


Optimal distinctiveness in platform markets: Leveraging complementors as legitimacy buffers

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Abstract

Research summary: Optimal distinctiveness theory highlights that firms need to balance opposing pressures for differentiation (to gain competitive benefits) and conformity (to gain legitimacy). Yet, extant optimal distinctiveness research rarely considers that the pressure for conformity can substantially vary between competing firms. Studying the positioning and growth performance of competing platforms in the market for Massive Open Online Courses (MOOCs), we find that platforms' access to high-status complementors—a common source of legitimacy in platform markets—substantially shapes the relationship between platforms' distinctiveness and user growth. Our longitudinal models show that platforms only benefit from a (moderately) distinctive positioning once they have buffered a certain amount of legitimacy. Our findings strongly suggest that firms can alleviate conformity pressures by accessing alternative sources of legitimacy.

Managerial summary: When does differentiation pay off? We study this question in the increasingly important context of platform markets to explain differences in platforms' user growth. Our longitudinal study of

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competition in the market for Massive Open Online Courses (MOOCs)—in which platforms like Coursera and Udacity compete for online learners as users—shows that the performance implications of a distinctive positioning substantially depend on the legitimacy that a platform has gained from attracting high-status organizations as complementors. Platforms only benefit from differentiation once they surpass a certain legitimacy threshold, and the legitimacy they gain beyond this threshold accelerates the benefits of a (moderately) distinctive positioning.

KEYWORDS

differentiation, institutional theory, legitimacy, platforms, positioning

1 | INTRODUCTION

When and to which degree should firms differentiate their strategic positions? Differentiated positions can create both benefits and liabilities because they reduce competitive pressure (Porter, 1980, 1985) but can also indicate a lack of conformity and may therefore threaten the firm's *legitimacy* (Deephouse, 1999). Optimal distinctiveness theory highlights this tension and proposes that there exists an “optimal” level of distinctiveness at which firms can balance the opposing pressures for differentiation and conformity—a proposition that has gained much currency in strategic management and organization theory (for a review, see Zhao, Fisher, Lounsbury, & Miller, 2017).

Recent optimal distinctiveness research started to challenge the assumption that there exists a stable level of optimal distinctiveness (Barlow, Verhaal, & Angus, 2019; Haans, 2019; Zhao, Ishihara, Jennings, & Lounsbury, 2018). This line of research suggests that the relative benefits (reduced competition) and liabilities (reduced legitimacy due to insufficient conformity) of distinctiveness can systematically differ between market categories (Haans, 2019) and may change over time as a market category becomes more institutionalized and crowded (Zhao et al., 2018). What is typically less accounted for is that the liabilities of distinctiveness can substantially vary within a market because conformity only represents only one potential *source of legitimacy* (Aldrich & Fiol, 1994). The degree to which a firm can tap into other sources of legitimacy (i.e., apart from conformity) will therefore determine the firm's pressure for conformity and should consequently determine the extent to which distinctiveness will reduce legitimacy. This oversight matters because what constitutes an optimally distinctive position for one firm may result in poor performance outcomes for other firms in the same market.

We develop our arguments by theorizing about the optimal distinctiveness of positions in platform markets, that is, product markets in which the focal firms (*platform providers*) enable and facilitate transactions of goods and services between external producers (*complementors*) and demand-side customers (*users*) via a technological product. Platform providers can gain legitimacy by attracting complementors with high organizational status (*high-status*

complementors) because affiliations with such organizations generally provide an important “stamp of approval” (Stuart, Hoang, & Hybels, 1999). Focusing on this important source of legitimacy in platform markets, we explore how affiliations with high-status complementors shape the relationship between platforms’ distinctiveness—in terms of the positioning of their complement portfolios—and user growth. Our main proposition is that alternative sources of legitimacy—such as affiliations with high-status complementors—shield to some degree against a loss of legitimacy due to distinctive (i.e., nonconforming) positioning because such *legitimacy buffers* will expand the *range of acceptability* within which a platform can differentiate its position without sacrificing its legitimacy (Deephouse, 1999; Fisher, Kotha, & Lahiri, 2016; Haans, 2019). Buffered legitimacy, we argue, therefore allows platform providers to derive greater benefits from a (moderately) distinctive positioning.

Our empirical study of competition in the market for Massive Open Online Courses (MOOCs) between 2013 and 2017 provides strong support for our proposition. In this market setting, platform providers like Coursera, Udacity, edX, and FutureLearn—and their respective complementor ecosystems—offered competing MOOCs portfolios to attract users to their platforms. The context is highly insightful for our research purpose because some platform providers compete with relatively undifferentiated portfolios, in which they offer MOOCs across nearly all subject genres, while others carved out distinctive market positions. For instance, *Udacity* differentiates its platform by focusing on MOOCs related to programming and computer science, while *Kadenze* focuses on MOOCs related to arts and music. Our sample consists of 12 competing MOOC platforms, which partnered with 963 complementors, including high-status organizations like MIT, Stanford, Microsoft, and Google, and launched 5,871 new MOOCs during our main observation period (2013–2017). Combining different data sources allowed us to reconstruct each MOOC platform’s complete portfolio of actively delivered MOOCs and complementor affiliations in order to calculate the distinctiveness of MOOC platforms’ complement portfolio and ecosystem characteristics for each given month. Our fixed effects times series models, which predict the number of platforms’ monthly active users, allowed us to fully isolate our main relationships from network effects, changes in the MOOC market’s legitimation and competitive pressure, and unobservable temporal dynamics at the market level.

Our study finds that distinctiveness has a negative effect on user growth for platforms that lack any high-status complementors in their ecosystem—suggesting that the liabilities of distinctiveness (reduced legitimacy) fully exceed the competitive benefits of distinctiveness for platforms without such a legitimacy buffer. In turn, we find an inverted U-shaped relationship between distinctiveness and user growth for platforms that attracted a minimum share of high-status complementors—suggesting that platforms with such a legitimacy buffer can convey some degree of nonconformity without sacrificing their legitimacy. An increase in the share of high-status complementors also leads to a substantial steepening of the inverted U-shaped relationship between distinctiveness and user growth for such platforms—suggesting that a moderately distinctive position enhances user growth the more a platform has buffered legitimacy through high-status complementors. This contingency is of high practical significance because a standard deviation increase in distinctiveness (from low to moderate) increases the expected number of platform users by 1.7 million (+55.1%) for platforms with an above-average share of high-status complementors, but decreases the number of users by 2.9 million (−53.5%) for platforms without high-status complementors in their ecosystem. These findings strongly suggest that access to even one alternative source of legitimacy—high-status complementors—can provide a buffer against an immediate loss in legitimacy, and such legitimacy buffers increase—to

a certain degree—the optimal level and performance benefits of distinctiveness. These findings have important implications for research on optimal distinctiveness (Barlow et al., 2019; Haans, 2019; Tauscher, Bouncken, & Pesch, 2020; Zhao et al., 2018) because they draw attention to intra-market heterogeneity in firms' optimal distinctiveness—highlighting firms' legitimacy buffers as an important contingency for the theorized trade-off between differentiation and conformity.

2 | THEORY AND HYPOTHESES

2.1 | Positioning in platform markets

Our theorization focuses specifically on the performance consequences of distinctive positioning in platform markets. Following the common conceptualization in strategic management (McIntyre & Srinivasan, 2017), we refer to *platforms* as technological products that serve to enable and facilitate transactions of goods or services (*complements*) between independent producers (*complementors*) and demand-side customers (*users*). Exemplary platform markets include the market for online food delivery—where platform providers like Grubhub facilitate transactions of meals between restaurants and consumers—or the market for crowdfunding—where platform providers like Kickstarter facilitate financial transactions between crowdfunders and crowdfunding-seeking ventures. To distinguish the context from related ones, strategic management scholars sometimes also specify such platforms and platform markets as transaction platforms (Dushnitsky, Piva, & Rossi-Lamastra, 2020) and multisided transaction markets (Cennamo, 2019).

Platform providers generally act as gatekeepers that deploy governance rules to strategically influence the type of complementors and complements they attract to their platform (Claussen, Kretschmer, & Mayrhofer, 2013; Logue & Grimes, 2019; Rietveld, Schilling, & Bellavitis, 2019; Zhang, Li, & Tong, 2020). For instance, platform providers in the video game market can restrict platform access to games of one specific genre (e.g., sports) in order to carve out a distinctive position in the market (Cennamo & Santaló, 2013). Following previous research on platform competition (e.g., Cennamo & Santaló, 2013; Seamans & Zhu, 2014, 2017), we thus focus on positioning at the level of complement portfolios and conceptualize *distinctiveness* as the degree to which a platform's complement portfolio deviates from the market's average complement portfolio.¹

A key feature of platforms is that they generate positive network externalities between complementors and users (Boudreau & Jeppesen, 2015; Clements & Ohashi, 2005; Corts & Lederman, 2009; Eisenmann, Parker, & van Alstyne, 2011). Given these indirect network effects, platforms generally become more attractive to users if they attract additional complementors and vice versa (Boudreau & Jeppesen, 2015). Under the presence of strong network effects, a platform market may even generate winner-take-all dynamics (Schilling, 2002), through which the platform with the largest network will eventually dominate the market

¹A general caveat in research on strategic positioning is that the observed distinctiveness of a market position does not necessarily result from a deliberate strategic decision but may also emerge unintentionally (Mintzberg, Ahlstrand, & Lampel, 2009). This caveat also applies to platform markets, where a platform may attract a distinctive complement portfolio without the strategic intent to do so. While a distinctive complement portfolio likely indicates a platform provider's differentiation strategy, we do not rely on such an assumption in our subsequent theorization.

(Sun & Tse, 2007). These market characteristics generally incentivize platform providers to rapidly grow their user base and complementor network (Cennamo & Santaló, 2013). The imperative for rapid growth is further accelerated for platforms provided by new ventures, who commonly prioritize rapid user growth over profitability (Huang, Henfridsson, Liu, & Newell, 2017). Our subsequent theorizing thus focuses on *user growth* as a critically important performance outcome in platform markets.

2.2 | Distinctiveness and user growth

Optimal distinctiveness theory provides a powerful theoretical perspective to study the performance implications of distinctiveness (Zhao et al., 2017). Integrating arguments from strategic management and institutional theory, the theory suggests that the relationship between distinctiveness (i.e., nonconformity) and firm performance is mediated by a positive and negative mechanism because distinctiveness reduces competitive pressure, but a lack of conformity also decreases the firm's legitimacy in the market (Deephouse, 1999). Applying the proposition to our context implies that distinctiveness—as a characteristic of a platform's positioning—will reduce both the platform's competitive pressure and legitimacy. The left plots in Figure 1 graphically illustrate these two mechanisms, with the gray line representing the effect of distinctiveness on competition—expressed in positive terms as *competitive benefits*—and the solid black line representing the negative effect of distinctiveness on *legitimacy*. We subsequently discuss

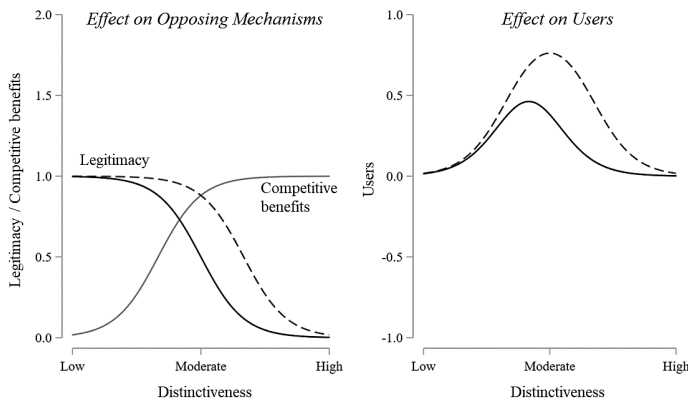


FIGURE 1 Graphic illustration of the theorized effects of distinctiveness. *Note:* The illustration is inspired by Haans (2019) but differs in that the positive mechanism (*Competitive benefits*) is inverted to facilitate the illustration of the shift in the *Legitimacy* curve. The illustrative curves in the left-hand plot represent a platform's *Legitimacy* and *Competitive benefits* as an inverse logit function $(\exp(b_0 + b_1X + b_2X^2))/(1 + (\exp(b_0 + b_1X + b_2X^2)))$, where X represents *Distinctiveness* and is bounded to values between 0.0 (low) and 1.0 (high). We specified the beta coefficients for the inverse logit function for *Competitive benefits* (gray line) as $b_0 = -4$, $b_1 = -12$, and $b_2 = 0$. We specified the beta coefficients for the inverse logit function of *Legitimacy* in baseline Scenario 1 (solid line) as $b_0 = 6$, $b_1 = -12$, and $b_2 = 0$, and the corresponding beta coefficients for Scenario 2 (with legitimacy buffer, dashed) as $b_0 = 8$, $b_1 = -12$, and $b_2 = 0$. The right-hand plot represents the sum of *Competitive benefits* and *Legitimacy* for the baseline scenario (solid line) and Scenario 2 (dashed) to illustrate a relative change in a platform's number of users. In both scenarios, *Competitive benefits* are assumed to be equal or larger than the loss of *Legitimacy*

the key assumptions underlying these two mechanisms to develop our baseline hypothesis about the relationship between distinctiveness and user growth in platform markets.

Distinctiveness generally allows a platform to compete in a less contested market space and to prevent head-to-head competition with other platforms (Deephouse, 1999; Porter, 1985)—as long as existing competitors are not already equally positioned across the entire market space (Haans, 2019). A distinctive position can further increase the fit between the platform's offering and users' preferences in the selected market niche (Porter, 1985)—therefore increasing the platform's relative attractiveness in the eyes of such niche users (Chernev, 2007). This effect will be particularly prevalent in those platform markets in which users exhibit strong heterogeneity in their tastes and preferences (Rietveld & Eggers, 2018; Tauscher, 2019). If switching costs between platforms are relatively low, users may also choose to use several differentiated platforms—rather than one platform that offers a broad but undifferentiated portfolio—in order to maximize the fit between their contextual needs and platforms' offering. For instance, a user in the MOOC market—our empirical context—may both use a MOOC platform specialized in programming courses when learning a new programming language and a MOOC platform specialized on business courses when aiming to develop new management skills. Counter to the observation that platform markets often exhibit winner-take-all dynamics, such conditions (heterogeneity in user preferences and low switching costs) can thus allow several distinctive platforms to sustainably co-exist in the same market (Cennamo & Santaló, 2013; Eisenmann, Parker, & van Alstyne, 2006). Our graphical illustration of these combined *competitive benefits* (left panel of Figure 1) follows previous optimal distinctiveness research (Haans, 2019) and represents the relationship between distinctiveness and competitive benefits as an S-shaped curve. The relationship is generally positive, but only to a minimal degree at very low levels of distinctiveness—which are insufficient to differentiate the platform in the eyes of potential users—and high levels of distinctiveness—at which a platform already occupies a unique market position and therefore does not derive any competitive benefits from further differentiation (Haans, 2019).

Distinctiveness simultaneously affects a platform's legitimacy—a “generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system” (Suchman, 1995, p. 574)—because a distinctive (i.e., nonconforming) market position can prevent potential users from recognizing the platform as a member of its product market (Deephouse, 1999) and consequently cause users to disregard the platform as a legitimate transaction partner (Zuckerman, 1999). Platform users may further lack a comparative baseline for evaluating a platform's quality when they cannot situate the platform in a specific market (Durand & Kremp, 2016), and these uncertainties will reduce their likelihood to join the platform (Podolny, 1994). Being distinctive thus increases the likelihood that potential users do not perceive the platform as a legitimate choice. Previous research suggests that users will perceive a platform as legitimate as long as it is positioned within a “range of acceptability”—the range around a market's average position within which a platform is sufficiently similar to be perceived as a legitimate choice (Deephouse, 1999). Hence, a loss of legitimacy only occurs once a platform is positioned outside the range of acceptability, and platforms can thus exhibit some degree of distinctiveness without the immediate loss of legitimacy (see Haans, 2019, for an illustration). Once a platform is positioned outside this range of acceptability, it risks being disregarded as a legitimate choice by potential users. The left plot of Figure 1 illustrates this mechanism as an S-shaped relationship between distinctiveness and legitimacy. The marginal loss in legitimacy is minimal at low levels of distinctiveness because the platform is still positioned within the range of acceptability and therefore perceived as a legitimate

choice. Positioning the platform outside the range of acceptability will, however, result in a rapid loss of legitimacy. Once a platform has completely lost its legitimacy, it does not suffer from further increases in distinctiveness and the relationship between distinctiveness and legitimacy consequently flattens out at high levels of distinctiveness.

The solid black line in the right plot of Figure 1 illustrates how the two latent mechanisms (legitimacy, competitive benefits) jointly affect a platform's user growth. The illustrative plot assumes an additive effect between the two mechanisms and therefore adds the values of the *competitive benefits* curve and *legitimacy* curve. At low levels of distinctiveness, the marginal competitive benefits exceed the marginal loss in legitimacy, and an increase in distinctiveness therefore yields a positive net effect on the platform's user growth. In turn, distinctiveness will unfold a negative net effect on user growth at distinctiveness levels at which the marginal loss in legitimacy exceeds the marginal increase in competitive benefits. This curvilinear relationship, where increases in distinctiveness have a positive marginal effect on user growth until the curve's turning point (the point of optimal distinctiveness) and a negative marginal effect beyond this point, is also in line with the baseline prediction in previous optimal distinctiveness studies (Deephouse, 1999; Zhao et al., 2017). We thus hypothesize:

Hypothesis 1 (H1). *There exists an inverted U-shaped relationship between platforms' distinctiveness and user growth.*

2.3 | The moderating role of high-status complementors

We subsequently theorize about how the relationship between distinctiveness and user growth is shaped by access to alternative sources of legitimacy. We specifically focus on the role of high-status complementors as a particularly relevant source of legitimacy in platform markets. Status refers to the “[s]ocially constructed, inter-subjectively agreed-upon and accepted ordering or ranking of individuals, groups, organizations, or activities in a social system” (Washington & Zajac, 2005, p. 284). Affiliations with high-status individuals or organizations represent one of the most important sources of legitimacy for new ventures in general (Fisher, Kuratko, Bloodgood, & Hornsby, 2017; Rao, Chandy, & Prabhu, 2008; Stuart et al., 1999; Überbacher, 2014), but the legitimating effect of such affiliations is particularly prevalent in platform markets. That is because the value created by platforms is inherently co-created by *complementors*—independent organizations or individuals that provide complementary goods and services (Eisenmann et al., 2011). Affiliation with high-status complementors—that is, complementors that are members of the high-status group in their organizational field—can provide an important source of legitimacy of platforms because it implies a positive legitimacy judgment (Pollock, Lee, Jin, & Lashley, 2015) and stakeholders generally place a strong weight on positive legitimacy judgments by high-status organizations (Pollock, Chen, Jackson, & Hambrick, 2010). High-status complementors' decision to join a platform ecosystem thus implies a positive evaluation of the platform' legitimacy—thereby increasing the platform's legitimacy in the eyes of other stakeholder groups.

Our main proposition is that high-status complementors—and alternative sources of legitimacy in general—provide a “legitimacy buffer” (Fisher et al., 2016) that enlarges a platform's range of acceptability and therefore increases the level of distinctiveness at which a platform starts losing legitimacy. Platform providers can stockpile legitimacy from different sources (Suchman, 1995), and stockpiled legitimacy can shield a platform against potential legitimacy

challenges. Among others, such a legitimacy buffer will increase the leeway for nonconforming behavior without the immediate loss of legitimacy (Fisher et al., 2016). Hence, affiliations with high-status complementors provide a legitimacy buffer that can shield a platform—to some degree—against the negative consequences of distinctiveness. Platforms that have buffered legitimacy through high-status complementors can thus exhibit a higher level of distinctiveness without the immediate loss of legitimacy because legitimacy gained through high-status complementors (one source of legitimacy) reduces pressure for conformity (another source of legitimacy).

The dashed black line in the left plot of Figure 1 illustrates how access to high-status complementors—through the legitimacy-buffering effect—can right-shift the distinctiveness–legitimacy curve.² A platform with access to high-status complementors can, *ceteris paribus*, exhibit a higher degree of distinctiveness without losing any legitimacy. However, even a high degree of buffered legitimacy does not prevent a reduction in legitimacy if the platform is positioned outside an (enlarged) range of acceptability. Hence, platforms with access to high-status complementors will equally lose some legitimacy if they exceed a certain level of distinctiveness—although the legitimacy loss at a given level of distinctiveness will be lower in comparison to platforms without such a legitimacy buffer. In other words, legitimacy buffered through high-status complementors provides more leeway for distinctiveness but does not completely protect against a loss in legitimacy. Attracting a higher share of high-status complementors will thus shift the distinctiveness–legitimacy curve to the right, where the partial or complete loss of legitimacy occurs at a relatively higher level of distinctiveness.

The dashed black line in the right plot of Figure 1—which adds the *competitive benefits* curve (gray line) and the changed *legitimacy* curve (dashed black line)—illustrates how such a right-shift in the legitimacy curve may affect the overall relationship between distinctiveness and user growth. The illustration builds on the assumption that an increased share of high-status complementors does not substantially change the competitive benefits of distinctiveness (gray line) because legitimacy buffering does not necessarily position a platform in a less contested market space. The plot suggests that access to high-status complementors will (a) shift the curve's turning point to the right and (b) steepen the positive and negative slope of the curve. A steepening of the curve implies that platforms with high-status complementors will attract more users at moderate levels of distinctiveness—that is, distinctiveness levels at which a platform without high-status complementors would lose some degree of legitimacy and a platform with high-status complementors does not yet lose its entire legitimacy. Hence, we hypothesize:

Hypothesis 2 (H2). *High-status complementors will moderate the relationship between platforms' distinctiveness and user growth in that a higher share of high-status complementors will shift the curve's turning point to the right.*

²Legitimacy is generally conceptualized as an asset that is clearly bounded (Deephouse, Bundy, Tost, Suchman, & Mark, 2017). As illustrated in the left plot of Figure 1, a platform is legitimate (1), illegitimate (0), or legitimate to some degree (values in between) but cannot gain or lose legitimacy outside these bounds (Deephouse et al., 2017). The conceptual characteristics of legitimacy imply that a fully legitimate platform cannot become “more legitimate” in the eyes of users through access to high-status complementors. Hence, the *legitimacy* curve does not move upwards beyond this upper bound (1).

Hypothesis 3 (H3). *High-status complementors will moderate the relationship between platforms' distinctiveness and user growth in that a higher share of high-status complementors will steepen the curve.*

3 | RESEARCH METHODS

3.1 | Study context and data

We test our hypotheses by studying platform competition in the market for Massive Open MOOCs between January 2013 and March 2017. Launched with the mission to deliver world-class education to millions of learners across the world, MOOCs—broadly defined as online courses aimed at large groups of learners—have been considered one of the most important innovations of the education industry in the last century (Belleflamme & Jacqmin, 2016). MOOC platforms target a broad range of users through technological platforms on which users can search for, enroll in, and engage with a platform's MOOC portfolio. The MOOC market gained global recognition in 2012, driven by substantial coverage in mainstream media (Reich & Ruipérez-Valiente, 2019). For instance, the New York Times publishes several articles about MOOCs during that year and declared 2012 as “The Year of the MOOC” (Pappano, 2012). The MOOC market provides a highly insightful context to study optimal distinctiveness in platform markets because the market represents a clearly distinguishable platform market—characterized by a unique label (“MOOCs”), specific product characteristics (e.g., free access to educational content), specialized market intermediaries (e.g., the meta-site *Class Central*), and coverage by market analysts (e.g., Absolute Reports, 2019).³ The MOOC market is further suited to test our hypotheses because different subject genres allow for clear market segmentation and therefore provide various opportunities for differentiation. Starting our observation window in 2013—that is, after the market had already gained recognition by the general public and 12 competitors had already entered the market—should also ensure that platform providers competed with each other rather than purely focused on collectively legitimating the MOOC market and differentiating it from other market categories (Navis & Glynn, 2010, 2011). The fact that the major MOOC platforms were provided by new ventures—who did not simultaneously compete in other markets—further increases confidence that changes in platforms' user growth result from platform providers' behavior in the MOOC market rather than their unobserved behavior in other markets.

Our initial sample includes all MOOC platforms launched up until December 2015. To identify all MOOC platforms and their complementors, we make use of the meta-site *Class Central* (classcentral.com), which claims to list all MOOC platforms and MOOCs. We collected data for all MOOC platforms listed on *Class Central* to develop our measure of *Distinctiveness*, but restricted our sample to MOOC platforms provided by new, growth-oriented ventures to rule out that platform providers could buffer legitimacy through unobserved behavior in other markets (e.g., in the case of platforms provided by multibusiness corporations). Focusing on

³MOOC platforms primarily competed with other MOOC platforms during our observation period (2013–2017). After this period, some MOOC platforms also started to compete directly with universities and other education providers by offering educational programs with formal degree credentials, competitive admission processes, and personalized learning support (Reich & Ruipérez-Valiente, 2019). Hence, the boundaries of the MOOC market likely have become more blurred since 2017.

platforms provided by new, growth-oriented ventures should further ensure that all sample firms aimed for user growth. To identify MOOC platforms provided by new, growth-oriented ventures, we aimed to match each platform provider with the four million companies listed in the startup database *Mattermark*. This database, targeted primarily at venture capitalists and other startup investors, provides comprehensive data points about growth-oriented ventures, and we thus considered a platform provider's inclusion in this database as an indicator of its growth ambition. Our sample thus consists of all MOOC platforms (identified through the MOOC meta-site *Class Central*) offered by new, growth-oriented ventures (identified through the startup database *Mattermark*). These two criteria resulted in an initial sample of 15 MOOC platforms. We subsequently reviewed these platforms manually to verify whether they aligned with our conceptualization of platforms (e.g., multisidedness) and aligned broadly with the basic characteristics of the MOOC market. We excluded three MOOC platforms from the sample because they did not align with these criteria (e.g., only providing self-created content). Our final sample consists of 12 MOOC platforms and these 12 platforms accounted for 92% of all MOOCs listed on *Class Central* at the end of our observation period.

Platform-months are our unit of analysis. Our study encompasses all platform-months between 2013 and 2017. The sample is unbalanced because some platforms entered the market at later points, and one platform filed for bankruptcy before the end of the observation period. We chose monthly observations to observe users' immediate reactions to changes in the positioning of platforms' MOOC portfolio. Our final sample encompasses 330 platform-month observations.

We leveraged the comprehensive data on *Class Central* to gather data points about each MOOC delivered on all MOOC platforms. We used web-crawling algorithms to access the data points provided by *Class Central*, including each MOOC's subject genre, the organization that created the MOOC (i.e., the complementor), and the dates at which a MOOC had been delivered in the past. Information about past start dates of each MOOC's delivery and the number of weeks over which each MOOC is taught allowed us to reconstruct each platform's entire portfolio of MOOCs for each month. An average MOOC is taught over a period of 9.4 weeks, and most MOOCs in the sample were delivered multiple times during our observation period. For instance, if a given MOOC is taught over 8 weeks and previously started in April 2014 and April 2016, we considered this MOOC to be part of the respective platform's complement portfolio for April 2014, May 2014, April 2016, and May 2016. During our observation period, MOOC platforms launched 5,871 new MOOCs and all MOOCs delivered in these platforms during the observation period accounted for 68,478 MOOC-month observations.

3.2 | Dependent variable

Our dependent variable aims to capture each platform's number of users in a given month. We benefit from the fact that users of MOOC platforms enroll in and engage with MOOCs directly via a platform provider's website, and we can thus infer platforms' number of users directly from the number of *monthly unique visitors* of platform providers' websites.⁴ The metric of

⁴This behavioral measure is particularly suited to represent changes in a MOOC platform's number of users as it accounts for potential users' decision to join a platform and existing users' decision to continue using the platform. This makes this measure preferable over counts of the number of registered users, which tend to overestimate the number of actual users. In fact, research on the behavior of MOOC platform users suggests that the majority of newly registered users never return to a MOOC platform in subsequent periods (Reich & Rupiérrez-Valiente, 2019). Hence, the number of monthly unique visitors presents a more reliable indicator of the actual number of platform users in a given month.

monthly unique visitors has been shown to represent a common and reliable metric to measure the growth performance of online platforms and internet-based firms in general (e.g., Gnyawali, Fan, & Penner, 2010; Kerr, Lerner, & Schoar, 2014; McDonald & Eisenhardt, 2019). We use data from the startup database *Mattermark*, which provides weekly data points for the metric of monthly unique visitors via an application programming interface (API). The metric is skewed as the largest platform (Coursera) attracted nearly 10 million unique users in its most successful month, while the smallest platform attracted only a few thousand visitors during its least successful month. To re-scale variation and reduce skew, we thus construct our dependent variable—*Users*—as the natural logarithm of the number of monthly unique visitors. Graphical analysis of the distribution of *Users* revealed seven platform-months in which a platform attracted less than 10,000 users—mostly in the month in which a respective platform just entered the market. To increase the robustness of our findings, we thus eliminated the first observation month for platforms that entered the market during our observation period.

3.3 | Independent variables

Distinctiveness is the main independent variable of our study, representing the degree to which a given platform's MOOC portfolio deviates from the average MOOC portfolio in the market in a given month (in terms of subject genres). We follow previous research, which also operationalized the distinctiveness of a platform's complement portfolios (Cennamo & Santaló, 2013), and calculate *Distinctiveness* as:

$$Distinctiveness_{it} = \sum_j abs(g_{it} - \bar{g}_t),$$

where g_{it} is the proportion of MOOCs in subject genre j among all MOOCs launched on platform i in period t , and \bar{g}_t is the proportion of MOOCs in subject genre j among all MOOCs delivered in period t . Calculating the market average based on all MOOCs delivered in a given period (including those offered on platforms excluded from the analysis) allows us to increase the stability and practical relevance of this reference point (we expand this point in our discussion of robustness tests). We follow the genre classification provided by *Class Central*, which consists of 12 different subject genres (e.g., business, natural sciences, and computer sciences). Low *Distinctiveness* thus indicates that a platform's MOOC portfolio closely mimics the market's average (i.e., prototypical) MOOC portfolio (in terms of its subject genres) and high *Distinctiveness* indicates that the MOOC portfolio substantially deviates from the average MOOC portfolio.

High-status complementors represents a platform's share of complementors that exhibits a high organizational status. Our operationalization of high-status complementors aimed to align with the common approach in the organizational status literature, which generally conceptualizes status as a binary variable and classifies a small percentage of actors in an industry or social setting as *high-status* (typically around 5%) based on their position in context-specific rankings (George, Dahlander, Graffin, & Sim, 2016). For instance, Ertug, Yogev, Lee, and Hedström (2016) classify art galleries and art museums as *high status* if they appear in the top 100 in respective rankings of art galleries and art museums. Other recent studies select firms that appear within the top 25 of their respective rankings (Graffin, Haleblan, & Kiley, 2016;

Pfarrer, Pollock, & Rindova, 2010). Following these approaches, we aimed to identify a relevant ranking for each of the two respective complementor populations (universities, non-universities) in order to classify a small subset of each population as high status.⁵ To avoid introducing a systematic bias between the two types of complementors, we aimed to classify a similar share of universities and non-universities as high status. To operationalize the status of universities, we relied on the Times Higher Education (THE) university ranking, which represents one of the leading global rankings for universities (Aguillo, Bar-Ilan, Levene, & Ortega, 2010). After analyzing the rank distribution among MOOC-providing universities in our sample, we decided to classify universities as high status if they were among the ranking's top 25 universities. This corresponds to around 3% of all MOOC-providing universities during the observation period. To identify high-status actors among the non-university complementors, we used the industry-independent Global Brand ranking (Brand Finance, 2017), which ranks firms by their brand value and should therefore provide a suitable approximation of organizations' perceived status in the eyes of general consumers (i.e., potential users of MOOC platforms). We classified non-universities as high status when they are listed in the top 100 of this ranking (e.g., Google, Microsoft) because this benchmark equally classified 3% of the non-universities as high status.⁶ We subsequently constructed our measure of *High-status complementors* by measuring the share of each platform's complementors that are classified as high status in a given month. We preferred this relative measure of high-status complementors over an absolute measure because an absolute measure would confound the effect of high-status complementors with general network effects. We lagged both independent variables by 1 month to mitigate potential concerns about reverse causality.

3.4 | Control variables

Due to the presence of network effects, MOOC platforms likely attract more users after an increase in their MOOC portfolio. We thus control for the number of new MOOCs added to a platform's MOOC portfolio in a given month to account for changes in portfolio size. *New MOOCs* represents the natural logarithm of the number of newly launched MOOCs on a platform in a given month, lagged by 1 month. The measure focuses on the number of newly added MOOCs—rather than a platform's cumulative number of MOOCs—because previous research suggests that cumulative measures of network size can easily overstate indirect network effects (Rietveld & Eggers, 2018).

We further aimed to control for additional differences in platforms' complementor ecosystem (beyond their status). Platform research provides substantial evidence that exclusive complementors can increase a platform's attractiveness to users (Cennamo & Santaló, 2013; Corts & Lederman, 2009; Landsman & Stremersch, 2011). We thus include *exclusive complementors* as a measure of a platform's proportion of complementors that only creates MOOCs for the given platform but does not contribute to any other platform. While a strategy focused on exclusive complementors can increase a platform's attractiveness to users, it may simultaneously limit

⁵The distinction between universities and non-universities follows the classification of complementors on Class Central. In our sample, 278 complementors (29.5%) classify as non-universities.

⁶In robustness tests, we used different cut-off points for each of these rankings to classify roughly 1% and 5% of the respective samples (e.g., top 10 and top 50 universities) as high status. Our main findings proved robust under different coding procedures.

the platform' supply-side growth and may therefore also unfold a negative effect on the platform's user growth (Cennamo & Santaló, 2013). To capture this potentially nonlinear effect, we also include a squared term of this measure (*Exclusive complementors*²) in our models. In our sample, 792 out of 963 complementors offer MOOCs on only one platform. We further aimed to net out any systematic differences between the two types of complementors—universities and non-universities—and therefore include a control variable (*Non-university complementors*) that measures the proportion of non-university complementors among all complementors of a platform in a given month.

We further aimed to control for changes in platform-level characteristics. We add *Platform age*—measured in months since the platform offered the first MOOC on Class Central—to control for any unobservable dynamics that occur over a platform's lifecycle stage. In particular, potential users may be more hesitant to join a MOOC platform in its early stages (Cennamo & Santaló, 2013). We also included a binary variable—*Certification*—which is 1 for all months in which a platform offers verified certificates and “0” in all other months. During the observation period, several MOOC platforms started to offer learners the opportunity to purchase a certificate after they successfully completed a MOOC. Certificates may increase the platform's attractiveness because they allow users to signal their educational progress to potential employers. We additionally control for the presence of a *Mobile app* with a dummy variable that equals 1 in months in which the platform offers a mobile app and 0 otherwise. We used data provided by AppAnnie.com to determine whether and when a given platform first launched a mobile app. We time-lagged *Certification* and *Mobile app* by 1 month.

We additionally control for the *Number of MOOC platforms*, measured as the total number of MOOC platforms that list at least one MOOC on Class Central in a given month because the number of competing MOOC platforms may determine both the level of competitive pressure and affect the market's overall legitimacy (Navis & Glynn, 2010).

3.5 | Statistical method and instrumentation approach

Many time-invariant platform-level factors—such as differences in the quality of their technology, management, or home market—could affect MOOC platforms' observed growth performance. Following common practices in platform research (Boudreau, 2012; e.g., Boudreau & Jeppesen, 2015; Cennamo & Santaló, 2013), we leverage the panel structure of our data and apply a fixed-effects approach that fully controls for cross-sectional variation. Fixed effects models allow isolating our time-variant variables (i.e., all variables described above) from static differences that exist between platforms and between platform providers. After including platform fixed effects, the remaining error term in the estimation of *Users* can be interpreted as differences in unobserved platform quality that may occur over the observation period. To also control for systematic changes that occurred over the course of our observation period, we additionally include year dummies. These dummies allow us to control for technological advances, shifts in consumer demand, and other time-dependent effects. We further include month dummies to account for potential seasonality in MOOC demand. Including these dummies substantially reduces the risk of omitted variables.

A central proposition of platform research is that the network size of demand-side users and supply-side complementors mutually influence each other (McIntyre & Srinivasan, 2017). Such simultaneous causality represents a major driver of endogeneity (Semadeni, Withers, & Trevis Certo, 2014). Hence, an increase in *New MOOCs* likely leads to an increase in *Users*, but an

increase in *Users* may simultaneously lead to an increase in *New MOOCs*. We aimed to account for this potential endogeneity problem through a two-stage least squares (2SLS) estimation approach, in which the first-stage models regress *New MOOCs* on all independent variables (including platform, year, and month dummies) and an additional exogenous variable. The second-stage model subsequently regresses *Users* on all other independent variables (including platform, year, and month dummies) and the first-stage estimation of *New MOOCs*. We therefore aimed to identify an exogenous variable that causally affects *New MOOCs* but does not affect *Users* (Wooldridge, 2010). Online Appendix S1 provides an in-depth discussion of our identification strategy and the construction of our excluded instrument (*Labor costs*). To further prevent concerns of potential reverse causality, we lag the measure by 12 months. This time frame accounts for the average delay between organizations' decision to create a MOOC and the launch of a MOOC (Hollands & Tirthali, 2014).

4 | RESULTS

Table 1 presents summary statistics and correlations. The table shows a relatively high correlation between *Platform age*, *Number of MOOC platforms*, and year dummies. The main models nevertheless include all control variables as fixed effects time series generally do not suffer from multicollinearity problems (Goldberger, 1991). In robustness tests, we confirmed that the presented relationships do not change if we exclude *Platform age* and/or *Number of MOOC platforms* from our models (excluding them generally increased the statistical significance of our hypothesis-testing relationships). Table 2 presents the second-stage models that estimate *Users*. All models are estimated with STATA's *ivreg2* command (Baum, Schaffer, & Stillman, 2002). Online Appendix S2 presents results for the respective first-stage regressions—that is, predicting the endogenous variable *New MOOCs*—and online Appendix S3 represents the full second-stage results, including all platform, year, and month dummies. The models and additional post hoc tests confirm that *Labor costs* satisfies both instrumental variable conditions (Wooldridge, 2010): (a) a partial correlation with *New MOOCs* after all other exogenous variables are netted out (at $p = .000$), and (b) no correlation with the error term of the second-stage model ($r = -0.001$, $p = .981$). In each of the models, we additionally present test statistics to test for potential under-identification and weak identification in our instrumentation approach (Semadeni et al., 2014). Anderson canonical correlations statistics (using a Lagrange Multiplier) suggest that the models do not suffer from under-identification problems (at $p = .000$ in all models) and the Cragg–Donald Wald F statistic consistently exceeds the suggested benchmark values provided by Stock, Yogo, and Andrews (2005) at the most conservative level⁷ and therefore suggests that the models do not suffer from weak identification problems.

Model 1 includes the controls and the single term of *Distinctiveness* to evaluate whether a linear specification would provide a better fit than a curvilinear relationship. The low statistical significance of *Distinctiveness* in Model 1 suggests that *Distinctiveness* does not have a linear effect on *Users*. Model 1 further shows that *High-status complementors* has a positive direct

⁷Stock et al. (2005) provide benchmark values for the Cragg–Donald Wald F statistic that account for test size, bias, the number of excluded instruments and endogenous regressors. For one endogenous regressor, one excluded instrument, and our sample characteristics, the critical benchmark for 10% (the most restrictive value) is at an F-value of 16.38. A test statistic larger than this critical benchmark allows to reject the hypothesis that the relative bias from the instrument is 10% or larger of the initial bias (from the excluded endogenous variable).

TABLE 1 Summary statistics and correlations

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1 Users	13.75	1.62	7.06	16.11	1.00										
2 Distinctiveness	0.94	0.47	0.14	2.13	-0.51	1.00									
3 High-status complementors	0.08	0.11	0.00	0.67	0.43	-0.52	1.00								
4 New MOOCs	1.11	1.24	0.00	4.79	0.54	-0.78	0.42	1.00							
5 Non-university complementors	0.22	0.26	0.00	1.00	0.15	0.46	-0.06	-0.22	1.00						
6 Exclusive complementors	0.74	0.34	0.0	1.00	0.25	0.03	0.18	0.22	0.37	1.00					
7 Platform age	27.49	15.81	2.0	65.0	0.66	-0.36	0.20	0.62	0.08	0.40	1.00				
8 Certification	0.51	0.5	0.0	1.00	0.29	-0.41	0.10	0.49	-0.02	0.22	0.16	1.00			
9 Mobile app	0.35	0.48	0.00	1.00	0.38	-0.09	0.10	0.38	0.25	0.18	0.69	-0.03	1.00		
10 Number of MOOC platforms	27.42	5.31	13.0	33.00	0.09	0.13	-0.28	0.18	0.30	0.26	0.51	0.23	0.40	1.00	
11 Labor costs	1969.8	205.3	1,672.8	2,524.6	-0.17	0.45	-0.52	-0.29	-0.02	-0.05	-0.07	-0.25	-0.16	0.05	1.00

Note: The summary statistics refer to the measures of Users and New MOOCs after their logarithmic transformation. Abbreviation: MOOCs: Massive Open Online Courses.

TABLE 2 Second-stage results of 2SLS estimation for users

	Model 1			Model 2			Model 3		
	Coef.	SE	p	Coef.	SE	p	Coef.	SE	p
Distinctiveness	-0.036	0.196	.855	-0.778	0.621	.210	-2.033	0.753	.007
Distinctiveness ²				0.304	0.240	.205	0.837	0.291	.004
Distinctiveness × high-status complementors							20.665	5.465	.000
Distinctiveness ² × high-status complementors							-15.304	3.734	.000
High-status complementors	2.009	0.933	.031	2.286	0.938	.015	-2.939	2.157	.173
Non-university complementors	2.593	0.331	.000	2.575	0.326	.000	2.941	0.355	.000
Exclusive complementors	2.875	0.794	.000	2.764	0.785	.000	3.345	0.787	.000
Exclusive complementors ²	-2.780	0.761	.000	-2.633	0.755	.000	-3.259	0.758	.000
New MOOCs	0.482	0.211	.022	0.459	0.209	.028	0.583	0.248	.019
Platform age	0.003	0.014	.849	0.003	0.014	.835	0.004	0.014	.758
Certification	-0.041	0.120	.735	-0.050	0.118	.669	-0.094	0.128	.464
Mobile app	0.622	0.142	.000	0.601	0.141	.000	0.745	0.174	.000
Number of MOOC platforms	0.021	0.017	.234	0.023	0.017	.178	0.025	0.018	.168
Platform dummies included		Yes			Yes			Yes	
Year dummies included		Yes			Yes			Yes	
Month dummies included		Yes			Yes			Yes	
Constant	12.916	0.666	.000	13.055	0.669	.000	12.907	0.890	.000
Anderson canon. corr. ^a	23.96 (<i>p</i> = .000)			23.63 (<i>p</i> = .000)			18.87 (<i>p</i> = .000)		
Cragg-Donald Wald F ^b	23.02			22.06			17.56		
<i>p</i>	.000			.000			.000		

^aThe Anderson canonical correlations statistics, using a Lagrange Multiplier (LM) version, tests for under-identification of the instruments.

^bThe Cragg-Donald Wald F statistic tests for weak instrument identification.

Abbreviation: MOOCs: Massive Open Online Courses.

effect on *Users* and therefore provides some support for the assumed legitimation effect of high-status complementors. The model also shows a strong positive effect of *Exclusive complementors* and negative effect of *Exclusive complementors*², which indicates that a moderate share of exclusive complementors attracts most users. The model further suggests that *Non-university complementors* and *Mobile app* have a positive effect on *Users*.

Hypothesis 1 stated that distinctiveness has an inverted U-shaped effect on platforms' user base. Model 2 adds *Distinctiveness*² to test for the predicted curvilinear relationship. A minimum condition for an inverted U-shaped effect would be a positive coefficient for *Distinctiveness* and a negative coefficient for *Distinctiveness*². Model 2 demonstrates that neither of the coefficients shows the expected sign. The low statistical significance of *Distinctiveness* and *Distinctiveness*² suggests rejecting Hypothesis 1—the relationship between *Distinctiveness* and *Users* does not unconditionally follow an inverted U-shaped curve.

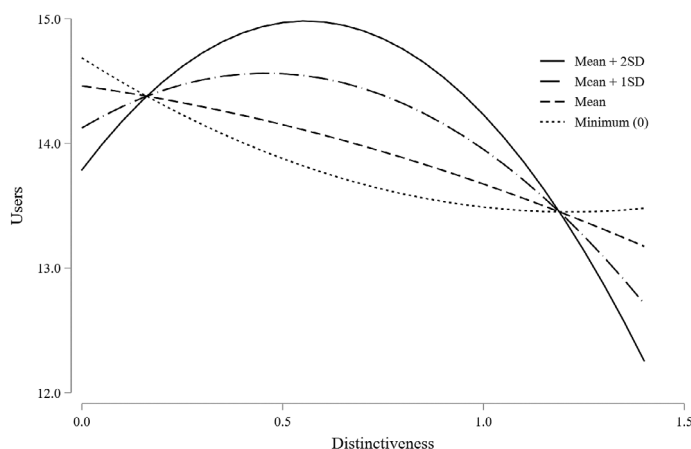


FIGURE 2 Relationship between distinctiveness and users at different levels of high-status Complementors. *Note:* The plot represents estimations for *Users* (i.e., the natural logarithm of the number of users), based on results of Model 3, at different levels of *Distinctiveness* (between 0 and 1 *standard deviation (SD)* above the mean) and at four levels of *High-status complementors*. The four curves correspond to the sample's minimum share of *High-status complementors* (0), mean, 1 *SD* above the mean (“Mean + 1 *SD*”), and 2 *SD* above the mean (“Mean + 2*SD*”)

Hypotheses 2 and 3 stated that high-status complementors moderate the relationship between distinctiveness and user growth in that a higher share of high-status complementors shifts the turning point to the right (Hypothesis 2) and steepens the curve (Hypothesis 3). Model 3 adds interactions between *Distinctiveness* and *High-status complementors* and *Distinctiveness*² and *High-status complementors*. We first plotted predictions for *Users* at different levels of *Distinctiveness* and *High-status complementors* to visually examine the relationship. Figure 2 represents these predictions at different levels of *Distinctiveness*—ranging from 0 (i.e., no distinctiveness) to 1 *SD* above the sample mean (i.e., high distinctiveness). We aimed to predict *Users* at four meaningful levels of *High-status complementors* by specifying the sample's minimum value (0.00), the sample mean (0.08), 1 *SD* above the mean (0.19), and 2 *SD* above the mean (0.30). The plots in Figure 2 reveal the strong impact of *High-status complementors* on the relationship between *Distinctiveness* and *Users*. Under the absence of high-status complementors, the relationship technically follows a U-shaped curve. At a mean share of *High-status complementors*, the relationship technically follows an inverted U-shaped curve. At these low levels of *High-status complementors*, *Distinctiveness* has a purely negative effect on *Users*—platforms attract most users by demonstrating high conformity in their complement portfolio's positioning. At above-average levels of *High-status complementors*, the curve steepens, and the curve's turning point slightly shifts to the right. We followed the procedure presented by Haans, Pieters, and He (2016) to formally test for a right-shift of the turning point (Hypothesis 2).⁸ The equation's numerator yields a positive value and therefore suggests a right-shift of the turning point at higher levels of *High-status complementors*. To test the statistical significance of such a

⁸We estimated the following equation: $(\beta_1 * \beta_4 - \beta_2 * \beta_3) / (2 * (\beta_2 + \beta_4 * Z)^2)$, where β_1 represents the slope for *Distinctiveness*, β_2 is the slope for *Distinctiveness*², β_3 is the slope of the interaction between *Distinctiveness*² and *High-status complementors*, β_4 is the slope of the interaction between *Distinctiveness*² and *High-status complementors*, and Z is the main term for *High-status complementors*. Higher levels of *High-status complementors* lead to a right-shift of the turning point when (a) the equation's numerator is positive and (b) the coefficient of the equation is significantly different from zero at meaningful values for Z (Haans et al., 2016).

right-shift, we calculated the turning point for different levels of *High-status complementors* (from 0 to 0.5 at increments of 0.01). Online Appendix S4 presents the full results for each level. The table shows that low values of *High-status complementors* lead to relatively high standard errors and broad 95% confidence intervals—suggesting that no significant turning point shift occurs at relatively low levels of *High-status complementors*. This finding is in line with the plot in Figure 2, which shows that the curve flips from U-shape to inverted U-shape at low levels of *High-status complementors* (which effectively prevents a continuous turning point shift in this range). The table further lays out that this formal test suggests a statistically significant turning point shift at higher levels of *High-status complementors* (0.3 and higher). The combined evidence suggests rejecting Hypothesis 2, showing that there exists no continuous shift in the turning point over the entire range of *High-status complementors* due to the curve's U-shape at low levels of *High-status complementors*. However, the tests and plot in Figure 2 suggest that the position of the turning point (i.e., the “optimal” level of distinctiveness) is contingent on *High-status complementors* and an increase in *High-status complementors* leads to a right-shift of the turning point for platforms that have surpassed a certain share of high-status complementors.

A negative and statistically significant interaction term between *Distinctiveness*² and *High-status complementors* would provide formal support for Hypothesis 3 (Haans et al., 2016). Model 3 shows a negative coefficient for the interaction between *Distinctiveness*² and *Users*, and the respective standard error and *p*-value (.000) suggest that this relationship has a high statistical significance. This finding provides strong support for Hypothesis 3 and suggests that the inverted U-shaped relationship between *Distinctiveness* and *Users* substantially steepens at higher levels of *High-status complementors*.

We further calculated the level of *High-status complementors* at which the relationship between *Distinctiveness* and *Users* flips from a U-shaped to an inverted U-shaped relationship. Using the formula provided in the study by Haans et al. (2016), we find that the curve flips at a *High-status complementor* value of 0.055. Our study therefore suggests that the relationship between *Distinctiveness* and *Users* follows a slightly U-shaped relationship if less than 5.5% of a platform's ecosystem consists of high-status complementors and an inverted U-shaped relationship for platform ecosystems with more than 5.5% of high-status complementors.

We ran various tests to confirm the robustness of our results. Online Appendix S6 presents models in which we confirmed the robustness of our findings for different operationalizations of *Distinctiveness*. The first models calculate *Distinctiveness* vis-à-vis the market's average position (\bar{g}_t) over longer time periods (3, 6, 9, and 12 months)—rather than the average position in the given period—to account for the fact that platform users may perceive changes in a market's average position only over longer time horizons. These alternative operationalizations of *Distinctiveness* are thus less sensitive to temporal changes in the market's average position. The models show that our findings are robust under these alternative operationalizations of *Distinctiveness*.

We further aimed to confirm that our findings are insensitive to the chosen measure of platforms' supply-side growth. Online Appendix S7 presents alternative models, in which the first-stage models estimate the logged number of MOOCs that a platform delivers in a given month (*Delivered MOOCs*) instead of the logged number of MOOCs that are newly launched on a platform in a given month (*New MOOCs*). These alternative models confirm that our findings do not depend on the selected operationalization of the platforms' supply-side growth.

Recent research highlights that the competitive benefits of a distinctive positioning substantially depend on the heterogeneity of competitors' market positions (Haans, 2019). Our fixed-effects models can fully account for temporal changes in the heterogeneity of MOOC platforms'

positions, but we nevertheless aimed to verify that such heterogeneity does not drive our findings. We closely replicated the measure of *Distinctiveness heterogeneity* in the study by Haans (2019) by counting the sum of standard deviations of genre distributions over all 12 subject genres. In line with our measure of *Distinctiveness*, we calculated the measure based on all MOOCs delivered in a given month (not just those delivered by our sample platforms). Alternative models, presented in online Appendix S8, show that our results do not change if we additionally control for *Distinctiveness heterogeneity*.

We further aimed to rule out that our findings are driven by systematic temporal changes in *Distinctiveness* and *High-status complementors*. The MOOC market was in a relatively early stage during our observation period, and previous research suggests that platform providers may have gradually increased their platforms' distinctiveness over time as the market category's legitimacy may have increased (Navis & Glynn, 2010, 2011). Similarly, market-level legitimation could have also facilitated platforms' access to high-status complementors over time. To formally test whether our independent variables systematically increased over time, we constructed alternative models in which we regressed either *Distinctiveness* or *High-status complementors* on all control variables. For a systematic temporal effect, we would expect a statistically significant effect of *Platform age* or the *Number of MOOC Platforms* in the respective models. Online Appendix S9 presents these alternative models. Standard errors and *p*-values in these models suggest that none of the time-dependent control variables has a statistically significant effect on either *Distinctiveness* or *High-status complementors*.

Plotting and clustering the empirically observed distribution of platform-month observations in our study indicates that MOOC platforms with distinctive positions less frequently attracted a high share of high-status complementors than those with undifferentiated positions.⁹ This distributional pattern could indicate that distinctive positioning may reduce a platform's ability to attract high-status complementors. To test for such an additional interdependency between our independent variables, we regressed *High-status complementors* on *Distinctiveness* and all control variables. If distinctive positioning would reduce access to high-status complementors, we would expect a negative effect of *Distinctiveness* on *High-status complementors*. The model in online Appendix S9 shows a slightly positive coefficient (0.024) for the relationship between *Distinctiveness* and *High-status complementors*, but the respective standard error and *p*-value (.085) imply that this effect is not statistically significant at conventional threshold levels. This result suggests that distinctive positioning does not affect a platform's access to high-status complementors.

These robustness tests and respective plots confirm that *Distinctiveness* has a negative effect on *Users* (which technically represents a slightly U-shaped relationship) under the absence of *High-status complementors* and an inverted U-shaped effect on *Users* at high levels of *High-status complementors*. Our robustness tests further confirm that higher levels of *High-status complementors* lead to a right-shift in the curve's turning point (although the right-shift is relatively small) and a steepening of the curve under the condition that *High-status complementors* surpasses a minimum level. These tests provide substantial support for our main proposition that platform' optimal distinctiveness is substantially contingent on their affiliations with high-status complementors.

⁹Dividing our sample's platform-month observations into four groups—by splitting *Distinctiveness* and *High-status complementors* by their means—shows that 18% exhibit low *Distinctiveness* and low *High-status complementors*, 28% exhibit low *Distinctiveness* and high *High-status complementors*, 38% exhibit high *Distinctiveness* and low *High-status complementors*, 15% exhibit high *Distinctiveness* and high *High-status complementors*.

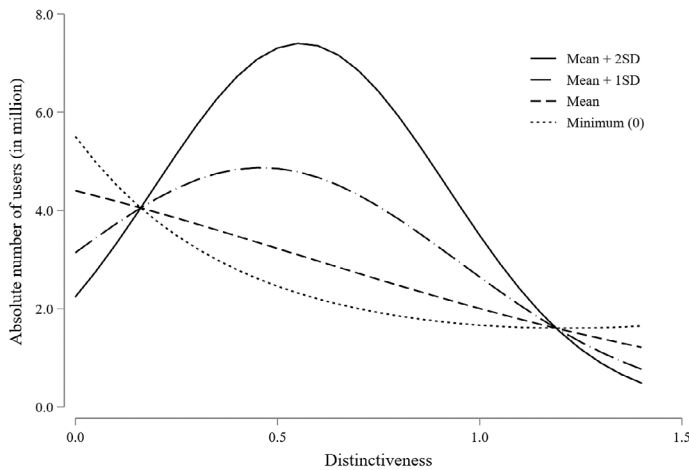


FIGURE 3 Relationship between *Distinctiveness* and the absolute number of users at different levels of high-status Complementors. *Note:* The plot represents estimates for the absolute number of users, based on reverse transformation of the results of Model 3, at different levels of *High-status complementors*. To estimate unbiased predictions for the absolute number of users, we included an estimate of the error variance (using the square of the prediction's root mean squared error) in the reverse transformation (Wooldridge, 2010)

Figure 3 further predicts and plots the effect of *Distinctiveness* on the absolute number of users to quantify the practical significance of our main findings. A standard deviation increase in *Distinctiveness*—under the prior absence of *Distinctiveness*—will lead to (a) a decrease of 2.9 million users (−53.5%) for platforms without high-status complementors, (b) a decrease of 1.1 million users (−24.8%) for platforms with an average share of high-status complementors, (c) an increase of 1.7 million users (+55.1%) for platforms with an above-average share of *High-status complementors* (standard deviation above mean) and (d) an increase of 4.9 million users (+219.9%) for platforms with a high share of *High-status complementors* (2 *SD* above mean). These large absolute effect sizes emphasize the practical significance of this contingency: whether a platform has buffered some legitimacy through affiliations with high-status complementors determines whether a given change in distinctiveness will substantially decrease or increase the platform's user growth.

5 | DISCUSSION

Optimal distinctiveness research highlights the tension between differentiation and conformity, suggesting that an “optimal” level of distinctiveness exists, at which firms can balance the competitive benefits of distinctiveness against the loss of legitimacy that results from non-conformity. Drawing on legitimacy research (Aldrich & Fiol, 1994; Fisher et al., 2016; Zimmerman & Zeitz, 2002), we argued that such an isolated view of the tension between differentiation and conformity may be overly simplistic because conformity only represents one of several potential sources of legitimacy. We suggested that legitimacy buffered through different sources of legitimacy—other than conformity—can reduce a firm's pressure for conformity and therefore protects to some degree against the liabilities of distinctiveness. Hence, we proposed that the

distinctiveness–performance relationship ultimately depends on the degree to which a firm has buffered legitimacy.

Our study of competition in the MOOC market provided empirical support for our arguments by showing that the relationship between MOOC platforms' distinctiveness and user growth is highly contingent on a platform's share of high-status complementors. We predicted an inverted U-shaped relationship between platforms' distinctiveness and user growth, but our study suggests that such a curvilinear relationship only exists for platforms that have surpassed a minimum threshold of high-status complementors. Platforms that have surpassed this threshold enhance their growth through moderately distinctive positions, and the growth benefits of a moderately distinctive position are accelerated at higher shares of high-status complementors. These findings have important practical implications as they (a) highlight the substantial impact of an “optimally” distinctive position on platforms' growth performance, (b) reveal that distinctiveness can harm user growth for platforms that lack high-status complementors in their ecosystem, (c) show that a moderately distinctive position enhances user growth for platforms with a minimum share of high-status complementors in their ecosystem, and (d) suggest that platforms can accelerate the growth benefits of a moderately distinctive position by increasing the share of high-status complementors in their ecosystem.

Our study directly contributes to optimal distinctiveness research that explores the impact of distinctive positioning on demand-side performance outcomes in entrepreneurial, dynamic, and heterogeneous market environments (Barlow et al., 2019; Haans, 2019; Tauscher et al., 2020; Zhao et al., 2018)—a shift from the traditional focus on positioning in highly stable market environments (e.g., Deephouse, 1999). This line of research advances understanding of the distinctiveness–performance relationship by delineating important contingencies that shape the benefits and/or liabilities of distinctiveness. Zhao et al. (2018), who studied competition in the video game market, found that highly conforming positions enhance video game sales during a category's emergence stage, whereas moderately distinctive positions enhance sales in categories that have surpassed a certain evolutionary threshold. Among others, their study showed that the competitive benefits of a moderately distinctive position can substantially increase over time as competitive intensity rises within a category. Haans (2019) highlighted that the competitive benefits of a distinctive position fundamentally depend on the heterogeneity of competitors' positions in a given market category. His multi-industry study showed that the distinctiveness–performance relationship can systematically differ between categories, where the performance benefits of a distinctive positioning are greatest in categories in which competitors occupy relatively similar positions. Tauscher et al. (2020) outlined that evaluating audiences differ in their tolerance of nonconformity and appreciation of novelty and distinctiveness, and highlighted that such audience-level characteristics can shape both benefits and liabilities of distinctiveness. Studying optimal distinctiveness in the context of crowdfunding, they find that the benefits of distinctiveness can strictly exceed the opposing liabilities in contexts in which audiences demonstrate a high tolerance of nonconformity and actively seek out novel and distinctive offerings. Our findings extend these previous studies in challenging the existence of a stable and unconditional point of optimal distinctiveness that would allow firms to achieve superior performance. Our study goes beyond these previous studies—which primarily emphasize how the distinctiveness–performance relationship is contingent on contextual characteristics—by showing that the performance consequences of distinctiveness can even differ within the same market category and for the same evaluating audience. Our study strongly suggests that direct competitors in a market category can face heterogeneous liabilities of distinctiveness and may therefore derive fundamentally different performance outcomes from being distinctive.

Our study further contributes to platform research in strategic management (Boudreau & Jeppesen, 2015; Cennamo & Santaló, 2013; Rietveld & Eggers, 2018; Seamans & Zhu, 2017; Zhu & Iansiti, 2012) by highlighting the role of legitimacy as a driver of platform performance. Attending to the tension between differentiation and conformity complements prior platform research, which primarily focuses on economic mechanisms to explain performance outcomes in platform markets (Afuah, 2013; Cennamo & Santaló, 2013; Rietveld et al., 2019; Rietveld & Eggers, 2018; Seamans & Zhu, 2017; Zhu & Iansiti, 2012). In particular, our study advances understanding of optimal positioning in platform markets, where previous research (Cennamo & Santaló, 2013) studied positioning in the video game market—a context in which mature firms like Microsoft and Sony compete as platform providers—and found a U-shaped relationship between platforms' distinctiveness and performance. Contrasting our findings with these previous findings suggests that platforms provided by new ventures—such as those in our study—may benefit much less from distinctive positioning than those provided by mature firms because mature firms may have developed substantial legitimacy buffers throughout their organizational lifecycle. Hence, platform providers' lifecycle stage may provide an important boundary condition that potentially limits to some degree the generalizability of previous findings in platform research, and attending more directly to platform providers' lifecycle stage and legitimation allows for important research opportunities for future platform research (but see Garud, Kumaraswamy, Roberts, & Xu, 2020; Logue & Grimes, 2019).

Our finding that a distinctive positioning can have purely negative performance implications—under the absence of legitimacy buffers—also sheds new light on the performance implications of differentiation more broadly (Chen & Hambrick, 1995; Ethiraj & Zhu, 2008; Hill, 1988; Porter, 1980). Specifically, it challenges the assumption that some degree of differentiation always enhances firms' demand-side performance. Our study of differentiation in an entrepreneurial setting, in which several competitors lacked legitimacy due to their newness and the newness of the market category, strongly suggests that some degree of legitimacy may be necessary to reap the differentiation benefits identified in previous studies. This finding therefore uncovers an assumption that is critical but unarticulated and taken-for-granted in the differentiation literature.

We are confident that our findings are generalizable beyond the context of MOOC platforms, although within certain boundary conditions. Anchoring to previous optimal distinctiveness studies, we first expect that our findings are most generalizable to market categories in which distinctiveness yields some competitive benefits because there exists some degree of competitive intensity (Zhao et al., 2018) and opportunities to reduce competitive intensity through differentiation (Haans, 2019). Second, our findings regarding the curvilinear effect of distinctiveness are generalizable to contexts in which there exists some pressure for conformity, but they may not hold up in contexts in which evaluating audiences tolerate a high degree of non-conformity and/or expect a high degree of novelty and distinctiveness (Taeuscher et al., 2020). Third, our arguments about the legitimacy-buffering effect of high-status complementors can be extended to other sources of legitimacy, and our empirical findings for the moderating effects of high-status complementors should also be generalizable to other contexts in which affiliations with high-status organizations can provide a visible stamp of approval (Stuart et al., 1999). There may exist some limits to the generalizability of our empirical findings to market categories in later lifecycle stages because a market category's development stage influences the opposing pressures for conformity and differentiation (Navis & Glynn, 2010, 2011). The pressure for prototype conformity may increase over time as the market category and categorical prototype become more established (Navis & Glynn, 2010), and differentiation pressures may

simultaneously increase if competitive intensity rises within the market category (Zhao et al., 2018). The MOOC market's early development stage may have affected our empirical findings, but we believe that our general propositions equally apply to market categories in later development stages.

Our study is not without limitations, and these limitations offer some future research opportunities. First, our study focuses on differentiation at the level of platforms' complement portfolio, but there may also exist other opportunities for platform differentiation. For instance, MOOC platforms may potentially differentiate themselves by attracting exclusive complementors or complementors with a unique style of delivery. This opens new research opportunities to theoretically elaborate, for instance, on the role of complementor exclusivity in platform markets (Corts & Lederman, 2009; Landsman & Stremersch, 2011) or the orchestration of optimal distinctiveness across multiple dimensions of differentiation (Zhao et al., 2017). A second limitation may result from the exogenous treatment of high-status complementors' decisions to create MOOCs for a specific platform. Future research could complement our study by exploring how platform-level properties, such as its business model (Zott & Amit, 2008), affect high-status complementors' decision to affiliate with specific platforms. Third, while affiliations with high-status organizations are generally conceptualized as a source of legitimacy, they may also differentiate a platform to some degree in the eyes of users. Future research may therefore attempt to directly measure the latent mechanisms that mediate the distinctiveness–performance relationship, although such efforts may require different data sources—such as experiments—that are not easily compatible with longitudinal panel data. Fourth, we tested our theoretical proposition for one specific source of legitimacy, but platforms may also access other sources of legitimacy to buffer against the liabilities of distinctiveness. Future studies could, for instance, draw on the rich literature in cultural entrepreneurship (Lounsbury & Glynn, 2001; Navis & Glynn, 2011) to study how firms can mitigate the tension between differentiation and conformity through identity claims, narratives, or other symbolic actions. We thus encourage future research to explore how firms can effectively buffer legitimacy in order to alleviate their pressure for conformity.

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