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Hu, Yimei; Zhang, Huanren; Gao, Yuchen

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In Search of Optimal Distinctiveness:
Balancing Conformity and Differentiation via Organizational Learning

Yimei Hu¹, Huanren Zhang², Yuchen Gao^{3*}

¹ Aalborg University Business School, Aalborg University, Aalborg, Denmark

yimei@business.aau.dk Fibigerstraede 11, 9220, Aalborg East, Denmark

² Department of Economics, University of Southern Denmark, Odense, Denmark

huanren@sam.sdu.dk Campusvej 55, 5230, Odense M, Denmark

³ School of Public Policy and Management, Tsinghua University, Beijing, China

* gaoych@sem.tsinghua.edu.cn School of Public Policy and Management, Tsinghua University, 10084,
Beijing, China

The first two authors contributed equally.

Corresponding author: Yuchen Gao (gaoych@tsinghua.edu.cn)

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Abstract

Firms in a nascent industry need to search across various technological trajectories and market opportunities with limited prior knowledge. While inter-firm learning (e.g., imitation) helps the focal firm adapt in the process of conformity, intra-firm learning (e.g., independent experimentation) helps a firm stand out from rivals in the process of differentiation, both of which can gain competitive advantages. This study investigates how the conformity-differentiation balance can be achieved from the cross-level learning perspective. Adopting a mixed-method design, we first conduct a case study on the Chinese photovoltaic industry. The case suggests that firms are inclined to conform in upstream and bottleneck technological domains but differentiate in the downstream market applications. We then extend the case findings through a computational simulation based on March's learning model. When experimentation and imitation are possible, the balance between conformity and differentiation can be reframed as the classical balance between exploitation and exploration across the firm and industry levels: while experimentation is often exploitative at the firm level but exploratory at the industry level, imitation is often exploratory at the firm level but exploitative at the industry level. The study makes a new attempt to bridge the optimal distinctiveness literature with the organizational learning literature.

Keywords: conformity; differentiation; exploration; exploitation; optimal distinctiveness; paradoxical balance

1. Introduction

When a technological area or a nascent industry is emerging, a group of competing firms will face multiple technological trajectories. In the presence of the uncertainty about the potential gains of these trajectories, firms acquire information through both intra-firm experimentation and inter-firm imitation (Levitt & March, 1988; March, 1991; Wan, Zhixi, & Levinthal, 2014). Intra-firm experimentation refers to the independent experiential learning from trial and error (Cyert & March, 1963; Denrell & March, 2001; Holmqvist, 2004), which exposes firms to distinct experiences and outcomes, giving rise to variations in choices in the industry (Lavie & Rosenkopf, 2006; McKnight & Zietsma, 2018). By experimentation, some firms may differentiate themselves from peers by finding the well-performing trajectories and thereby achieve competitive advantages (Benner & Tushman, 2013; Raisch, Birkinshaw, Probst, & Tushman, 2009). Pursuing differentiation, however, may trap a firm in a technological periphery that peer firms or the market do not appreciate. Thus, intra-firm experimentation without considering peers' choices may harm firms' performance (Stettner & Lavie, 2014). In contrast to experimentation, firms can also apply inter-firm imitation, which is also referred to as vicarious learning in the literature (Baum, Li, & Usher, 2000; Bruneel, Yli-Renko, & Clarysse, 2010; Ingram & Baum, 1997). Imitation can greatly increase business performance by adapting quickly and efficiently, reducing uncertainties by enhancing legitimacy, and accelerating innovation diffusion and other network externalities (Haunschild & Miner, 1997; Mazzucato & Mazzucato, 2017).

The existence of this cross-level (intra-firm and inter-firm) learning confronts firms with two major paradoxes while orchestrating various technological alternatives. On the one hand, firms need to manage the traditional organizational ambidexterity paradox—i.e. balancing exploitation and exploration at the firm level (March, 1991; Raisch et al., 2009). On the other hand, firms can balance their the intra-firm learning (experimentation) and inter-firm learning

(imitation), which seem to be related to the *conformity-differentiation paradox* for the *optimal distinctiveness* as strategic balance (Deephouse, 1999; Haans, 2018; Zhang, Wang, and Zhou, 2020; Zhao *et al.*, 2018; see Zhao *et al.*, 2017 for a review). In other words, experimentation can help a focal move ahead of rivals in the process of differentiation or divergence, while imitation can help the focal firm avoid falling behind rivals in the process of conformity or convergence.

A major gap in the extant literature is the lack of attention to the inherent link between the organizational ambidexterity paradox and the conformity-differentiation paradox. Focusing on the context of nascent industries, we seek to answer the following research question: *How do firms manage the conformity-differentiation tension through cross-level learning behaviors in terms of exploration and exploitation?* Specifically, we examine both *the extent* and *from whom* firms should learn to manage the conformity-differentiation paradox for the best performance.

A mixed method approach is adopted to answer the research question. We first conduct a case study on the technological trajectory in the Chinese photovoltaic (PV) industry. The catch-up and growth of the Chinese multicrystalline silicon manufacturers in recent years demonstrate a clear pattern in the balance between conformity and differentiation, which is achieved through cross-level learning behaviors in interdependent technological domains along the value chain. With imitation, firms converge in the trajectory of the upstream bottleneck technologies, demonstrating conformity at the industry level. With experimentation, firms diverge across various technological trajectories for the development of distinctive products in the downstream market, demonstrating differentiation at the industry level.

To verify and extend the case findings, we draw on James March's exploitation-exploration model (Levinthal & March, 1981; March, 1991, 2003) and adopt a computational experiment to reflect a learning setting in which a group of competing firms face various technological trajectories (Bitektine, Lucas, & Schilke, 2018; Raisch *et al.*, 2009). Following institutional

theory and the notion of mimetic isomorphism (DiMaggio & Powell, 1983; Haunschild, 1993; Haunschild & Miner, 1997; Haveman, 1993), we conduct computational experiments in which organizations can engage in inter-firm learning using three possible imitation modes: imitate the best-performing firm (*imitate the best*); imitate the largest firm (*imitate the big*); and imitate the most-selected choice (*imitate the crowd*). Results suggest that while a firm can improve its performance under all three imitation modes, it achieves the best performance by learning from the firms with the best recent performance. Besides, over-reliance on imitation may deteriorate firms' long-term performances.

The study theoretically contributes to the strategy and organization research streams by generating an important dialogue between the organizational learning literature and the optimal distinctiveness literature. First, we extend March's learning model by introducing inter-firm learning opportunities. March's original model focuses mainly on the tension between exploitation and exploration at the intra-firm level (March, 1991), but organizational interdependence is prevalent in almost any industry (Miller, Zhao, & Calantone, 2006): while choosing a popular trajectory can potentially increase its return due to legitimacy, making identical choices can reduce profitability because of intensified competition (Deephouse, 1999; Haans, 2018; Haveman, 1993; Zhao et al., 2018). Second, the conformity-differentiation balance literature pays limited attention to the value of the learning model in terms of finding the optimal distinctiveness (Zhao, Fisher, Lounsbury, & Miller, 2017). Our study shows that the model of exploitation and exploration (March 1991, 2003, 2010), with some extensions, can be applied effectively to the conformity-differentiation paradox. The research findings demonstrate that the balance between conformity and differentiation can be framed as the balance between exploitation and exploration across the levels of firm and industry. While imitation helps a focal firm explore new knowledge, it exploits the existing opportunities and knowledge pool at the industry level. Meanwhile, experimentation tends to exploit firm-level

experiences, but it explores novel opportunities with diverging knowledge pool at the industry level. Knowledge accumulated and maintained by experimentation is diffused as a spillover to the industry via imitation.

Our findings also shed light on managerial practices. Besides the “success trap” highlighted by March (1991), we suggest the need to pay attention to the “imitation trap.” When faced with technological uncertainties, firms are tempted to rely too much on imitating others because it is an effective strategy in the short run, but in the long run it is self-defeating. In addition, firms often tend to follow the industrial giants. However, our findings challenge this approach and suggest that firms should learn from their peers that have the best recent performance, even though these firms may not be large players with a long-standing reputation in the industry.

The theoretical background of the study will be discussed in Section 2, followed by a case study of the Chinese PV industry in Section 3. Then, based on the case findings, we conduct a follow-up computational simulation in Section 4. We discuss the theoretical and practical implications and conclude the paper in Section 5.

2. Theoretical Background: Balancing Conformity-Differentiation

Rooted at the intersection of institutional theory and the strategic management literature (Brewer, 1991; Deephouse, 1999; Durand & Kremp, 2016; Zhao et al., 2017), the conformity-differentiation paradox implies that firms should, on the one hand, conform to the requirements imposed by external stakeholders to gain legitimacy and earn institutional resources (DiMaggio & Powell, 1983), while, on the other hand, differentiate from peers to reduce competition and gain competitive advantage (Deephouse, 1999; Porter, 1996). As both improved legitimacy and reduced competition enhance firms’ performance (Haans, 2018; Haveman, 1993), how distinctly a firm should position itself in order to achieve optimal distinctiveness has become a focal research agenda, receiving increased attention in recent years (Durand & Jacqueminet, 2015; Durand & Kremp, 2016; Zhang et al., 2019; Zhao et al., 2017; Zuckerman, 2016).

The extant literature has investigated optimal distinctiveness in various empirical scenarios, such as corporate governance and social responsibility (Durand & Jacqueminet, 2015; Zhang et al., 2019); entrepreneurial resource acquisitions and new venture founding (Fisher & Lahiri, 2016); new entrants and platform strategies (Barlow, Verhaal, & Angus, 2019; Cennamo & Santalo, 2013; Zhao et al., 2018); business model design (Zott & Amit, 2007); distinctiveness strategies in different population categories (Durand & Kremp, 2016; Haans, 2018); and public and private family firms (Miller, Amore, Le Breton-Miller, Minichilli, & Quarato, 2018). The implications of these studies vary: while some suggest that moderate distinctiveness leads to improved business performance (Deephhouse, 1999), others argue that, by strategically positioning itself as moderately distinctive from its peers, a firm will largely damage its performance (Cennamo & Santalo, 2013; Haans, 2018; Miller et al., 2018). Faced with the disparate and even contradictory findings, the recent literature highlights the importance of a synthesized understanding of the conformity-differentiation balance (Haans, 2018; Zhao et al., 2017).

The balance between conformity and differentiation is traditionally regarded as solving a unidimensional problem (e.g. Deephouse 1999). Recent literature recognizes that the conformity and differentiation paradox is, by its nature, multifaceted and multiplex (Durand & Jacqueminet, 2015; Haans, 2018; Mazzelli, Kotlar, & De Massis, 2018; Zhao et al., 2018). Due to methodological limitations, however, the extant empirical studies are based on settings in which organizations have simple choices that are inadequate to capture the multiplexity of the conformity-differentiation issue. Thus, studies with an updated view of the conformity-differentiation paradox, as well as new methodological approaches, are needed.

A major gap in the current research on optimal distinctiveness is that it neglects the fact that managing the conformity-differentiation paradox is inherently a learning process that involves proactive adaption based on one's own and others' experiences (see Zhao *et al.*, 2017

for a review). Specifically, Zhao et al. (2017) call for a renewed research agenda by incorporating the perspective of organizational ambidexterity with that of conformity-differentiation balance, especially across the levels of firm and industry.

Institutional theory highlights another fundamental pressure that triggers organizational isomorphism and conformity (DiMaggio & Powell, 1983; Haunschild, 1993; Haunschild & Miner, 1997; Haveman, 1993). In the presence of uncertainties, organizations tend to imitate peer organizations' experiences to reduce risks, lower costs, and improve legitimacy to gain institutional resources, leading to "mimetic isomorphism" (DiMaggio & Powell, 1983; Haunschild & Miner, 1997; Haveman, 1993). However, "new developments in institutional theory have redirected attention away from isomorphism and toward the theorization of organizational heterogeneity...As part of this redirection, institutional environments are conceptualized as fragmented, contested, and dynamic" (Zhao et al., 2017: 99). In this sense, firms' adaptability via learning will become highly salient in terms of gaining institutional capital (McKnight and Zietsma, 2019; Zhao et al., 2017).

According to the organizational learning literature, experiential learning and vicarious learning are two basic learning mechanisms (Baum et al., 2000; Denrell, 2003; Ingram & Baum, 1997). Experiential learning refers to a firm's independent experimentation, while vicarious learning refers to imitation of other firms' choices (Baum et al., 2000; Bruneel et al., 2010). When faced with an unknown field with various choices, both experiential learning and vicarious learning are present. Differentiation is a natural outcome of experiential learning because firms are exposed to distinct outcomes in their learning process. Yet, according to the strategic management literature, firms may also intentionally pursue distinctiveness from other firms to generate and sustain competitive advantages (Benner & Tushman, 2013; Junni, Sarala, Taras, & Tarba, 2013; Luger, Raisch, & Schimmer, 2018; Raisch et al., 2009; Stettner & Lavie, 2014).

In experiential learning, firms are more inclined to engage in exploitation instead of exploring new opportunities and may fall into the familiarity trap (Baum et al., 2000; March, 1991). In contrast, vicarious learning by imitating others' experiences often remedy the costs and uncertainties associated with exploration (Baum et al., 2000; Bruneel et al., 2010; Ingram & Baum, 1997). As highlighted in the organizational learning literature, inter-firm learning is a common strategy to diffuse knowledge and innovation, deal with uncertainty, and earn adaptability (Levinthal and March 1993, Levitt and March 1988). For example, Levitt and March (Levitt & March, 1988), in an influential learning article, argue that isomorphism promotes adaptability and innovation diffusion:

“The particular professions, policies, programs, laws, and public opinion... become powerful institutionalized myths that are adopted by organizations to legitimate themselves and ensure public support. . . . In the organizational literature, these three processes have been labeled coercive, mimetic, and normative (DiMaggio & Powell 1983). All three are involved in a comprehensive system of information diffusion.” (Levitt & March, 1988).

Despite the strong linkage indicated in the classic organizational learning and institutional theory literature, studies integrating organizational learning and the conformity-differentiation paradox are lacking. In particular, the above views are from the perspective of a single firm, which may differ from the industry-level perspective, so a cross-level approach is necessary. As both the conformity and differentiation strategies can be seen as results of organizational learning, we are motivated to explore how organizational learning across the intra- and inter-firm levels contributes to the proper balance between conformity and differentiation in terms of optimal distinctiveness as strategic balance (McKnight & Zietsma, 2018; Zhao et al., 2017).

3. Conformity-Differentiation in the Chinese Photovoltaic Industry

3.1 Case Background, Data Sources, and Data Analysis

Informed by the gap in the current conformity-differentiation literature and driven by our interest in nascent industries from emerging economies, we conducted a case study to investigate how the conformity-differentiation balance is achieved from the organizational

learning perspective. The case study provides an in-depth investigation and analysis of emerging phenomena that the existing literature cannot explain. Additionally, it offers theory-building opportunities (Eisenhardt & Graebner, 2007; Siggelkow, 2007; Yin, 2017). We chose the technological trajectory development of the multicrystalline silicon manufacturers in China's photovoltaic industry as our case.

The photovoltaic (PV) industry is one of the fastest-growing emerging industries in China. At present, China's PV industry has formed a competitive landscape with monocrystalline silicon (mono-Si) and multicrystalline silicon (mc-Si) as the two main component materials, which are also associated with distinct technological trajectories. Starting in 2007, along with the development of China's PV industry, mc-Si-based components gradually expanded and reached a 95% market share in 2014. However, since then, mono-Si based components have observed rapid growth in its market share, from 5% in 2014 to 15% in 2015, and then to 45% in 2018.

Challenged by the mono-Si-based technological trajectory and its rapid rise in market share, mc-Si manufacturers explored and quickly diffused the technological combination of “diamond wire sawing (DWS) + black silicon texturing + passivated emitter and rear contact (PERC) battery” through interactive learning. The technological innovation in mc-Si slicing and batteries reduced the development and production costs of the entire mc-Si technological trajectory, improved the conversion rate of the mc-Si batteries, and strengthened the competitiveness of the mc-Si trajectory. While technology diffusion clearly benefited the mc-Si group, it also led to isomorphism and, inevitably, intensified the competition among mc-Si manufacturers. Thus, we find that the mc-Si manufacturers incorporated both adaptability considerations and individual distinction, which served as a suitable setting for this research. Our case study adopts a multi-embedded units design. We focus on the technological development of the Chinese PV industry from 2014 to 2018 and choose companies such as

GCL, CSIQ, Jinko, and *Yingli* as the multiple embedded units. The selected companies include industrial leaders, mainstream manufacturers, and technology followers.

We collected both primary and secondary data to enable data triangulation. Secondary data came from various sources. We conducted desk research on the annual industrial reports published by the China PV Industry Association (2016-2019) and the annual reports (2014-2018) of the top ten listed PV companies. We also followed the highlights and publications from nine industrial conferences and technology forums on DWS and black silicon texturing technology from 2014 to 2018, to strengthen our understanding. These secondary data sources provide rich information on the development of the PV industry and the technological trajectory adoption of PV manufacturers.

Regarding the primary data, from July 2018 to January 2019, we conducted field investigations and nine in-depth interviews with technological and business executives from four PV companies specializing in mc-Si. A summary of the interviews appears in Table 1. In addition, since 2018, one author has participated in two WeChat groups of the PV industry (each with 500 participants) to observe and conduct informal discussions with the PV experts.

[Insert Table 1 about here]

Coding and categorical analysis were adopted inductively in the data analysis (Gioia, Corley, & Hamilton, 2013; Miles & Huberman, 1994). We sorted and documented the primary and secondary data into a database consisting of sub-databases of individual mc-Si manufacturers. We first gained an overview of the development and innovation trend in the Chinese PV industry through desk research. We also identified the technological trajectory choices of individual mc-Si manufacturers. Two authors open coded our data independently according to critical events, technological trajectories, industry development, challenges, market share, etc. Then, they worked together to compare the open coding results and conducted axial coding together, categorizing and synthesizing open nodes into conceptual

themes. We further identified the second-level themes that are related to three core dimensions of our research goal: conformity, learning, and differentiation. We then scrutinized the underlying relationships and mechanisms across the theoretical constructs to generate theoretical propositions regarding how the conformity-differentiation balance is achieved through organizational learning behaviors. The three authors exchanged reflections and thoughts constantly to mitigate potential bias. The data coding scheme is shown in Table 2.

[Insert Table 2 about here]

3.2 Findings

Technological Conformity

An essential factor enabling the mono-Si group to challenge the mc-Si group's market share is the introduction of the diamond wire sawing technology in the wafer slicing process. Crystal silicon wafers account for 40% of the total costs of solar cell component production, and silicon squaring and wafer slicing are the most costly processes in wafer production. Therefore, reducing the cutting costs can contribute greatly to lowering the cost of the solar cell component.

Conventional crystalline silicon slicing typically employs a slurry-based wafer sawing technique. Compared with slurry-based wafer sawing, DWS has three major advantages. First, the silicon consumption per production unit is greatly reduced, and the consumables per wafer are far lower. Second, the cutting speed and the wafer production capacity are greatly increased, which reduces the depreciation, electricity, and labor costs spent on wafer cutting. This leads to the rapid decline of non-raw material costs in wafer production. Third, replacing the difficult-to-process slurry can significantly reduce the auxiliary costs and pollution during the slicing process.

The introduction of DWS technology to the Chinese PV industry is owing to the mono-Si leader, *Longi Green Energy*, and its research and development since 2013. A 100% replacement rate of the DWS technology in mono-Si slicing was reached in 2017. Confronted

by the rise of the mono-Si group powered by DWS, the mc-Si group also started to investigate the possibility of adopting DWS. However, due to the lattice order features, adopting DWS technology in mc-Si slicing faces two major bottlenecks. First, the hard spots existing in the ingot crystal may cause broken lines during the cutting. Second, it is difficult to prepare the anti-reflection coatings with the traditional acid vapor texturization; thus, the reflectivity rate of processed mc-Si wafers is too high.

According to the Chinese Photovoltaic Association, the adoption rate of DWS among mc-Si manufacturers was only 5% in 2016 but rose to 35% in 2017. According to the 2017 prediction of the International Technology Roadmap for Photovoltaic, the adoption rate of DWS in mc-Si in 2018 was supposed to be around 50%. It was believed that texturing technology would be the major bottleneck for the popularity of DWS in mc-Si. However, beyond all expectations, the adoption rate of DWS in mc-Si jumped to 95% in 2018. The unexpected fast diffusion of DWS was due to the introduction and popularization of the black silicon texturing technology that solved the previously mentioned bottlenecks. Specifically, *GSL*, the leading mc-Si company, freely and fully disclosed the black silicon texturing technology to the industry in 2017. The wide application of DWS thereby increased the wafer output from 48 per kilo of the mc-Si ingot in 2016 to 63 per kilo in 2018, and it lowered the non-silicon cost of mc-Si by 0.8 RMB per slice.

Although adopting the “DWS + black silicon” technological combination significantly improved the productivity and lowered the slicing costs of the Chinese mc-Si companies, the market share of the mc-Si group was still declining. The mc-Si companies needed to continuously improve the conversion efficiency of their PV products to remain competitive. Therefore, based on “DWS + black silicon,” mc-Si manufacturers further introduced and adopted the PERC battery technology. Although the PERC technology was first adopted by mono-Si battery, it generated greater technological synergy with the mc-Si material after the

breakthrough and diffusion of the bottleneck black silicon texturing technology solved the compatibility issue.

In 2017, mainstream mc-Si manufacturers, such as *CSIQ*, *Yingli*, *GCL*, and *Risen Energy*, started to apply the PERC technology to the mc-Si solar cells that are pre-processed by the black silicon texturing technique. The application of PERC technology, therefore, significantly increased the conversion efficiency of mc-Si cells from 18.5% in 2016 to 20.3% in 2018 and narrowed the gap with mono-Si cells in terms of conversion rates (see Figure 1). As the cost of mc-Si solar cells is significantly lower than that of mono-Si based products, the overall benefits and cost-efficiency of the mc-Si cells even outperformed the mono-Si cells.

[Insert Figure 1 about here]

Market Differentiation

The competition was concentrated mainly on the market application of the solar cells—namely, PV module development and the respective markets. In contrast to the convergence in solar cell technologies, mc-Si companies presented differentiated trajectory choices on the downstream module technologies to avoid patent protection, serve various market demands, and, thus, achieve differentiated market performances.

As described above, the mc-Si manufacturers have conformed to the technological combination of “DWS + black silicon + PERC” in the upstream solar cell development. Yet in the application of solar cells—i.e., module development—the mc-Si manufacturers have demonstrated divergence. Currently, high-efficiency PV modules that are compatible with the black silicon and PERC include half-cell module, double glass bifacial module, shingled module, and multi-bus bar module (MBB). Each module trajectory has its advantages in coping with different optimization methods, application scenarios, and market demands. To pursue differentiated advantages, the Chinese mc-Si manufacturers demonstrate differentiated module technologies through licensing from or partnering with foreign leaders, or through independent

R&D. For example, the shingled technology outperforms other module technologies due to its significant reduction in electrical losses and improvement of efficiency. However, the shingled technology patents are owned mostly by foreign leaders such as *SunPower* and *Solaria*. The only licensed Chinese companies are *DZS*, *Seraphim*, and *GCL*. Among them, *DZS* is a joint venture with *Sunpower*, and *Seraphim* has established a strategic partnership with *Solaria*. Chinese manufacturers such as *Risen* and *Longi* developed the shingled technology independently. Some other Chinese companies explored alternative technologies, such as *Jinko*'s self-developed tiling ribbon technology, to avoid the patent restrictions.

Table 3 summarizes the mainstream mc-Si manufacturers' adoption of upstream solar cell and downstream module technologies. Through the development of different module technological trajectories, the Chinese PV manufacturers can compete differently, based on the technical isomorphism of "DWS + black silicon + PERC." As the table shows, mastering the bifacial module technology and the self-developed TR technology, *Jinko* has led in global shipments since 2016. With the shingled module technology, *Risen* entered the top ten in 2017, and its ranking has been steadily increasing.

[Insert Table 3 about here]

The differentiation and competition in the downstream market has also greatly promoted the overall performance of the mc-Si solar cell modules. As shown in Figure 2, the average power of traditional mc-Si modules was only 275 watts in 2018, whereas the average power output of black silicon PERC modules increased from 270 watts in 2016 to 295 watts in 2018, and the gap with the mono-Si modules has been narrowed.

[Insert Figure 2 about here]

Cross-level Learning

The case depicts a setting in which PV manufacturers within a nascent industry are faced with various technological trajectories. Due to limited information on trajectories that perform

better, firms are engaged in intensive experimentation across different options. Our coding results show the presence of cross-level learning: intra-firm experimentation and inter-firm imitation are both salient at interdependent technological domains along the value chain.

The fast development and diffusion of the “DWS + black silicon + PERC” technological combination has been achieved primarily through imitation. “DWS + black silicon” was first introduced by Japanese researchers and engineers at China’s 2014 SoG Silicon and PV Power (CSPV) Conference. One year later, China’s mc-Si leading manufacturers began to scale up production based on the new solar cell technologies. At the 2015 CSPV, Chinese mc-Si leaders such as *CSIQ* and *GCL* replaced the Japanese experts and took the lead in sharing technological advancements. In 2016, a considerable number of Chinese mc-Si manufacturers, such as *JA* and *JK*, began to engage in the R&D and application of DWS and black silicon texturing technologies. In the same year, the first technological seminar on “DWS + black silicon” was held. Major mc-Si manufactures, including *GCL*, *CSIQ*, *JA*, *JK*, *CSG*, and *Suntech*, openly shared their experiences with DWS and two major black silicon texturing methods: Reactive Ion Etching and Metal Catalyzed Chemical Etching. Interviews with business managers suggested that knowledge disclosure had greatly promoted the advancement and maturity of the new technologies, which benefited both the leaders and the imitators. A *GCL* manager explained:

“It is beneficial to the promotion of our products and technology route. We will disclose this technology to everyone, and everyone can use it. This can also help solve the (potential) technological problems by utilizing others’ efforts.” (I1)

Besides leaders’ purposeful knowledge disclosure, employee movement across different firms also enriched the industrial knowledge sharing and innovation diffusion. As a top executive from *JY* explained:

“These newly joined engineers are way ahead of most of our current engineers in certain technologies. After they came, the technological replacement and upgrade were achieved in only half a year.” (I7)

While inter-firm learning is salient in the bottleneck solar cell technologies, intra-firm learning is predominant in the downstream solar module development. There are two major reasons why firm-level experimentation became the dominant learning mode in downstream module development and market application. The first is competitive pressure from peer firms. To reduce direct competition in the same market, mc-Si manufacturers chose different technological trajectories in module development through various intra-firm learning efforts, such as in-house development or licensing from foreign leaders. Second, the final solar panel application scenarios imposed diversified and distinct market requirements, and different application scenarios were associated with distinct and tacit knowledge that was difficult to communicate and share. Thus, the mc-Si manufacturers chose to individually develop solar modules to fit the specific market segments. For example, based on the bifacial technological trajectory, *TW Solar* developed solar modules to fit the scenario of fishing grounds, proposing a sustainable model that integrated intelligent fishing and green energy.

3.3 Case Discussion

The case clearly shows a pattern of conformity and differentiation in a balance achieved through cross-level organizational learning behaviors. The underlying connections between the three core theoretical constructs—i.e., learning, conformity and differentiation—are shown in Figure 3. In terms of the upstream solar cell technologies, the mc-Si companies conformed to the technology combination of “DWS + black silicon + PERC.” Achieving technological conformity depended mainly on imitation enabled by industrial leaders, industrial communications, and talent turnover.

[Insert Figure 3 about here]

The technological convergence increased the adaptability of promising technological trajectories, reduced the technological exploration costs, and, therefore, improved the market share of the whole mc-Si group. For bottleneck technological areas that are costly to conquer, firms can exploit the common industry-level knowledge through imitation, so that they can

explore new opportunities with lower costs and fewer uncertainties. Meanwhile, as a similar choice in nature may intensify competition, the mc-Si manufacturers differentiated themselves in the downstream market segmentation in the module development through trial-and-error experimentation such as in-house R&D.

It is also worth noting that, though the case findings suggest inter-firm learning and technological conformity for bottleneck technologies, intra-firm learning was never absent. For example, the “DWS+Black Silicon+PERC” combination was developed and constantly improved by industrial leaders and followers through independent experimentation. Similarly, peer comparison and conformity remained when differentiation was the dominant strategy in the downstream market. As Table 3 shows, though the mc-Si manufacturers demonstrated differentiated technological trajectory choices and showed diversified market performance, they shared consensus on several better-performing technological trajectories.

The case findings lead to the following theoretical propositions:

Proposition 1: In a nascent industry, the conformity-differentiation balance can be achieved in interdependent technological areas with asymmetrical focuses: (1) conformity is reflected in the bottleneck or core technological areas with a primary dependence on inter-firm learning (i.e., convergence by exploiting others’ experiences), and (2) differentiation is reflected in downstream market applications with a primary dependence on intra-firm learning (i.e., divergence by exploring unique opportunities).

Proposition 2: The balance between conformity and differentiation can be framed as balancing exploration and exploration across the firm and industry levels.

4. The Computational Simulation

The case findings show that, while exploiting industry-level collective experiences through imitation leads to conformity, firms’ own experimentation enriches the industry’s knowledge pool. *The extent to which firms should learn from others, and from whom firms should learn to achieve best performances* are still unclear. To investigate the degree and target of imitation that may lead to optimal distinctiveness, we conduct computational simulation to verify and generalize the case findings and theoretical propositions. Our investigation of the effect of

organizational learning on the conformity-differentiation paradox is based primarily on the multi-armed bandit problem. March and other researchers have extensively used the bandit problem to study organizational learning (March, 1996, 2003, 2010; Posen & Levinthal, 2012; Reypens & Levine, 2017).

4.1 Learning Model

In the original bandit problem, an organization chooses from a set of A alternatives in each period t of the organization's lifespan T , seeking to maximize the flow of returns over time. To capture the conformity-differentiation tradeoff exhibited in a nascent industry, we follow the case findings and extend the original bandit problem in the following ways (technical details of the computational model can be found in the Appendix):

1. A firm faces a hierarchical bandit problem: it needs to first choose one of A primary technological trajectories and then choose one of B complementary technologies. The primary trajectory (e.g., solar cell technology in the PV industry) requires a complementary technology (e.g., the downstream module technology) to realize synergy and to achieve commercialization. The payoff from choosing a combination of technologies is probabilistic and follows a normal distribution. Unknown to the organization in advance, the mean of the distribution is determined by the productivity of the trajectory and its complementary technology. The structure of the hierarchical bandit problem is shown in Figure 4.
2. Firms' experiences are passed around in the industry, making inter-firm learning possible. Firms reveal only their primary technology, without information on their complementary technology choices.
3. Popular primary technologies enjoy enhanced adaptability. This adaptability comes from competence derived from a learning-by-doing process at the industry level, which decreases the costs of development, production, and marketing.

4. Firms choose the identical primary and complementary technologies to compete in the same market segment. The payoff that a firm receives from the bandit problem is discounted by the number of existing firms in the same market segment.

In the extended bandit problem, firms are interdependent because their choices inevitably influence the adaptability of technology and the intensity of competition. Through a learning-by-doing process, an organization, or the whole industry, develops competence in specific markets, technologies, and strategies. This learned competence at the industry level is the main source of adaptability (Denrell & March, 2001). The increased adaptability can, thus, reduce the potential costs of the diffusion and the adoption of a technology. At the same time, firms using identical technologies will compete with each other due to their confrontation in the same market segment or technological area.

This extension allows us to examine the underlying principle that conformity and isomorphism are associated with increased adaptability and competition. As shown in Figure 5, it is assumed that an inverted U-shaped relationship exists between the average return of adopting a technological trajectory and the number of firms choosing the same trajectory (Haans, 2018). The combination of adaptability and competition determines that firms have to find a balance between conformity and differentiation (Haans, 2018; Haveman, 1993): a popular technology is usually more mature and widely accepted by the market, but using the same technology as other firms leads to intense competition that undermines a firm's competitive advantage.

[Insert Figure 4 and Figure 5 about here]

Intra-firm experimentation

Following firms' behavioral assumptions, we assume that firms adopt an experiential learning process to improve their performance in an adaptive way (Cyert & March, 1963; Denrell & March, 2001; March, 2010). Experiential learning was popularized by James March

in his seminal studies (Cyert & March, 1963; Levitt & March, 1988), which claim that the propensity to select a particular alternative depends on the outcomes of this alternative when it was chosen previously.

Inter-firm imitation

Based on the case findings and the institutional theory literature (e.g., Haunschild, 1993; Haunschild & Miner, 1997; Haveman, 1993), we introduce three imitation modes to the experiential learning model: firms can imitate the trajectory chosen by most firms (imitate the crowd), by the best performing firm (imitate the best), or by the firm with the highest cumulative payoffs (imitate the big). In the *no imitation* treatment, firms focus on intra-firm learning and do not compare their choices with those of other firms. In the other treatments, a firm tries to conduct inter-firm imitation with probability λ and implements the choice made by other firms if it believes that this choice could potentially bring a higher payoff. In the *imitate the best* treatment, the target is the firm with the best performance in the past five periods. In the *imitate the big* treatment, the target is the firm with the highest cumulative payoff. And in the *imitate the crowd* treatment, the imitating firm compares its payoff with the average industry payoff in the past five periods; it then implements the choice that has been most frequently chosen in the past five periods if it performed worse than the industry average.

Firms actively share experiences with and knowledge of a primary technology to help its maturity and diffusion, but they seldom reveal information on the specifics of the complementary technologies. We base this assumption on observations derived from the case study—i.e., imitation largely happens in the upstream bottleneck technological area.

4.2 Computational Experiment

A firm's learning strategy can be characterized by its *exploration tendency* τ (the likelihood of engaging in exploration over exploitation) and its *imitation tendency* λ . In the experiments, we set the default λ as 0.02, and default τ as 0.1. The values for τ explored under

the default λ include $\{0.02, 0.1, 0.2, 0.5, 1\}$, and the values of λ explored under the default τ include $\{0.02, 0.1, 0.2, 0.5, 1\}$.

The computational experiments with four treatments are seeded with 20,000 industries, each consisting of $N=30$ firms. Firms are faced with multi-armed bandit problems with $A = 20$ and $B = 3$, with timespan $T = 500$. Firms in the same industry face the same bandit problem and use the same exploration (τ) and imitation (λ) strategies. These industries are divided equally among ten sets of exploration(τ)-imitation(λ) strategies and the four treatments.¹

In the following analysis, we first investigate how exploration and imitation tendencies influence performance under different imitation modes. We then investigate how imitation affects the conformity-differentiation tradeoff and follow that with a discussion of the results.

Exploration tendencies

We first briefly look at the exploration strategies to investigate whether the classical organizational ambidexterity paradox—the tradeoff between exploration and exploitation—applies to situations in the presence of competition and adaptability. Figure 6 demonstrates the average performance as a function of the exploration strategy (τ), which visualizes the tradeoff between exploration and exploitation and the advantage of imitation. The advantage of imitation (*imitate the best/big/crowd*) is more salient with small τ : *imitate the best* slightly outperforms *imitate the big*, while both lead to significantly better performance than *imitate the crowd*. These differences dissipate as τ increases.

[Insert Figure 6 about here]

Even in the presence of organizational interdependence, we still observe the classical

¹ To make sure that the treatment effect is directly comparable and not caused by the randomness in the bandit problem and the initial conditions, we generate 500 industries, each faced with a different bandit problem, and assign them to each of the four different treatment conditions and ten sets of learning strategies for solving. In the computational model, the same seed is used for the random number generator when an industry is assigned to different treatment conditions or learning strategies. We are, therefore, confident that any treatment effect is caused only by the imitation modes and learning strategies, not by the inherent randomness in the model.

tradeoff between exploration and exploitation that has been documented in previous studies (Denrell & Fang, 2010; Levinthal & March, 1993; March, 1991; Posen & Levinthal, 2012; Raisch et al., 2009). Under all imitation modes, the functions exhibit an inverted-U shape: exploring either too little or too much undermines performance. At low levels of exploration, the firm has little knowledge to exploit; at high levels of exploration, the firm has abundant knowledge, but it is never exploited to enhance performance.

It is interesting to observe that inter-firm learning reduces the level of exploration necessary to achieve the best performance: when only intra-firm learning is allowed, the best exploration strategy is $\tau = 0.2$; when inter-firm imitation is possible, the best exploration strategy reduces to $\tau = 0.1$. In a sense, revealing the choice of a better-performing firm substitutes for a firm's individual exploration. Revealing information improves performance because the most popular choice, as well as the choice of the best-performing firms, is likely to be the optimal choice, and imitation helps the firms to explore and identify the optimal choice. This holds true even when competition reduces the returns from a choice when a large number of firms make the same choice.

Imitation strategies

Figure 7 demonstrates the time series of the average payoffs under different imitation modes and imitation strategies λ . Because inter-firm imitation is nonexistent in the *no imitation* treatment, the imitation strategy does not influence behaviors and the function demonstrates a horizontal line. Moreover, the behaviors and performance in all treatments overlap when $\lambda = 0$. Under all imitation modes and exploration strategies, we observe that the average payoff has an initial jump and then gradually stabilizes. It seems that as the probability of imitation λ increases, the average payoff observes a sharper initial increase, but the long-run performance is undermined.

[Insert Figure 7 and Figure 8 here]

Figure 8 visualizes this tendency by showing the average performance as a function of the exploration strategy (λ) separately for the first 50 periods and the last 50 periods. In both time spans, the function exhibits an inverted-U shape: either too much or too little imitation would negatively influence performance. Note that the imitation strategy that maximizes the expected payoff in the first 50 periods is $\lambda = 0.5$ under all imitation modes, while the strategies that maximize the expected payoff in the last 50 periods is $\lambda = 0.02$. This temporal comparison provides an important insight: active imitation without individual exploration is likely to be effective in the short run but self-defeating in the long run.

Conformity-Differentiation Tradeoff

Because of competition, inter-firm imitation and the ensuing conformity cannot guarantee a performance improvement. Figure 9 provides the distributions of choices in the last five periods of each simulation under different imitation modes, along with the optimal distribution of choices that brings the best industry performance.²

Recall that the choices towards the left generally lead to higher expected payoffs, while too many firms adopting the same choice reduces their return because of the increased competition. This optimal distribution, which takes into consideration the conformity-differentiation tradeoff, is almost impossible to achieve due to the uncertainty inherent in the bandit problems and the interdependence of firms' decisions: when one firm switches to another choice, it significantly changes the average return of different choices due to the changed level of competition. It is obvious, however, that inter-firm learning significantly improves the balance between conformity and differentiation: while without imitation, firms place too much weight on the underperforming choices, inter-firm learning significantly shifts the distribution of

² Only the frequencies of the first 30 choices are shown for clarity: the frequencies of the last 30 choices are negligible, and the optimal distribution would assign zero frequencies to these choices. The optimal distribution is averaged over all the 500 bandit problems.

choices towards the left, closer to the optimal distribution. This shift is more salient under the *imitate the best* and *imitate the big* modes than under *imitate the crowd*.

[Insert Figure 9 and Figure 10 about here]

Figure 10 further demonstrates the expected payoffs given by the corresponding distributions of choices under different imitation modes. Although the expected payoffs with inter-firm learning still fall short of the optimal payoff, it significantly increases the expected payoff compared to intra-firm learning alone in the presence of the conformity-differentiation tradeoff.

4.3 Simulation Results

Our simulation extends the previous organizational learning models (Levinthal & March, 1993; March, 1991; Posen & Levinthal, 2012) by adding inter-firm learning possibilities, adaptability concerns, and competition. We conduct additional experiments with different hierarchical structures of the bandit problem ($A = 60, B = 1$, and $A = 12, B = 5$) and different specifications for competition. The general conclusions are similar, demonstrating the robustness of the results.

The computational experiments provide strong evidence that inter-firm sharing greatly facilitates the tradeoff between conformity and differentiation, greatly improving the overall performance of individual firms and the industry as a whole.

Several insights can be derived. First, the simulation results confirm *Proposition 2*: the tradeoff between experimentation and imitation is inherent in the conformity-differentiation paradox, and this tradeoff can be considered the classical exploitation-exploration tradeoff at both the firm and industry levels. A firm can achieve optimal distinctiveness through an appropriate balance between intra- and inter-firm learning. Imitation helps a firm utilize industry knowledge to improve its performance, but if all firms only resort to imitation without independent experimentation, the knowledge pool in the industry will be drained and become

ineffective in generating advancement. As shown in Figure 8, overreliance on imitation can help a firm catch up to the leaders in the short run but undermines its long-run performance.

Second, inter-firm imitation, when its frequency is kept low, helps firms and the industry balance conformity and differentiation. As we have emphasized all along, inter-firm imitation has two opposite effects: it both enhances the adaptability and intensifies competition. Our experiment shows, however, that low frequency of imitation helps promote firms' performance by achieving an appropriate level of distinctiveness. In comparison to the situation in which firms conduct only intra-firm learning (*no imitation*), when firms engage in inter-firm learning, they adopt technologies that bring higher returns while keeping the negative effect of competition low.

Third, the results show that *imitate the best* generally outperforms *imitate the big*. An important insight for managers is to try to identify the firm that recently performed well instead of the leaders with years of reputation or accumulated success. Finally, as Figure 6 shows, even after introducing the competition and adaptability concerns, the tradeoff between exploitation and exploration, as documented by March (March, 1991), still exists, demonstrating the generality and prevalence of this classical ambidexterity issue. We hereby propose:

Proposition 3: Inter-firm learning opportunities tend to help a focal firm achieve its optimal distinctiveness. Yet overreliance on exploiting existing industry knowledge may hurt the focal firm's performance in the long run.

Proposition 4: Imitating the leading firm with the best recent performance can better facilitate the optimal distinctiveness of a focal firm.

5. Discussion and Conclusion

5.1 Overall Discussion

This study seeks to unfold the conformity-differentiation paradox through the perspective of organizational learning. We focus on a research setting in which, with little prior knowledge, nascent industry firms need to manage the classic organizational ambidexterity issue: i.e.,

experimenting between various technological trajectories in different technological areas. Meanwhile, as firms strive to strategically position themselves as distinctively as possible while remaining adaptability, they also face the challenge of balancing conformity with differentiation. The tension is probably more salient in nascent technological areas in which innovation diffusion and market acceptance are important for both individual performance and industry development.

The case evidence suggests that the key to managing the conformity-differentiation paradox is to balance exploitation with exploration at the industry level. Technological conformity is suggested at the upstream bottleneck technological domain. We find that the convergence in trajectory choice allows firms to exploit collective experiences at the industry level—just as it helped the mc-Si group to quickly improve its industrial performance and market share. Besides differentiating firms' choices in the downstream market, firm-level experimentation has an unintended by-product of exploring novel opportunities and enriching the knowledge pool for the whole industry.

The follow-up computational simulation proves the case findings that when imitation opportunities are available, both individual firms and the whole industry can improve their performances. Yet the imitation tendency—or, in other words, the reliance on inter-firm learning—should be kept relatively low, and overreliance on imitation may deteriorate long-run performance. This is in line with Lazer and Friedman's (Lazer & Friedman, 2007) study on how knowledge dissemination impacts the exploitation-exploration tradeoff under different network structures. Further, our simulation allows us to distinguish and compare different imitation modes and suggests that learning from and adopting the experiences of the organizations with the best recent performance can best help firms to reach optimal distinctiveness.

5.2 Reflection on Paradox

The paradoxical opposites—i.e., exploitation vs. exploration, and conformity vs. differentiation—in both the case and the simulation findings are shown to be both conflicting and complementary. For example, differentiation and intra-firm learning, without considering others' choices and adaptability, may harm competitiveness, while overreliance on inter-firm learning may deteriorate performance. Thus, we argue that it is insufficient to treat the conformity-differentiation balance as an “*either/or*” choice, or to simply apply the *separation* mechanism suggested by some paradox literature (e.g., Raisch et al., 2009; Schad, Lewis, Raisch, & Smith, 2016). The “*either/or*” notion neglects the co-existent nature of paradoxical opposites and fails to leverage the complementarity between them.

As discussed in Section 2, most existing optimal distinctiveness studies treat a paradox as a unidimensional continuum: balancing a paradox is to find the optimal cutting point while walking along the tightrope (Deephouse, 1999; Haans, 2018; Zhao et al., 2017). In contrast, our findings and theoretical propositions suggest that the conformity-differentiation paradox and the exploitation-exploration paradox are multifaceted and multi-dimensional. The paradoxical opposites co-exist at both the intra-firm and the inter-firm levels, and the co-existence persists at different but interdependent technological domains.

The paradox of conformity and differentiation is then reconciled with *asymmetrical* focuses on cross-level learning behaviors. Conformity, i.e., convergence in the upstream bottleneck technologies, relies largely on inter-firm learning; however, intra-firm learning still plays an important role. Similarly, differentiation in downstream product development and market segmentation relies mainly on intra-firm learning, but the achieved divergence is also based on a certain consensus. Demonstrating asymmetrical focuses at the upstream and downstream of the value chain is also in line with the suggestion of Mudambi et al. (2018).

Further, the study shows the inherent connection between the organizational ambidexterity

paradox and the conformity-differentiation paradox: managing the conformity-differentiation paradox relies on balancing exploitation and exploration at cross levels. As March suggested (Levinthal and March 1993, March 1991), learning is dynamic and evolutionary in nature. Thus, the conformity-differentiation paradox should also be scrutinized through a dynamic lens. As our simulation results show, firms' imitation tendencies influence the dynamic interactions between firms in the same industry and give rise to contrasting performances in the short run vs. the long run. That is to say, the benefit of imitation and the dominance of the conformity strategy may shift in the long run, demonstrating a *transitional* mechanism.

Our study, in general, suggests that the conformity-differentiation balance should consider both contradiction and complementarity, which is in line with Smets et al. (2015) and Lin et al. (2015). This is illustrated in the case and further proven by our simulation results. When considering the interdependence between adaptability and competition, there is an inverted U-shaped relationship between the industry-level exploitation-exploration tradeoff and business performance. The curvilinear relationship indicates that the two opponents of conformity and differentiation are contradictory for tradeoff and complementary for synergy (Li, 2014). This is also in line with the Chinese wisdom of Yin-Yang (Li, 2014; Li, Leung, Chen, & Luo, 2012). As in the Yin-Yang framework, the results from our study demonstrate both the tradeoff and synergy between paradoxical elements, and provide evidence in support of the asymmetrical, transitional, and curvilinear balancing mechanisms (Li, 2014), especially from the cross-level perspective.

5.3 Contributions and Implications

Integrating the paradoxes of organizational ambidexterity and conformity-differentiation balance, this study identifies two learning mechanisms across the levels of firm and industry, i.e., intra-firm experimentation and inter-firm imitation. Such learning mechanisms can shed light on how to explain and manage the dynamic and multiplex features of both organizational

ambidexterity and conformity-differentiation balance, especially concerning the optimal distinctiveness in strategic balance. Hence, this study contributes to the general research on organization by bridging the theoretical bifurcation between institutional theory and strategy management via organizational learning (McKnight & Zietsma, 2018; Zhao et al., 2017).

First, we enrich March's exploitation-exploration model by adopting the lens of cross-level learning. March's original model focuses primarily on intra-firm experiential learning, but it is imperative to recognize the salience of organizational interdependence and inter-firm interaction. We incorporate inter-firm learning into March's original model and examine the effects of learning at the cross-levels. Specifically, when experimentation and imitation are possible, the classical balance between exploitation and exploration may exhibit different effects at the firm and the industry levels: while experimentation is often exploitative at the firm level but exploratory at the industry level, imitation is often exploratory at the firm level but exploitative at the industry level. Hence, the enriched learning model helps us obtain a more comprehensive picture and deeper understanding of organizational ambidexterity by linking it with the conformity-differentiation paradox. This is the primary contribution of this study.

Second, the study makes a timely attempt to explain the conformity-differentiation paradox from the perspective of organizational learning. We find that the balance between conformity and differentiation can be reframed as the classical balance between exploitation and exploration across the levels of firm and industry, demonstrating the inherent connection between the paradoxes of organizational ambidexterity and conformity-differentiation balance. Specifically, this study reveals that intra-firm experimentation and inter-firm imitation serve as the two core mechanisms underlying the optimal distinctiveness in strategic balance. In this regard, the three specific mechanisms of *yin-yang* balancing (i.e., asymmetrical, transitional, and curvilinear balancing) shed light on how to achieve the optimal distinctiveness in the

conformity-differentiation paradox by specifying the thresholds of appropriate balancing under different boundary conditions. For example, both intra-firm experimentation and inter-firm imitation are like double-edged swords: conformity through inter-firm imitation can improve firms' performances by facilitating adaptability up to a point, but beyond that point it will reduce firms' performances by intensifying competition; differentiation through intra-firm experimentation can improve firms' performance by fostering healthy competition up to a point, but beyond that point it will reduce firms' performance by suppressing adaptability. Further, the curvilinear tradeoff between exploitation and exploration remains robust when extending March's original model to a cross-level and multi-dimensional setting with adaptability and competition considerations. Hence, March's model has the potential to explain and manage paradoxes other than organizational ambidexterity, such as the paradox of transaction cost and transaction value (Li, 1998; Li, Li, Liu, & Yang, 2010).

In practical terms, this study also sheds light on how firms in nascent industries should strategize their learning behaviors when faced with both adaptability and competitive differentiation requirements. First, for a nascent industry with limited legacy and prior knowledge, knowledge sharing, even with competitors, can help individual firms, as well as the whole industry, to lower the exploration costs and improve performance. Such inter-firm sharing is more relevant to bottleneck technologies or technological domains that are crucial for the formation of industrial standards.

Second, while March highlights the "success trap" caused by staying in the firm's current comfort zone, our findings warn firms to avoid the "imitation trap." When collective experiences are available to be shared, firms should keep the imitation tendency at a relatively low level to ensure long-run performance. Moreover, when few variations exist in an environment with few dominant leaders, lead firms may lure the whole industry into a trap that harms innovation and long-term performance. Although firms tend to follow the long-

established giants with accumulated success, our findings suggest following the “rising stars,” firms with the best recent performance, regardless of their reputation or size. Take the development of the mobile phone industry as an example. Apple launched the first iPhone in 2007 and drew widespread attention, even though, at that time, Nokia’s dominance in mobile phones was undoubtable. For a mobile phone manufacturer, the wise choice was to follow Apple’s emerging smartphone trajectory rather than staying in the traditional cellphone camp with giants such as Nokia and Motorola.

5.4 Conclusion and Future Research

To answer the research question of *how firms manage the differentiation-conformity tension through cross-level learning behaviors*, we adopted a mixed-method design. We first conducted a case study on the Chinese PV industry to provide a contextual setting for technological trajectory choice and learning. We further conducted a computational simulation to investigate the extent to which firms should rely on inter-firm learning (imitation) and from whom they should learn, in order to manage the conformity-differentiation paradox for the best performance. This study demonstrates that it is highly fruitful to integrate the theoretical streams on institutional theory, strategy, and organizational learning. In particular, the organizational ambidexterity paradox can be linked with the conformity-differentiation paradox to shed light how to enrich the research streams on both paradoxes.

The study focuses on one specific form of inter-firm learning: imitation. Imitation is closely related to the concept of vicarious learning in the organizational learning literature (Baum et al., 2000; Ingram & Baum, 1997). Besides, imitating or adopting others’ experiences is in line with the inbound or “outside-in” mode of open innovation (Felin & Zenger, 2020; West & Bogers, 2014). Future research can investigate whom firms should imitate in open innovation and also the optimal degree of openness. This line of research can shed further light on the research streams of absorptive capacity (Cohen & Levinthal, 1990; Zahra & George,

2002) and dynamic capabilities (Teece, 2007; Teece, Pisano, & Shuen, 1997).

The positive effect of imitation depends on the diversity of the firms in the industry, and the level of diversity in turn depends on how firms balance between imitation and experimentation, as well as how they balance between exploration and exploitation during firm-level experimentation. In the current study, we assume that firms' tendencies for exploration and imitation are exogenously determined. In order to deepen our understanding of these paradoxes, future studies can allow firms to actively adapt these tendencies while searching for the optimal distinctiveness.

Our computational experiments assume a relatively low intensity of competition across organizations. This is appropriate for an emerging industry such as the PV industry, in which competition across organizations is mild compared to their collective effort to establish adaptability. The Chinese photovoltaic industry is now striving for the adaptability of the whole industry—i.e., the grid-parity—so its leading firms are more willing to share their knowledge to promote the adaptability of both the technology and the industry. As an industry becomes more established, competition within that industry intensifies, the balance may be tilted towards differentiation, although the trade-off between conformity and differentiation still exists. Moreover, in the presence of intense competition, it is questionable that the lead firms of an industry that has already established industry-level adaptability would still be willing to voluntarily share their information and knowledge. Future research can consider the possibility that an organization can choose whether to share its information and how leading firms' tendency to share can influence the effect of inter-firm learning. In addition, it could take into account of the impact of environmental turbulence and investigate the effect of heterogeneity on firms' learning capacity, imitation tendencies and aspirational levels.

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Appendix. Description of the computational model

Hierarchical decision structure

A firm needs to first choose a primary trajectory $i \in \{1, 2, \dots, A\}$ and then determine a complementary technology $j \in \{1, 2, \dots, B\}$. To facilitate exposition, for the rest of this paper, we will call the A primary technological *trajectories* and the B complementary technologies *alternatives*, and we will simply say *technological combinations* or *choices* when referring to any of the total AB choices without referring to the hierarchical structure.

The payoff from a choice (i, j) follows a normal distribution with the mean $\mu_{i,j}$ and unit variance. The mean of this distribution is determined as follows. The average payoffs from each technological path μ_i are drawn independently from a normal distribution with a zero mean and a variance δ_A^2 , while the average payoff for each sub-alternative under the i -th alternative $\mu_{i,j}$ is drawn independently from a normal distribution with the mean μ_i and a variance δ_B^2 .

Without loss of generality, we order the alternatives by their average payoff, so $\mu_1 > \mu_2 > \dots > \mu_A$ and $\mu_{i,1} > \mu_{i,2} > \dots > \mu_{i,B}$ for $i = 1, 2, \dots, A$. In other words, the average payoff of the alternatives decreases with its index, and the average payoffs of the sub-alternatives under each alternative also decreases with its index. The average payoff of the i -th alternative μ_i is greater than that from an inferior alternative μ_{i+1} . However, it is still possible that the best alternative in the $(i+1)$ th trajectory has a greater average payoff than the worst alternative in the i th trajectory ($\mu_{i,B} < \mu_{i+1,1}$).

The organization forms its beliefs about the expected returns from these alternatives based on its previous experiences. It can choose to exploit its current knowledge by choosing the alternative that is believed to be the best, or to explore other alternatives to obtain more-accurate beliefs, with the hope of identifying a better alternative with a higher payoff.

The state of the environment can be represented as the expected payoffs from each of these

alternatives $\mu = [\mu_{1,1}, \dots, \mu_{1,B}, \mu_{2,1}, \dots, \mu_{A,B}]$. Beliefs and decision rules are the two central components of experiential learning. Beliefs at time t , $q_t = [q_{1,1,t}, q_{1,2,t}, \dots, q_{A,B,t}]$, are a subjective assessment of the expected payoffs of the alternatives. Beliefs are initialized as the expected payoffs of the alternatives—a zero vector in our setting. Denote $s = (i, j)$. If a firm receives a payoff R_t from choice s , its belief is updated as follows:

$$q_{s,t+1} = q_{s,t} + a(R_t - q_{s,t}),$$

where $0 \leq a \leq 1$ is the rate of updating: in light of the new payoff R_t , the belief is updated in the direction of the new payoff. The parameter a represents the weight placed on the most recent experience: if $a = 1$, then the new belief is always the same as the most recent payoff; if $a = 0$, then the belief is never affected by the new experience. If $0 < a < 1$, the new belief is a weighted average of the old belief and the new payoff. In the experiment, we use $a = \frac{1}{k_s+1}$, where k_s is the number of times alternative s has been chosen before, so the belief is the average of all the previous experienced payoffs. For all the other alternatives that are not chosen in period t , beliefs do not change: $q_{s',t+1} = q_{s',t}, \forall s' \neq s$.

In each period t , a firm first chooses an alternative i with the following probability based on the SoftMax rule (Fang & Levinthal, 2009; Posen & Levinthal, 2012)

$$p_i = \frac{e^{\bar{q}_i/\tau}}{\sum_k e^{\bar{q}_k/\tau}},$$

where $\bar{q}_i = \frac{1}{B} \sum_j q_{i,j}$ is the belief of the average payoff of all i 's sub-alternatives, and τ is a parameter reflecting the firm's tendency for exploration. When $\tau \rightarrow 0$, the firm uses a greedy strategy and chooses the alternative it believes to be the best with certainty. When $\tau \rightarrow \infty$, all the alternatives are chosen with the same probability, regardless of the beliefs on their expected payoff, and the firms take the time to explore all the alternatives.

After choosing alternative i , the firm uses the same rule in choosing a sub-alternative j with the following probability conditional on i is chosen:

$$p_{i|j} = \frac{e^{q_{i,j}/\tau}}{\sum_k e^{q_{i,k}/\tau}},$$

In addition to intra-firm learning, a firm can also choose to imitate the choice made by other firms. A firm's learning strategy can be characterized by its exploration tendency τ , defined above, and its imitation tendency λ , which denotes the probability that a firm will decide to engage in inter-firm imitation instead of intra-firm learning in a period. As mentioned above, firms have information only on the level-1 choice of other firms and can, therefore, only imitate the level-1 choice. When a firm decides to engage in inter-firm imitation in a period (with probability λ), instead of using the decision rule, it will copy the level-1 choice of the imitation target. This adaptive and iterative process of organizational learning is illustrated in Figure A1.

Adaptability and the experience curve effects

When a new technological trajectory $i \in \{1, 2, \dots, A\}$ emerges in an industry, it incurs an adoption cost of c_A for all firms adopting this technology, and this cost decreases with the number of times the technology has been adopted by firms in the industry as the technology has become more mature. This adoption cost decreases in the following manner:

$$c_{i,t}^A = c_A \beta^{(k_{i,t}-1)},$$

where $k_{i,t}$ represents the number of times technology i has been chosen by all firms in the industry at time t ; the parameter β ($0 \leq \beta \leq 1$) measures the intensity of the experience curve effect, and a smaller β represents steeper learning curves. Similarly, when an organization f starts to adopt a new technology $s \in \{(i, j) | i \in \{1, 2, \dots, A\}, j \in \{1, 2, \dots, B\}\}$, it bears an adoption cost of c_B , and this cost decreases exponentially over time as an organization becomes more adept in the use of this technology.

$$c_{f,s,t}^B = c_A \beta^{(k_{f,s,t}-1)},$$

$k_{f,s,t}$ represents the number of times technology s has been chosen by firm f at time t . Based

on empirical evidence from previous studies, we set $\beta = 0.8$ (The Boston Consulting Group, 1970), $c_A = 2$, and $c_B = 1$.

Competition

When firms choose the same market, that increases competition with the incumbents. The payoff that a firm receives from the bandit problem is discounted by the number of existing firms in the market.

Suppose that, in time t , firm f chooses alternative s , and a total of $n_{s,t}$ firms choose the same alternative. Without competition, the payoff received by firm f is $R_{f,s,t}$, which is determined from the random draw from bandit s minus implementation costs. Competition would negatively influence the payoff and be [?] discounted by a factor $\delta^{n_{s,t}-1}$, where $0 < \delta < 1$ measures the intensity of competition. In other words, if there is only one firm that chooses s in period t , the payoff will not be influenced, while an increasing number of firms choosing the same action discounts the payoff received by the firm.

To model the first-mover advantage, we also assume that the payoff is partially dependent on how long a firm has been in the corresponding market. Denote $k_{f,s,t}$ as the number of times firm f has chosen alternative s so far; and $\bar{k}_{f,s,t} = \frac{1}{n_{s,t}} \sum_{f'} k_{f',s,t}$ as the average number of times alternative s has been used by all $n_{s,t}$ firms. Combining these two effects, the payoff received by firm f in period t can be expressed as

$$R_{f,t} = \frac{k_{f,s,t}}{\bar{k}_{f,s,t}} R_{f,s,t} \delta^{n_{s,t}-1}.$$

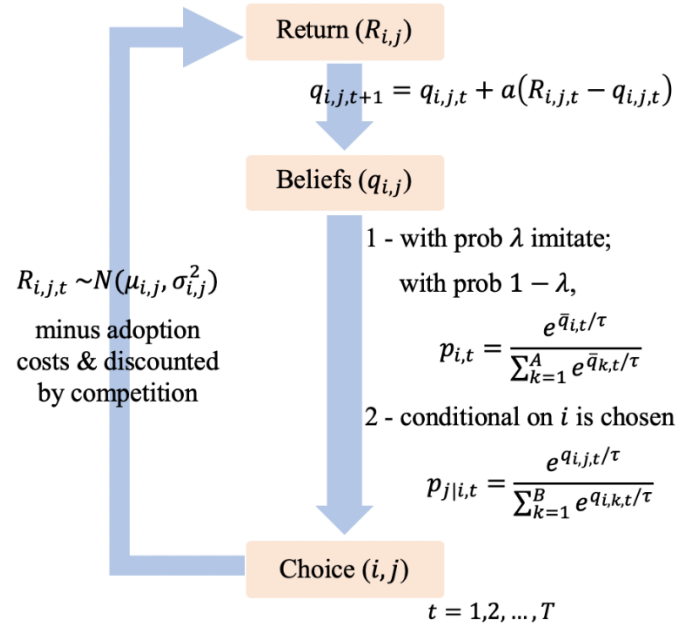


Figure A1. The adaptive process of organizational learning. In each period t , an organization chooses an alternative i, j based on its beliefs $q_{i,j,t}$ (with probability $1 - \lambda$) or based on imitation (with probability λ). The return from this alternative is drawn from a normal distribution, minus adoption costs, and discounted by competition. The return influences the belief $q_{i,j,t}$ on the expected return, which, in return, changes the probability that each alternative is chosen.

Tables and Figures

Table 1. Summary of interviews.

Interviewee	Time	Company	Interviewee Position	Length
I1	2018.07	GCL	Deputy Manager	65 min
I2	2019.01	SL	Vice president	50 min
I3	2019.01	SL	Technical Manager	30 min
I4	2019.01	GCL	Deputy Manager	30 min
I5	2019.01	AK	Production Director	60 min
I6	2019.01	AK	Technical Director	60 min
I7	2019.01	JY	Vice president	60 min
I8	2019.01	JY	R&D Manager	30 min
I9	2019.01	JY	Project Manager	30 min