise.

### *2.6.1.3 Control variables*

I control for a broad range of variables to reduce omitted-variable bias. Firstly, the audience-centric view argues that product categorization is a purely exogenous process. If that is the case, the perceived genres of a film will only be related to the contents of the film, such as stories, patterns, styles, and themes, regardless of the filmmakers who produce the film. I control *topic diversity of a film script* in the model to consider this possibility. Using a newly developed text analysis technique, structural topic model (STM), I analyze 14,431 film scripts downloaded from an online script database and calculate the diversity of topics of

each film based on the results of STM. STM is a natural language processing technique that uses statistical models to “discover” the topics that occur in a collection of documents. A standard STM-based text analysis starts with document ingestion and preparation, follows with model estimation, and exports the probability that each word belongs to a certain topic and the probability that a topic is associated with a certain document (Roberts, Stewart, and Tingley, 2016). Compared to traditional topic models such as Latent Dirichlet allocation (LDA) and Correlated Topic Model (CTM), STM can use document-level covariate information and yield more accurate results (Roberts, Stewart, and Airoldi, 2016). The Appendix summarizes the process of text analysis based on STM in detail. In brief, for each film project in my data (denoted by subscript  $i$ ), the STM will report the proportion of script document that belongs to topic  $k$ . The sum of topic proportions,  $\mu_{ik}$ , is one. Therefore, the topic diversity of each film script is given as:

$$\text{Topic}_i = 1 - \sum_{k \in K} \mu_{ik}^2,$$

where the number of topics,  $k$ , is twelve in my analysis (see Appendix for how I determine the number of topics). The topic diversity of a film script ranges from zero to one. The smaller the value of this variable, the more likely that the document is dominated by a certain topic; a larger value, on the contrary, indicates that the focal film involves multiple topics and is more likely to be perceived as a

multi-genre production. The expected sign of topic diversity is positive. The Appendix explains the details of the text analysis procedure.

The first perspective of producer-centric view believes that producers undertake a limited number of categorization responsibilities by monitoring the external environment and choosing the category labels that are in coherence with public opinion. I use two variables to operationalize this perspective. The first one is *category reputation*. Previous research found that some producers expand into multiple categories because they want to acquire the reputation spillover of high-profile market players, or dilute the negative impression of stigmatized home categories such as tobacco, weaponry, and gamble (Vergne, 2012). The worse the reputation of their home category, the more likely they diversify into a reputable category. I control the reputation of home category (genre) of a feature film in the model. The reputation of a genre is measured as the mean IMDb rating of all produced films with this genre one year before the focal film is released. The second variable is *market space*. Ecological research indicates that organizations tend to expand into resource-rich niches to increase their survival probability (Hsu, 2006). To control for category spanning driven by exogenous changes in market space, I measure the annual box office of the home category (genre) to

which the focal film belongs<sup>4</sup>. The less exuberant the market of home genre is, the more likely producers expand the elements of their offerings. This variable is lagged one year in my model. Alternative lagging periods were also utilized, and the results are consistent. These results are not presented due to article length considerations).

A definition of “home category” of a film is required when measuring category reputation and market space. Intuitively, home category is the most prominent and visible genre label(s) a film has. But there is usually no official information on the “home category” of a film since filmmakers tend to not make any comments on the genres of a film for marketing reasons and IMDb lists the genres alphabetically on its film information page. I therefore define the home category as the genres with full membership (which means both IMDb and TMDb raters endorse these genres for the focal film), for the reason that the genres that external audiences unanimously agree with are more likely to be the home genre of the focal film.

Besides the audience-centric and producer-centric views, other competing explanations are also considered. High-budget productions often aim at mass

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<sup>4</sup> Annual box office of a category (genre) is the sum of box office of all films in that genre in a certain year. For a film with multiple genres, I divide the box office by the number of genres labels it has.

markets. I thus include *film budget* in the estimations. Films released by major studios and indies are significantly different in terms of artistic style, target market, and distribution channels; such differences may affect how they are categorized. Moreover, the film studio is a “filter” connecting external environment and film projects (see Figure 2-1). The film studio researches the market trends and customer preferences and in accordance, shapes the categorization of films via budget control and final cut privilege. I use a dummy variable, *major studio*, to control such studio effects. Major studios are the six largest Hollywood studios consisting of Warner Brothers, Disney, Universal Pictures, 20th Century Fox, Columbia Pictures, and Paramount Pictures.

In addition, film studios have multiple options when handling a film project. They can offer a distribution deal, under which they only provide distribution and marketing resources for the production companies, or an equity partnership, under which they integrate the development and principal photography stage of filmmaking and share profits with production companies. In the latter case, film studios have greater power throughout the value chain and are more likely to affect the categorization process based on their own interests. I use a dummy variable, *in-house production*, in which studios play both a distributor and a producer, to capture this effect. Lastly, I include the *number of production*



*companies* to control for the conflicts between production companies in filmmaking process. The more companies that participate in the film project, the more likely there are to be disagreements regarding the categorization of the focal film. One possible solution is to broaden the genre elements the focal film exhibits to reconcile the diversified perspectives of production companies. Therefore, it is reasonable to believe that the more production companies participate in filmmaking, the more likely the focal film will become a multiple-genre film.

#### 2.6.1.4 Identification strategy

I employ OLS with robust standard errors to examine the antecedents of film's genre width:

$$\text{Width}_i = \beta_d \text{Diversity}_{ic} + \beta_n \text{Newness}_c + \mathbf{X}'\boldsymbol{\beta} + \varepsilon_i,$$

where Diversity and Newness are the mechanisms I propose to explain the categorization of film projects, and  $\mathbf{X}$  is a vector of control variables. I test the corollaries derived from my hypotheses by decomposing Diversity into two parts: *typecast of crew members* and *overlap between crew members*, and divide Newness into three dummies: *new producer*, *new director*, and *new cast(s)*.

## **2.6.2 Ex post analysis of strategic categorization**

### *2.6.2.1 Dependent variable*

In the second stage, I focus on the indirect effects of filmmakers on a film's economic outcomes. There are multiple outcome indicators in feature films such as audience and critics rating (Hsu et al., 2009), audience admission (Hsu, 2006), and box office revenue (Zhao et al, 2013). I choose box office as the dependent variable because it is the major reason why film crew members engage in the categorization of their offerings. I adjust the box office data using the average ticket price from MPAA to offset the variation in box office data generated from currency inflation.

### *2.6.2.2 Independent and mediating variables*

The independent variables are the same as in ex ante analysis. The mediator is the *perceived genre width* of the film. The operationalizations of independent and mediating variables have been previously discussed in the ex ante analysis

### *2.6.2.3 Control variables*

I include a number of control variables that capture individual-, film-, and market-level determinants of a film's box office. I provide only a brief rationale for the choice of these variables since there is an abundance of literature using that uses these variables to account for a film's box office. Bankable actors and directors

can attract more theater admissions (Basuroy et al., 2003). Following Moul (2007), I measure *star power* as the average box office of the starring casts in the previous five years. I consider only the first four credits in the billing since protagonists and main supporting casts are usually the most prominent figures in the film. *Director power* is measured as the total prior 5-year revenue of director (Moul, 2007). At the film-level, I control for *film budget*, *audience rating*, *award record*, *distributor*, and *MPAA ratings*. Budget is the U.S. dollar value of a film project's total investment. Audience rating is operationalized as the IMDb rating ranging from one to ten. Award record is a dummy variable taking the value of one if the focal film received the Academy Best Picture, and zero otherwise. The data on Oscar awards were collected from the Academy Awards Database ([awardsdatabase.oscars.org](http://awardsdatabase.oscars.org)). Distributor is a dummy variable taking the value of one if a major six studio takes part in the distribution process, and zero otherwise. MPAA ratings is a series of dummy variables measuring the rating of MPAA. There are five rating symbols: G, PG, PG-13, R, and NC-17. Restrictive ratings such as R and NC-17 usually attract much narrower market niches than lenient ratings, such as G, PG, and PG-13 (Waguespack and Sorenson, 2011). The effects of ratings are controlled in my model.

I also control for a series of market-level factors including *opening screens*, *genre reputation*, *market space*, and *genre crowding*. Opening screen is measured as the number of screens on which a film played in its first week of exhibition. Genre reputation and market space measures the overall attractiveness of genre(s) to the audiences. I described how they have been operationalized in the last section. Genre crowding measures how competition between the focal film and other films exhibited in the same period affects the focal film's box office. Audiences may become satiated if the market is inundated with homogenous films. To capture the competitive pressure from other films, I calculate the accumulated overlap of a film with all other films (Hsu, 2006; Hsu et al., 2009; and Zhao et al., 2013). Specifically, I first calculate the extended Jaccard similarity in genres between the focal film and all other films exhibited in the same month when the focal film was released. Subsequently, I sum up the similarity index together to obtain the overall competitive pressure faced by the focal film.

Lastly, I consider seasonality in my model (see Einav, 2007 for detailed discussion). I control for *low season*, *Friday*, and include year fixed effects. Low season is a dummy variable taking the value of one if a film is released during the traditional low seasons, May, September, October, and November, and zero otherwise. Most films are released on Friday to harvest high opening weekend

gross (Einav, 2007). I use a dummy variable which captures such Friday effects. Additionally, I use year dummies to capture other unobserved year-fixed heterogenous effects.

#### *2.6.2.4 Identification strategy*

I employ multiple approaches to detect the indirect effects of strategic categorization. First, the traditional Baron and Kenny (1986) procedure is used to test the mediating role of genre width. Second, a structural model which simultaneously estimates the relationship between film crew characteristics and genre width, as well as between genre width and box office, is fitted. Based on the structural model, I analyze the indirect effects of film crew characteristics on a film's box office using the Sobel test and bootstrapping. Lastly, I use a control function approach to examine the endogeneity of perceived genre width. The control function approach is identical to two-stage least square (2SLS) estimates in linear models but has many additional attractive features (Wooldridge, 2015). It provides an easy and intuitive way to perform the Hausman test with heteroskedasticity and cluster correlation of unknown form considered (Wooldridge, 2015). To execute a control function method, one should first regress the variable that is believed to be endogenous on all variables that may affect that variable, and then include the residuals of the first equation as a control variable

in the model of interest. The point estimation of the coefficient of the residual term is akin to a Hausman test—significant result suggests that the variable of interest is endogenous to the model, and regressions without controlling for endogeneity may yield biased results.

## **2.7 Results**

### **2.7.1 Genre width equation: ex ante evidence**

Table 2-2 presents the descriptive statistics and pairwise correlations for variables used in genre width regression.

**Table 2-2:** Descriptive statistics of genre width equation

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
N	7,479	6,743	6,621	4,210	10,994	10,994	10,994	10,994	4,837	5,784	7,471	7,471	3,463	10,100	4,752
Mean	0.49	0.71	0.35	0.35	0.92	0.31	0.46	0.14	0.40	2.92E+07	6.12	7.94E+08	0.66	2.57	0.44
S.D.	0.27	0.24	0.24	0.24	0.96	0.46	0.50	0.35	0.49	3.70E+08	0.65	4.38E+08	0.13	1.93	0.50
Min.	0	0	0.09	0	0	0	0	0	0	0	4.50	830447.2	0.02	1	0
Max.	0.90	0.92	1	1	3	1	1	1	1	2.80E+10	7.57	1.82E+09	0.87	26	1
(1) Perceived genre width															
(2) Film crew diversity	0.28 <sup>z</sup>														
(3) Typecasting of crew members	-0.26 <sup>z</sup>	-0.92 <sup>z</sup>													
(4) Overlap of experience between crew members	-0.11 <sup>z</sup>	-0.55 <sup>z</sup>	0.24 <sup>z</sup>												
(5) Film crew newness	-0.17 <sup>z</sup>	-0.23 <sup>z</sup>	0.14 <sup>z</sup>	0.05 <sup>y</sup>											
(6) New producer	-0.15 <sup>z</sup>	-0.19 <sup>z</sup>	0.12 <sup>z</sup>	0.01	0.79 <sup>z</sup>										
(7) New director	-0.12 <sup>z</sup>	-0.10 <sup>z</sup>	0.04 <sup>y</sup>	-0.02	0.81 <sup>z</sup>	0.45 <sup>z</sup>									
(8) New casts	-0.09 <sup>z</sup>	-0.19 <sup>z</sup>	0.17 <sup>z</sup>	0.16 <sup>z</sup>	0.55 <sup>z</sup>	0.19 <sup>z</sup>	0.19 <sup>z</sup>								
(9) Major 6 studios	0.23 <sup>z</sup>	0.25 <sup>z</sup>	-0.22 <sup>z</sup>	-0.05 <sup>y</sup>	-0.26 <sup>z</sup>	-0.18 <sup>z</sup>	-0.22 <sup>z</sup>	-0.13 <sup>z</sup>							
(10) Budget	0.04 <sup>y</sup>	0.03 <sup>x</sup>	-0.04 <sup>x</sup>	-0.01	-0.05 <sup>z</sup>	-0.04 <sup>y</sup>	-0.05 <sup>z</sup>	-0.02	0.06 <sup>z</sup>						
(11) Reputation of home genre(s)	-0.36 <sup>z</sup>	-0.19 <sup>z</sup>	0.17 <sup>z</sup>	0.15 <sup>z</sup>	0.16 <sup>z</sup>	0.16 <sup>z</sup>	0.10 <sup>z</sup>	0.09 <sup>z</sup>	-0.22 <sup>z</sup>	-0.01					
(12) Market space of home genre(s)	0.03 <sup>y</sup>	0.12 <sup>z</sup>	-0.09 <sup>z</sup>	-0.03	-0.15 <sup>z</sup>	-0.16 <sup>z</sup>	-0.07 <sup>z</sup>	-0.10 <sup>z</sup>	0.01	0.01	-0.13 <sup>z</sup>				
(13) Topic diversity	0.08 <sup>z</sup>	0.07 <sup>z</sup>	-0.06 <sup>z</sup>	0.04 <sup>x</sup>	-0.06 <sup>z</sup>	-0.04 <sup>x</sup>	-0.04 <sup>x</sup>	-0.06 <sup>y</sup>	0.03	-0.01	-0.05 <sup>y</sup>	0.11 <sup>z</sup>			
(14) Number of production companies	0.22 <sup>z</sup>	0.31 <sup>z</sup>	-0.29 <sup>z</sup>	-0.16 <sup>z</sup>	-0.29 <sup>z</sup>	-0.27 <sup>z</sup>	-0.22 <sup>z</sup>	-0.13 <sup>z</sup>	0.13 <sup>z</sup>	0.03 <sup>x</sup>	-0.11 <sup>z</sup>	0.14 <sup>z</sup>	0.04 <sup>x</sup>		
(15) In-house productions	0.13 <sup>z</sup>	0.14 <sup>z</sup>	-0.11 <sup>z</sup>	-0.03	-0.14 <sup>z</sup>	-0.10 <sup>z</sup>	-0.12 <sup>z</sup>	-0.07 <sup>z</sup>	0.18 <sup>z</sup>	0.03	-0.19 <sup>z</sup>	0.01	0.03	0.20 <sup>z</sup>	

Note: <sup>x</sup>  $p < 0.05$ , <sup>y</sup>  $p < 0.01$ , <sup>z</sup>  $p < 0.001$ . Two-tailed test.

Table 2-3 reports the estimates of OLS to assess the effects of film crew on a film's genre width. The topic diversity of a film script only has only a marginal effect on the perceived genre width of a film throughout the table ( $p < 0.1$  for most models). This suggests that the audience-centric view alone cannot explain the variances in the perceived genre width of a film. The first version of producer-centric view explains quite a portion of variance in a film's perceived genre width, as market space and reputation of home genres significantly shorten the genre width of a film ( $p < 0.001$ ). With variables regarding the audience-centric perspective and the first version of producer-centric view controlled, my hypotheses and corollaries emphasizing the strategic nature of filmmakers receive abundant support. Hypothesis 1 argues that the perceived genre width of the focal film will be wider for a film crew with diversified experience in different genres. I find considerable support for this hypothesis, as can be seen from the results in Column 2 of Table 2-3. The two corollaries of Hypothesis 1, which argue that the typecasting of crew members and overlap of experience between crew members will be negatively associated with the genre width of the focal film, are tested in Column 3. I find strong support for Corollary 1 and marginal support for Corollary 2. This suggests that the cognition-based mechanism might be the driving force of audiences' perception of the focal film. Hypothesis 2 predicts that a film created by



a new film crew is more likely to be perceived to have multi-genre features. This hypothesis receives strong support, as can be seen from the results in Column 4. Furthermore, the corollary of Hypothesis 2, which argues that new producers have stronger effects than new directors and casts in shaping the genre width of the focal film (Corollary 3), is supported, as evidenced by the results in Column 5. The differences in their effect size are 0.06 between producer and director ( $p < 0.01$ ) and 0.05 between producer and casts ( $p < 0.1$ ), confirming my conjecture that the categorization power of a new producer is significantly larger than that of a director and cast. Column 6 through 8 present results from a regression in which the independent variables are stacked together to check the robustness of the estimates. The key independent variables, *film crew diversity* and *newness*, remain significant, lending further support for Hypothesis 1 and 2. On the other hand, the parameters regarding Corollary 1 through 3 are quite similar to those in previous models, providing strong support for Corollary 1 and 3 and only partial support Corollary 2.

**Table 2-3:** The effects of film crew on the genre width of feature films

DV: Perceived genre width	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Audience-centric view</i>								
Topic diversity of film script	0.06 <sup>†</sup> (0.03)	0.06 <sup>†</sup> (0.03)	0.04 (0.03)	0.06* (0.03)	0.06 <sup>†</sup> (0.03)	0.06 <sup>†</sup> (0.03)	0.04 (0.03)	0.04 (0.03)
<i>Producer-centric view (version 1)</i>								
Market space of home genre(s) (log)	-0.06*** (0.01)	-0.08*** (0.01)	-0.08*** (0.01)	-0.06*** (0.01)	-0.06*** (0.01)	-0.08*** (0.01)	-0.08*** (0.01)	-0.08*** (0.01)
Reputation of home genre(s)	-0.09*** (0.01)	-0.08*** (0.01)	-0.07*** (0.01)	-0.09*** (0.01)	-0.10*** (0.01)	-0.07*** (0.01)	-0.07*** (0.01)	-0.07*** (0.01)
<i>Producer-centric view (version 2)</i>								
Hypothesis 1: Film crew diversity		0.30*** (0.07)				0.31*** (0.07)		
Corollary 1: Typecasting of crew members			-0.28*** (0.06)				-0.27*** (0.06)	-0.29*** (0.06)
Corollary 2: Overlap of experience between crew members			-0.04 <sup>†</sup> (0.03)				-0.04 <sup>†</sup> (0.03)	-0.04 (0.03)
Hypothesis 2: Film crew newness				0.02* (0.01)		0.03** (0.01)	0.02 <sup>†</sup> (0.01)	
Corollary 3: New producer (0/1)					0.06*** (0.02)			0.09*** (0.02)
Corollary 3: New director (0/1)					0.01 (0.01)			0.00 (0.01)
Corollary 3: New casts (0/1)					0.01 (0.02)			0.06 <sup>†</sup> (0.02)
<i>Control variables</i>								
Distributed by Major 6 studios (0/1)	-0.02 <sup>†</sup> (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.02 <sup>†</sup> (0.01)	-0.02 <sup>†</sup> (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Budget (log)	0.06*** (0.00)	0.05*** (0.00)	0.05*** (0.01)	0.06*** (0.00)	0.06*** (0.00)	0.05*** (0.00)	0.05*** (0.01)	0.05*** (0.01)
Number of production companies (log)	0.00 (0.01)	-0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	-0.00 (0.01)	-0.01 (0.01)	-0.01 (0.01)
In-house production (0/1)	-0.01 (0.01)	-0.01 (0.01)	-0.00 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.00 (0.01)	-0.00 (0.01)
Year Fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES
Constant	1.47*** (0.26)	1.53*** (0.28)	1.93*** (0.32)	1.38*** (0.26)	1.36*** (0.26)	1.44*** (0.28)	1.89*** (0.32)	1.90*** (0.31)
N	2404	2362	2101	2404	2404	2362	2101	2101
R <sup>2</sup>	0.18	0.19	0.19	0.18	0.18	0.19	0.19	0.20
Adjust R <sup>2</sup>	0.17	0.18	0.18	0.17	0.18	0.19	0.18	0.19

Notes: † p < 0.1 \* p < 0.05 \*\* p < 0.01 \*\*\* p < 0.001. Two-tailed test. Robust standard errors in parentheses.

### **2.7.2 Box office equation: ex post evidence**

Table 2-4 displays the descriptive statistics and correlations for variables used in the box office regression. I present the results of Baron and Kenny (1986) method in Column 1 through 3 of Table 2-5, fit a structural model and report the tests of indirect effects in corresponding variables, and apply the control function approach to examine the endogeneity of genre width in Column 4.

**Table 2-4:** Descriptive statistics of box office equation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
N	4,578	10,994	4,014	5,784	10,994	4,837	9,677	6,491	10,994	10,994	7,471	10,994	7,471	10,994	7,479
Mean	3.28E+07	6.21	1574.77	2.92E+07	0.00	0.40	2.26E+07	7.01E+07	0.44	0.37	6.12	8.57	20.19	2007.6	0.49
S.D.	5.17E+07	1.45	1369.3	3.70E+08	0.04	0.49	7.41E+07	1.00E+08	0.50	0.48	0.65	5.60	1.00	6.07	0.27
Min.	170.64	1	1	0	0	0	0	0	0	0	4.50	0	13.63	1995	0
Max.	7.73E+08	10	9300	2.80E+10	1	1	1.04E+09	1.08E+09	1	1	7.57	38.15	21.32	2015	0.90
(1)Box office (\$)															
(2)IMDb rating	0.26 <sup>z</sup>														
(3)Opening weekend screens	0.47 <sup>z</sup>	-0.14 <sup>z</sup>													
(4)Budget (\$)	0.64 <sup>z</sup>	0.12 <sup>z</sup>	0.58 <sup>z</sup>												
(5)Oscar award (0/1)	0.14 <sup>z</sup>	0.14 <sup>z</sup>	-0.08 <sup>z</sup>	0.00											
(6)Major 6 studios	0.30 <sup>z</sup>	-0.03	0.42 <sup>z</sup>	0.41 <sup>z</sup>	-0.04 <sup>x</sup>										
(7)Director power	0.38 <sup>z</sup>	0.11 <sup>z</sup>	0.30 <sup>z</sup>	0.44 <sup>z</sup>	0.02	0.23 <sup>z</sup>									
(8)Star power	0.30 <sup>z</sup>	0.10 <sup>z</sup>	0.33 <sup>z</sup>	0.43 <sup>z</sup>	0.04 <sup>x</sup>	0.22 <sup>z</sup>	0.36 <sup>z</sup>								
(9)Friday	0.16 <sup>z</sup>	0.05 <sup>x</sup>	0.06 <sup>y</sup>	0.15 <sup>z</sup>	0.03	0.08 <sup>z</sup>	0.10 <sup>z</sup>	0.07 <sup>z</sup>							
(10)Low season	-0.02	0.08 <sup>z</sup>	-0.03	0.01	0.02	-0.02	0.00	0.02	0.00						
(11)Reputation of home genre(s)	-0.11 <sup>z</sup>	0.22 <sup>z</sup>	-0.18 <sup>z</sup>	-0.11 <sup>z</sup>	0.06 <sup>y</sup>	-0.07 <sup>z</sup>	0.01	0.11 <sup>z</sup>	0.03	-0.02					
(12)Genre crowding	-0.23 <sup>z</sup>	0.14 <sup>z</sup>	-0.20 <sup>z</sup>	-0.27 <sup>z</sup>	0.05 <sup>x</sup>	-0.16 <sup>z</sup>	-0.06 <sup>y</sup>	0.04 <sup>x</sup>	-0.07 <sup>z</sup>	0.14 <sup>z</sup>	0.48 <sup>z</sup>				
(13)Market space of home genre(s)	-0.07 <sup>z</sup>	0.04 <sup>x</sup>	-0.04	-0.05 <sup>x</sup>	0.01	-0.02	0.01	0.15 <sup>z</sup>	-0.01	-0.02	0.38 <sup>z</sup>	0.38 <sup>z</sup>			
(14)Released year	-0.01	0.05 <sup>x</sup>	0.24 <sup>z</sup>	0.14 <sup>z</sup>	-0.00	-0.04 <sup>x</sup>	0.11 <sup>z</sup>	0.27 <sup>z</sup>	-0.01	-0.02	0.43 <sup>z</sup>	0.46 <sup>z</sup>	0.26 <sup>z</sup>		
(15)Perceived genre width	0.15 <sup>z</sup>	-0.03	0.22 <sup>z</sup>	0.28 <sup>z</sup>	-0.01	0.13 <sup>z</sup>	0.11 <sup>z</sup>	0.09 <sup>z</sup>	0.04 <sup>x</sup>	-0.03	-0.26 <sup>z</sup>	-0.24 <sup>z</sup>	-0.26 <sup>z</sup>	-0.04 <sup>x</sup>	

Note: <sup>x</sup>  $p < 0.05$ , <sup>y</sup>  $p < 0.01$ , <sup>z</sup>  $p < 0.001$ . Two-tailed test

**Table 2-5:** Indirect effects of strategic categorization on a film's box office

DV: box office(log)	(1)	(2)	(3)	(4)
Typcasting of crew members		0.89*(0.35)	0.71*(0.35)	
Hypothesis 3: Sobel test of indirect effects		0.20*** (0.06)		
Bootstrap s.e. of indirect effects		0.20*(0.09)		
Bias-corrected 95% confidence intervals		[0.05, 0.39]		
Bootstrap s.e. of indirect effects (standardized)		0.02*(0.01)		
Overlap of experience between crew members		0.39*(0.16)	0.37*(0.15)	
Hypothesis 3: Sobel test of indirect effects		0.03*(0.02)		
Bootstrap s.e. of indirect effects		0.03*(0.02)		
Bias-corrected 95% confidence intervals		[0.01, 0.07]		
Bootstrap s.e. of indirect effects (standardized)		0.003*(0.001)		
Film crew newness		0.15 <sup>†</sup> (0.09)	0.15 <sup>†</sup> (0.09)	
Hypothesis 3: Sobel test of indirect effects		-0.004(0.006)		
Bootstrap s.e. of indirect effects		-0.004(0.008)		
Bias-corrected 95% confidence intervals		[-0.02, 0.01]		
Bootstrap s.e. of indirect effects (standardized)		-0.001(0.003)		
Perceived genre width	-0.33*(0.16)		-0.48** (0.18)	-2.26*(0.95)
Corollary 4: Endogeneity test (Hausman test)				1.78 <sup>†</sup> (0.96)
IMDb rating	0.47*** (0.03)	0.45*** (0.03)	0.44*** (0.03)	0.43*** (0.03)
Number of opening screens (log)	0.25*** (0.02)	0.22*** (0.02)	0.22*** (0.02)	0.21*** (0.03)
Budget (log)	0.40*** (0.05)	0.50*** (0.04)	0.52*** (0.04)	0.59*** (0.07)
Oscar award (0/1)	1.18*** (0.21)	0.86*** (0.18)	0.86*** (0.18)	0.89*** (0.17)
Major 6 studios (0/1)	0.39*** (0.06)	0.34*** (0.06)	0.33*** (0.06)	0.30*** (0.06)
MPAA: NC-17	-0.86** (0.28)	-0.78** (0.25)	-1.09*** (0.29)	-2.31*** (0.66)
MPAA: PG	-0.24 <sup>†</sup> (0.14)	-0.27 <sup>†</sup> (0.15)	-0.28* (0.14)	-0.34* (0.14)
MPAA: PG-13	-0.40** (0.13)	-0.45** (0.14)	-0.49*** (0.14)	-0.67*** (0.15)
MPAA: R	-0.73*** (0.13)	-0.75*** (0.14)	-0.80*** (0.14)	-0.99*** (0.17)
Director power (log)	0.01*** (0.00)	0.01** (0.00)	0.01** (0.00)	0.01* (0.00)
Star power (log)	-0.00 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Friday (0/1)	0.22** (0.08)	0.21** (0.08)	0.22** (0.08)	0.24** (0.08)
Low season (0/1)	-0.23*** (0.06)	-0.23*** (0.06)	-0.23*** (0.06)	-0.24*** (0.06)
Reputation of home genre(s)	-0.24** (0.09)	-0.25** (0.09)	-0.29*** (0.09)	-0.43*** (0.12)
Genre crowding (log)	-0.01 (0.01)	-0.00 (0.01)	-0.00 (0.01)	-0.01 (0.01)
Market space of home genre(s)	-0.11 <sup>†</sup> (0.06)	-0.05 (0.06)	-0.09 (0.06)	-0.24* (0.10)
Year fixed-effects	Included	Included	Included	Included
Constant	Included	Included	Included	Included
N	9.78*** (1.54)	6.64*** (1.39)	7.71*** (1.40)	11.99*** (2.33)
R <sup>2</sup>	1995	1744	1744	1742
Adjust R <sup>2</sup>	0.54	0.53	0.53	0.53

Notes:

1. <sup>†</sup> p < 0.1 \* p < 0.05 \*\* p < 0.01 \*\*\* p < 0.001. Robust standard errors in parentheses.

2. Two-tailed test.

In Column 1 I replicate previous research on the relationship between category spanning and economic outcomes. The negative sign of perceived genre width confirms once more the categorical imperative argument (Zuckerman, 1999). Column 2 and 3 of Table 2-5, along with the Column 7 of Table 2-3, present the results of the Baron and Kenny (1986) procedure. The results suggest that perceived genre width partially mediates the relationship between film crew characteristics and a film's box office. To further examine the effect size of cognition-, capability-, and newness-based mechanisms, I refit a structural model shown in Figure 2-3 and conduct the Sobel test. The test results suggest that only crew member typecasting (cognition-based mechanism) and experience overlap among crew members (capability-based mechanism) have spillover effects on the box office of a film. The Sobel test assumes a normal distribution of indirect effects. With regards to the concern that the coefficients of indirect effects (i.e., spillover effects, which is the product of two normally distributed coefficients) are not normally distributed, I use a bootstrapping procedure to generate adjusted standard errors of the coefficients (Preacher and Hayes, 2008). The percentile bootstrap confidence interval, which is recommended in Preacher and Hayes (2008), is also reported. Again, I find that recruiting typecast actors and adjusting the experience overlap of crew members will ultimately shape the box office of a film ( $p < 0.05$ ). This is further confirmed by the bias-corrected 95% confidence intervals of the indirect effects of typecasting and genre overlap, which do not include zero within their upper and lower bound. These findings hence lead to the

conclusion that at least part of categorizing work of filmmakers will have an affect on performance. Therefore, hypothesis 3 receives partial support.

If perceived genre width (partially) mediates the relationship between film crew characteristics and a film's box office, then perceived genre width will be not strictly exogenous—it can be intentionally manipulated by internal agents (filmmakers) who attempt to boost the expected returns from the film. The model in Column 4 of Table 2-5 tests this idea. It is a replication and extension of the model in Column 1 in that the residuals of genre width equation are added into the model as an explanatory variable to controls for the endogeneity of genre width<sup>5</sup>. A significant residual variable suggests that the regression without the residual variable included would suffer from endogeneity issue. As predicted in Corollary 4, the residual variable is marginally significant ( $p < 0.1$ ), suggesting that genre width is endogenous to the box office a film (though not seriously endogenous). Corollary 4 is thus supported.

## **2.8 Discussions**

Existing research assumes that the categorization process is exogenous, and that organizations are passive recipients of the categories imposed by current classification schemes and social norms. Building upon this argument, the categorical imperative penalizes actors who confuse audiences by claiming

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<sup>5</sup> Wooldridge (2015) suggests that all exogenous variables of the two-equation system, including the variables that are exogenous to the dependent variable of second-stage equation, should be added into the first equation when proceeding the control function approach. Therefore, the genre width equation is slightly different from the one I run in ex ante analysis—all exogenous variables of box office equation are also included in this regression.

membership in multiple categories. It can be observed that category spanning is widely seen in our social lives, from wineries to feature films; from restaurants to software industry. Why is category spanning then so common, given wide consensus of its negative impacts? An intuitive answer is that the effects of category spanning may have more complicated and far-reaching implications. This has been confirmed in recent research (e.g., Paolella and Durand, 2016; Wry, Lounsbury, and Jennings, 2014), in which category spanning brings about some benefits in certain contexts.

Following this logic, if category spanning is beneficial under certain conditions, rational organizational agents should respond by manipulating the memberships of their products to optimize economic gains. I argue that categorization is not purely exogenous and given, but endogenous to organizations. Recent nascent literature recognizes the roles of organizational agents in the categorization process. Most literature undervalues the role of internal agents, assuming that external audiences hold a dominant position and merely recognizing organizational agents as “buffers” who transmit external pressure to organizations (Castor and Wry 2017; Pontikes and Kim, 2017). I propose a producer-centric view of categorization, arguing that organizational agents are involved deeply in the categorization process. As such, their team- and individual-level characteristics will determine how organizations categorize their offerings.

A review of filmmaking in North America provides some preliminary evidence of the effect of organizational agents in a film’s categorization process. I



identify three important players in the feature film industry: producer, director, and actors. They are either the head of a film project, the “brain” of the creative division of the film crew, or a bridge between the external audiences and the focal project. They are capable of shaping audiences’ perception of the focal film, and have the economic motivation to do so. I propose that cognition-, capability-, and newness-based mechanisms will shape audiences’ genre perception of the focal film, and I argue that a film crew’s involvement in shaping the genres of its film will ultimately affect the economic gains its film can obtain.

I conduct two empirical tests using a large dataset extracted from online film databases. Results show that a feature film produced by a diversified film crew tends to be labelled using multiple genre labels, and a film produced by newcomers are more likely to be recognized as a multiple-genre film. In addition, an in-depth investigation of individual-level attributes shows that the typecasting of film crew members also affects the extent to which a film is classified as a multi-genre production. My findings suggest that organizational agents do manipulate the genres of films presented to audiences, and such manipulation mostly occurs through cognition-, capability-, and newness-based mechanisms. This provides *ex ante* evidence of strategic categorization.

Results also indicate that the categorizing work of filmmakers will ultimately shape a film’s box office. This effect is achieved when filmmakers attempt to manipulate audience perception via cognition- and capability-based mechanisms. The standardized indirect effects of categorization via these two

mechanisms are not trivial (see Table 2-5). A 1 S.D. increase in the value of film crew typecasting leads to 0.02 S.D. increase of logged box office return and a 1 S.D. increase in the value of experience overlap among crew members leads to 0.003 S.D. increase of logged box office return. This finding not only acts as an *ex post* proof of strategic categorization, but also reveals that categorizing work occurs in North American feature film market. My article hence offers to business managers practical advice about preferable approaches for strategic categorization. If a studio intends to create a blockbuster targeting multiple segments whilst wanting to suffer a weaker penalty from category spanning, two types of strategies are available. In one, a film crew is hired that is highly typecast, and in the other, crew members have homogenous work experience. The former strategy delivers clear cognitive message to audiences that the film crew will create a certain type of film, while the latter strategy ensures that the crew members are capable of producing the film they are “claiming” to create.

This paper is not without its limitations. First, it points out that strategic categorization will ultimately affect a film’s box office, but does not specify which kind of categorizing work can bring about more beneficial results. Organizational agents can aim at wider audiences than the categories its products naturally fit into (be a “pseudo” generalist), or target a specific segment even if its product is considered “Jack-of-all-trade” (be a “pseudo” specialist). An interesting direction for future research is to investigate which strategy is preferable. Second, this paper relies on second-hand data to depict the antecedents and implications of strategic

categorization in the feature film industry rather than using direct evidence of strategic categorization. Future research should explore how categorizing work is conducted in the field using first-hand data such as interviews and surveys. Third, the measures of category spanning used in this study could be more fined-grained. The genre width used in this article does not consider the symbiotic relationships between genre tags. For films with common combinations of genres (e.g., action and crime; thriller and horror; romance and drama), the cognitive hurdles in understanding these films are trivial. On the other hands, there may be substantial confusion regarding firms that are a rare combination of genres (e.g., western and Sci-Fi, horror and sport, etc). Future research could take this possibility into account and examine how symbiosis between categories affect the categorization process.

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## Appendix

### Measuring topic diversity of the film script

Structural topic model (STM) is an unsupervised machine learning technique aiming at discovering the “topics” from a collection of documents. It is a part of the broader probabilistic topic model family, which treats the latent topic as a probability distribution over words and documents as mixtures of topics (Blei, 2012), but has better statistical inferences (Roberts, Stewart, and Airoldi, 2016). Compared to other probabilistic topic models, STM can utilize document-level covariates in the estimation, hence making it possible to directly investigate the relationship between topics and independent variables that researchers are interested in. It has been applied in several social science studies (Lucas et al., 2015; Roberts et al., 2016).

Note the object of my research is to identify the proportion of topics over a film script and calculate its topic diversity ( $1 - \sum_{k \in K} \mu_{ik}^2$ ). To obtain the information about topic proportion ( $\mu_{ik}$ ), we need to fit a STM. The first step is to collect linguistic materials. I downloaded the film scripts from *Springfield! Springfield!* ([www.springfieldspringfield.co.uk](http://www.springfieldspringfield.co.uk), SS hereafter) and used them to construct the corpus. SS provides TV and movie scripts for videophiles and cinephiles. I retrieved all 22,677 film scripts using web scraping techniques. Since I only considered films released between 2000 and 2015 in the regression analysis, I dropped the film scripts before 2000 in building STM. In addition, scripts that are not in English are dropped. My corpus finally included 14,431 film scripts.

I used the `stm` package from R to do the analysis. To run a structural topic model, one should designate several parameters: covariates, maximum times of expectation-maximization (EM) iteration, initialization method, and number of topics. I chose release year (information retrieved when downloading all scripts) as the covariate. Including more covariables are possible, but it requires an additional matching process between my script database and film database and will greatly decrease the sample size of STM. Because a rich corpus is essential for estimations of topic models, I only included release year as covariate in my research. For maximum times of EM iteration and initialization method, I used the default option recommended by STM developers (Roberts et al., 2016).

The conundrum here is to decide the number of topics ( $k$ ). The number of topics needs to be determined priori, while we usually don't know the accurate number of topics before we do the analysis. In addition, to the best of my knowledge there is no authentic statement on how many topics are covered in modern films. To solve this issue, I estimated structural topic models with different number of topics assigned (ranging from four to eighteen, more topics are possible but unnecessary according to my analysis below). After I estimated the models, I examined their statistical attributes of those models and select the one that has better fit for my data.



Fifteen STMs were estimated. I evaluated the model fit for each model in terms of semantic coherence, exclusivity, and held out likelihood. Semantic coherence measures the extent to which the most probable words in a given topic co-occur together (Roberts et al., 2016). High semantic coherence suggests high quality of the emerged topic. The exact formula can be found in Roberts et al. (2016). Exclusivity measures the extent to which a certain word is exclusively owned by a topic. The high exclusivity of a topic means the emerged topic has clear boundaries and does not overlap with other topics. Roberts et al., (2016) suggested that we consider semantic coherence and exclusivity at the same time using a FREX index (Bischof and Airolidi 2012). I calculated the average FREX of each STM and presented the results, along with the semantic coherence metric, in Figure 1A.

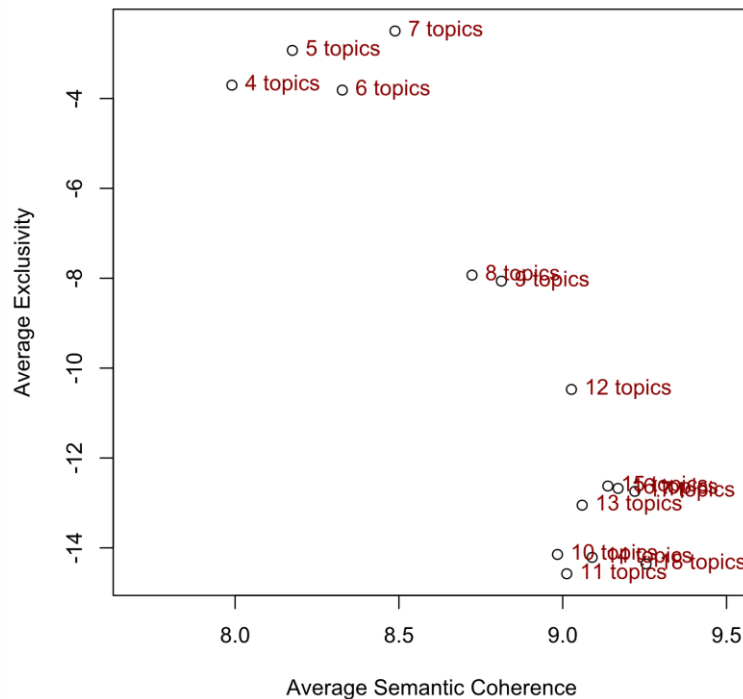


Figure 1A Mapping the average exclusivity and semantic coherence of topic models

Figure 1A shows that semantic coherence and exclusivity are contradictory objects. A good topic model needs to achieve high semantic coherence whilst not lagging behind in exclusivity metric. STMs with seven, eight, nine, twelve, fifteen, and eighteen perform better in terms of these metrics and were selected for held out test. Held out test is widely applied in machine learning and statistics. The workflow of held test is as follows: First, a document set where some of the words within the documents had been removed was created; second, I trained the STMs on the document set with missing words; lastly, I examined the probability of held-out words appearing in the trained models. The higher the probability, the less likely the model is overfitting and thus the better model we have. The results of held out tests are in Table 1A. It can be seen that the held-out likelihood tends to decrease when the number of topics fitted in STM increases. If I solely use the

results from held out likelihood test, I would choose STMs with seven topics. However, because all selected models are very similar in held out likelihood, I decided not to make any decisions until I finish other tests.

Table 1A Held out likelihood of topic models

Model	4 topics	5 topics	6 topics	7 topics	8 topics	9 topics	10 topics	11 topics
Held out likelihood	-15.75	-16.02	-15.98	-16.19	-16.30	-16.39	-16.43	-16.51
Residual dispersion	24.62	23.59	19.98	18.48	17.73	17.27	16.86	15.73
Model	12 topics	13 topics	14 topics	15 topics	16 topics	17 topics	18 topics	
Held out likelihood	-16.55	-16.59	-16.62	-16.66	-16.66	-16.68	-16.78	
Residual dispersion	15.08	14.33	14.00	13.60	13.33	12.99	12.66	

Next, I performed a residual analysis suggested by Taddy (2012). The residual analysis computes the multinomial dispersion of the STM residuals (Roberts et al., 2018). If the residuals are overdispersed ( $> 1$ ), it could be that more topics are needed to soak up the extra variance (Roberts et al., 2016). Nevertheless, one should be very cautious when explaining the results because the dispersion can easily blow up when the documents are long (Roberts et al., 2018). Contrary to the held-out test, the residuals tend to over-disperse less when the number of topics in a STM increase. If I solely rely on the residual test, the STM with eighteen topics would be the best. The residual analysis yields totally contradictory results to the held-out likelihood test. To balance between high held-out likelihood and overdispersion of residuals, I decided to choose the STM with twelve topics as the basis to calculate topic diversity of a film script.

Table 2A and Figure 2A display the key words of each topic from the selected STM. The most common words are very similar, as the documents I used contain a plenty of dialogues, which by nature contain a lot of common words. The pattern will be clearer when we focus on the words in each topic with highest FREX level (Bischof and Airolidi 2012). For example, Topic 10 includes several sound-related words (e.g., laugh, music, chuckl, sigh, etc.), implying that this topic might be related to plots with rich emotional conflicts; Topic 6 contains a lot of LGBT related words; Topic 9 is basically a collection of insulting words. It can be arguably say that films with high proportion of this topic might contain fierce violence, crime scenes, and adult-only contents.

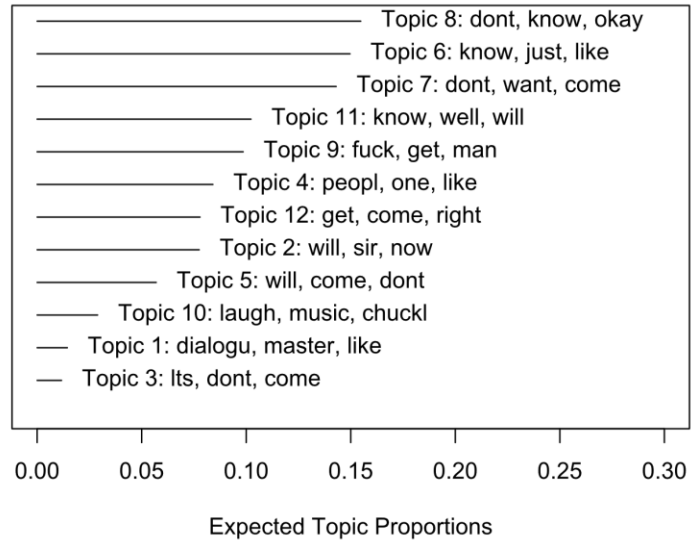


Figure 2A Expected topic proportions across all scripts

Table 2A Topic words for selected STM

Topic	Indicator	Words
Topic 1	Highest Probability	dialogu, master, like, dont, will, let, right
	FREX	defaulti, yuki, inuyasha, defaultand, defaultit, hachi, defaultim
	Lift Score	abarai, achiwa, aishita, akiyo, akizuki, akko-chan, allna dialogu, defaulti, defaultand, defaultit, defaultwhat, inuyasha, defaultim
Topic 2	Highest Probability	will, sir, now, can, one, get, come
	FREX	hornblow, asgard, victini, sesshomaru, colonel, lycan, sounga
	Lift Score	---book, -clash, -command, -measur, -niner--, -peac, -wall will, kill, sir, soldier, colonel, majesti, lieuten
Topic 3	Highest Probability	lts, dont, come, lll, know, get, iik
	FREX	iik, aii, wiii, weii, teii, pieas, taik
	Lift Score	-iimit, -short, abnormai, acaba, accoiad, admirabi, adrenaiin wiii, lts, aii, teii, iik, taik, weii
Topic 4	Highest Probability	peopl, one, like, know, time, can, just
	FREX	bitcoin, wikileak, ture, assang, global, congress, industri
	Lift Score	--real, -articul, -basic, -big--fail, -code, -director, -infrastructur peopl, bitcoin, film, narrat, wikileak, senat, presid
Topic 5	Highest Probability	will, come, dont, sir, get, like, one
	FREX	lakh, rahul, vikram, anjali, aditya, rohit, hyderabad
	Lift Score	--kind--guy, -entri, -grad, -nohe, -yr, aaaaaaaaaaaaaaaaaaaaaa, aadmi hesh, will, lakh, bhai, lll, crore, arjun
Topic 6	Highest Probability	know, just, like, yeah, dont, your, okay
	FREX	prom, sex, gay, lesbian, roommat, peni, hilari
	Lift Score	---mind, -ca-bitch, -ladi, -layer, -lunch, -sharer, -slash- yeah, okay, gonna, realli, like, well, just
Topic 7	Highest Probability	dont, want, come, can, know, yes, get
	FREX	dafu, recep, sang-woo, seo, da-eun, jie, ceren
	Lift Score	-dong, -fact, -obi, -san, -ward, -youn, aachenerstrass ill, dafu, will, pleas, fuck, tell, polic
Topic 8	Highest Probability	dont, know, okay, just, get, come, right
	FREX	sarah, rachel, jake, kate, connor, cassi, matt
	Lift Score	-littl, aaaarrgghh, actmti, ahchoo, allendal, anemomet, anti-zombi okay, gonna, yeah, hey, ill, pleas, well
Topic 9	Highest Probability	fuck, get, man, got, dont, yeah, right
	FREX	nigga, motherfuckin, blud, fuckin, pooti, bruh, crackhead
	Lift Score	--nothin, --scene, -ab-ba, -buy, -dirt, -hustl, -singin fuck, gonna, fuckin, shit, nigga, motherfuck, yeah
Topic 10	Highest Probability	laugh, music, chuckl, sigh, man, scream, grunt
	FREX	chuckl, grunt, scoob, scoff, whimper, indistinct, groan
	Lift Score	-agadda-da-vida, -andrea, -bashin, -bitin, -crashin, -got--life-back, -insan chuckl, grunt, gasp, groan, sigh, indistinct, music
Topic 11	Highest Probability	know, well, will, dont, love, yes, come
	FREX	thou, monsieur, byou, hath, thi, maud, haman
	Lift Score	-goer, -wash, -within, -yy, acomod, actb, aintre well, will, ill, love, pleas, mum, tell
Topic 12	Highest Probability	get, come, right, got, well, just, good
	FREX	coach, christma, santa, kris, championship, tigger, merri
	Lift Score	-coach, -haul, -ou, -rs, -score, -woah, babywith gonna, christma, well, hey, yeah, ill, gotta

To ensure that the choice of STM does not affect the main results. I also calculated the topic diversity of film scripts using different STMs (with seven, eight, nine, fifteen, sixteen, seventeen, and eighteen topics) and included it in my regression models. The results are literally the same, except that Corollary 2 becomes insignificant in some cases (Corollary 2 is marginal significant in the main results).

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## **3 A Bundle-based Perspective of Category Membership**

### **3.1 Abstract**

Extant studies in category research has increasingly focused on the hierarchical structure of the category system and incorporated the interconnectedness between categories into their analyses. However, we know relatively little on different types of connections a category can build with other categories and to what extent different types of connections will affect a category's usage in products. We argue that categories bundle together and form different clusters. We refer to a group of aggregated categories as "category bundle" in this paper. We argue that market participants (i.e., producers, audiences, and market intermediaries) are aware of category bundles, and they utilize the bundle-based approach in their evaluation of products. In this sense, not only the overall position of a category in the hierarchical structure of categories, but also a category's membership in the category bundle, affects its chances of appearing in the description of a product. We find support for the bundle-based perspective in our empirical analysis of feature films produced in Canada and the U.S. Our study enriches the understanding of the structure of category system and its impacts on the product market. We also provide a novel explanation on why category spanning remains ubiquitous although existing studies propose that category-straddling products are prone to be punished harshly.

Keywords: category membership; category bundle; category spanning

## 3.2 Introduction

Understanding product categories is a critical task in management and organization studies, as categories and the classification system constituted by categories lay the foundation for social interaction. From the perspective of audiences, categories “provide an anchor for making judgements about value and worth” (Vergne and Wry, 2014, p. 58); from the perspective of producers, categories highlight the specialities of a producer and draw attention from audiences who are interested in the offerings. By enabling social comparison and navigating market segmentation, category labels facilitate market transactions and benefit both producers and audiences.

But what determines the category membership of a product? Despite its theoretical and practical importance, previous research paid disproportionately little attention to the antecedents of category membership (Wry and Castor, 2017; a few exceptions include Carnabuci, Operti, and Kovács, 2015; Negro, Hannan, and Rao, 2011; Pontikes and Barnett, 2015; Pontikes and Kim, 2017), compared to extensive literature on the implications of membership in multiple categories (e.g., Zuckerman, 1999; Hsu, 2006a; Hsu, Hannan, and Koçak, 2009; Lo and Kennedy, 2015; Paoletta and Durand, 2016; Wry, Lounsbury, and Jennings, 2014; etc.). In the latter stream of inquiry, researchers take category-straddling products as given, and examine the effects of category straddling without asking why categories appear simultaneously in a product in the first place (e.g., Hsu et al., 2009; Paoletta and Durand, 2016; Wry et al., 2014). Without sufficient knowledge of what

determines the categories to which a product belongs , we are not able to resolve the paradox between the well-established argument that products and organizations spanning categorical boundaries entail economic and social penalties (i.e., “the categorical imperative”, see Zuckerman, 1999), and the well-documented empirical observations that products and organizations commonly fall into multiple categories (e.g., Lo and Kennedy, 2015; Paoletta and Durand, 2016; Wry et al., 2014).

This paper aims to offer a novel explanation for the antecedents of a product’s category membership. By doing so, we address the conundrum between the categorical imperative argument and the ubiquity of category spanning. We propose that revisiting the interconnectedness between categories will deepen our understanding of why some categories appear concurrently in the category membership of a product while others do not. Categories are not equally influential or salient (Vergne and Wry, 2014). Some market categories have crispy boundaries and are exclusively used in the category description of a product. Other categories, on the contrary, are less independent and often bundled together to depict a product. In the latter case, the “category bundle”, which consists of closely-related categories, becomes a notion that is more recognizable than the categories nested in it by market participants (e.g., producers, audiences, and intermediaries). The bundling of categories in the product market further strengthens the social cognition on the hierarchies of categories (Porac, Thomas, and Baden-Fuller, 1989; Vergne and Wry, 2014) and finally, affects the consensus of market participants on



the category membership of a product. All else being equal, a category label is more likely to appear in the category membership of a product when it can form a meaningful category bundle with other category candidates.

Our distinctive approach builds on a recent stream of category research, which proposes that categories vary in their positions in the category hierarchies: some can be easily grouped together as a superordinate category, whereas some do not share much linkage with other categories (Durand and Boulongne, 2017; Pontikes and Barnett, 2015; Vergne and Wry, 2014; Wry and Lounsbury, 2013). We argue that a category's linkage with other categories matters, though not in a way suggested by recent research. While prior research focuses on how the overall connectivity of a category (to all other categories) affects the category "entry" decision (i.e., whether a category appears in a product or not, see also Carnabuci et al., 2015; Pontikes, 2012; Pontikes and Barnett, 2015; Wry and Castor, 2017), we examine how the local structure of a category (i.e., a category's connections to other categories in a category bundle) affects the category entry decision. Specifically, we argue that a category that contributes to a coherent bundle in the category descriptions of a focal product has asymmetrical advantages over other categories. To this end, we adopt a novel measurement from ecology literature that captures the overall fitness of an assembly containing two or more elements (Arita, 2017), and carry out a comprehensive set of empirical analyses.

Our sample includes all feature films produced in North America (U.S. and Canada) and released between 2000 and 2015. Feature film industry has a long

history of using *genres* to categorize films. As the most common classification system in feature films, different genres can convey totally different messages: some genres reveal the content of a film (e.g., *Action*, *Crime*, *Sci-Fi*, etc.), whereas others disclose the form of the film (e.g., *Animation*, *Documentary*, *Short*, etc.). The various functions of genres imply the innate heterogeneous positions of genres in the classification system and the possibility that some genres may need to gather together to properly describe a product. Both features mentioned above make the genres in feature film context particularly suitable for our research. Using the feature film data, we examine the entry decision of 20 commonly used genres in each film<sup>6</sup>. We formulate novel hypotheses to explain why and how variation in the fitness of the focal genre in a genre bundle affects a genre's appearance in films. Because our sample only includes realized film-genre pairs (i.e., the treatment group), we employed a case-control design using coarsened exact matching (CEM) to construct a balanced sample (for examples, see Carnabuci et al., 2015; Rogan and Sorenson, 2014; also see Iacus, King, and Porro, 2012 for methodologic discussion). The findings support our hypotheses: the fitness of genre in a genre bundle significantly affects the realization of the focal genre in a film, even if alternative hypotheses that capture the overall structural position of a genre (e.g., fuzziness, leniency, similarity, etc.) proposed by previous researchers (e.g.,

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<sup>6</sup> We use the following genres in this paper: *Action*, *Adventure*, *Animation*, *Biography*, *Crime*, *Comedy*, *Documentary*, *Drama*, *Family*, *Fantasy*, *History*, *Horror*, *Musical*, *Mystery*, *Romance*, *Sci-Fi*, *Sport*, *Thriller*, *War*, and *Western*. *Short*, *TV-movie* and *News* are removed since they are not used on feature films in IMDb. *Film Noir* is also not considered since IMDb defines Film Noir as a period-specific genre starting at 1927 (*Underworld*) and ending at 1958 (*Touch of Evil*), which is not covered by our observation window.

Carnabuci et al., 2015; Hsu, Negro, and Perretti, 2012; Pontikes, 2012; Pontikes and Barnett, 2015; Wry and Castor, 2017), and conventional wisdom that emphasizes the category-level attributes of a genre (e.g., density, resource space, reputation, etc.), are controlled in the model. Furthermore, because a category's overall position in the classification system is constituted by its (balanced or imbalanced) linkages with different categories, the variables that capture a category's overall structural position (e.g., fuzziness, leniency, similarity, etc.) should preserve some information on a category's fitness in genre bundles. As previous studies did not differentiate two types of connections (fitness in a bundle and overall fitness) a category could have in the classification system, the estimates on the effects of a category's overall structural position on its usage in products might be biased. With a category's bundle fitness controlled in our model, we argue that the bundle-based variable will weaken the effects of structure-based variables and increase the overall fit of the model. These hypotheses are also supported, with the effects of some structure-based variables shrinking significantly after the inclusion of the bundle-based variable in the model and superior performance of the full model in post-estimation analyses.

Focusing on a meso-level phenomenon—the local aggregation of certain genres—in the genre classification system, this paper offers a more nuanced interpretation of the determinants of the category membership of a product. In addition, the bundle-based category membership in the real world generates the “category spanning” phenomenon observed by category researchers. The tension

between the categorical imperative argument and routinely observed category spanning is hence relieved.

### **3.3 Theory and Hypotheses**

#### **3.3.1 Antecedents of category membership**

Categories are “social agreements about the meanings of labels” applied to products (Negro, et al., 2011, p. 1450). Once a product is categorized, it can be arguably said that market participants (producers, audiences, and intermediaries) have reached a consensus on the features (e.g., technologies, potential uses, cultural meanings, and values) of the focal product (Vergne and Wry, 2014). Extending this argument, we view the category membership of a product a reflection of its actual position in the product feature space (Askin and Mauskapf, 2017), since a subjective, unilateral declaration of a product’s category by a part of market participants (e.g., consumers) will hardly be accepted by the whole market. The neutrality of category membership is commonplace in consumer goods industries (e.g., feature films, restaurants, etc.), because most market participants have the required knowledge and capabilities to categorize products. In contexts where professional knowledge is needed in categorization (e.g., patent application, winemaking, stock market, etc.), the category membership of a product might become less neutral, manifested in the advantageous position of a part of market participants in determining the categories of a product (e.g., patent examiners in patent application; securities analysts in stock market, etc.).

The power asymmetry between market participants suggests that there is room for strategic categorization (Bower, 2019; Durand and Khaire, 2017; Pontikes and Kim, 2017; Vergne and Wry, 2014). From the perspective of producers, they tend to position their products in niches that can ease competitive pressure and maximize returns, even if the actual features of their product do not completely support their category membership claims. Empirical evidence suggests that software developers keep shifting their category membership claims by moving to adjacent and less competitive categories (Pontikes and Kim, 2017). In stigmatized industries (e.g., arms, tobacco, etc.), producers face persistent criticism from hostile audiences (Durand and Vergne, 2015), and they react by entering less stigmatized categories in order to dilute the negative impression on them (Vergne, 2012). Audiences (consumers) and market intermediaries (e.g., financial analysts, film critics, consulting firms, etc.) also have motivations to shape the category membership of a product. Market intermediaries want to not only ensure the orderly functioning of markets, but also enshrine their unique value in the market (Bowers, 2019; Pontikes and Kim, 2017). Toward this end, they draw more attention to the categories that are growing or are affiliated with high-status producers (Pontikes and Kim, 2017). In addition, market intermediaries and audiences, as ordinary people, have cognitive limitations: they tend to interpret the products via their own cognitive maps (Bowers, 2015a; Hsu, 2006b). In doing so, market intermediaries and audiences may “drag” product categorization into the fields with which they are familiar (Bowers, 2015a). For example, in patent

applications, when an invention draws less from the technological domains where an examiner specializes in, the examiner will add more citations for the focal invention (Tan and Roberts, 2010).

Despite divergent motivations of market participants in participating in product categorization, the mechanisms identified by prior studies are similar. First, categories that can arouse the interests of market participants (producers, market intermediaries, and audiences), no matter what market participants categories attract, are more likely to be chosen. Second, though category attributes valued by participants are different, the screening of categories takes place at the *category level*. This idea implies that the entry-or-not of a category hinges on its own features. Producers focus on the competitive intensity, profitability, and reputation of a category (Pontikes and Kim, 2017; Wry and Castor, 2017; Vergne, 2012); market intermediaries treasure the prospect of a category, which often comes down to the account of (high-status) actors in the focal category (Pontikes and Kim, 2017); and audiences, due to their cognitive limitations, value a category more when it is within their specializations (Hsu, 2006b; Zuckerman et al., 2003). In other words, whether the focal category falls into the conceptual structure of audiences matters (Bowers, 2015b; Hsu, 2006b; Kovács and Hannan, 2010; Tan and Roberts, 2010). Lastly, in most of the cases when no one possesses overwhelming power over categorization, market participants jointly shape the categories of the focal product. Taken together, a product's category membership will be determined by multiple category-level factors:

*Baseline hypothesis 1 (category-based antecedents): Market participants consider the category membership of a product at the category level, such that the more salient the focal category per se, in terms of high level of density, reputation, resource space, etc., the more likely it will appear in a product's categorical descriptions.*

### **3.3.2 Category structure and category membership of a product**

Categories are connected. Recent research suggests that the interrelatedness between categories, namely the structural attributes of a category system, has implications for the potency of category effects (Montauti and Wezel, 2016; Paolella and Durand, 2016; Vergne and Wry, 2014; Wry and Lounsbury, 2013). The appearance of a category in product descriptions will be affected by its structural position in the classification system. On the negative side, when a category is often associated with *different* categories from the classification system, it becomes difficult for audiences to develop a shared understanding of the focal category (Montauti and Wezel, 2016; Pontikes, 2012). As a result, the identity of the focal category becomes fuzzy. Because fuzzy categories often create confusion and cognitive hurdles for audiences to appraise a product, fuzzy categories are less likely to appear in the descriptions of a product's category profile (Carnabuci et al., 2015; Hsu et al., 2012; Pontikes, 2012). The frequent co-appearance of a category with *different* categories, on the positive side, also suggests that the focal category is a lenient label that can encompass a wide range of activities (Pontikes and Barnett, 2015). For producers who would like to pursue a flexible market position or underline the versatility of their products, they may be interested in adopting a lenient category (Hsu et al., 2012; Pontikes and Barnett, 2015). In consistence with the leniency argument, Wry and Castor (2017) also

proposes that similarity between a category to other categories in a classification system also constitutes a vantage point of the focal category in categorization. The rationale here is that when categories are put together, audiences tend to see relationally similar categories as “fitting together” and are hence more positive toward the products labelled by fitted categories than by unfitted combinations.

In summary, the structural position of a category in the classification system will affect its appearances in product categorization, and, not surprisingly, market participants focus on different structural attributes when they evaluate products. Consumers, as “market-takers” (Pontikes, 2012), generally dislike vagueness (Carnabuci et al., 2015; Pontikes, 2012); Producers and investors, on the contrary, prefer vagueness because of the flexibility and market potential of categories marked by high vagueness (Pontikes, 2012; Pontikes and Barnett, 2015). Taken together, multiple structure-level factors jointly determine the category membership of a product:

*Baseline hypothesis 2 (structure-based antecedents): Market participants consider the category membership of a product at the category-structure level, such that the more salient the position of the focal category in the category structure, in terms of low level of fuzziness and high levels of leniency and similarity, etc., the more likely it will appear in a product’s categorical descriptions.*

The ideas on the structural attributes of categories above, such as fuzziness, leniency, and similarity, share one thing in common: they focus on how the *overall* connectedness of a category to all other categories in the classification system affects the appearance of focal category in product descriptions. Because the local structural position of a category, namely the interrelatedness between the focal



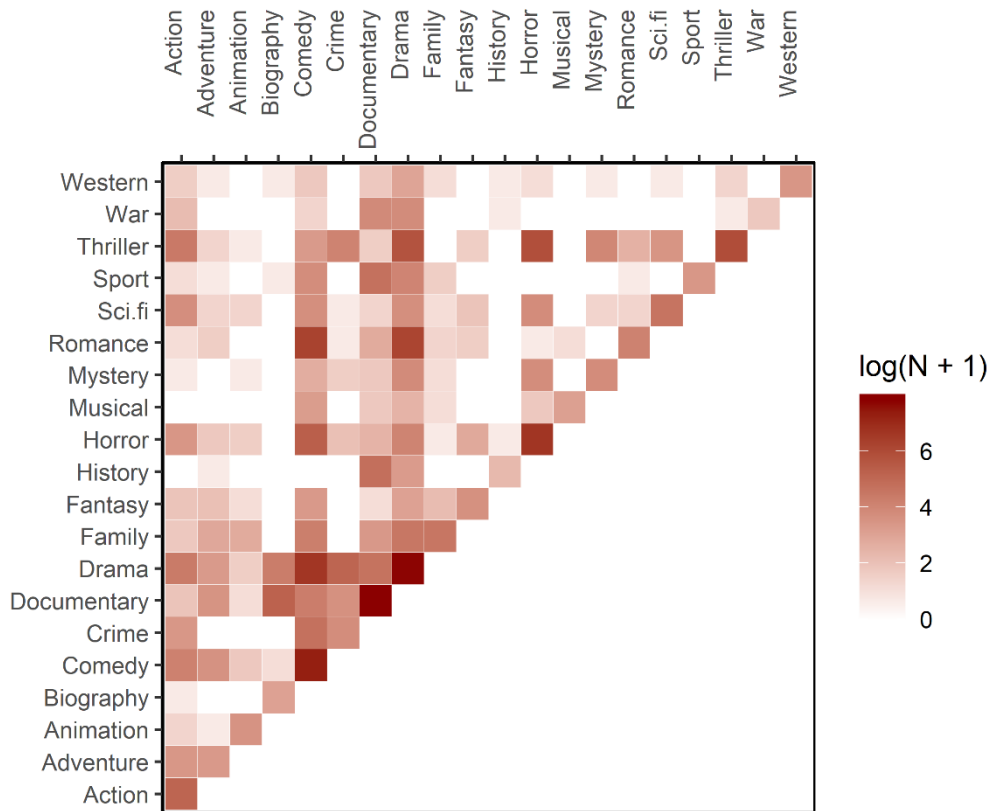
category and its neighbouring categories, is not acknowledged, the category system modelled in previous research (e.g., Carnabuci et al., 2015; Pontikes, 2012; Pontikes and Barnett, 2015; Wry and Castor, 2017) is a flat topography (Wry and Lounsbury, 2013), with all categories equidistant and evenly distributed on the category surface. Such a setup not only neglects the progress in recent research that suggests that categories are unevenly positioned within a classification (Paolella and Durand, 2016; Vergne and Wry, 2014), but also violates the observations that category systems are hierarchically structured (Kovács and Johnson, 2014 for restaurants; Wry and Lounsbury, 2013 for nanotube patents). The next section draws the attention to the local structure of a category and how it affects the category membership of a product. Our original hypotheses are proposed afterwards.

### **3.3.3 Considering the local structure of a classification hierarchy**

The major thesis of this section is that categories vary not only in their overall connectivity, but also in their patterns of connections. A highly lenient category may have equidistant connections with all other categories; it may also draw heavily upon its strong connections with certain, rather than all, categories. For example, in the restaurant industry, *sandwiches* is a lenient category widely connected with different cuisine categories (Kovács and Johnson, 2014), and its central position in the cuisine classification system does not rely on its special bonds with specific cuisines. On the other hand, *Chinese* is another lenient

category, yet it often concurrently appears with other specific categories such as *Dim Sum* and *Thai*.

We argue that the inborn differences in connection patterns between categories render the local aggregation of categories. Such local aggregations can be visualized in clustering of points in a multidimensional scaling plot or “hot spots” in the heatmap of categories. Figure 3-1 is a heatmap of feature films produced in Canada and the United States between 2000 and 2015. The depth of color represents the number of films in designated genre(s), the diagonal boxes denote the frequency of single-genre films, and the non-diagonal boxes denote the frequencies of films with two genres. The heatmap of genres reproduces the variations of categories in local aggregations. Some genres tend to be bound together. The frequency that *Thriller* co-appears with *Horror* is higher than the frequency that *Thriller* appears alone in feature films, whereas some genres, such as *Fantasy* and *Adventure*, have roughly equivalent connection with other genres. In addition, genres such as *Animation* and *Documentary* are quite independent, manifested in their abundant appearance in single-genre films and roughly equal connection with other genres.



Note: The data used to draw this figure are all U.S. and Canadian feature films that have one or two genre labels released between 2000-01-01 and 2015-12-31, accounting for 76.6% of all feature films released in U.S. and Canada films during the time period we are interested in. Log is taken in calculating genre(s) frequencies. We only analyze single- and binary-genre films here to export a visually-analyzable figure. In real cases a genre bundle can consist more than two genres.

**Figure 3-1:** The heatmap of feature films with one or two genres released between 2000 and 2015

We argue that the local aggregation of categories is theoretically distinct from the structural attributes of a category examined by prior studies (e.g., contrast or fuzziness in Carnabuci et al, 2015; fuzziness in Pontikes, 2012; leniency in Pontikes and Barnett, 2015; similarity in Wry and Castor, 2017): while structural attributes portrayed in extant literature focus on the overall connection of a genre to all other genres, local aggregations capture the micro structures within a

classification system (e.g., Paoletta and Durand, 2016; Leung, 2014). In the heat map (Figure 3-1), the structural attributes of a category can be approximated by the shade of all boxes in the same row and column of the focal genre, and local aggregations are illustrated in uneven connections of a genre to other genres. We refer to the local aggregations of categories as “category bundles” in this paper.

As a meso-level construct, category bundles reveal the imbalanced inter-category relations in the classification system. The discussion of a category bundle becomes meaningful when the bundle per se appears more frequently than the categories forming the bundle in the market. In such a case, market participants can easily recognize the special inter-relations between certain categories (i.e., category bundles) and take the relations into account when they classify a product that may be subject to bundle-prone categories. For example, since Shakespeare’s time, a romantic comedy structure is often used in plays (e.g., *A Midsummer Night’s Dream* and *The Merchant of Venice*). Filmmakers inherited such a formula and started to apply it to feature films in 1920s (Grindon, 2011). Their practices result in the frequent bonding of romantic and comedic elements in films and less works that contain only romance elements. Nowadays, when moviegoers and critics review a film with apparent romantic elements (e.g., kissing scenes, emotional conflicts, wedding, etc.), in addition to labelling the focal film as a *Romance* film, they are prompted to consider whether *Comedy* is also a part of the category membership of the focal film. When they pay more attention to the inspection of *Comedy* elements than that of other genres, *Comedy* will be more

likely to appear in the focal film as a result. In fact, *Rom-Com* has become an acknowledged category bundle worth more than 240 million dollars in 2018 (The Numbers, n.d.).

The logic from extra attention to related genres to their increasing chances of appearance proceeds through multiple channels. From the perspective of producers, populated bundles are more legitimate and perhaps more fertile than less populated bundles (Hsu, 2006a; Pontikes and Kim, 2017; Wry and Castor, 2017). By constructing a well-known bundle in a film, producers are less likely to encounter legitimacy issues and more likely to draw a large number of moviegoers. From the perspective of critics, they aim to set the agenda for the field (Bowers, 2019; Pontikes and Kim, 2017). By endorsing popular bundles, critics can reinforce their position in the field. Lastly, from the viewpoint of general audiences, their categorical evaluation is based on their own cognition schemas (Hsu, 2006b; Tan and Roberts, 2010). Since their knowledge of the market was built upon their prior experience in the market, their cognition schemas should have reserved the information on inter-relations between categories. In this sense, audiences will reproduce the inter-category structure in their categorization of new films (Carnabuci et al, 2015). In sum, producers, critics, and audiences share consistent belief on the effects of category bundle in determining the category membership of a product: conditional on the appearing of Category A in a product, the categories that can form a meaningful bundle with A are more likely to co-appear with A in

the focal product than other categories that don't. We theorize such an argument as a bundle-based perspective in the following hypothesis:

*Hypothesis 1 (H1, bundle-based antecedents): Market participants consider the category membership of a product at the genre-bundle level, such that the more fit between the focal genre and other genres in the film, the more likely the focal genre will appear in a product's categorical descriptions.*

A commonality of the bundle-based and structure-based mechanisms is that they are deeply rooted in the classic social psychological theory, which emphasizes the linkage among semantic categories and its impact on individuals' understanding and evaluation of categories (Rosch, 1975; Rosch and Mervis, 1975; Rosch, Simpson, and Miller, 1976). However, the two mechanisms examine the linkage between categories from different research vantage points. The structure-based mechanism deliberates on the effects of categorical linkage in a holistic manner. Though not explicitly stated in literature, the tendency to concern the overall connectivity of a category manifests itself in the operationalizations of structural constructs. In particular, category fuzziness is often measured as:

$$Fuzziness_g = 1 - \frac{\sum_{i=1}^{Density_g} GoM_{gi}}{Density_g}, \quad (1)$$

where the denominator,  $Density_g$ , is the number of products that are assigned category  $g$ , and the numerator,  $GoM_{gi}$ , denotes the grade of membership (GoM) of category  $g$  in product  $i$ . GoM takes the reciprocal of the number of categories included in product  $i$ . For example, if a film is assigned to three genres, *Horror*, *Romance*, and *Sci-Fi*, we will give 1/3 GoM to each genre this film is attached to (see also Kovács and Hannan, 2010; Pontikes, 2012). Formula (1) suggests that

fuzziness is sensitive to the number of categories that co-appear with the focal category, rather than *which* categories the focal category is associated with (see Carnabuci et al., 2015; Kovács and Hannan, 2010; Pontikes, 2012). Similarly, an “updated version” of fuzziness, category leniency, takes the following algorithm in previous literature:

$$Leniency_g = Fuzziness_g \times \ln N_g, \quad (2)$$

where  $Fuzziness_g$  is calculated by Formula (1) and  $N_g$  is the number of distinct other categories co-appearing with category  $g$  across all products. When counting the number of distinct other categories the focal category  $g$  has connected to ( $N_g$ ), researchers give the same weight to all categories that overlap with category  $g$ , no matter the times they co-appear with  $g$  (Pontikes, 2012; Pontikes and Barnett, 2015; Pontikes and Kim, 2017). In other words, a category that co-occurs with category  $g$  once will have the same contribution as the categories that co-occur with category  $g$  1000 times in counting  $N_g$ . In this sense, the leniency measurement focuses on the *breadth* of connections instead of the *depth* of connections that a category has had with other categories (see Hsu et al., 2012; Pontikes, 2012; Pontikes and Barnett, 2015).

The last example of structure-based variable is category similarity. Category similarity captures the similarity between a category and all other categories in the category system (Wry and Lounsbury, 2013; Wry and Castor, 2017). To calculate the category similarity of category  $g$ , researchers calculate the pair-wise Pearson’s correlation coefficients between category  $g$  and all other categories and take

average afterwards. Because any close connections a category has with other categories will be evened out after an average is taken, the current similarity measurement delivers more information on the general connectedness of a category (i.e., core or periphery) than on the special connections the category forms with certain categories.

The bundle-based mechanism, on the contrary, concerns the effects of local aggregations a category has had on its usage in products. For example, when we consider why *Thriller* does not appear in the descriptions of *Aquaman*, a 2018 superhero film with four genre labels (*Action*, *Adventure*, *Fantasy*, and *Sci-Fi*), the structure-based mechanism may argue that the high fuzziness or low leniency and similarity of *Thriller* limit its appearance in the focal film (Carnabuci et al., 2015; Kovács and Hannan, 2010; Negro et al., 2011; Pontikes and Barnet, 2015; Wry and Castor, 2017), whereas the bundle-based mechanism will ascribe the absence of *Thriller* to its poor fit with pre-existing genres (*Action*, *Adventure*, *Fantasy*, and *Sci-Fi*). By restraining the discussion of “fit” on the genres that are at stake, the bundle-based mechanism is capable of investigating the fitness of a genre at the genre-bundle level and exploring how the variances in a genre’s bundle fitness will affect its appearance in products (Paolella and Durand, 2016), both of which are not fully accommodated in the structure-based and genre-based explanations. In empirical analysis, a model that incorporates the bundle-based mechanism should have greater explanatory power than models that only take genre-based and structure-based mechanisms into account.



If the bundle-based mechanism finds support in the empirical analysis, it will also suggest that previous estimations on the effects of genre-based and structure-based mechanisms in consumers' category decision might be confounded by the missing bundle-based variable. In other words, previous estimations might exaggerate the effects of genre-based and structure-based mechanisms in consumers' evaluation of film genres. After we independently measure the bundle-based variable in our models, the effect sizes of genre-based and structure-based mechanisms should become weaker. Therefore, we hypothesize:

*Hypothesis 2a (H2a, relative predictability): A model incorporating the bundle-based explanation will have stronger explanatory power than models that only consider the genre-based and structure-based explanations.*

*Hypothesis 2b (H2b, effect sizes): After the bundle-based explanation is incorporated into the model, the effect sizes of genre-based and structure-based variables will decrease.*

### **3.4 Data and Methods**

#### **3.4.1 Setting and Data**

We tested our hypotheses in the feature film industry in North America (U.S. and Canada). One distinctive feature of feature film industry is that it has had an institutionalized category system, *genres*, for more than a century. In addition, our preliminary analysis suggested that genres do possess different patterns of aggregation (see Figure 3-1). We thus deemed that feature film industry is an appropriate setting to examine how the aggregation of categories at the bundle level will affect the appearance of a category in product descriptions. The data were

retrieved from the Internet Movie Database (IMDb), a comprehensive online film database of more than 500 thousand feature films and 9 million genre descriptions (as of December 2018). We limited our sample to feature films produced and released between 2000 and 2015 because late works usually receive sufficient audience attention in terms of genre classification, and sufficient attention is a prerequisite for the functionality of bundle-based mechanism. Moreover, earlier films tend to have more missing information for our construction of control variables, although the causes of missing information are irrelevant to our research question.

We considered 20 genres in the present paper (see footnote 1). These genres are universally recognized categories that are employed by most film databases (e.g., IMDb, Rotten Tomatoes, The Movie Database, etc.). We maintain that the established category labels sufficiently embody category bundles as socially constructed ideas among market participants (Durand and Khaire, 2017). Following previous studies (Hsu, 2006a; Hsu et al., 2009; Zhao, Ishihara, and Lounsbury, 2013), less commonly used genres (such as TV-movie, Adult, Film-Noir, News, etc.) were ignored in the analysis. Because IMDb has less information on non-North American films, we dropped the films created outside Canada and the U.S. Films with missing values were also excluded. The final sample included 6,159 feature films released from January 1, 2000 to December 31, 2015.

Because IMDb allows ordinary audiences to edit film pages, two questions arise. First, is the information provided by IMDb accurate? Second, does the genre

information on IMDb reflect the opinions of all market participants (producers, critics, and audiences)? For the accuracy issue, it is stated that each edit submission will go through careful checks by IMDb employees before its display on a webpage, and the mass collaboration method adopted by IMDb ensures that inaccurate and biased contents will be corrected by community members (moviegoers and editors), especially for high-profile works that have a large fanbase. For the second question, indeed moviegoers and IMDb editors finalize the categorization of feature films, and studios avoid explicit claims on the genre membership of their products for marketing reasons (Hsu, 2006a). Nevertheless, studios can strategically shape the perception of audience *ex ante* (Hsu, 2006a; Zhao et al., 2013). Their categorization strategies include choosing specific names (Zhao et al., 2013), using filmmakers (casts, directors, and producers) that are renowned for specific genres (Yang, 2018), and launching pertinent marketing campaign during the exhibition stage (Hsu, 2006a), and so on. In sum, we are confident that the genre information on IMDb to a large extent correctly reflects the actual contents of a film and embodies the thoughts of all market participants. It is, by definition, a consensus between audiences, movie critics, and studios.

The unit of analysis is genre-film. A genre is set to one if it appears in the film descriptions and zero otherwise. However, our sample only includes all realized observations (for example, a three-genre film will have three ones in this case). Ideally, one would have complete information on the unrealized genres considered by market participants for each film, but no such data exist. We thus

employed multiple strategies to construct a complete sample. We firstly used a full-sample design, in which all 20 genres are assumed to be considered for each film. We got 123,180 ( $6,159 \times 20$ ) observations based on this approach. We also used coarsened exact matching (CEM) to pair each realized genre with observationally-equivalent unrealized counterparts. CEM can improve the estimation of causal effects by constructing a balanced sample in which the differences between the control and treatment groups are minimized (Iacus et al., 2012). It has been applied in alliance-partner selection analysis (Rogan and Sorenson, 2014) and categorization research (Carnabuci et al., 2015). Our main purposes are to compare the explanatory power of models before and after the bundle-based explanation incorporated and examine the effects sizes of structure- and bundle-based explanations. These require that we minimize the variances between realized and unrealized samples in film- and genre-level variables and maximize the variances in structure- and bundle-level variables. To this end, we independently conducted CEM for each film so that film-level differences were eliminated. Conducting CEM independently for each film involved a trade-off: though we completely eliminated the variances between realized and unrealized genres in film-level variables, the number of available matches decreased significantly in a small sample (20 observations for each matching). We hence selected relatively coarser matching criteria to ensure more realized genres can be matched with unrealized equivalent genres. We trisected the observations by genre-level variables (*fuzzy density*, *category reputation*, and *category resource space*), and we only included

unrealized genres that were in the same trisection of the realized genres. The measurement of genre-level variables is in the control-variables section. Observations that did not find their equivalent pair(s) were dropped. This resulted in 16,673 observations from 4,677 films. The genres considered in each film ranged from two to thirteen. Although the sample size decreased significantly in the pruned data, we believe the imbalance in film- and genre-level variables between realized and unreleased genres was minimized. We improve causal inferences in the well-balanced data set at the cost of less observations.

#### *3.4.1.1 Dependent variable*

Dependent variable is a dummy variable coded as one if the focal genre  $g$  is chosen in film  $i$  and zero otherwise. Since we consider the choice of 20 genres for each film (i.e., *Action, Adventure, Animation, Biography, Comedy, Crime, Documentary, Drama, Family, Fantasy, History, Horror, Musical, Mystery, Romance, Science-Fiction, Sport, Thriller, War, and Western*; each choice is non-exclusive), there are 20 binary choices (to use genre  $g$  or not) for each film. We will discuss how these choices are pooled together later.

#### *3.4.1.2 Bundle fitness*

We used a four-step procedure to calculate the bundle fitness of a genre in a film. Table 3-1 summarizes the four steps and present some illustrative examples. We describe the four steps in details below.

**Table 3-1:** The four steps to calculate the bundle fitness of a genre in a film

Procedure	Formula and Example	Note
<p><b>Step 1</b> Choose a formula to calculate the level of coherence (local aggregation) between two or more than two genres.</p>	<p>An extended Jaccard index (Formula 3) that measures the multi-dimensional aggregations among elements of a combination (Arita, 2017).</p>	<p>Take the average of pair-wise similarity is not suitable here since pair-wise similarity takes the assumption that only bilateral relationships exist in a network. In the meanwhile, a core assumption in our paper is that a category bundle can consist of more than two genres.</p>
<p><b>Step 2</b> Consider how local aggregations affect the entry-or-not of a genre in a specific film. For a genre in a specific film, there are multiple combinations of genres that might be considered by market participants. We list all possible combinations that could be considered by market participants. Example 1: Consider why <i>Action</i> appears in <i>Aquaman</i> (2018), a four-genre film with <i>Action</i>, <i>Adventure</i>, <i>Fantasy</i>, and <i>Sci-Fi</i>. Example 2: Consider why <i>Thriller</i> does not appear in <i>Aquaman</i> (2018), a four-genre film with <i>Action</i>, <i>Adventure</i>, <i>Fantasy</i>, and <i>Sci-Fi</i>.</p>	<p>In Example 1, there are seven possible combinations of local aggregations considered by market participants: <i>Action-Adventure</i> <i>Action-Fantasy</i> <i>Action-Sci-Fi</i> <i>Action-Adventure-Fantasy</i> <i>Action-Adventure-Sci-Fi</i> <i>Action-Fantasy-Sci-Fi</i> <i>Action-Adventure-Fantasy-Sci-Fi</i>. In Example 2, there are fifteen possible combinations of local aggregations: <i>Thriller-Action</i> <i>Thriller-Adventure</i> <i>Thriller-Fantasy</i> <i>Thriller-Sci-Fi</i> <i>Thriller-Action-Adventure</i> <i>Thriller-Action-Fantasy</i> <i>Thriller-Action-Sci-Fi</i> <i>Thriller-Adventure-Fantasy</i> <i>Thriller-Adventure-Sci-Fi</i> <i>Thriller-Fantasy-Sci-Fi</i> <i>Thriller-Action-Adventure-Fantasy</i> <i>Thriller-Action-Adventure-Sci-Fi</i> <i>Thriller-Action-Fantasy-Sci-Fi</i> <i>Thriller-Adventure-Fantasy-Sci-Fi</i> <i>Thriller-Action-Adventure-Fantasy-Sci-Fi</i></p>	<p>More formally, conditional on genre <math>g</math> is chosen (Example 1) or not (Example 2) in a film with <math>n</math> genres, the total number of combinations can be easily written in combination notations: <math>NumBundle_g =</math> <math display="block">\begin{cases} \sum_{k=1}^{n-1} \binom{n-1}{k}, &amp; \text{if } g \text{ is chosen} \\ \sum_{k=1}^n \binom{n}{k}, &amp; \text{if } g \text{ is not chosen} \end{cases}</math></p>
<p><b>Step 3</b> Calculate coherence (local aggregation) of each combination listed in Step 2 using the formula determined in Step 1.</p>		
<p><b>Step 4</b> Determine which category bundle is the real bundle considered by market participants in their evaluations of a film</p>	<p>Use Formula 4 to take the weighted average of local aggregations we get in Step 3.</p>	<p>Three reasons why finding the “real” bundle is very difficult: a. we don’t have private information on market participants’ decision making process; b. in a choice set of a large number of potential bundles, even market participants do not know exactly the bundles they are thinking about; and c. there are multiple market participants with divergent interests in the market. We then use the weighted average to holistically consider the fitness of different local aggregations in shaping market participants’ categorization decisions.</p>

The first step is to choose a measurement that can measure the fitness or coherence of a bundle. We adopted a novel measurement from ecology literature to measure the fitness among categories that form a category bundle. Organization theorists used to measure the fitness (or coherence) between elements of a combination with pair-wise similarity indices (e.g., Pearson’s coefficient, Jaccard, Dice, and Sørensen similarity, etc.). Examples include Zuckerman (2004) and Wry and Lounsbury (2013). The rationale is that the more similar the elements that form a combination, the more likely the combination is regarded as coherent by market participants (Wry and Castor, 2017; Zuckerman, 2004). When the combination involves more than two elements, researchers calculate the pair-wise similarity between all elements and take average among the elements in which the focal product claims identity (e.g., Wry and Lounsbury, 2013). The averaged pair-wise similarity is not applicable in the present paper, since it only considers the binary connections between categories and contradicts our core arguments that multiple categories may form a “superordinate” category and that market participants consider categories as an ensemble in their sensemaking of products (Vergne and Wry, 2014). Moreover, recent ecology research finds that the average of pairwise (dis)similarity indices may not truly reflect the overall coherence among multiple species or sites (Arita, 2017; Baselga, 2013). Considering the drawbacks of previous approaches, we used an extended Jaccard index that measures the multi-dimensional aggregations among elements of a combination (Arita, 2017). Assuming that  $C$  is a set including  $k$  genres:  $C = \{g_1, g_2, \dots, g_k\}$ , we

calculated the extent of local aggregations between  $k$  genres of  $C$  using the following formula:

$$LocAgg_c = \begin{cases} \frac{\sum_{j=1}^m (NumGenre_j^C - 1)}{m(k-1)}, & k > 1, \\ 0, & k = 1 \end{cases} \quad (3)$$

where  $k$  is the number of genres that form the set  $C$ ,  $m$  is the number of films in the past five years that include at least one of the  $k$  genres, and  $NumGenre_j^C$  is the number of genres that belong to  $C$  in film  $j$ 's genre profile. In the extreme cases, when all  $k$  genres of  $C$  appear together in all films, the local aggregation between genres reaches one. In contrast, when none of the  $k$  genres appear together in the past five years, the level of local aggregation will be zero. This measurement returns to the classic Jaccard index when we restrict the genres being considered to two. When  $k$  equals one, local aggregation doesn't exist, and zero is given for this variable. Appendix 1 provides a detailed illustration of how local aggregation of genres is calculated.

With the algorithm to calculate the level of local aggregations of a bundle decided, the second step is to consider how local aggregations affect the entry-or-not of a genre in a specific film. Imagine we are considering why *Action* appears in the genre profile of *Aquaman* (2018), a four-genre film with *Action*, *Adventure*, *Fantasy*, and *Sci-Fi*, one question will emerge: which category bundle (local aggregation of genres) are we talking about? An intuitive answer is that market participants think about the fitness of the four-genre bundle, *Action-Adventure-Fantasy-Sci-Fi*, when they reflect on the categories of the film. However, lacking



sufficient information on market participants' decision-making process, we do not know exactly the category bundle that market participants have in mind. They might only consider the fitness of a subset of *Aquaman's* genres, say, *Action-Adventure-Fantasy* or *Action-Adventure*, when they determined the entry-or-not of *Action* in *Aquaman*. Which subset they considered depends on their own cognitive models and prior experience (Bowers, 2015a; Hsu, 2006b; Tan and Roberts, 2010). Indeed, this is private information inaccessible to researchers. Technically, for a four-genre film, conditional on whether the genre we concern was realized or not in the film, there are correspondingly seven and fifteen combinations of category bundles that might be considered by market participants (see how we counted bundles in Step 2 of Table 3-1). In Step 2, we listed all possible combinations of category bundles, conditional on whether the focal genre is realized in the film or not. We then calculated the level of local aggregations of all category bundles by applying Formula (3) on all bundles in Step 3.

In Step 4, we deliberated on which category bundle is the “real” category bundle considered by the market participants in their categorization of a film. As we mentioned before, finding the “real” bundle will be rather difficult with imperfect information on market participants' decision-making process. In some cases in which the number of potential category bundles are large, decision makers rely on heuristics or rules of thumb to select the categories they prefer (Simon, 1979). This indicates that even the decision makers per se might not recall exactly the category bundle(s) that they considered. Furthermore, the multiplicity of

market participants (studios, film critics, and audiences) with different interests in our context makes a reasonable guess of the chosen category bundle almost impossible. We hence proposed a weighted measurement to holistically consider the fitness of different category bundles in shaping market participants' categorization decisions. We argued that market participants are more likely to consider the category bundles that appear more often in the market than bundles that are less common. We used the ratio of density of the category bundle to the density of the genre as a weight in calculating the bundle fitness of a genre in a film. The formula is:

$$BundleFit_g^i = \frac{\sum_{C=1}^{NumBundle_g} (LocAgg_c \times \frac{Density_c}{Density_g})}{NumBundle_g}, \quad (4)$$

where subscript  $C$  represents the category bundles we list in Step 2,  $LocAgg_c$  represents the level of local aggregation we calculate in Step 3,  $NumBundle_g$  denotes the number of bundles we get in Step 2, and  $Density_c$  and  $Density_g$  respectively measure the frequencies of bundle  $C$  and genre  $g$  in the past five years. In general, Bundle fitness of genre  $g$  in film  $i$  is a weighted average of local aggregations on all possible category bundles  $g$  can form in film  $i$ .

As a side note, with the assumption that more common bundles are more likely to be noticed and proceeded by market participants, the weighted sum of local aggregation is consistent with the measurements of the same kind in early category literature (see Zuckerman, 1999; 2004).  $NumBundle_g$  serves as a penalty term here to offset the advantages of multi-genre films in calculating bundle

fitness. The value of bundle fitness ranges from zero to one, where one suggests that genre  $g$  is a perfect fit for film  $i$  and zero suggests that genre  $g$  should never be included in the focal film.

#### 3.4.1.3 Control variables

We included a number of control variables to account for other factors that may confound the relationship between bundle fitness and entry decision, including category-level, structure-level, and film-level control variables. We included *fuzzy density* of a genre to control for the advantages of popular genres in the categorization of feature films (Hsu, 2006a). We measured the fuzzy density of genre  $g$  as the sum of number of films having genre  $g$  in the past five years, weighted by the grade of membership (GoM) of genre  $g$  in each film. Following previous literature, we defined GoM of genre  $g$  in film  $i$  as one divided by number of genres in the film (Hsu et al., 2009; Kovács and Hannan, 2010). We also controlled for *category reputation* and *category resource space* to account for the effects of niche fertility in film categorization. Category reputation was measured as the average IMDb rating of all films with genre  $g$  in the past five years (Vergne, 2012). Resource space of genre  $g$  is the sum of box office of all films with genre  $g$  released in the past five years, weighted by the GoM of genre  $g$  in each film, we took log to normalize the distribution of this variable.

We also controlled three variables that capture the effects of overall structural position of a category in the classification system in the present paper. The first variable is *category fuzziness*. Category fuzziness reflects the “dark side”

of occupying a central position in the classification system: when a category is frequently connected with different categories, its identity becomes blurry (Kovács and Hannan, 2010). When it becomes difficult for audiences to reach a consensus on the quality of product to which a fuzzy category is allocated, market participants will avoid using fuzzy categories as a result (Carnabuci et al., 2015). We use Formula (1) (see before) to measure the fuzziness of a category.  $Density_g$  is the number of films that are assigned to genre  $g$  in the previous five years.  $GoM_{gi}$  denotes the grade of membership (GoM) of genre  $g$  in product  $i$ . GoM takes the value of one if  $g$  is the only genre film  $i$  claims and zero if  $g$  is not used in film  $i$ . When a film claims multiple genres,  $GoM_{gi}$  is measured as one divided by number of genres film  $i$  has.

The second structure-level variable is *category leniency*. Leniency is a relatively new concept proposed in Pontikes (2012), Pontikes and Barnett (2015), and Vergne and Wry (2014). It captures the “positive side” of occupying a central position in the classification system. Although lenient categories may confuse audiences, they are attractive to producers and audiences that are “market-makers” (Pontikes, 2012) due to their high flexibility and wide range of fit. Pontikes and Barnett (2015) argue that highly lenient categories will be more popular among market makers than less lenient categories (e.g., producers, venture capitalists), reflected in their higher market entry and exit rate. We made some minor changes to Formula (2) to ensure the validity of this variable in our research context:

$$\text{Leniency}_g = \text{Fuzziness}_g \times \ln(N'_g + 1),$$

where  $N'_g$  is the number of other distinct genres that *frequently* co-appear with genre  $g$  in the past five years. Previous researchers defined two categories as “co-appearance” when two categories appear simultaneously on one occasion (e.g., Pontikes, 2012; Pontikes and Barnet, 2015). Since the number of available categories (20 genres) in the feature film context is significantly less than the number of available categories in previous research (e.g., 456 labels in Pontikes, 2012), the probabilities that two genres co-appear increase exponentially in our context. Following Pontikes’ leniency measurement, the correlation between fuzziness and leniency is so high ( $r > 0.98$ ) that splitting up the effects of fuzziness and leniency becomes impossible. We hence adopted a stricter standard of “co-appearance” in the current paper. We defined other categories as co-appearing with genre  $g$  if their co-appearances take up to 10% of the appearances that genre  $g$  has in the past five years. We also added one to the count of  $N'_g$  to ensure positive values of leniency measurement. We drew a scatter plot of fuzziness and leniency to check the validity of our leniency measurement. We found the scatter plot is very similar to the one in Pontikes (2012: p. 94).

The last structure-level variable is *category similarity*. Category similarity reflects the extent to which categories shall attributes in common (Vergne and Wry, 2014). Previous research found that the more similar a category is to other categories, the more likely it will be used concurrently with other categories (Wry and Castor, 2017). Following Wry and Castor (2017), we measured the relative

similarity of a category to all other categories using Pearson's correlation coefficient. For a given year, we calculated the pair-wise Pearson correlation of all genres using all film data in the past five years; we then calculated a genre's overall similarity with other genres by taking the average of Pearson correlations it has with all other categories (Wry and Lounsbury, 2013).

Film-level variables that may affect category membership of a film were also controlled. To control the variances of films in their category membership having different levels of quality, we included *IMDb rating* of the focal film (one to ten) in the model. Studios are motivated to control the number of genres in their works because genre-spanning films incur lower evaluations among audiences (Hsu, 2006; Hsu et al., 2009; Zhao et al., 2013). We thus used the *number of genres a film already has* (log) to account for the motivation of studios to manipulate genre numbers. For in-house production, studios enjoy higher power over the filmmaking process. We used a dummy variable, *in-house production*, in which a studio acts as both distributor and producer, to account for the impacts of studios in the categorization process. Film budget is another driven factor of a genre's appearance in films. For example, Compared to *Drama*, *War* or *Sci-Fi* films often need to shoot more big scenes, which require high costs in location shooting or post-production. We thus controlled film budget (log) to control the effects of budget on the selection of a film's genre(s). Major 6 studios have different filmmaking and distributing strategies vis-à-vis indie studios. We thus used a dummy representing whether the studio making the focal film is a "Major 6" studio

(Warner Brothers, Disney, Universal Pictures, 20th Century Fox, Columbia Pictures, and Paramount Pictures) to approximate the effects of studios on a film's genre decisions. Table 3-2 reports summary statistics and correlations.

**Table 3-2:** Descriptive statistics and correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Mean	0.10	1.72*10 <sup>7</sup>	6.26	2.02	1.90	0.33	0.05	268.42	1.40*10 <sup>7</sup>	6.19	0.58	1.139	0.10	0.01
S.D.	0.30	3.00*10 <sup>8</sup>	1.45	1.13	1.42	0.47	0.22	369.1	1.18*10 <sup>7</sup>	0.56	0.12	0.38	0.10	0.02
Min	0	0	1	1	1	0	0	5.65	141756	4.82	0.13	0	-0.16	0
Max	1	2.8*10 <sup>10</sup>	10	11	21	1	1	1920.6	5.51*10 <sup>7</sup>	7.36	0.76	1.82	0.4116	0.20
1.Entry (0/1)														
2.Budget number (US dollar)	0.01**													
3.IMDb rating	-0.00	0.01***												
4.Number of genres	0.19***	0.05***	-0.00											
5.Number of distributors	0.04***	0.03***	0.02***	0.20***										
6.Inhouse production (0/1)	0.03***	0.04***	0.12***	0.14***	0.13***									
7.Major 6 (0/1)	0.04***	0.03***	0.02***	0.20***	-0.02***	-0.02***								
8.Fuzzy density	0.25***	-0.00	-0.00	-0.03***	-0.01***	-0.02***	-0.05***							
9.Genre resource space (weighted by GoM)	-	0.00	0.00	0.04***	0.01***	0.03***	0.08***	-0.42***						
10.Genre reputation	-0.10***	-0.00	-0.00	-0.00	-0.00	-0.01*	-0.01**	0.08***	-0.27***					
11.Category fuzziness	-0.12***	-0.00	0.00	0.02***	0.00	0.01***	0.03***	-0.72***	0.60***	-0.21***				
12.Category leniency	-0.14***	-0.00	0.00	0.02***	0.00	0.01***	0.03***	-0.70***	0.68***	-0.30***	0.90***			
13.Category similarity	0.29***	0.00	0.00	0.02***	0.01*	0.01***	0.04***	0.40***	0.20***	-0.36***	0.11***	-0.01**		
14.Bundle fitness	0.24***	-0.01**	0.00	-0.16***	-0.02***	-0.03***	-0.02***	0.03***	0.05***	-0.16***	0.10***	-0.03***	0.33***	

Note: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$



### 3.4.2 Analytical methods

Since our theoretical framework considers both choice-alternative (i.e., genre-, structure-, and bundle-based) and case-alternative (film-related) variables, we fitted the alternative-specific conditional logit (McFadden's choice) model in this paper:

$$\ln\left(\frac{P_{ig}}{1-P_{ig}}\right) = \beta_0 + \alpha BundleFit_{ig} + \mathbf{X}'\boldsymbol{\beta}_g^g + \mathbf{Y}'\boldsymbol{\beta}_g^s + \mathbf{Z}'\boldsymbol{\beta}_{ig} + \varepsilon_{ig},$$

where  $\mathbf{X}$  specifies genre-related variables,  $\mathbf{Y}$  is a vector of structure-based variables, and  $\mathbf{Z}$  is a vector of film-level controls. Compared to conditional logit model, which treats case-alternative variables as fixed effects and does not estimate case-alternative variables in the regression, our approach is more realistic by acknowledging the effects of case-alternative variables (in our case, film-level variables  $\mathbf{Z}$ ) on the likelihood that a genre is chosen or not. In the real world, film-level factors, such as budget, producer capabilities, and number of genres that a film already has, do have heterogenous impacts on the selection of different genres. For example, a large budget is often a prerequisite for a *War* film, which requires a large crew to shot war scenes and expensive postproduction to create a real atmosphere. In contrast, a *Drama* film is less constraint by budget. Our approach allows an independent set of estimates of film-level variables for each genre, making it superior to other discrete choice models that assume fixed effects of film-level variables across choices. Lastly, the genre choices in our model are not mutually exclusive. Compared to multinomial or conditional logit models, the alternative-specific conditional logit model allows more than one alternative to be

selected (Cameron and Trivedi, 2010). We used clustered standard errors in the regressions to correct for correlation of residuals from the same film.

Hypothesis 2a argues that a model into which the bundle-based explanation is incorporated will have stronger explanatory power than models that only include genre- and structure-based explanations. We examined this hypothesis using a receiver operating characteristic (ROC) curve analysis. ROC curve has been extensively used in biostatistics, clinical medicine, and machine learning to evaluate the diagnostic accuracy of tests or assessment of classification models (Bradley, 1997; Erdreich and Lee, 1981). ROC curve analysis plots the true positive rate (TPR, i.e., the proportion of actual positives that are correctly identified, or statistical power in hypothesis testing) against the false positive rate (FPR, i.e., the proportion of actual negatives that are correctly rejected, or Type I error in statistics) of a model at various cutoff settings. The goal of ROC curve analysis is to find the model that achieves the higher TPR at the given level of FPR. The better performance of a model in terms of FPR and TPR, the larger area the model will occupy under the ROC curve in the plot. We used a statistical test suggested by DeLong, DeLong, and Clarke-Pearson (1998) to examine the equality of area under the curves in this paper. We argued that a model considering the bundle-based explanation will have larger area under the ROC curve.

Hypothesis 2b suggests that the structure-based variables contain information on a genre's local aggregations. In other words, the effect sizes of structure-based variables will decrease after the bundle-based variable is

separated out the model. In linear models, the change in the effect sizes of variables due to the inclusion of a confounding variable can be easily expressed as the differences in the coefficients of those variables before and after the confounding variable is included in the model. It is not the case in logit models, since the coefficients of logit models reflect not only the impacts of independent variables but also the degree of unobserved heterogeneity of the model (Mood, 2010). Two issues arise when we compare coefficients between nested logit models based on the same sample: on the one hand, as long as the new variable can (partly) explain the unobserved heterogeneity of the model, it will change the coefficients of pre-existing variables by “rescaling” the estimation of coefficients, even if the new variable is not correlated with the pre-existing variables (Karlson, Holm, and Breen, 2012; Mood, 2010); on the other hand, the two models will have different distribution of error terms, making it more difficult to compare them (Karlson et al., 2012). We hence used a new method developed by Karlson, Holm, and Breen (KHB) to assess the change of coefficients due to the confounding effect relative to the rescaling effect (Karlson et al., 2012; Kohler, Karlson, and Holm, 2011). The KHB method constructs a Z-statistics. The null hypothesis is that the effects of confounding, net of rescaling, is zero. Rejecting the null hypothesis suggests that the change in the coefficient of interest can be attributed to confounding effect of the new variable.

### 3.5 Results

Table 3-3 reports the estimates of McFadden's choice model to assess the condition under which a genre is selected. To make sure that coefficients are comparable, we standardized major variables (resource space, reputation, fuzzy density, fuzziness, leniency, similarity, and bundle fitness) in all regressions. Model 1 includes control variables and genre-level variables only. In Model 2, we estimated the likelihood that a genre is chosen with the bundle-level variable included. A genre's bundle fitness is positively associated with the probability it is selected in a film ( $p < 0.001$ ). A one-standard-deviation increase in the level of bundle fitness will increase the genre's odds of appearing in film descriptions by 271 percent ( $e^{1.31} - 1$ ). Model 2 hence provides strong support for Hypothesis 1. In Model 3 we dropped the bundle-based variable and instead added three structural attributes. We used this model to replicate previous research investigating the effects of fuzziness, leniency, and similarity on an organization's categorization decisions. Consistent with Baseline Hypothesis 2, fuzziness decreases the likelihood a genre is selected ( $p < 0.001$ , see also Carnabuci et al., 2015; Negro et al., 2011), and leniency and similarity enhance the likelihood ( $p < 0.1$  and  $p < 0.001$ , see also Pontikes and Barnett, 2015; Wry and Castor, 2017). In Model 4, we simultaneously included variables at the genre-, structure-, and bundle-level to examine the explanatory power of models with and without the bundle-level variable. With the bundle-based variable included, the  $\chi^2$  statistics increases significantly (from 3733 to 5359). This provides preliminary support for

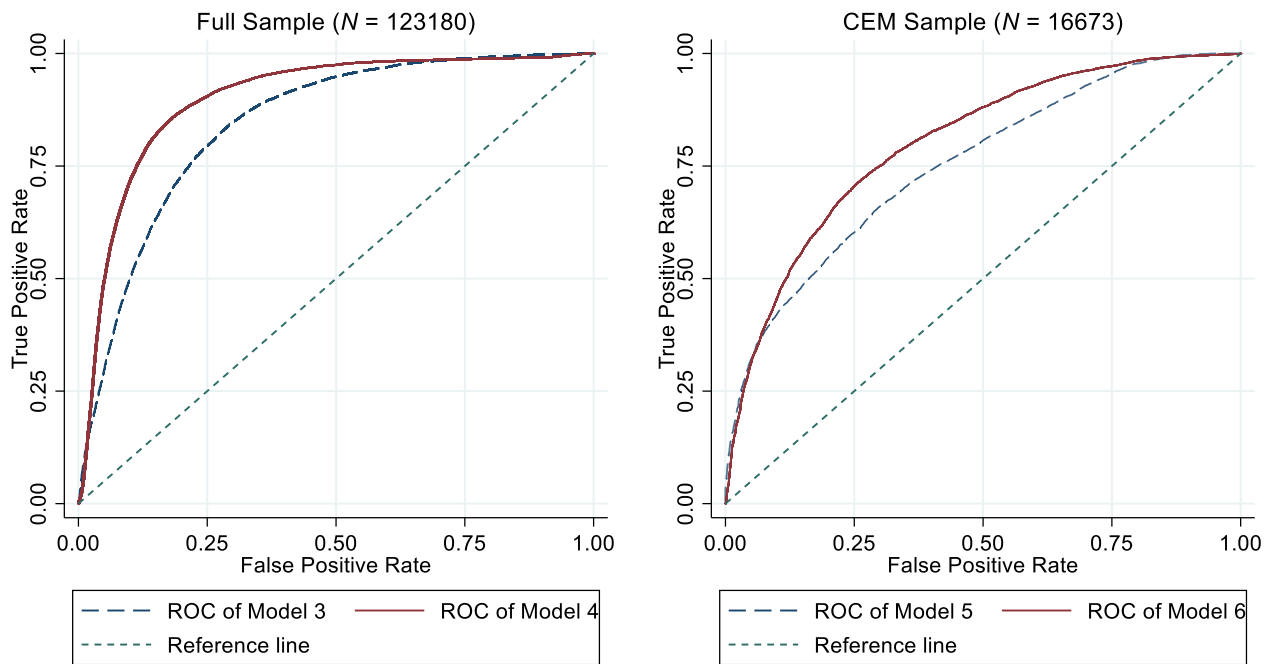
Hypothesis 2a. To further pin down the explanatory power of two models, we drew their ROC curves in Figure 3-2 (left plot). The solid line represents Model 4 (with the bundle-level variable), while the long-dashed line denotes Model 3 (without the bundle-level variable). Except at the extreme cut-offs (near zero or near one), the ROC curve of Model 4 occupies higher position than that of Model 3. The higher position of ROC curve suggests that at any given level of FPR (Type I error), Model 4 has greater TPR (power) than Model 3. We also conducted the equality of area test suggested by DeLong et al. (1988). We found the ROC area of Model 4 is significantly larger than that of Model 3 (*0.90 versus 0.85*,  $\chi^2(1) = 2036$ ,  $p < 0.001$ ). Taken together, we found strong support for Hypothesis 2a.

**Table 3-3:** McFadden's choice model of genre entry: 2000-2015

	(1) Full sample	(2) Full sample	(3) Full sample	(4) Full sample	(4B: KHB) Full sample	Confounding effects Coef <sup>4B</sup> - Coef <sup>4</sup>	(5) CEM	(6) CEM
<i>Genre-based mechanism</i>								
Fuzzy density	-0.13*** [0.88] (0.03)	-0.15*** [0.86] (0.03)	-0.16*** [0.85] (0.03)	-0.17*** [0.84] (0.03)	-0.17*** [0.84] (0.03)		0.33*** [1.39] (0.07)	0.31*** [1.37] (0.07)
Resource space	-0.01 [0.99] (0.07)	0.16* [1.17] (0.07)	0.25** [1.28] (0.08)	0.27*** [1.30] (0.08)	0.27*** [1.30] (0.08)		0.33 <sup>†</sup> [1.39] (0.17)	0.30 <sup>†</sup> [1.35] (0.16)
Reputation	-0.07 [0.94] (0.07)	0.04 [1.04] (0.07)	-0.06 [0.94] (0.07)	-0.02 [0.98] (0.07)	-0.02 [0.98] (0.07)		0.14 [1.15] (0.14)	0.15 [1.16] (0.14)
<i>Structure-based mechanism</i>								
Fuzziness			-0.68*** [0.51] (0.11)	-0.56*** [0.57] (0.11)	0.09 [1.10] (0.11)	0.65*** Z value: 36.64	-0.89*** [0.41] (0.23)	-0.96*** [0.38] (0.23)
Leniency			0.13 <sup>†</sup> [1.14] (0.08)	0.23** [1.26] (0.09)	-0.39*** [0.68] (0.09)	-0.60*** Z value: -36.34	0.25 <sup>†</sup> [1.29] (0.14)	0.28 <sup>†</sup> [1.32] (0.14)
Similarity			0.37*** [1.44] (0.06)	-0.03 [0.97] (0.06)	0.31*** [1.36] (0.06)	0.34*** Z value: 37.68	0.27* [1.31] (0.12)	0.27* [1.31] (0.13)
<i>Bundle-based mechanism</i>								
Bundle fitness		1.31*** [3.69] (0.03)		1.31*** [3.70] (0.03)	1.31*** [3.70] (0.03)			0.78*** [2.18] (0.06)
Film-level control variables	YES	YES	YES	YES	YES		YES	YES
N	123180	123180	123180	123180	123180		16673	16673
Log likelihood	- 2.5e+04	-2.1e+04	-2.5e+04	-2.1e+04	-2.1e+04		-5339.95	-4910.62
$\chi^2$	3696.99	5337.31	3733.02	5358.85	5358.85		980.21	1033.43

Notes:

1. <sup>†</sup> p < 0.1 \* p < 0.05 \*\* p < 0.01 \*\*\* p < 0.001. Standard errors clustered by film in parentheses. Odds ratios in square brackets.
2. Film-level control variables include IMDb rating, number of genres (log), number of distributors (log), inhouse production (0/1), Major 6 (0/1), and film budget (log). There are nineteen sets of control variables in the model (95 = 19 × 5 film-level controls, one genre acts as the benchmark).



For Model 3, ROC Area = 0.845, S.E. = 0.002, 95% CI = (0.842, 0.848);  
 For Model 4, ROC Area = 0.900, S.E. = 0.001, 95% CI = (0.898, 0.903);  
 For Model 5, ROC Area = 0.754, S.E. = 0.004, 95% CI = (0.746, 0.761);  
 For Model 6, ROC Area = 0.800, S.E. = 0.003, 95% CI = (0.793, 0.807).

**Figure 3-2:** Receiver operating characteristic (ROC) curves of Model 3, 4, 5, and 6

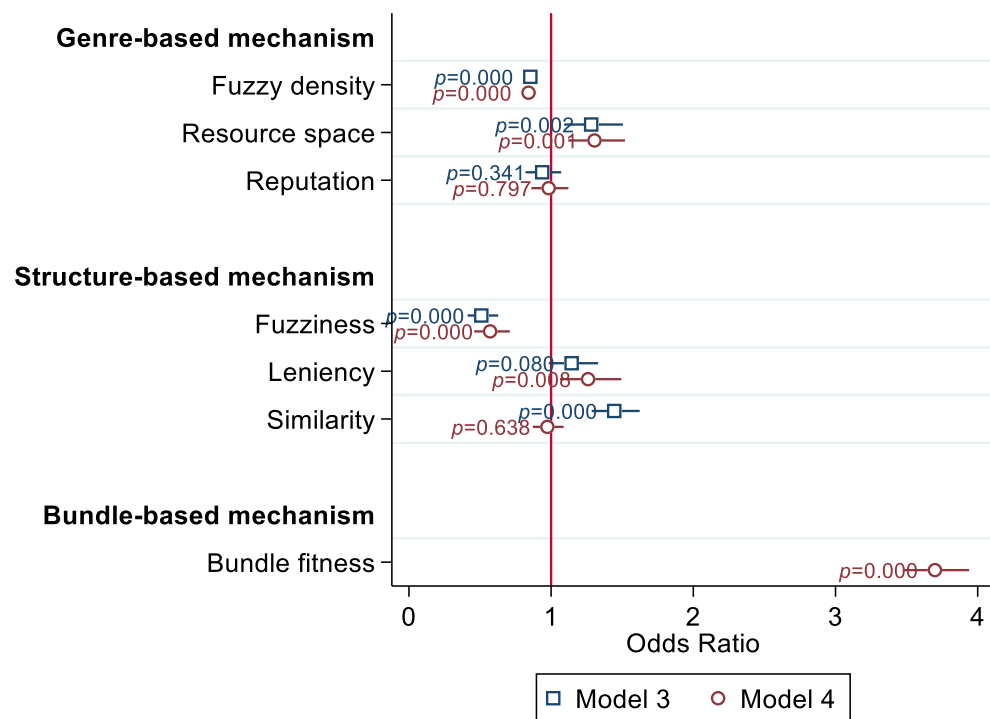
In Model 5 and 6, we used CEM to construct a dataset in which unrealized genres have similar genre- and film-level attributes as the realized genres chosen by market participants. Even though the matching algorithm significantly reduces the sample size (from 123,180 to 16,673), the model with bundle-based mechanism considered (Model 6) performs better than the model that only considers genre- and structure-based mechanisms (Model 5). As we expected, the  $\chi^2$  statistics increases from 980 to 1033 from Model 5 to 6 (See Column 5 and 6 of Table 3-3), the ROC curve of Model 6 is located above that of Model 5 (see the right plot of Figure 3-2), and equality of area test also suggests that Model 6 has larger ROC

Area than Model 5 (*0.80 versus 0.75*,  $\chi^2(1) = 613$ ,  $p < 0.001$ ). The tests on CEM sample provide further support for Hypothesis 2a.

Hypothesis 2b argues that the effect sizes of structure-based variables (fuzziness, leniency, and similarity) decrease after the inclusion of the bundle-based variable. We presented the odds ratio of Model 3 and 4 in Figure 3-3. The odds ratio of fuzziness and similarity decrease from Model 3 to 4, while the odds ratio of leniency increases in Model 4. The results seem inconsistent with Hypothesis 2b. Nevertheless, as we mentioned before, in nested logit models the change in odd ratios depends on both the confounding effects of the new variable and rescaling effects of the new error variance (Karlson et al., 2012; Kohler et al., 2011). In our context in which bundle fitness has strong effects on a genre's usage in films, the error terms of Model 4 will surely be smaller than that of Model 3. Because the coefficients of structure-based variables are scaled (divided) by a very small error term, the scaling effects will mask the confounding effects of bundle-based mechanism on structure-based mechanism by overestimating the coefficients of structure-based variables in Model 4 (Karlson et al., 2012). We empirically examined confounding effects net of scaling effects using a four-step KHB method (Karlson et al., 2012; Kohler et al., 2011). The first step was to regress the bundle-based variable, bundle fitness, on the structure-based variables it may confound. We then used the residual of bundle fitness to refit Model 4. The results are presented as Model 4B in Table 3-3. In Step 3 we subtracted the coefficients of fuzziness, leniency, and similarity in Model 4 from the coefficients in Model 4B,



and the differences are the confounding effects (in Column 6 of Table 3-3). We found that after crowding-out the scaling effects, bundle fitness does help decrease the effects sizes of fuzziness and leniency (by making the negative fuzziness variable less negative and the positive leniency variable less positive, respectively). Nevertheless, bundle fitness increases the effect size of similarity (by making the positive similarity measurement more positive). The results here only provide partial support for Hypothesis 2b. In Step 4, we used the  $Z$  statistics proposed by Karlson et al. (2012) to further test the significance of confounding effects. We found that bundle fitness significantly decreases the effect sizes of fuzziness and leniency and increases the effect size of similarity. In sum, Hypothesis 2b receives partial support.



**Figure 3-3:** Odds ratio plot

### **3.5.1 Robustness checks**

We performed a number of robustness checks. We first checked the construct validity of the core independent variable, bundle fitness, and examined whether measurement error affected the results. In our algorithm, we manually give zero value to the genres appear in single-genre films in the calculation of local aggregations (see Formula (3)). The rationale is that a genre that frequently appears in single-genre films would be less likely to fit with other genres if included in a bundle. However, there may be a concern that the results are driven by a manually created mathematical truism. To mitigate such a concern, we dropped all single-genre films and re-run the regressions. The results are in Table 3-4. The coefficients of bundle fitness in Model 7 through 10 are positive, lending support for Hypothesis 1. In unrepresented ROC curve analyses, we found that the ROC area of Model 8 and 10 is respectively larger than that of Model 7 and 9, lending further support for Hypothesis 2a. We also conducted KHB method in the sample. The results are the same as we found in the full sample.

**Table 3-4:** McFadden's choice model of genre entry with single-genre film excluded

	(7) Full sample	(8) Full sample	(9) CEM	(10) CEM
<i>Genre-based mechanism</i>				
Fuzzy density	-0.16*** (0.03)	-0.27*** (0.03)	0.36*** (0.08)	0.12 (0.10)
Resource space	0.26** (0.09)	0.25** (0.09)	0.34 <sup>†</sup> (0.17)	0.42* (0.18)
Reputation	-0.11 (0.07)	-0.15 (0.08)	0.15 (0.14)	0.04 (0.15)
<i>Structure-based mechanism</i>				
Fuzziness	-0.73*** (0.12)	-0.99*** (0.14)	-0.95*** (0.23)	-1.28*** (0.27)
Leniency	0.18* (0.08)	0.41*** (0.11)	0.28 <sup>†</sup> (0.15)	0.42* (0.18)
Similarity	0.34*** (0.08)	-0.27*** (0.08)	0.31* (0.15)	0.22 (0.16)
<i>Bundle-based mechanism</i>				
Bundle fitness		2.95*** (0.05)		2.10*** (0.08)
Film-level control variables	YES	YES	YES	YES
<i>N</i>	86880	86880	14025	14025
Log likelihood	-2.2e+04	-1.4e+04	-4612.99	-3398.56
$\chi^2$	2536.03	5639.93	1642.35	1989.97

Notes:

1. <sup>†</sup>  $p < 0.1$  \*  $p < 0.05$  \*\*  $p < 0.01$  \*\*\*  $p < 0.001$ . Standard errors clustered by film in parentheses.
2. Film-level control variables include IMDb rating, number of genres (log), number of distributors (log), inhouse production (0/1), Major 6 (0/1), and film budget (log). There are nineteen sets of control variables in the model ( $95 = 19 \times 5$  film-level controls).

The second issue also revolves around the validity of bundle fitness. To further prove the idea that bundle fitness is meaningful in market participants' categorization decisions, we listed all highly matched and mismatched category bundles based on the calculation of our algorithm here and checked if the results are in tune with our intuition. The bundles are listed in Table 3-5. As we can see, the five most matched bundles include *Animation-Family*, *Crime-Thriller*, *Action-Thriller*, *Drama-Romance*, and *Comedy-Romance*, whereas the five most mismatched bundles are *Action-Documentary*, *Adventure-Documentary*,

*Documentary-Thriller*, *Documentary-Fantasy*, and *Documentary-Sci-Fi*. We believe the algorithm-generated bundle fitness measurement coincides with general audience’s perception about the market.

**Table 3-5:** The ten most matched and mismatched category bundles

Rank	Most matched	Bundle Fitness	Most mismatched	Bundle Fitness
1	<i>Animation-Family</i>	0.207	<i>Action-Documentary</i>	0
2	<i>Crime-Thriller</i>	0.196	<i>Adventure-Documentary</i>	0
3	<i>Action-Thriller</i>	0.185	<i>Documentary-Thriller</i>	0
4	<i>Drama-Romance</i>	0.167	<i>Documentary-Fantasy</i>	0
5	<i>Comedy-Romance</i>	0.161	<i>Documentary-Sci-Fi</i>	0
6	<i>History-War</i>	0.158	<i>Action-Adventure-Documentary-Thriller</i>	0
7	<i>Adventure-Family</i>	0.144	<i>Documentary-Romance</i>	0
8	<i>Mystery-Thriller</i>	0.141	<i>Documentary-Musical</i>	0
9	<i>Crime-Thriller</i>	0.134	<i>Horror-Musical</i>	0
10	<i>Crime-Drama-Thriller</i>	0.130	<i>Documentary-Western</i>	0

Note: Results are based on all films released between 2000 and 2015. To qualify for the ranking, the genre bundle should appear at least once between 2000 and 2015. Single-genre films and repeated genre bundles are dropped in the ranking.

### 3.6 Discussion

Our starting point is that categories are hierarchically structured in the classification system and their interconnectedness will be manifested in the category membership of a product. Our particular concern has been with the influence of a meso-level phenomenon—the local aggregation of categories—on the categorization decisions of market participants. We developed a new construct, category bundle, to represent the level of local aggregations in the market, and we

examined to what extent category bundles shape the categorization of feature films. We have shown that a genre that achieves higher level of bundle fitness is more likely to be chosen by market participants (studios, critics, and audiences), indicating the significance of bundle-based mechanism. Further, we also proposed that the bundle-based mechanism has stronger explanatory power than the genre-based and structure-based mechanisms in predicting the category membership of products. We found that bundle fitness has the largest effect size in the model investigating the antecedents of category membership, and it significantly increases the overall fit of the model. These results provide compelling evidence that the local aggregation a category has had is a more prominent feature than its overall position in the classification system.

Our study enriches the understanding of categorization theory in two aspects. First, it significantly extends the literature on the structure of category system and its effects on the categorization process. Recently, scholars have pointed out that the patterns of linkage among the categories determine the usage of categories and shape the audience perception on products bearing those category labels (e.g., Leung, 2014; Negro et al., 2011; Paoletta and Durand, 2016; Wry and Castor, 2017). They do not, however, differentiate various connection patterns that a category can have with other categories (local aggregation *versus* macro aggregation) and mostly focus on the overall relatedness that a category keeps with other categories of the classification system (e.g., Pontikes, 2012; Pontikes and Barnett, 2015; Wry and Castor, 2017). Without fine-grained analyses

of how a category's linkage with other categories is formed in different ways, existing studies fall short of explaining why categories are still chosen given their less lenient or high fuzzy identities. We address this puzzle by suggesting that a category's overall position in the category hierarchy is a "summation" of its local connection and that a category can significantly increase its chance of being chosen as long as it forms a strong "superordinate category" (i.e., category bundle) with other categories.

Second, we offer a novel interpretation of the paradox between the categorical imperative argument and the persistence of category spanners. Quite a number of studies have committed to resolving this conundrum (Alexy and George, 2013; Paolella and Durand, 2016; Wry et al., 2014; Zhao et al., 2013). They either claim that category spanning produces some unrecognized benefits (e.g., Hsu et al., 2006a; Tang and Wezel, 2015; Wry et al., 2014), or suggest that spanning behaviors are preserved with the concurrent implementation of special strategies that mitigate the negative effects of spanning (e.g., Zhao et al., 2013). We offer a different explanation. We suggest that category spanning might simply embody the bundle-based structures in new products. As long as a "superordinate" category, namely the category bundle, is needed to describe a product, it will appear in products regardless of underappreciated benefits or strategic manipulation of market participants. In this sense, category spanning becomes a self-organizing process that is beyond the control of agents.

This study certainly has its limitations. We argue that market participants unanimously apply the bundle-based logic in their reasoning of product categories, but little is known about relative power of producers, critics, and audiences in the utilization of bundle-based logic. One natural extension of our study is to consider who is the major proponent of bundle-based logic and their motivation to do so. In addition, the present paper regards category bundles as given and explores their effects in categorization without considering how they come into being in the first place. How does a category bundle emerge in the field? Is it based on the semantic similarities between categories or created to accomplish specific goals (Durand and Boulongne, 2017; Durand and Paoella, 2013)? Future research can use longitudinal data to investigate the institutionalization of category bundles in the classification system.

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## Appendix

This section provides an illustration of how we calculate the local aggregation of genres using a hypothetical example. To simplify our analysis, we assume that only ten films were released in the past five years. We consider the level of local aggregation among *Crime*, *Drama*, and *Thriller*. Table 3-6 presents the genre information of the films.

**Table 3-6:** An illustrative example

Film	Genres	$NumGenre_j^c$	$k$	$m$
Film 1	<i>Action-Crime-Thriller-Sci-Fi</i>	2	3	$10 - 3 = 7$
Film 2	<i>Adventure-Crime-Drama-Thriller</i>	3	3	$10 - 3 = 7$
Film 3	<i>Drama-History</i>	1	3	$10 - 3 = 7$
Film 4	<i>Animation-Family</i>	0	3	$10 - 3 = 7$
Film 5	<i>Drama-Documentary</i>	1	3	$10 - 3 = 7$
Film 6	<i>Biography-History</i>	0	3	$10 - 3 = 7$
Film 7	<i>Crime-Drama</i>	2	3	$10 - 3 = 7$
Film 8	<i>Comedy-Romance</i>	0	3	$10 - 3 = 7$
Film 9	<i>Drama</i>	1	3	$10 - 3 = 7$
Film 10	<i>Adventure-Drama-Sci-Fi-Thriller</i>	2	3	$10 - 3 = 7$

We use Formula (3) to calculate local aggregation. Because we are considering the local aggregation of three genres,  $k$  equals three; seven of the films include at least one genre of the bundle (*Crime-Drama-Thriller*) we are considering, hence  $m$  equals seven ( $10 - 3 = 7$ ). The number of genres that belong to the *Crime-Drama-Thriller* bundle in the seven films is listed in Table 3-6. We calculate the local aggregation using the following formula:

$$LocAgg_c = \frac{(2-1)+(3-1)+(1-1)+(1-1)+(2-1)+(1-1)+(2-1)}{7 \times (3-1)} \approx 0.357.$$

This suggests that the level of local aggregation of the hypothetical bundle, *Crime-Drama-Thriller*, is 0.357.

In other cases, when we calculate the level of local aggregation among *Adventure*, *Animation*, and *Documentary* using the information in Table 3-6, the level of local aggregation will be zero, since they never appear together in films. Similarly, if we consider the local aggregation between *Animation* and *Family*, the level of local aggregation will reach one, as they appear simultaneously in their only appearance in the market (Film 4).

## **4 The Persistent Specialist Advantage: Typecasting Dynamics in Feature Films**

### **4.1 Abstract**

Whether to be a specialist or generalist is a long-standing question for job candidates. The extant literature argues that the excess returns to labor market specialization exists, and the returns will decrease as job market candidates climb the career ladder. Should the aforementioned argument be valid, a job candidate with a long tenure will avoid being specialized. This argument, nevertheless, is contradictory to an observation in the feature film labor market that the ratio of specialists is stable among job candidates across different career stages. We argue that considering the effects of external audiences on hiring decisions can help reconcile the classic argument with the observation. Specifically, we argue that specialist advantage may sustain among the specialists whose skills and ability are highly matched with their image among audiences. We use rich longitudinal data from 1990 to 2015 on the careers of 21,914 actors and actresses in English-speaking films to test our hypotheses. We find that the moderating effects of actors' tenure on specialist advantage is contingent on their public among audiences. For actors whose skills and public image are highly matched, a long tenure will not decrease, but enlarge their specialist advantage. Our research contributes to the labor market identity research by presenting hiring decisions as dual-matching processes in which both the hiring firms and external audiences are involved.

Keywords: specialist, generalist, category, typecasting, audience perception.

## 4.2 Introduction

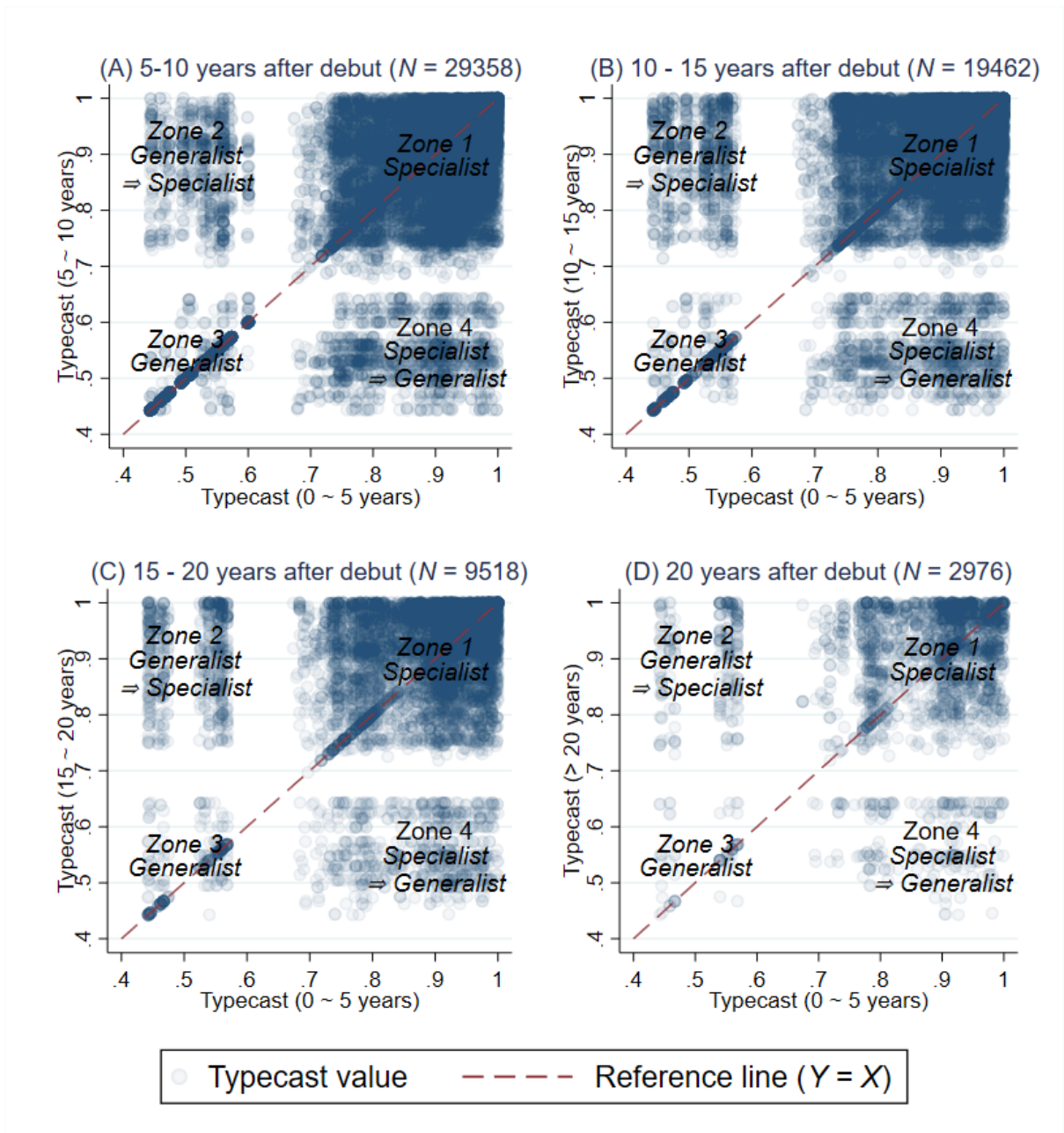
Choosing career patterns is an important decision for job seekers. There are considerable discussions on the effects of being a specialist versus a generalist on an individual's career prospect. Organization theorists advocate that establishing a specialized (focused) identity will benefit early-career candidates (Ferguson and Hasan, 2013; Zuckerman et al., 2003). First, because early-career candidates lack a proven track record, presenting himself or herself as an expert in a market category can signal his or her ability to perform jobs related to the specific job category. Second, for early-career candidates attempting to build a "robust identity" that can perform a variety of tasks, it is difficult for employers to differentiate such a candidate from a random person who is unattached to any one category (Leung, 2014; Zuckerman et al., 2003). As a result, focused job market candidates are more likely to be hired (Ferguson and Hasan, 2013; Zuckerman et al., 2003), especially in a labor market in which the skills and ability of candidates are difficult to discern and the hiring firm relies on categories attached to candidates to anticipate their potential (Zuckerman et al., 2003). The organizational perspective of specialist advantage has parallels with the matching theory proposed by labor economists (e.g., Becker, 1962) but the source of advantage: Economists believe that the specialist advantage comes from an individual's investments in human capital and the match between their human capital and the job; organization theorists not only accepts the human capital and matching based explanations, but also argues that the unique strength of

specialists in signaling their ability and potential in the market is the third source of specialist advantage (Ferguson and Hasan, 2013; Zuckerman et al., 2003).

Though specialization is beneficial for labor market candidates, recent research suggests that the rewards associated with specialization only hold under limited conditions. Specialist advantage will diminish when employers do not use market categories to navigate recruitment. For example, Merluzzi and Philips (2016) found that elite MBA graduates who have focused profiles receive fewer job offers in investment banking industry. The reason specialization is discounted for elite MBAs is that investment banks have strong screening mechanisms to evaluate the qualifications of candidates. As hiring firms can minimize the uncertainty about a candidate's commitment and potential via private screening processes, they are less reliant on the categorical information a candidate claims to make hiring decisions, which are the grounds for favoring focused candidates in previous studies (e.g., Ferguson and Hasan, 2013; Leung, 2014; Zuckerman et al., 2003). Another scope condition is the candidate's tenure (Zuckerman et al., 2003). For a job market candidate who claims talent in multiple categories, a challenging task is to convince the potential employers that he or she is a "Renaissance" person who is truly versatile rather than an erratic person who drifts around different jobs (Custódio, Ferreira, and Matos, 2013; Leung, 2014). As the tenure of the focal candidate increases, this becomes less an issue as employers can get access to his or her detailed career history to make hiring decisions (Ferguson and Hasan, 2013). In feature films, though actors and actresses specializing in a given category

enjoy more future employment opportunities, the positive effects of specialism are less salient for veteran actors/actresses (Zuckerman et al., 2003).

Following this logic, in a labor market in which hiring decisions are structured by market categories, rational job candidates will intentionally reduce their levels of specialization as their tenure increases. This is, nevertheless, not what we found in data. Figure 4-1 shows the career dynamics of actors and actresses who debuted in English-language films between 1990 and 2010. The four scatter plots respectively depict the relationships between an actor/actress' level of specialism in the first five years of their careers and his/her levels of specialism in fifth to tenth, tenth to fifteenth, fifteenth to twentieth, and after-20th years respectively. We use the typecast index, which measures the extent to which actors/actresses repeatedly play certain genres (Zuckerman et al. 2003), to operationalize specialism. If the specialist advantage recedes with the increase of individual tenure, veteran actors and actresses should gradually move out of the specialist zone (Zone 1) and into other zones. This idea is not supported: The proportion of typecast actors/actresses is stable across different stages of their careers, suggesting that specialist candidates maintain high levels of specialism even though the asserted specialist advantage should have long gone.



**Figure 4-1:** Typecasting (Specialization) of Actors and Actresses after Their Debuts

Inspired by the feature film case, this research asks, what enables the persistent specialism in a labor market and how does the underlying contingency



prevent the specialist gains from dissipating? To address this question, we turn to the external audience that was not theorized in previous hiring literature. In certain industries, external audiences control substantial material and symbolic resources that affect the success of a product (Hsu and Hannan, 2005). Because external audiences (i.e., consumers) grant or withhold legitimacy of products, their perception on the final product will inevitably affect organizations' practices (Bower, 2015a). Feature film labor market represents a typical industry in which the perception of audience is non-trivial in companies' hiring decisions, which is regarded as a purely capability- and match-based assessment in past studies (e.g., Becker, 1962; Ferguson and Hasan, 2013; Leung, 2014; Merluzzi and Philips, 2016). In show business (movie, drama, fashion, etc), artists (e.g., actor, performer, model, etc) are the most visible feature of a product. Moviegoers generally browse credits, anticipate the quality of a film, and make consumption decisions. A film with a strong cast, especially "stars" that are on the top of the profession, draw more attention from moviegoers and is more likely to achieve box-office success (Elberse, 2007). As a result, studios' hiring decisions move beyond an assessment of actors/actresses' skills and credentials and take into account the perceptive influence of actors/actresses. In such a case, specialist candidates may maintain additional advantage even after a long tenure if they are strongly regarded as specialists by external audiences. In contrast, generalist candidates could have built robust identities with credible experience in different

jobs, but they may not cash in on their versatile skills if they are not accredited for doing so by external audiences.

We investigate the effects of specialism and audience perception on career advancement of individuals using a dataset of 21,914 actors and actresses over 26 years (from 1990 to 2015). We find that typecast actors and actresses that are also well-recognized by moviegoers as specialists will obtain additional opportunities than those who only attest to their ability among hiring studios. In addition, though generalists, i.e. actors/actresses who claim “robust identities” by acting in different types of films, may signal their ability as well as specialists after their long tenure in the industry (Zuckerman et al., 2003), they are not be able to increase employment opportunities if their profiles are not aligned with moviegoers’ impressions. Taken together, consistent audience perception on a job market candidate, i.e., actors and actresses, constitutes a boundary condition of specialist advantage.

This paper makes two contributions to theory and practice. First, we contribute to the labor market identity research by presenting hiring decisions as a dual-matching process in which both hiring firms and external audiences are involved; that is, hiring firms not only evaluate whether or not candidates can work in the categories they claim, they must also anticipate whether the categorical claim of candidates is consonant with the perceptions of external audiences (Hsu, Hannan, and Koçak, 2009). Second, by presenting a boundary condition of persistent specialism, our results reconcile the contradictions between a

theoretical prediction that specialist advantage will ultimately fade away and the fact that specialism is common even among veteran candidates.

### **4.3 Specialism and hiring**

Management and organization researchers have long recorded the application of market categories in labor markets. Categories are socially constructed consensus on the partitioning of social space (Negro, Koçak, and Hsu, 2010). In labor markets, employers confront a primary question: How do they select a job market candidate whose skills and talent satisfy their needs? Market categories provide an interface between employers and job seekers and “ease comprehensibility for employers” (Leung, 2014: 138; Zuckerman et al., 2003). With market categories, the candidate pool is segmented into distinctive groups. Employers can thus focus on the group(s) they are interested in and decrease the search and hiring costs.

When a labor market is structured by categories, job market candidates have two major strategies: to be a generalist that spans multiple categories or a specialist that is only associated with a single category (Carroll and Swaminathan, 2000; Hannan and Freeman, 1977). Organization theorists generally recommend that becoming a specialist benefits early-career job seekers (Ferguson and Hasan, 2013; Romanelli, 1989; Zuckerman et al., 2003). First, staying in one type of jobs signals to employers that the focal job seeker is both committed to and capable of completing the tasks to which he or she is assigned (Ferguson and Hasan, 2013; Zuckerman et al., 2003). Second, though performing jobs in disparate areas may

suggest that the focal job seeker is multi-talented, such a job seeker may run the risk of being recognized as a jack-of-all-trades by employers (Leung, 2014; Zuckerman et al., 2003; Zuckerman, 2005). The competitive advantage of specialist vis-à-vis generalist is in tune with the accounts offered by resource-partitioning theory and the economics of human capital (Becker, 1962; Carroll, Dobrev, and Swaminathan, 2002; Rosen, 1962), which suggest that specialized organizations/individuals have either unique capabilities or unique strength in signaling their capabilities (Ferguson and Hasan, 2013).

Both organization theorists and economists presume that skills (or human capital), which job market candidates are eager to exhibit and employers carefully assess, are the cornerstone of hiring decisions. With that in mind, employers utilize market categories to gauge the skillset of the candidate corresponding to the position. Yet these accounts draw on non-trivial assumptions. First, current accounts assume that the market categories attached to a job seeker accurately reflect his/her skills and ability (Ferguson and Hasan, 2013). But as a socially constructed consensus between market actors (e.g., producers, audience, and market intermediaries), categories are subject to strategic manipulation of market actors (Pontikes and Kim, 2017; Vergne and Wry, 2014). In such a case, an individual's market categories are, at most, loosely-coupled with his/her actual skills and ability. Second and more importantly, current research assumes that hiring decisions are akin to a "matchmaking" between skill providers (i.e., job seekers) and skill users (i.e., employers) in which signals about skills are

transmitted, yet hiring often involves sociocognitive dimensions beyond skills. For example, during 1950s, artists in the US film industry who were associated with blacklisted communists in film projects were less likely to be hired later (Pontikes, Negro, and Rao, 2010). The tainted career prospects due to connections with stigmatized ideology hold even for high-status artists and artists who only had one exposure to blacklisted co-workers (Pontikes, Negro, and Rao, 2010). The reason artists were penalized is that their associations with rival ideology arouse moral panic and negative evaluations from the public (Pontikes, Negro, and Rao, 2010; Vergne, 2012). In turn, employers conform to social expectation and put aside skill-based considerations.

We argue that in certain markets, the hiring decisions not only hinge on skill-based matchings between job seekers and positions posted by employers, but also rest with external audience who will be exposed to the offerings from hiring companies. With respect to the specialist-generalist debate, job seekers are evaluated on whether or not the skills in their toolkits support their claimed identities, as well as whether they are perceived as specialists or generalists among external audience. The more influential the external audience in the market, the more likely the specialist-generalist trade-off deviates from the skill-based analytical framework and should take into consideration the audience perception. We offer conditions under which audience perception affects the specialist-generalist trade-off in hiring and propose testable arguments in next section.

#### **4.3.1 Audience perception and specialism**

The tenet that audience perception is critical to the orderly functioning of markets is well documented in organization theory literature (Bower, 2015b). Violations of audience perception, such as straddling of incongruent categories and inconsistent status cues (Zhao and Zhou, 2011; Zuckerman, 1999), will confuse audiences and affect the rewards organizations obtain from markets (Hsu et al., 2009; Leung and Sharkey, 2014). Audience perception is particularly essential in industries in which consumers “pay for their own experiences” (Pine and Gilmore, 1998: p. 101). For example, in premium wine market, audiences consume an image, a sincere brand story, or a culture (Beverland, 2005; Zhao and Zhou, 2011), when they enjoy expensive wines. For wineries failing to deliver consistent high-status cues of their products, consumers are less willing to pay high prices (Zhao and Zhou, 2011). On eBay’s engagement ring market, diamond solitaire rings that violate audience expectation (e.g., from a failed relationship) have lower sales prices than rings that fit audience expectation (e.g., from a happy marriage), even if their physical attributes such as stone, shape, and design are exactly the same (Bower, 2015a). Audience perception is less associated with rational calculations of the physical features that a product possesses. It is more about the unique value audiences capture when consuming the product.

When the underlying expectation of audience has a marked impact on the market success of a product, the basic principle is that firms endeavor to make their practices consonant with audience perception. Hiring decisions are among the practices that are to be fined-tuned when they decide the overall perception

audiences gain from the product (Kuppuswamy and Younkin, 2019). Feature film industry is a typical setting in which the hiring of film crew directly constitutes the experience of moviegoers (e.g., Kuppuswamy and Younkin, 2019; Pontikes, Negro, and Rao, 2010). First, moviegoers decide whether to see a film (Liu, Liu, and Mazumdar, 2014), yet their decisions are highly related with the composition of film crew members (Elberse, 2007). Films with reputable actors and actresses tend to have higher office revenues (Elberse, 2007; Liu, Mazumdar, and Li, 2015). Second, moviegoers are subject to cognitive bias and social stereotypes when making sense of the film crew. While studios discern the skills and ability of an actor by comprehensively dissecting the genres the focal actor played before, moviegoers tend to interpret the actor using their own cognitive maps (Bowers, 2015b; Hsu, 2006). For example, moviegoers may only recall the most representative work the focal actor played in; sometimes they mix up the character that left them a deep impression with the actor who played the character. Sylvester Stallone is often cited as an action figure by moviegoers, even though he attempted to shake off his stereotype in several comedies and dramas (Huffer, 2003; Zuckerman et al., 2003). The cognitive bias of moviegoers is particularly pronounced for actors/actresses in movie franchises. William Shatner became a cultural icon for his characterization of Captain Kirk in the Star Trek series, yet his casting in other works is often neglected. Since the last Harry Potter film in 2011 (Harry Potter and the Deathly Hallows – Part 2), Daniel Radcliffe has actively

played roles that are vastly different from the schoolboy wizard to distance himself from his past records. A journalist summarized Radcliffe's effort in an interview:

*"... he has done everything he possibly could to distinguish himself from Harry: riding a horse naked and aroused on stage in Peter Shaffer's Equus, limping around stage as Billy Claven in The Cripple Of Inishmaan, haunted by ghosts in the horror movie The Woman In Black. Now he's at it again, with another part from which Harry Potter would run a mile: in Kill Your Darlings, he plays gay beat poet Allen Ginsberg, sexually infatuated with the dangerous Lucien Carr." (Hattenstone, 2013)*

The effort of Daniel Radcliffe in the "post-Potter" era is an example of how persistent moviegoers' perception on an actor/actress can be and how difficult it is to change an established perception. Moviegoers are often not interested in the performances of a star in genres beyond his or her primary area (i.e., the genre for which he/she becomes famous), even if the focal actor/actress can act in those genres as good as in his/her home "turf" (Huffer, 2003). An audience member stated his preference in a survey of the relationship between stars and fandom:

*"If you want to watch a comedy you don't watch an action star trying to deliver it, you want a comedian. Would Jim Carey [sic] try to play Rambo? No, so why does Stallone try comedy?" (Huffer, 2003)*

In fact, even though actors/actresses want to break out of their stereotyped image among audience, studios often take advantage of such a cognitive bias by crafting hiring that (studios believe) caters to audience perception (Kuppuswamy and Younkin, 2019; Zuckerman et al., 2003). The strategic consideration of studios drives the structural reproduction of specialism (i.e., typecasting) in feature film industry. Once an actor/actress is known to moviegoers, the sustained perception on the focal actor/actress' on-screen image will shape studios' hiring decisions,



making the focal actor/actress more likely to be picked in future for his/her established image than for his/her unknown talent.

The above arguments lead to the core idea of this paper: Specialist advantage in hiring is not purely driven by skills (i.e., specialists have better skills and ability) and skill-based signalling (i.e., specialists have advantages in signalling skills than generalists). In contexts in which hiring decisions directly affect audience experiences, the specialist advantage of a job market candidate is contingent on how audience perceive the focal candidate. In feature films, the advantage of a specialist will be more prevalent if the market category (i.e., genre) in which the focal actor/actress is skilled is consistent with his/her image among moviegoers. Conversely, the advantage of a specialist will be weakened if the market category for which the focal actor/actress is hired is incongruent with the way moviegoers feel about the focal actor/actress. This suggests the following hypothesis:

*Hypothesis 1: The positive effects of specialism on job market candidates' work opportunities will be stronger for a candidate who is also accepted by audiences as a specialist in the area for which he/she is hired.*

#### **4.3.2 Tenure as a boundary condition of specialist advantage**

In addition to the perceptive factor we propose above, previous research has studied the boundary conditions that moderate the advantage of specialists in the job market. First, specialist advantage looms large in markets without strong qualification systems that systematically evaluate the credentials of job seekers (Zuckerman et al., 2003). Feature film labor market is a classic case of no

prerequisites for job seekers . In such a context, employers refer to the market categories (i.e., genres) the focal job seeker was in to have a reasonable “guess” of what the focal job seeker can do. In markets with strong qualification systems, which category the job seeker was in becomes less important. Merluzzi and Phillips’ (2016) description of elite MBAs in investment banking is a typical example: Because investment banks have strong screening mechanisms to assess the quality of job seekers, specialist MBAs (who only worked in investment banking before) do not enjoy any premiums over generalist MBAs (who worked in multiple departments).

Second, given that professional qualification systems are not available, tenure becomes a feasible approach to eliminate the differences between specialists and generalists (Zuckerman et al., 2003). The problem for generalists is that they cannot clearly signal their ability (Ferguson, 2013). Specifically, multi-talented job seekers are indistinguishable from jack-of-all-trades candidates in terms of the breadth of market categories they are attached to. Because diverse skills can hardly be obtained in a short period of time, tenure provides additional information that helps employers demarcate generalist job seekers. The longer tenure a job seeker has, the more likely the focal job seeker is truly a multi-talented person. The disadvantage of generalists should thus be diluted for veteran job seekers. This logic leads to Zuckerman et al.’s (2003) boundary condition:

*Zuckerman et al.’s (2003) moderating effects: The positive effects of specialism will be weaker (stronger) among veteran (novice) candidates.*

### **4.3.3 Three-way interaction of specialism, tenure, and audience perception**

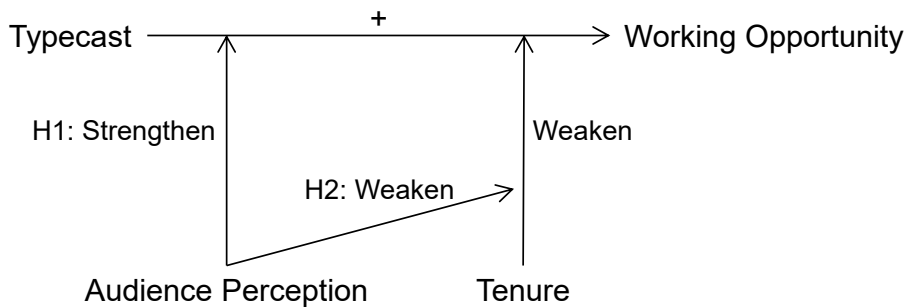
The logic above presumes that hiring practices of organizations are independent of the perception of external stakeholders. Yet in contexts in which external stakeholders are influential in new product success, additional strands of theory can offer an extension of the tenure hypothesis. A long tenure not only erases the gap between generalists and specialists in signaling their skills (Ferguson and Hasan, 2013; Zuckerman et al., 2003), but makes the focal actor/actress more likely to be recognized by moviegoers. Since moviegoers use casts to navigate consumption decisions (Liu, Liu, and Mazumdar, 2014), and studios capitalize on this in cast selection (Liu, Mazumdar, Li, 2015; Kuppuswamy and Younkin, 2019; Zuckerman et al., 2003), it is meaningful to discuss how veterans confront varied hiring opportunities due to their disparate image among moviegoers.

To begin with, an actor/actress' skills and ability are not always coupled with their on-screen image among audiences. This decoupling is common for veterans. It is often the case that veterans have accumulated multiple acting skills throughout their careers, but moviegoers only recognize part of the works that they are exposed to or interested in (Bowers, 2015b; Hsu, 2006). In other words, moviegoers tend to assume that “old dogs cannot learn new tricks” (Zuckerman et al., 2003). For generalist veterans who are competent for multiple roles, incongruent audience perception—that they are regarded as specialists of certain genres—sends a dangerous signal, making them less likely to be picked.

For specialist veterans, as they persistently compete for hiring opportunities in certain areas, it is less likely that audiences form incongruent perception on them. Furthermore, congruent audience perception—that the actors/actresses are accepted as specialists by both internal stakeholders (i.e., employers) and external stakeholders (i.e., moviegoers)—offers additional advantage for specialists, making them more likely to be picked. These arguments suggest the following hypothesis:

*Hypothesis 2: Audience perception masks the relationship among specialism, tenure, and future work opportunities, such that the weakening effects of tenure on the specialism-hiring relationship reduce (enhance) for a candidate who is (not) accepted by audiences as a specialist in the area for which he/she is hired.*

Figure 4-2 displays the theoretical framework of this paper.



**Figure 4-2:** Theoretical framework

## 4.4 Data and Method

We test our hypotheses using data on casting records of actors and actresses in English-speaking films from 1990 till 2015. The data on casting records come from the Internet Movie Database (IMDb). IMDb is the largest online movie

database with records of more than 40 million actors and actresses and 516,726 feature films as of May 2019. Feature film labor market represents a suitable context for the following reasons. First, the feature film industry is structured by genres, a mature, widely-accepted category system used by studios, film critics, and moviegoers for decades. For actors and actresses, the acting skills required for various genres are often divergent, rendering the genre record of an actor/actress a legitimate proxy of their specialities (Zuckerman, 2005). Second, without strong screening mechanisms in the feature film labor market, studios take full advantage of the candidate information they can possibly collect (casting records, tenure, etc) to discern the skills of an actor/actress (Zuckerman et al., 2003). The latter distinguishes the feature film industry from other contexts such as investment banking and government organizations (Ferguson and Hasan, 2013; Merluzzi and Phillips, 2016), where employers have multiple mature, institutionalized approaches in hiring (qualifications, several rounds of interviews, etc). Lastly, detailed, transparent career records of actors and actresses are available in the North American feature film industry, making longitudinal analysis of the effects of a person's specialism on his/her career prospects possible for job seekers.

We examine the implications of an actor/actress' level of specialism in film genres on his/her likelihood of getting work opportunities. Our dataset includes actors and actresses who made their debuts in English-speaking films during this period. We choose this period because IMDb tends to have complete information on recent films and active workers. Uncredited actors/actresses are dropped. Since

we focus on the feature film labor market, short films are also excluded. We set 1990-01-01 as the starting date of our “social experiment”, we then observe actors/actresses who entered the industry and calculate their specialist indices once they have stayed in the industry for five years (1826 days since the debut date). The reason we do not consider work histories in the early stage is that we use specialist index as a skill-based measurement (see Measures section for details). For rookies, they often cannot obtain sufficient working opportunities in the very early stage, and even if they do, they are not fortunate enough to be able to pick the job offer they like. In this case, they simply accept the first offer they can to gain a foothold in the industry (Zuckerman et al., 2003). Since the early specialist index cannot accurately reflect the skills and ability of rookie actors/actresses, we only consider actors/actresses who have at least five years of working experiences in the industry. Nevertheless, we include early specialist index in regressions to control the imprinting effects of early experience on individuals’ career advancement.

We keep recording the career path of an actor/actress unless he/she is reported deceased. In this case, the films that are released after their death will be dropped, as it is meaningless to discuss the career development of a dead person. We also drop the actor/actress after ten years of his/her last work, as a ten year leave usually suggests that the focal person has left the business. If neither of conditions occur, we monitor the careers of actors/actresses until 2015-12-31, the censoring time of our research. Our final sample includes the working records of

21,914 actors and actresses from 1995 to 2015, creating 176,324 individual-year pairs in our regressions

#### **4.4.1 Measures**

##### *4.4.1.1 Dependent variable*

In the feature film labor market where jobs are organized through short-term film projects, getting a steady job is the primary measure of an actor/actress' career success. The dependent variable is the likelihood actor  $i$  gets job contracts in year  $t$ . An actor/actress that does not get any contract in year  $t$  will be coded as zero and receives at least one contract will be coded as one. Because the actual date when an actor/actress signs an offer is often unavailable for outsiders, we use the release date of a film in which he/she works to approximate the time when he/she obtains an opportunity.

##### *4.4.1.2 Specialism*

Following Zuckerman et al. (2003), we adopt a simulation-based measurement of an actor/actress' index of specialism. This measurement has its unique strength in separating the specialization of actors created by ability-based reasons from the specialization purely driven by chance. As a set-up, we consider eighteen most common genres in this paper. These genres are *Action, Adventure, Animation, Biography, Crime, Comedy, Documentary, Drama, Family, Fantasy, History, Horror, Musical, Mystery, Romance, Sci-Fi, Sport, Thriller, War, and Western*. For each film  $f$ , we create a vector of eighteen dummy variables ( $g^{act}$ ,  $g^{adv}$ , ...,  $g^{wes}$ ), where one represents that genre  $g$  is assigned to film  $f$  and zero means not

assigned. We repeat the procedure for all films in our dataset. After that we start to calculate the simulation-based specialist index.

For any actor  $i$  in year  $t$ , we first register, in the past five years  $[t - 5, t - 1]$ , the total number of films ( $N$ )  $i$  acted and the numbers  $i$  acted in the eighteen genres ( $N_g^{act}, N_g^{adv}, \dots, N_g^{wes}$ ). Note that the sum of ( $N_g^{act}, N_g^{adv}, \dots, N_g^{wes}$ ) is usually larger than  $N$  because a film, in most cases, is assigned multiple genre labels. The ratio of films that  $i$  acted in genre  $g$  can thus be represented by ( $N_g^{act}/N, N_g^{adv}/N, \dots, N_g^{wes}/N$ ).

We next list a table of all actors/actresses who worked in the past five years and the films they worked in. An actor/actress that worked in  $N$  films will have  $N$  rows in this table, and each row represents a realized actor-film pair. We then conduct 200 random permutations of films in the table. For each permutation we assign actors with randomly matched films, and the permutations will generate 200 new tables. Random simulation can control the probability that the observed records of actor in different genres are merely caused by random chance (Zuckerman et al., 2003). After we complete the permutations, we count the number of permutations ( $P_g$ ) in which actor  $i$  has worked in genre  $g$  as often as observed in the real world (which means the ratio of  $i$  in genre  $g$  in the randomly-paired sample is equal to or more than the ratio in the realized sample). Because we consider eighteen genres in this paper, we get eighteen numbers for each actor  $i$  ( $P_g^{act}, P_g^{adv}, \dots, P_g^{wes}$ ). We repeat this procedure until the numbers for all actors in year  $t$  are calculated.



In step three, we take means over all actors who have the same number and ratio of films in a particular genre. This procedure is used to eliminate the random noise that creates variation among actors with exactly the same level of participation in a particular genre (Zuckerman et al., 2003: 1054). Arithmetically, we take the means of  $P_g^{act}$  over all actors who have the proportion of action films ( $N_g^{act}/N$ ) in the past. We do the same for the remaining genres. For each actor we will get eighteen numbers. We use a vector,  $(S_g^{act}, S_g^{adv}, \dots, S_g^{wes})$ , to denote the results.

In step four, we normalize the index. We subtract the vector by 200, the number of random permutations we did, and then divide it by 200. By normalizing we control the range of the index, where zero represents a low level of specialization in the particular genre and one represents a high level of specialization in that genre.

Lastly, we calculate the overall level of specialism of an actor. With the assumption that an actor's specialization can be represented by the genre that he/she achieves the highest level of specialism, we measure the highest specialization index he/she has:

$$Specialism_{it} = \max\left(\frac{200 - S_g^{act}}{200}, \frac{200 - S_g^{adv}}{200}, \dots, \frac{200 - S_g^{wes}}{200}\right),$$

where an actor with a value of zero will be regarded as a complete generalist and a value of one suggests a complete specialist.

Note the calculation of specialist index is based on an actor/actress' history in the recent five years. In rare cases, actors/actresses may temporarily leave the

industry and resume their careers afterwards. If the gap periods are longer than five years, we will have null values in the specialist indices in the year they come back to the business. Nevertheless, it is reasonable to assume that studios still regard such actors/actresses as insiders who have accumulated some experiences rather than a rookie without any specializations. We hence fill these null indices with the last available observations they had. Our results, though, are largely the same whether or not we make this imputation.

#### 4.4.1.3 Moderators

*Tenure.* We measure the tenure of an actor/actress by counting the number of films the focal actor/actress got credited, regardless of the order, throughout his/her career.

*Specialist perception.* Our goal is to test whether audience perception masks the relationships between specialism, tenure, and hiring opportunities. To do this, we create an index of the audience perception regarding the specialization of an actor based on his/her past performance and on-screen image. We consider four sub-indices in measuring audience perception: (1) the number of films an actor/actress worked in his/her specialized genre as a protagonist (i.e., the first four credits) in the past five years (*SpecialistNum<sub>i</sub>*); (2) the sum of domestic box office of films he/she worked in his/her specialized genre as a protagonist in the past five years (*SpecialistBox<sub>i</sub>*); (3) among all films an actor/actress led, the proportion of films that were assigned the genre he/she specializes in (*SpecialistNumRatio<sub>i</sub>*); and (4) within the overall box office he/she contributed to,

the proportion of box office that came from the films to which his/her specialized genre is assigned (*SpecialistBoxRatio<sub>i</sub>*). The first two sub-indices capture how well an actor/actress is treated as specialists among moviegoers, and the last two measure if he/she is perceived as a person who can only do one type of jobs. As we believe that an actor/actress that has strong specialist image among perception tends to share high value across the four sub-indices, we take the principal component analysis to find the factor(s) that can proximate specialist perception among audiences. A lot of actors/actresses do not receive jobs in feature film projects; this means they will have zero as denominators in ratio indices. We give these cases a value of zero so as to ensure sample size. The principal component analysis suggests that the first factor is the only component that has an eigenvalue of larger than one, and it alone explained 75.86% of the total variance. We thus use the first factor as a proxy of specialist perception. By using principal component analysis rather than four raw sub-indices, we also alleviate measurement error that may decrease the power of the regression. The equation below explains how specialist perception is composited:

$$SpecialistPerception_{it} = 0.53 \times SpecialistNum_i + 0.37 \times SpecialistBox_i + 0.55 \times SpecialistNumRatio_i + 0.53 \times SpecialistBoxRatio_i.$$

#### 4.4.1.4 Control variables

We control for multiple individual-level variables to reassure that there are no underlying factors confounding the effects of audience perception on the specialism-hiring relationship. First, we control the specialism index of an

actor/actress in the first five years to control the imprinting effects of early work experience on his/her future career dynamics. To reduce the possibility of multicollinearity from including both early-stage and current specialism indices in the same regression, we regress early-stage specialist index on current index and use the residual value of early-stage specialist index in the model.

Second, there are theories arguing that the actor/actress' social network plays an important role in their career development (Rossman, Esparza, and Bonacich, 2010; Zuckerman et al., 2003). Particularly, researchers argue that works might be shared within cliques so that an actor/actress who is an insider of a group would be more likely to get working opportunities (Zuckerman et al., 2003). We control the *concentration of an actor/actress with particular directors* in this paper. The calculation is similar to the specialism variable. We first calculate, in the past five years, the concentration score of an actor  $i$  with directors using a Herfindahl index in year  $t$ . We then list in a table all actors and the directors they worked with in the past five years and do 200 random permutations. For each permutation we calculate the concentration score of actor  $i$  across directors, and we get 200 hypothetical concentration scores in the end. We count the number of times in which the hypothetical concentration score is as high as we observed in the realized sample. This procedure is to exclude the probability that the observed concentration of actor-director pairs is purely driven by random pairing (Zuckerman et al., 2003). Finally, we subtract the number by 200 and then divide it by 200 to normalize this variable. The concentration variable ranges from zero

to one, where zero means the focal actor/actress has a highly diversified network and one suggests a highly concentrated network. The clique theory of hiring predicts that the concentration of an actor across directors is positively related to the likelihood that he/she gets hired.

Third, we control for demographic factors that may shape their career prospects. We include the *gender* and *age* of the actor that are known to be important in Hollywood (De Pater, Judge, and Scott, 2014). We coded age when an actor/actress receives a job or when he/she is censored in the data. Gender is coded as one for male and zero otherwise. We also control *star power*, an important factor driving film success (Elberse, 2007; Liu, Mazumdar, and Li, 2105), in this paper. Star power is measured as the accumulated box office of an actor/actress in which they played the leading roles in the past five years. We add the raw value by one and then take log to ensure the normality of this variable.

Lastly, we control for *genre fixed-effects* to account for unobserved genre-level heterogeneity that may shift the career path of an actor/actress. We include eighteen dummies in the regression. Each dummy takes the value of one if the focal actor/actress specializes in this genre and takes the value of zero otherwise.

#### **4.4.2 Analytical strategy**

Following previous career dynamics research (Leung, 2014; Pontikes, Negro, and Rao, 2010; Zuckerman et al., 2003), we tested the effects of audience perception on winning a job in a given year utilizing a logit model. The models have the following terms:

$$\ln\left(\frac{P_{it}}{1-P_{it}}\right) = f(\textit{Specialism}_{it}, \textit{Perception}_{it}, \textit{Specialism}_{it} \times \textit{Perception}_{it}, \mathbf{X}_{it}), (1)$$

$$\ln\left(\frac{P_{it}}{1-P_{it}}\right) = f(\textit{Specialism}_{it}, \textit{Tenure}_{it}, \textit{Specialism}_{it} \times \textit{Tenure}_{it}, \mathbf{X}_{it}), \text{and} (2)$$

$$\ln\left(\frac{P_{it}}{1-P_{it}}\right) = f(\textit{Specialism}_{it}, \textit{Perception}_{it}, \textit{Tenure}_{it}, \textit{Specialism}_{it} \times \textit{Perception}_{it}, \textit{Specialism}_{it} \times \textit{Tenure}_{it}, \textit{Perception}_{it} \times \textit{Tenure}_{it}, \textit{Specialism}_{it} \times \textit{Perception}_{it} \times \textit{Tenure}_{it}, \mathbf{X}_{it}). (3)$$

$\mathbf{X}$  is a vector of control variables. We expect the interaction between *Specialism* and *Perception* to be positive in Equation 1 and the interaction between *Specialism* and *Tenure* to be negative in Equation 2. In addition, the three-way interaction of *Specialism*, *Perception*, and *Tenure* should be significant in Equation 3. We will also draw a three-dimensional plot to interpret the moderated moderating relationship based on the estimate of Equation 3.

## 4.5 Results

Table 4-1 presents the summary statistics and correlations for the variables for the data. Note the statistics are based on raw value. The largest correlation is 0.67 (between early-stage and current typecast indices). This is not an issue as we use the orthogonalized variable in the model. In addition, multicollinearity does not violate any assumptions of logit regression and only affects the standard errors of variables that have high correlations. With a large sample size (more than 170,000 observations), the concern that the power of estimation is compromised should be alleviated.

**Table 4-1: Summary statistics and correlations**

	1	2	3	4	5	6	7	8	9
N	770713	745718	196532	743622	770713	770713	770713	744878	770713
Mean	0.37	\$1,487,635	40.08	0.03	0.79	0.80	1.98	0.00	0.07
S.D.	0.48	\$21,100,000	13.01	0.16	0.16	0.16	2.45	1.74	0.25
Min	0	0	5	0	0.44	0.44	1	-0.25	0
Max	1	\$1,790,000,000	115	1	1	1	52	53.60	1
1. Gender (Actress = 0; Actor = 1)									
2. Star Power (US dollars)	0.01***								
3. Age (Years)	-0.13***	-0.05***							
4. Actor's concentration of directors	-0.03***	0.23***	-0.01***						
5. Specialism at time <i>t</i>	-0.05***	0.12***	-0.00	0.19***					
6. Specialism in the first 5 years	-0.04***	0.08***	-0.02***	0.12***	0.67***				
7. Tenure (number of works done)	-0.01***	0.36***	0.04***	0.25***	0.26***	0.24***			
8. Specialist Perception	0.02***	0.63***	-0.08***	0.24***	0.19***	0.12***	0.49***		
9. Hired or not (0/1)	-0.02***	0.19***	-0.03***	0.13***	0.14***	0.10***	0.38***	0.26***	

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 4-2 shows the estimates from logit models for the likelihood that an actor/actress is hired in a certain year of his/her career. Model 1 is the baseline model with the independent variable and controls. As shown, the coefficient of specialism is positive and significant ( $p < 0.001$ ), indicating that high level of specialization will increase the working opportunities of actors/actresses. Model 2 adds the interaction term to examine the strengthening effects of audience perception on the relationship between specialism and hiring. The parameter of the interaction term of specialism and specialist perception is positive ( $p < 0.001$ ), suggesting that actors who have specialized skillsets are more likely to be hired if they have built a specialist image among moviegoers. We also use Akaike's information criterion (AIC) to compare the fit between models. Compared to the Model 1, Model 2 includes audience perception and its interaction with specialism and yields smaller values of AIC. Hypothesis 1 is thus supported.



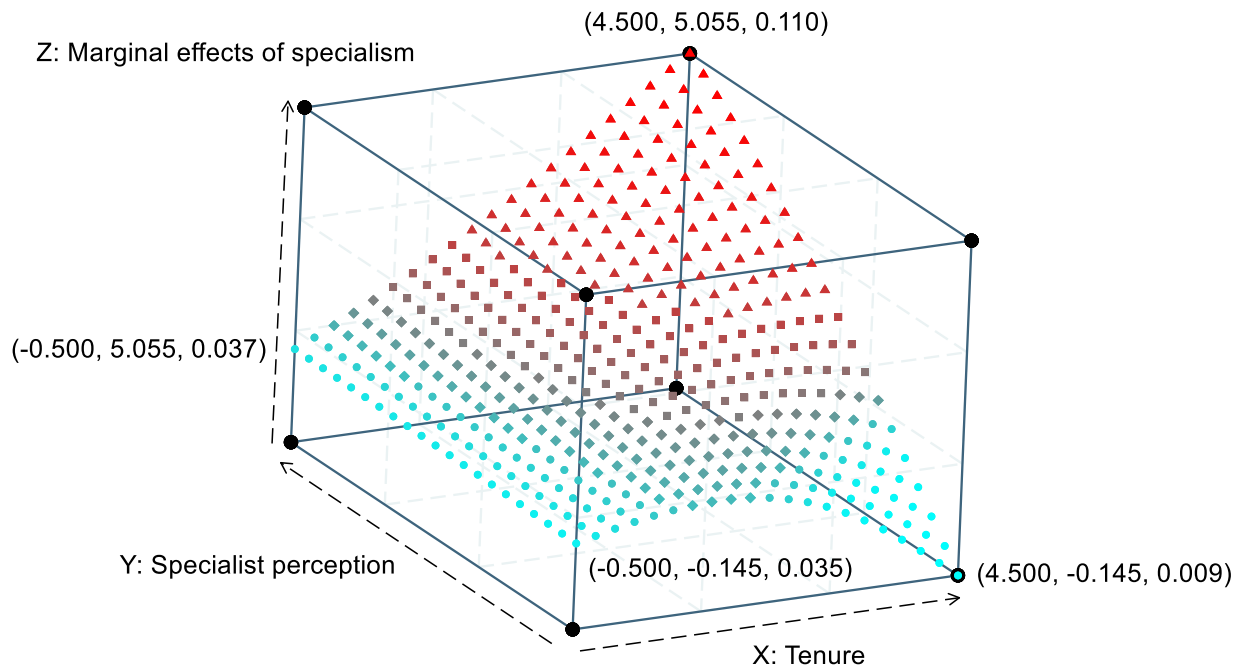
**Table 4-2:** Logit model of hiring opportunities

DV: Hired in year $t$ or not	(1)	(2)	(3)	(4)
<i>Independent variables</i>				
Specialism (standardized)	0.76*** (0.02)	0.81*** (0.02)	0.39*** (0.02)	0.38*** (0.02)
Specialist Perception (standardized)		-0.12*** (0.01)		0.05*** (0.01)
H1: Specialism × Specialist Perception		0.04*** (0.01)		-0.00 (0.01)
Tenure (standardized)			0.44*** (0.01)	0.48*** (0.01)
Zuckerman: Specialism × Tenure			-0.10*** (0.01)	-0.07*** (0.01)
Tenure × Specialist Perception				-0.05*** (0.00)
H2: Specialism × Tenure × Specialist Perception				0.02*** (0.00)
<i>Control variables</i>				
Gender (Actor = 1; Actress = 0)	-0.12*** (0.02)	-0.12*** (0.02)	-0.12*** (0.02)	-0.12*** (0.02)
Star Power (log)	0.09*** (0.00)	0.12*** (0.00)	0.05*** (0.00)	0.05*** (0.00)
Actor's concentration of directors	0.23*** (0.04)	0.22*** (0.04)	0.12*** (0.04)	0.11** (0.03)
Specialism in the first 5 years	0.54*** (0.10)	0.57*** (0.10)	-0.39*** (0.09)	-0.37*** (0.09)
Age	0.00 (0.00)	-0.00 (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
Typecast genre dummies	Yes	Yes	Yes	Yes
Constant	-2.66*** (0.08)	-2.78*** (0.08)	-2.22*** (0.06)	-2.26*** (0.06)
$N$	176324	176324	176324	176324
Pseudo $R^2$	0.105	0.107	0.146	0.150
Log likelihood	-6.9e+04	-6.9e+04	-6.6e+04	-6.5e+04
AIC	1.4e+05	1.4e+05	1.3e+05	1.3e+05

Clustered standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

In Model 3, we examine the weakening effects of tenure on the positive relationship between specialism and hiring. Consistent with Zuckerman et al. (2003), when we assume that the hiring of a job candidate is unrelated with audience perception, the advantage of specialists in receiving job decreases for job market candidates with long tenure ( $p < 0.001$ ). This is to say, hiring is a purely skill- and signal-based process between employers and job candidates, and veteran specialists will lose their advantage in obtaining job offers relative to veteran generalists. This finding, nevertheless, does not address the phenomenon of persistent specialism we illustrate in Figure 4-1. We argue that audience perception, as an underlying factor, complicates the skill- and signal-based mechanisms expounded in Zuckerman et al. (2003) and Ferguson and Hasan (2013). We test our hypothesis in Model 4. In Model 4, we interact specialism with audience perception and tenure and create a three-way interaction term. the coefficient estimate of the interaction term is positive and statistically significant ( $p < 0.001$ ), indicating that audience perception does moderate the weakening effects of tenure on the relationship between specialism and hiring opportunities. To further illustrate the direction and effect sizes of three-way interaction, we visualize their relationships with a three-dimensional plot in Figure 4-3.



**Figure 4-3:** Average marginal effects of specialism on the likelihood of hiring based on Model 4

Figure 4-3 uses the parameters from Model 4 of Table 4-2. X-axis is the tenure of an actor, ranging from its 1% quantile to 99% quantile. We curtail the range by one percent at both ends to ensure the results are not driven by extreme values. Y-axis is the specialist perception of the focal actor among audiences ranging from its 1% quantile to 99% quantile. Z-axis denotes the corresponding average marginal effects of specialism on the probability that an actor is hired when X- and Y-axis are set to different values. The reason for drawing Figure 4-3 is two-fold: First, a three-dimensional plot can better reveal the varied moderating effects of tenure on the specialism-hiring relationship at different levels of

specialist perception. Second, we would like to provide readers with intuitive information on the effect sizes of our findings. With an extremely large sample (> 100,000 in our case), the *p*-values of regression coefficients go quickly to zero (Lin, Lucas Jr., and Shmueli, 2013), making almost all variables significant. To ensure we are not producing statistically significant but practically meaningless results, we review our findings in Figure 4-3 and present the analysis below.

Regarding the moderating effects of audience perception and tenure, two findings are worth discussing here. First, Figure 4-3 shows that audience perception does strengthen the positive relationship between specialism and hiring probability: the marginal effects of specialism become larger along with the increase of the extent to which the focal actor/actress is perceived as a specialist. The strengthening relationship holds regardless of the tenure of job seekers. This result lends further support for Hypothesis 1. Second, the weakening effects of tenure on the specialism-hiring relationship only hold under limited conditions. The increase of tenure does decrease the advantage of specialists vis-à-vis generalists for actors who are not perceived as specialists by audiences (see the front side of the figure). But this relationship is overturned for actors who successfully leave a strong specialist image among audiences. Hypothesis 2 is supported. Accordingly, our results suggest that Zuckerman's (2003) tenure hypothesis are more applicable in settings in which external audience takes no account in the hiring practices.

The effects of specialist perception are also large enough to yield practical impacts. When specialist perception is at its 99% quantile, a one unit increase in tenure (standardized) will averagely *increase* the average marginal effects of specialism (standardized) on hiring by 0.015. When the perception variable is at its 1% percentile, a one unit increase in tenure (standardized) will averagely *decrease* the average marginal effects of specialism (standardized) by 0.005.

Our models yield interesting results for control variables. Gender is negatively related with hiring probability, suggesting that actors are less likely than actresses to receive job offers. This result is incompatible with the findings of gender discrimination literature and deserves further inquiries (Lincoln and Allen, 2004). Consistent with film literature (e.g., Liu, Mazumdar, Li, 2015), star power increases the probability that an actor/actress is hired. In addition, an actor's concentration of directors significantly increases the chance that he/she receives an offer. This finding supports the idea that a centralized social network (i.e., strong connections with a small proportion of directors) will help actors/actresses obtain future work opportunities (Rossman, Esparza, and Bonacich, 2010; Zuckerman et al., 2003). Lastly, as we predicted, the specialist index of an actor/actress in their start-up stage does not clearly reflect their skills and ability. This idea explains the undecided relationship between the early specialist index and hiring probabilities.

#### **4.5.1 Excluding alternative explanations**

We found support for our argument that audience perception on the job candidates not only directly strengthens the specialization-hiring link, but also moderates the weakening effects of tenure on that link. Still, other explanations that lead to the same results exist. For example, one might argue that actors/actresses who are regarded as specialists may have better talent than generalists. If this is the case, it could be their talent, rather than the fit between skills and audience perception, that enhances actors' hiring probability. We used two approaches to address this concern: firstly, we controlled star power in the main regressions. Star power denotes the box office an actor/actress created in the past five years and can be used as a proxy of his/her talent. Secondly, in case that star power does not accurately reflect a job candidate's skills and talent, we tested the relationship between a job seeker's specialism-related variables (specialist index and specialist perception) and the quality of films they worked in. If specialist actors tend to have superior talent, then the films they worked in should have higher quality as a result. On the left side of the equation, we considered three film-level quality indicators: the likelihood of being nominated the Academy Award, the likelihood of receiving the Academy Award, and IMDb rating. On the right-hand side, we controlled the same vector of individual-level factors as we did in the main regressions. The results are in Table 4-3. Conflicting with the superior-talent argument, an actor/actress with specialized skills are more likely to appear in low-quality films. For perception variable, an actor/actress that is perceived as a specialist may be more likely to appear in Oscar-nominee films ( $p < 0.05$ ), but

the positive effects disappear in predicting Academy Awards and IMDb ratings. Since we do not find consistent patterns between an actor/actress' specialist variables and the quality of films they work in, we argue that the fit between the skillsets of job seekers and audience perception is the main driver of persistent specialist advantage in the feature film labor market.

**Table 4-3:** Specialized artists and the quality of their works

Dependent variable	(1) Logit Academy Award nominee	(2) Logit Academy Award	(3) OLS IMDb rating
Specialism	-1.27* (0.60)	-0.76 (1.56)	-0.05 (0.08)
Specialist Perception	0.03* (0.01)	0.05 (0.03)	0.00 (0.00)
Gender (Actor = 1; Actress = 0)	-0.21 (0.12)	-0.38 (0.30)	-0.03 (0.02)
Star Power (log)	0.01 (0.01)	0.03 (0.02)	0.01*** (0.00)
Actor's concentration of directors	0.05 (0.17)	-0.63 (0.54)	0.04 (0.03)
Specialism in the first 5 years	-0.40 (0.45)	2.17 (1.23)	-0.12 (0.07)
Age	0.01 (0.01)	0.01 (0.01)	0.01*** (0.00)
Typecast genre dummies	Yes	Yes	Yes
Constant	-2.62*** (0.66)	6.64*** (1.53)	5.81*** (0.09)
<i>N</i>	27866	24751	27866
Log likelihood	-2103.52	-409.84	-4.2e+04
pseudo <i>R</i> <sup>2</sup>	0.017	0.041	
<i>R</i> <sup>2</sup>			0.01

Standard errors in parentheses  
\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Another possibility is that the relationship between specialism and talent is partial: for rookie actors/actresses, there are no subtle differences between specialists and generalists; but for veteran actors/actresses, specialists are more talented than generalists. This perspective is in tune with the general belief that specialization benefits skill accumulation and deserves further examinations (Becker, 1962). We re-run the regressions in Table 4-3 using three subsets: actors/actresses that are more experienced than 50%, 75%, and 90% of the population. We got nine regressions in total. In all regressions, specialist index is negatively related with the quality of a film; though specialist perception is positively related to film quality, but it is only significant in one of the nine regressions (the likelihood of being nominating an Academy Award for actors/actresses who are more experienced than 50% of the population). We hence believe that the strengthening effects of specialist perception we observe in the right part of Figure 4-3 are not driven by talent differences. The detailed results are available upon request.

## **4.6 Discussion**

Economists and organization theory researchers have identified specialized investment of human capital and skill signaling as the theoretical underpinning of specialist advantage. Following their logic, the advantage of specialists vis-à-vis generalists should fade within veteran job market candidates, as a long tenure not only ensures that generalists sharpen their skills in different fields, but also allow generalists to signal their skills as well as specialists. Such an argument contradicts



findings in feature film labor market, in which the ratios of specialists and generalists are largely stable in job seekers across actors in different stages of their careers. Our theory and evidence support the contention that specialist advantage can sustain in labor markets under certain circumstances. In industries in which external audiences are key determinants of a company's product market success, the perception of external audiences may extend the advantage of specialist job candidates. Specifically, specialists whose skills and ability are consistent with their on-screen image among audiences will enjoy persistent advantage over other job seekers. Even if a long tenure weakens the advantage of specialists, it is less the case for specialists who have created established image among moviegoers. Our findings are robust even when we control other individual characteristics such as their gender, age, star power, social network, and genres they specialize in. Furthermore, we rule out the alternative explanations that veteran specialists enjoy additional hiring opportunities because they are more competent than veteran generalists in terms of professional ability. This suggests that varied audience perception on actors/actresses do bring the persistent advantage of some specialists.

The longitudinal nature of actors/actresses' career data makes it a perfect site to investigate the dynamic marginal returns of specialization over time. Many contemporary studies have focused on, at one point, the differences in returns between job market candidates who achieve different levels of specialization. For example, Zuckerman and his colleagues (2003) compare the hiring likelihood of

typecast, non-typecast, veteran, and novice actors during 1995-1997 using their casting records in the previous three years; Leung (2014) explores how coherences of job seekers' profiles (which is termed as "erraticism") affect freelancers' hiring opportunities in 2004. Tracing complete career paths of job market candidates since 1990, our research not only provides a snapshot of career-development discrepancies between job market candidates at a certain time, but also tracks the career dynamics of an individual due to the changes of his/her profile. The latter attribute is especially useful for us to tackle the key question of this paper: how do some specialists maintain their competitive advantage over other job market candidates, given that the skill- and signal-driven edge should have long gone over time?

#### **4.6.1 Managerial implications**

An important implication of this paper is the value of attending to external audience when companies search for talents in the labor market (Priem, Butler, and Li, 2013). When the outcome of hiring directly forms the impression of consumers toward the final product, employers should preconceive the reactions of consumers on the job candidates and incorporate such reactions into their hiring decisions. In this case, hiring becomes a complicated strategic decision in which questions regarding the value of customers should be thoroughly pondered: Are the job candidate's skillsets commensurate with his/her image among the potential customers? Or further, does the product the company is scheming confirm to customer demand? By shifting the hiring from a skill-based matching to customer-

oriented matching process, our research echoes the demand-side research emerging in strategic management field recently (e.g., Priem, Butler, and Li, 2013; Priem, Li, and Carr, 2012). A company that employs a demand-side perspective will look downstream from the focal company and emphasize customer value in managerial decisions (Priem, Li, and Carr, 2012). The pursuit of customer value will help companies gain competitive advantage, even if they don't have rare, inimitable resources (Adner and Zemsky, 2006; Preim, Li, and Carr, 2012). The demand-side approach is emerging in media industry and is well-received: Netflix is using a tremendous amount of customer data it gathered to develop hit films and TV-episodes. When making *House of Cards*, Netflix analyzed the preferences of users who potential would watch its work (e.g., watching David Fincher's films, having watched the British version of "House of Cards", preferring Kevin Spacey, etc.), and made the U.S. version accordingly. The customer-oriented filmmaking approach has gained Netflix sustained competitive advantage in streaming services and made it a serious competitor of Hollywood studios.

Job market candidates can also benefit from our study, which reiterates the importance of audience perception in the experience economy. Gaining a foothold in the feature film industry is extremely difficult for every actor/actress. For rookie actors/actresses, getting the first role in Hollywood is often a result of serendipity far beyond their control. But once they are known to moviegoers, the way they climb the career ladder may significantly affects the height they can achieve in the future. One hurdle artists may encounter is the "sophomore slump". Sophomore

slump refers to the common perception that artists (musicians, actors, etc.) often fail to produce a second work as good as their first (Askina and Mauskapf, 2017). While our study does not specifically concern the hiring probability of actors for their second job, the results suggest that reviewing the perception of audiences on their debuts and selecting jobs that accord with audience expectation may help them get more opportunities and cross the sophomore slump.

#### **4.6.2 Limitation and future research**

There are some limitations to this research. For example, we do not directly measure the perception of audiences on a specific actor/actress. We anticipate that an actor's resume contains information (number, box office, and genres of films) on his/her image among moviegoers. To avoid the risks that a single indicator does not fully embody the perception of moviegoers, we use principal component analysis to mitigate the measurement errors. However, we cannot entirely account for the notion that certain actors/actresses' on-screen image is decoupled with the genres in which they worked. For example, Morgan Freeman has served as a voice actor for numerous film projects. Though Freeman has a typecast image ("wise old man") among audience, his image is not tied to a specific genre. Future research may refine the measurement of an actor's on-screen image by combining second-hand data with first-hand information collected via survey and interviews.

A second limitation refers to a behavioral assumption we put on moviegoers. We argue that moviegoers not only have a general perception on the casts of a film (i.e., is he/she famous or not), but also are familiar with the work

histories of casts (i.e., is he/she good in Genre A). We believe this assumption reasonably summarizes the consumption characteristics of a general audience in the movie industry, but we also admit that some consumers may not confirm to the assumption we set. For less knowledgeable moviegoers, their consumption decisions may vary depending on the overall fame of a cast, rather than the identity of the cast as a specialist vis-à-vis generalist. We welcome future studies to test this boundary condition by comparing the hiring decisions in markets dominated heterogeneous consumer groups (e.g., amateur or adept consumers).

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## 5 Conclusion

Since Zuckerman's (1999) seminal work on the categorical imperative, the research interest in market categorization has grown significantly over the past two decades. Although much progress has been made in sociology, organization theory, and strategic management fields, more questions remain that merit further discussion. The main purpose of this dissertation is to gain a better understanding of the antecedents and implications of categorization. Specifically, I examine three interrelated issues in this dissertation: (1) the mechanisms through which producers manipulate the category labels of their products, (2) the effects of the connectiveness of a category system on the usage of categories in a product, and (3) the long-term effects of category labels on individuals' career advancement. I summarize my main findings below.

In Chapter 2, I review the filmmaking process in the feature film industry. I identify three important players in film categorization: producers, directors, and cast members. I find that they shape audiences' genre perception of the focal film via cognition-, capability-, and newness-based mechanisms. I also find that the film crew's involvement in shaping the genres of its film will ultimately affect the economic gains that the focal film can obtain from the market. Chapter 2 contributes to category research by redirecting researchers' attention to the active roles of producers in the categorization process.

In Chapter 3, I investigate the interconnectedness of categories in the category system and examine how different interconnected relationships between



categories will affect the usage of a category in product descriptions. I develop a new construct, the category bundle, to represent the local aggregations of categories in some industries. I find that a category that achieves higher fitness in category bundles is more likely to be chosen by market participants. Chapter 3 enriches the understanding of categorization theory in two aspects. First, it significantly extends the literature on the structure of a category system and the effects of the categorical structure on the categorization process. Second, it provides a novel explanation of category spanning. According to my findings in Chapter 3, category spanning might be a self-organizing process that embodies the bundle-based structures of category systems. This explanation may solve the paradox between the categorical imperative argument and the persistence of category spanners in our social lives.

In Chapter 4, I apply the category literature to the discussion of actors' and actresses' career advancement in the feature film labor market. I address a long-standing question in career advancement research: is specialism or generalism more advantageous to the career advancement of job market candidates? I find that the audience perceptions of actors/actresses are a scope condition of the specialist advantage. First, the positive effects of specialism on job market candidates' work opportunities will be stronger for candidates who are widely accepted as specialists by audiences. Second, audience perceptions also moderate the moderating effects of tenure on the specialism-hiring link, extending the specialist advantage of old-timers who build consistent images among the public.

The findings of Chapter 4 reveal the value of attending to external audiences when companies search for talent in the labor market (Priem, Butler, and Li, 2013).

In combination, the investigation of the antecedents and outcomes of the categorization process in the feature film context leads to new insights on how organizations and individuals can manipulate categorization to maximize returns. Due to the universal application of category labels in modern society, the insights from this dissertation can also be generalized to other contexts. I encourage more research to further refine the theoretical foundations and managerial applications of category research.

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