Journal of Business Venturing 34 (2019) 105944

Contents lists available at ScienceDirect

Journal of Business Venturing

journal homepage: www.elsevier.com/locate/jbusvent

Reputation and new venture performance in online markets: The moderating role of market crowding

Karl Taeuscher

Manchester Institute of Innovation Research, Alliance Manchester Business School, University of Manchester, Booth St W, M15 6PB Manchester, United Kingdom

ARTICLE INFO

Keywords:
New venture performance
Reputation
Signaling theory
Resource-based view
Online markets
Platform entrepreneurship

ABSTRACT

Reputation represents an important driver of new venture performance. This article shows that the performance benefits of reputation are substantially contingent on ventures' market conditions. My study of 797,087 sales transactions by 5760 new ventures in 119 platform-mediated online markets provides strong evidence that market crowding attenuates the reputation–performance relationship. Ventures benefit 38% to 42% more from a favorable reputation when they compete in an uncrowded (versus crowded) market. By disentangling the underlying mechanisms of reputation, my study allows for more accurate predictions about why, when, and how ventures benefit from reputation.

Executive summary

New ventures face important challenges in attracting stakeholders. They need to stand out to attract stakeholders' attention and convey their quality to reduce stakeholders' uncertainty. Entrepreneurship research has started to explore how a favorable *reputation* can provide both a source of competitive advantage and a quality signal and therefore help ventures to overcome these challenges.

I contribute to this line of research by exploring how market conditions – specifically market crowding – shape the benefits of reputation for new ventures. I revisit and combine arguments from two of the most popular theoretical perspectives on reputation: economic signaling theory and the resource-based view. Signaling theory suggests that quality signals are most important in noisy environments. As market crowding is associated with strong informational noise, it may increase the benefits of quality signals like reputation. The resource-based view considers reputation as an intangible resource and a potential source of competitive advantage. As only rare resources can lead to a competitive advantage, crowding may reduce the competitive benefits of reputation when a favorable reputation no longer represents a rare resource in crowded markets. I develop these arguments for the context of online markets and propose that a favorable reputation becomes less valuable when such markets become more crowded.

I test my hypotheses with data from 797,087 sales transactions for 5760 new ventures and 10,449 products across 119 platform-mediated online markets. My main finding is that crowding strongly attenuates the positive relationship between ventures' reputation and sales performance. Even conservative estimates show that a favorable reputation is 38% to 42% more beneficial in markets with low (versus high) crowding. My study's theoretical propositions and empirical findings allow for more accurate sales predictions in online markets and a better understanding of when and how firms benefit from a favorable reputation.

E-mail address: Karl.Taeuscher@manchester.ac.uk.

https://doi.org/10.1016/j.jbusvent.2019.06.005
Received 14 February 2018; Received in revised form 19 June 2019; Accepted 23 June 2019
Available online 02 July 2019

1. Introduction

New ventures face essential challenges in attracting customers and other stakeholders. Stakeholders are often unaware of ventures' existence (Aldrich, 1999; Petkova et al., 2013; Petkova, 2016; Pollock and Gulati, 2007) and, even after they gain awareness, face high levels of uncertainty about the quality of the ventures' products (Navis and Glynn, 2010; Stuart et al., 1999). Prior entrepreneurship research suggests that new ventures can mitigate these challenges by developing a favorable *reputation* – broadly defined as "stakeholder perceptions with regard to an organization's ability to deliver valued outcomes" (Rindova et al., 2010) – because a favorable reputation allows them to raise awareness and signal their quality to stakeholders (Dimov et al., 2007; Fischer and Reuber, 2007; Petkova, 2016; Reuber and Fischer, 2009; Rindova et al., 2007).

Reputation research generally agrees that firms benefit from favorable reputations but there exists little understanding about the environmental conditions that foster or inhibit these benefits (Barnett and Pollock, 2012). In this research, I address this shortcoming by theorizing about the effect of market crowding on reputation benefits. Arguments from economic signaling theory (Shapiro, 1982, 1983) suggest that crowding increases the noise in a market environment and that consumers may consequently rely more strongly on quality signals like reputation. The resource-based view (RBV) considers reputation as a resource and suggests that resources only allow for a competitive advantage when they are valuable and rare (Barney, 1991). A favorable reputation may no longer present a rare resource in highly crowded markets and crowding may thus decrease the role of reputation as a source of competitive advantage. I extend and integrate arguments from these two theoretical traditions to hypothesize about the interplay between reputation and market crowding.

I focus my theorization and hypotheses on the context of *online markets* – product or resource markets that are mediated by an internet-enabled platform. Platforms like Amazon Marketplace, the Google Play app store, or Etsy have led to the emergence of a variety of new markets. These markets are particularly attractive for entrepreneurs and new ventures due to their low entry barriers (Barlow et al., 2019; Srinivasan and Venkatraman, 2017). For instance, 73% of products on the Amazon Marketplace are offered by individual entrepreneurs or micro ventures (Statista, 2019). Beyond their increasing practical significance, these markets also represent an insightful context to study the relationship between new ventures' reputation and performance under heterogeneous levels of market crowding. Due to their low entry barriers, online markets tend to become "so crowded and noisy that it is difficult to distinguish one particular firm from its rivals" (Reuber and Fischer, 2009). For the context of online markets, I predict that market crowding will reduce ventures' reputation benefits as it decreases the competitive effect of a favorable reputation.

I test my hypotheses with data for 10,949 products in 119 platform-mediated online markets. The study confirms the positive relationship between ventures' reputation and sales performance and shows that differences in ventures' reputation explain 30% of their sales heterogeneity. The study's main finding is that crowding strongly attenuates the relationship between reputation and sales performance. The more crowded a market, the weaker the positive effect of reputation on sales performance. This effect is robust for the two main dimensions of reputation: *perceived quality* and *prominence* (Rindova et al., 2005). The benefits of a high perceived quality and a high prominence are 38% and 42% stronger in uncrowded (versus crowded) markets.

My study directly contributes to the literature on new venture reputation (Petkova, 2016; Rindova et al., 2007) and reputation as a performance driver in online markets (Loane et al., 2004; Reuber and Fischer, 2009, 2011). I contribute to these lines of research by theoretically and empirically disentangling different mechanisms behind the reputation–performance relationship. In demonstrating how reputation benefits are strongly contingent on a market's level of crowding, my study suggests that previous empirical findings on reputation in online markets (Duan et al., 2008; Li and Hitt, 2008; Reuber and Fischer, 2009) may be highly sensitive to market-level characteristics and dynamics.

2. Theoretical background

2.1. Reputation and new venture performance

Entrepreneurship research commonly suggests that there exists a positive relationship between reputation and new venture performance (Dimov et al., 2007; Fischer and Reuber, 2007; Petkova, 2016; Pollock and Gulati, 2007; Rindova et al., 2007). Less understanding exists about the theoretical mechanisms behind this relationship. I thus draw on the broader reputation literature in organizational theory, where there exists a long-standing discussion about the theoretical nature of reputation (Barnett and Pollock, 2012; Lange et al., 2010; Rindova and Martins, 2012). While it is beyond this paper's scope to revisit this discussion, I subsequently present two of the most popular perspectives on reputation to highlight the main mechanisms that drive the reputation–performance relationship.

One popular perspective conceptualizes reputation as a signal about unobservable organizational characteristics, in particular about product quality (Dimov et al., 2007; Jensen and Roy, 2008; Rindova et al., 2005; Rindova et al., 2010). This perspective aims to predict whether a consumer will, ceteris paribus, enter an economic exchange with a given firm and explain consumer demand for specific products (Shapiro, 1982). From this perspective, reputation reflects stakeholders' expectations about a firm's ability to create value and produce high-quality products (Shapiro, 1983). Reputation thus allows firms to signal their "true" quality to stakeholders and, consequently, reduces consumers' uncertainty about the firm's product quality. As reputation decreases consumers' uncertainty, it increases their likelihood of purchasing a given product from a given firm (Shapiro, 1982, 1983). I refer to this mechanism as the *signaling effect* of reputation.

A second popular perspective on reputation draws on the resource-based view (RBV) (Barney, 1991). The RBV, a major framework in the field of strategic management, generally aims to explain heterogeneity in firm performance (Newbert, 2007). RBV-based

reputation research considers reputation as an intangible asset or resource (Barney, 1991; Boyd et al., 2009; Deephouse, 2000; Rindova et al., 2010).[1] Importantly, reputation is conceptually distinctive from the tangible and intangible resources invested to develop reputation (Rindova et al., 2007; Rindova et al., 2010). As a resource, reputation can provide a powerful source of competitive advantage and is thus expected to positively contribute to firms' performance (Bergh et al., 2010; Roberts and Dowling, 2002). The underlying assumption is that not all competing firms hold the same resources (heterogeneous distribution) and that resources cannot be easily traded (imperfect mobility) (Barney, 1991). I consequently label the described mechanism as the *competitive effect* of reputation. Table 1 summarizes the main differences between the signaling and competitive effects of reputation.

The conceptual distinction between the two effects aims to highlight that the competitive effect is necessarily contingent on a firm's competition, whereas the signaling effect is not. Even if a product is offered in a monopolistic market, as assumed in the original models by Shapiro (1982, 1983), the signaling effect of reputation will increase the sales performance of this product under the assumption that (1) information asymmetries exist, and (2) consumers have a choice about whether to enter *any* transaction. In turn, the competitive effect of reputation would be meaningless in a monopolistic market.

2.2. Reputation in online markets

Consumers in online markets commonly infer a product's quality from other consumers' product ratings and reviews (Chen et al., 2011; Chevalier and Mayzlin, 2006; Floyd et al., 2014; Langhe et al., 2016; Reuber and Fischer, 2011). In online markets, consumers often evaluate their purchased products via a standardized evaluation scale (e.g., one to five stars), and online platforms aggregate these ratings and saliently display the aggregated rating scores. Such rating scores "allegedly provide an almost perfect indication of product quality" (Langhe et al., 2016), while incurring only marginal search costs for consumers (Simonson and Rosen, 2014). The aggregated score of online ratings is thus conceptualized as easily accessible reputation signals (Moreno and Terwiesch, 2014; Reuber and Fischer, 2009, 2011).[2] Even as studies have shown the mismatches between product ratings and actual product quality (Anderson and Simester, 2014; Koh et al., 2010; Langhe et al., 2016; Mayzlin et al., 2012), there exists strong evidence that consumers consider rating scores as a highly trustable signal about product quality (Langhe et al., 2016).

Previous entrepreneurship research further conceptualizes the *volume* of customer ratings and reviews as a similarly important reputation signal (Reuber and Fischer, 2011). Online marketplaces, aggregation sites, and internet-enabled platforms often represent a product's average rating side-by-side with the product's rating volume, i.e., the number of previous ratings of the product (Reuber and Fischer, 2009). Research in the area of marketing suggests that the volume of ratings increases consumers' awareness of a product (Anderson and Salisbury, 2003; Godes and Mayzlin, 2004; Mayzlin et al., 2012) and their perceptions of the product's quality (Duan et al., 2008; Floyd et al., 2014; Khare et al., 2011). One explanation is that consumers tend to consider the volume of ratings and reviews as an extrinsic cue about the social approval of products (Khare et al., 2011), which reduces their uncertainty about the product's quality.

In this research, I follow the conceptualization of reputation as a construct that consists of two dimensions: *perceived quality* and *prominence* (Rindova et al., 2005; Rindova et al., 2010).[3] Perceived quality refers to how favorably a stakeholder group evaluates the quality of a firm's product ("being good"). Prominence refers to the degree to which a firm is known by a stakeholder group within a specific context ("being known"). Rindova et al. (2005) developed this two-dimensional conceptualization based on an extensive review of the literature to integrate differing understandings of reputation (Rindova et al., 2005; Rindova et al., 2010). In the context of online markets and new ventures, research generally focuses on these features at the product level (Reuber and Fischer, 2009, 2011). Following this conceptualization, I consider aggregated rating scores as cues about perceived product quality (PPQ) and the displayed rating volume as a cue about product prominence (PP). As both constructs are continuous, I will refer to high and low levels of PPQ and PP, where a high level of PPQ indicates a high rating score, and a high PP indicates a high number of ratings.

3. Hypotheses

3.1. Reputation and sales performance in online markets

How will PPQ and PP as central reputation cues affect new ventures' sales performance in online markets? Based on the reviewed theoretical perspectives, I will now turn my attention to the signaling and competitive effects of these reputation cues. PPQ and PP will likely cause some signaling effects – that is, reduce uncertainties about the venture's product quality (Fombrun and Shanley,

[1] It is important to notice that reputation differs from other resources in that it is not owned by the firm but held within stakeholders' collective perceptions of the firm (Rindova et al., 2010). The RBV, nevertheless, considers reputation to be one of the most important resources (Barney, 1991).

[2] While I follow these perspectives, I highlight that the scores and volume of online ratings do not fully correspond with the conceptualization of "signals" in signaling theory because they are not at the discretion of the signaler (here: new ventures). Rating content and volume rather correspond to the concept of *indices* in Spence's foundational formulation of signaling theory (Spence, 1973). While this distinction is important for signalers, it is less relevant when considering the perspective of the signal receiver (i.e., consumers) because signal receivers consider both signals and indices in their evaluation.

[3] It is noteworthy that there exists a long debate about whether reputation represents a one-dimensional or multi-dimensional construct (for a review of different perspectives, see Lange et al., 2010). Some reputation scholars also conceptualize a third reputation dimension – "being known for" (Lange et al., 2010) – that relates to stakeholders' expectations about a firm's future rather than expectations about desirable *outcomes* (e.g., Mishina et al., 2012; Parker et al., 2019). Such behavioral conceptualizations of reputation are, however, outside the scope of this work.

Table 1
Mechanisms underlying the reputation–performance relationship.

	Signaling effect of reputation	Competitive effect of reputation
Underlying theory	Economic signaling theory (Shapiro, 1982, 1983)	Resource-based view (Barney, 1991)
Conceptualization of reputation	Reputation as consumers' expectation of quality	Reputation as an intangible asset
Consequence of high reputation	Reduced consumer uncertainty	Competitive advantage
Underlying mechanism	Reputation reduces information asymmetries between the focal firm and consumers. Lower information asymmetries reduce consumers' uncertainty about the quality of the firm's product(s) and consequently increase the likelihood that a consumer enters an economic exchange with the focal firm.	Reputation allows the focal firm to deliver superior value for customers and thus differentiate itself from competitors. A competitive advantage allows one to capture superior value, and therefore has a positive effect on firm performance.
Boundary conditions	Markets in which consumers lack perfect information about the product quality of potential exchange partners and have a choice about whether to enter any economic exchange.	Markets in which resources are heterogeneously distributed and imperfectly mobile.

1990; Rindova et al., 2005; Shapiro, 1982). PPQ will provide customers with direct information about the product's quality and this information will reduce consumers' uncertainty. PP will reduce consumers' uncertainty as it signals products' social approval to consumers (Khare et al., 2011; Rindova et al., 2005). Social approval generally decreases consumers' uncertainty about a firm and its product(s) (Podolny, 1994). Reduced uncertainty will, ceteris paribus, increase a consumer's likelihood of purchasing the product. Hence, higher levels of PPQ and PP will increase the likelihood that a consumer enters an economic exchange with the venture.

PPQ and PP may further generate competitive effects because reputation represents a common source of competitive advantage (Barney, 1991; Flanagan and O'Shaughnessy, 2005; Hall, 1992). The RBV suggests that resources lead to a (temporary) competitive advantage if they are valuable and rare (Barney, 1991).[4] There exist different understandings about what constitutes a valuable resource, but economic perspectives generally agree that a resource can be considered as valuable if it improves "specific qualities of the product perceived by customers in relation to their needs" (Bowman and Ambrosini, 2000).[5] Supported by the above-presented arguments, there exists a common understanding that reputation represents a valuable resource (e.g., Boyd et al., 2009; Rindova and Martins, 2012). Being valuable is a necessary but insufficient criterion for a resource-based competitive advantage (Barney, 1991). The RBV suggests that resources that are valuable but not rare – i.e., possessed by more than a few competitors (Barney, 1991) – lead to competitive parity but not to a competitive advantage. Competitive parity refers to the absence of a competitive disadvantage in regard to a specific resource. Whether high PPQ or high PP can generate a competitive advantage for a venture thus depends on the rarity of such an asset within a given market. Nevertheless, these arguments suggest that higher levels of PPQ and PP will, all else being equal, increase a venture's likelihood of achieving a competitive advantage. Based on the signaling and RBV-based arguments, I thus hypothesize:

Hypothesis 1a. Perceived product quality has a positive effect on sales performance in online markets.

Hypothesis 1b. Product prominence has a positive effect on sales performance in online markets.

3.2. Interplay between reputation and crowding in online markets

Crowded markets are associated with stronger noise (Connelly et al., 2010) and competitive pressures (e.g., Ketchen et al., 2004). If market crowding affects ventures' pressure to signal their quality and to stand out, how will this shape the signaling and competitive effects of reputation?

Crowding likely shapes the signaling effect of PPQ and PP. First, crowding may increase consumers' demand for quality signals due to the noisiness of such markets. Signaling research suggests that a larger number of signal providers and signal receivers lead to greater noise in a signaling environment (Connelly et al., 2010). In noisy market environments, consumers tend to increase their reliance on quality signals (Carlsson and Dasgupta, 1997; Haan et al., 2011). Hence, crowding may increase a market's noisiness, and consumers may thus rely more strongly on quality signals to filter through noisy information (Haan et al., 2011).

The importance of PPQ and PP as filtering mechanisms may, however, be relatively low in online markets due to the presence of search and filter algorithms (Bakos, 1997; Dellarocas, 2003). Such algorithms allow consumers to specify their search criteria and, consequently, block out a substantial share of the noise that results from competing products. The presence of efficient algorithms may allow consumers to deal with additional noise without increasing their reliance on PPQ and PP as filtering mechanisms.

Second, crowding may reduce the attention consumers pay to PPQ or PP relative to other information. Signaling theory suggests that the added value of a signal decreases as it becomes highly adopted in a signaling environment (Carlsson and Dasgupta, 1997;

[4] The RBV framework further suggests that resources can lead to a sustained competitive advantage when they are not only valuable and rare but also imperfectly imitable and not substitutable (Barney, 1991). Given our focus on new ventures and the rapidly changing environment of online markets, I focus on temporary rather than sustained competitive advantages.

[5]

Haan et al., 2011). For instance, if many job applicants hold a higher education degree, the signal loses its value as a filtering mechanism for high-quality candidates.[5] As a signal becomes widely adopted, signal receivers may thus shift their attention to alternative signals that allow for better discrimination between candidates. The more crowded a market, the more likely it is that consumers will encounter many products with high PPQ and high PP. While a nearly perfect rating score may provide a strong quality signal in a market with five products, such a high rating no longer serves as an efficient filtering mechanism when fifty out of 200 competing products have a similarly high rating. Consumers may thus reduce the relative weight they assign to PPQ and PP in their evaluations when many competing products exhibit similar levels of reputation. For instance, they may shift their attention to other quality signals, such as a producer's high status (Podolny, 1994), or filter through the large choice set by seeking out award-winning products. This effect may be particularly strong for PPQ because bounded rating scales (e.g., one to five stars) strongly limit the potential for PPQ-based diversity in a crowded market. Crowding may, therefore, increase consumers' general reliance on quality signals, but may simultaneously reduce consumers' relative attention to PPQ and PP vis-à-vis other quality signals.

Crowding will further shape the competitive effect of reputation. Section 3.1 highlighted that reputation provides a common source of competitive advantage and that resources only lead to a competitive advantage if they are rare in a market (Barney, 1991). Above, I argued that the standardized and one-dimensional nature of PPQ and PP limits their value as discriminatory quality signals in highly crowded markets because crowding will, ceteris paribus, increase the number of products with a given level of PPQ and PP. This argument affects expectations about the competitive effect of PPQ and PP even more directly. A high level of PPQ and PP likely represents a rare resource in a relatively uncrowded market. The more crowded a market, however, the less likely will a venture's PPQ or PP provide a rare resource. A resource will cease to provide a competitive advantage when many competing ventures hold the same resource. The RBV framework thus suggests that crowding decreases the likelihood that a venture can generate a competitive advantage based on a given level of PPQ or PP.

Combining arguments from both signaling and RBV suggest that crowding may (1) increase the importance of quality signals, (2) decrease the relative attention consumers pay to PPQ and PP vis-à-vis other quality signals, and (3) reduce the likelihood that a given level of PPC and PP can lead to a competitive advantage. All else being equal, a product with a given level of PPQ or PP will therefore be less likely to stand out in crowded markets. I thus hypothesize:

Hypothesis 2a. Crowding has a negative moderating effect on the relationship between perceived product quality and sales performance in online markets.

Hypothesis 2b. Crowding has a negative moderating effect on the relationship between product prominence and sales performance in online markets.

4. Methodology

4.1. Study context

To test my hypotheses, I developed a proprietary dataset of online markets for self-paced online courses. Self-paced online courses are products that contain a bundle of edited video lectures and supporting text material about a specific topic. Self-paced online courses share many product characteristics with e-books, digital music, or software as they also represent a type of digitized information goods. Most importantly, they incur insignificant costs of reproduction, storage, and delivery (Bakos and Brynjolfsson, 2000). The characteristics of such online markets are particularly suited for studying the interplay between reputation, crowding, and new venture performance. First, these markets reduce new ventures' barriers to entry by decreasing commonly faced resource limitations, and the need for costly investments in tangible resources (Varian, 1999). Second, online markets for information goods are often inherently global (Varian, 1999), and ventures can easily target consumers beyond their geographic proximity. These characteristics reinforce the crowding effect because local markets tend to become pooled into one global market. Access to a large global market further enables and incentivizes the entry of ventures from regions with low local demand and resource availability. Third, online markets for information goods often exhibit high information transparency about the market-entry choices of other actors. Such transparency allows rapid imitation and is, consequently, conducive to herding behavior (Reuber and Fischer, 2011). Fourth, consumers tend to demonstrate demand heterogeneity for information goods (Sundararajan, 2004). Rather than competing on a single value attribute (e.g., price), these markets allow for differentiation along the lines of a variety of product and service attributes. As consumers can only fully evaluate such value attributes during or after consumption, they face substantial upfront uncertainties about product quality. Fifth, information goods promise strong economies of scale (Brynjolfsson et al., 2010), and therefore provide ventures with an incentive to aim for high sales volume. The empirical setting is thus highly suited for testing my hypotheses as its characteristics foster crowding, create uncertainty about product quality, and incentivize ventures to maximize their sales performance.

I gathered data from the largest marketplace platform for self-paced online courses at the time. On the platform, entrepreneurial individuals and ventures (subsequently: *producers*) sell self-created online courses to consumers. Producers can choose a price for

[5] It is important to highlight that a commonly adopted signal will still allow signal receivers to eliminate options at the lower end of the quality spectrum. Hiring employers – similar to consumers – generally seek to identify one of the options with the highest quality. Hence, the signal will still affect the selection likelihood of any given option but will play a less central role relative to other signals that provide more differentiation at the higher end of the quality continuum.

their course, and receive the yielded price minus a proportional commission fee captured by the platform provider. When consumers purchase a course from one of the producers via the platform, they gain unlimited access to the course material and can consume the course content online or offline via a web-based platform and mobile application. Consumers are asked to rate a purchased course after they have engaged with a minimum number of lectures. At the time of analysis, the platform attracted around 10 million users on the demand side. It offered courses in 133 distinctive genres, such as content marketing, dance, dieting, graphic design, travel, or Spanish. I follow research on similar types of online platforms (e.g., Barlow et al., 2019) and treat each genre as an individual market. This operationalization builds on the assumption that any given course likely competes primarily with other courses in the same genre. Appendix 1 gives an overview of the individual markets and provides descriptive statistics.

4.2. Data collection

Data about products and their sales performance were scraped from the platform's website. The platform presents each course (i.e., each product) on a separate webpage, and these product pages follow an identical structure. On the top of the page, they provide key information about the course, including a short description, the average rating, the number of course ratings and reviews, the course price, the length of the course, and the number of lectures in the course. The data were scraped at two different points in time to ensure causality and construct a meaningful performance variable. The first measurement (end of December 2015) provided data for the independent variables. A second measurement (beginning of April 2016) allowed estimating each product's sales performance during the first quarter of 2016. For a rapidly growing online marketplace platform, a three-month period seemed appropriate to capture meaningful performance differences, while ensuring that no substantial changes in the marketplace design or business model of the marketplace provider occurred during the time. To ensure data consistency and to isolate the effects of interest, I only focused on courses that were offered in the English language. Courses in the English language represented around 85% of all courses on the platform at the time.

Initial analysis of the data revealed that half of the producers offered four or fewer courses. Visual examination of the course distribution across producers revealed eight outliers (offering more than fifty courses). I inspected these extreme cases and found that most of these producers represented established education companies rather than new ventures. Eliminating these eight extreme cases led to the loss of 811 observations but likely increased the findings' robustness. The dataset further contained 14 markets with three or fewer products. I eliminated products from these markets from the analysis as the lack of competition in these markets may bias the findings. Further eliminating observations with missing data points resulted in a final sample of 10,949 products offered by 5760 ventures across 119 markets. These products accounted for 797,087 sales transactions during the observation period.

4.3. Measures

Sales represents the study's dependent variable. The variable measures the number of times a course was sold between the end of December 2015 and the beginning of April 2016. I exploit the fact that the marketplace platform displays each course's number of "enrolments" – the number of unique individuals that have access to the course. I use the difference in "enrolments" between the beginning and end of the observation period as a close proxy for the number of unit sales during the observation period. Although consumers could theoretically withdraw from a course (which would under-estimate the unit sales), they have little incentive to do so as purchased courses does not incur any subsequent costs, and the platform provides unlimited "shelf space" to its customers (similar to e-book libraries). In line with general sales distributions in online markets, the variable shows a skewed distribution. I thus log-transformed the variable after adding a value of 1 to prevent the logarithmic transformation of zero values. The resulting distribution resembles a normal distribution more closely.

PPQ (perceived product quality) and *PP* (product prominence) represent the two main independent variables. *PPQ* is operationalized as a course's aggregated rating score, as displayed on the course's webpage. On the platform, consumers evaluate courses with zero to five stars. On each product page, the aggregated rating score is displayed in numeric form (e.g., 4.2) and with a corresponding star-based visualization. *PP* measures the number of ratings provided for a given course. The rating volume is saliently presented on each product page next to the rating score. As the number of ratings is skewed, I log-transform the measure after adding a value of 1 to prevent the logarithmic transformation of zero values.

Naturally, there exists no data points for *PPQ* if a product has not yet received any reviews. Due to this missing data point, these observations would be eliminated in the models. Eliminating these observations from the sample could, however, introduce an important bias, as courses with zero ratings represent meaningful observations. To include products without any ratings in the sample, I built on the proposition that "[w]hen an organization's reputation is unknown, the organization will most likely be treated as reputation neutral, since neither positive nor negative predictions about its future behavior normally can be made when there is a lack of information" (Bitektine, 2011). Hence, I assume that consumers evaluate the absence of any ratings as quality neutral. The sample's mean *PQ* (4.2) is thus assumed as a quality neutral level for all products without any product ratings. While this level may seem surprisingly high in light of the overall rating scale, such high average ratings are typical for online markets (e.g., Proserpio and Zervas, 2017). Post hoc tests show that the presented findings are robust under alternative assumptions (3.0, 3.5, 4.0) about consumers' level of reputation neutrality.

Crowding measures the number of products offered in a given course's product market. As discussed above, I follow previous research and use the marketplace platform's own classification system to distinguish between markets. In the default mode, the

Table 2
Overview of dependent and independent variables.

Function	Variable	Definition	Variable transformation
Dependent variable	Sales	A product's number of sold units during the observation period.	Log-transformed (*untransformed in ZINB models*)
Independent variables in the main models	PPQ (perceived product quality)	A product's rating score as displayed by the platform, based on a scale from zero to five stars.	–
	PP (product prominence)	A product's number of ratings as displayed by the platform.	Log-transformed
	Crowding	The number of products in a given product's market.	Log-transformed
Independent variables in additional models	PPQ Advantage	A product's PPQ relative to other products in the same market.	Transformed into z scores (each market: $\mu = 0$, $\sigma = 1$)
	PP Advantage	A product's PP relative to other products in the same market.	Transformed into z scores (each market: $\mu = 0$, $\sigma = 1$)

platform presents products from the same market side-by-side to consumers. The measure is log-transformed to reduce the skew between uncrowded and highly crowded markets.[6]

In my theorizing, I assumed that reputation has a signaling and a competitive effect. The competitive effect should partly depend on the *PPQ* and *PP* of other ventures in the same market. Ventures in markets with higher crowding may exhibit higher average levels of *PPQ* and *PP* because these markets may be more developed. To account for this heterogeneity, I constructed the measures *PPQ Advantage* and *PP Advantage*. These measures represent the degree to which a venture's PPQ and PP, respectively, exceeds the average PPQ and PP in its market. To do so, I standardized ($\mu = 0$, $\sigma = 1$) the values of *PPQ* and *PP* within each market. A *PPQ Advantage* of 0 thus indicates that *PPQ* exactly matches the market's average *PPQ*, whereas values of 2 and -2 indicate that *PPQ* is two standard deviations above and below, respectively, the market average. Table 2 summarizes the main variables.

I include five product-level attributes as controls: *Course Price*, *Course Length*, *Course Lectures*, *Course Level*, and *Age Rank*. Qualitative analysis of sales transactions revealed that courses on the platform were frequently offered at a flat promotional price (e.g., for $19) for limited time periods. Thus, the displayed nominal price may not represent actual sales prices. As price often represents a quality signal to consumers (Milgrom and Roberts, 1986), the displayed nominal prices may represent a quality signal rather than the price asked from consumers. *Course Length* refers to the number of video hours offered in a course, while the measure *Course Lectures* counts the total number of different lectures in a course (with or without video content). Products are further distinguished into beginner, intermediate, and advanced courses. The models further control for *Course Level*, as beginner courses may systematically attract more sales than intermediate or advanced courses. The measure *Age Rank* aims to control for potential early-mover advantages. This measure orders all courses by their launch date based on platform-specific identification numbers and is normalized to values between 0 and 1. Values close to zero indicate courses that have been created in early market stages.

I further include two control variables at the producer level: *Courses* and *Categories*. *Courses* represents the number of courses offered by the same producer. I include this measure to account for potential synergies between multiple products of the same producer. Such effects are commonly acknowledged in the diversification literature in strategic management (Hoskisson and Hitt, 2016). Each of the individual markets belongs to one of fifteen broader categories (e.g., business, languages, IT & software, personal development). Spanning multiple market categories may result in lower attention or less favorable evaluations by stakeholders (Hsu, 2006; Negro and Leung, 2013; Wry et al., 2014). I thus add the measure *Categories*, which represents the number of different categories in which a producer offers courses.

Market categories are considered to be more legitimate the stronger they contrast with other categories (Kovács and Hannan, 2010; Pontikes, 2012; Ruef and Patterson, 2009). In our context, some categories may have a high contrast and may, therefore, primarily attract specialized producers, whereas other categories may more likely attract producers that also offer courses in other categories. To control for potential heterogeneity in *Category Contrast*, I include a measure that aggregates the average number of category memberships per producer at the category level. The measure represents the inverse: categories have a low *Category Contrast* if an average producer in the category also offers courses in other categories.

4.4. Analysis

I tested my hypotheses with ordinary least squares (OLS) regression with heteroskedasticity-robust standard errors. Robust standard errors allow for dealing with a dependent variable that does not follow a normal distribution. I further aimed to test the hypotheses with the nontransformed dependent variable. Sales units – the basis for the dependent variable – represented an over-dispersed count variable with a substantial number of zero outcomes (i.e., no sales during the period). Several regression techniques allow for analyzing dependent variables with this characteristic. I conducted a Vuong test (Desmarais and Harden, 2013) to decide

[6] In robustness tests, I further measured crowding in aggregated categories (e.g., business, software & IT, languages). Models with this alternative measurement yielded the same general findings. I chose the more granular market level in the presented models because this level likely provides more meaningful competitive sets.

Table 3
Correlations and descriptive statistics.

		Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1	Sales[a]	72.8	133.6	0	632	1										
2	PPQ	3.6	0.8	1	5.0	0.07*	1									
3	PP[a]	8.2	18.8	0	644	0.25*	0.01	1								
4	Crowding[a]	278	215	4	649	−0.05*	−0.04*	0.17*	1							
5	Course Length[a]	3.4	4.0	1	109	0.10*	0.01	0.10*	0.07*	1						
6	Course Lectures[a]	32.0	33.1	2	892	0.10*	0.01	0.10*	0.08*	0.72*	1					
7	Age Rank	–	–	–	–	−0.02*	−0.02*	−0.05*	−0.01	−0.02	−0.02	1				
8	Price	85.8	77.5	7.9	395	0.10*	0.01	0.13*	0.05*	0.25*	0.25*	0.00	1			
9	Cat. Contrast	−1.8	0.3	−2.3	−1.3	−0.03*	0.10*	−0.13*	−0.28*	−0.18*	−0.18*	0.00	−0.03*	1		
10	Courses	6.3	9.5	1	50	0.11*	−0.06*	−0.06*	0.07*	0.10*	0.15*	0.02*	0.01	−0.18*	1	
11	Categories	1.6	1.1	1	8	−0.03*	−0.05*	−0.05*	0.00	0.08*	0.11*	−0.04*	0.09*	−0.16*	0.56*	1

* Significant at $p < 0.05$.
[a] Values before logarithmic transformation.

between a zero-inflated negative binomial regression (ZINB) and an ordinary negative binomial regression analysis (NBREG). A significant z-test (z = 5.94; $p = 0.000$) suggested that the zero-inflated model was preferable over the ordinary one. I also tested whether a poison model would be preferable for the given sales distribution (Cameron and Trivedi, 2013). To do so, I executed the ZINB and analyzed whether the resulting alpha value significantly differed from zero. In ZINB, alpha represents the coefficient that accounts for overdispersion in the dependent variable. An alpha coefficient close to zero would indicate that a Poisson regression model was better suited than ZINB. A likelihood ratio test (for alpha = 0) suggested that ZINB is significantly more suited than a Poisson regression (chibar2 = 0.000). I thus reran all models with the ZINB technique. As results from OLS and ZINB were robust, I decided to present the results of the OLS regressions for ease of interpretation. I used STATA 15.1 to execute the analyses. Appendix 2 presents the respective ZINB models.

5. Results

5.1. Main models

Table 3 represents descriptive statistics and the correlation matrix for the transformed measures. Products sold between zero and 644 units during the observation period (mean = 72.8). Among all variables, *PP* has the strongest correlation with sales. *PPQ* and *Sales* are also significantly positively correlated – but at a much lower degree. *Crowding* is negatively correlated with *Sales*. As expected, *Sales* correlates positively with *Category Contrast*, *Course Length*, and *Course Lectures*. In line with the above-discussed observation that many courses are sold at a fixed promotional price, I find that nominal prices correlate positively with *Sales*. The correlation table further reveals high correlations between *Course Lectures* and *Course Length* ($r = 0.72$) and between *Courses* and *Categories* ($r = 0.56$). To prevent multicollinearity, I excluded *Course Lectures* and *Categories* from the subsequent regression models.[7]

Tables 4 and 5 present the regression results. Model 1, which only includes controls, confirms that *Course Length* and *Course Price* have a significant positive effect on product sales. *Category Contrast*, *Courses*, and *Age Rank* have a significant negative effect.

Hypotheses 1a and 1b stated that PPQ and PP positively influence product sales. Model 2 provides strong support for these Hypotheses 1a, 1b, 2a, and 2b as *PPQ* ($\beta = 0.13$, $p = 0.000$) and *PP* ($\beta = 0.97$, $p = 0.000$) have a significantly positive effect on *Sales*. The positive effects are also significant in all other models (at $p < 0.01$). Across all models, the slope of the relationship between *PP* and *Sales* is substantially steeper than that of the relationship between *PPQ* and *Sales*. Model 2 further shows that the direct relationship between *Crowding* and *Sales* is significantly negative ($\beta = -0.27$, $p = 0.000$). Additional tests, in which I added a squared term of *Crowding* to the models, show that a linear specification is superior to a curvilinear relationship between *Crowding* and *Sales*.

Hypotheses 2a and 2b suggested that crowding has a negative effect on the relationship between PPQ/PP and sales. Model 3 tests Hypothesis 2a and shows a negative effect of the interaction of *PPQ* and *Crowding* on *Sales* ($\beta = -0.06$, $p = 0.044$). Model 4 demonstrates a significantly negative effect of the interaction between *PP* and *Crowding* ($\beta = -0.09$, $p = 0.000$). Model 5, which includes both interaction terms, confirms that both interactions have a negative effect on sales. These findings provide strong support for Hypotheses 2a and 2b.

5.2. Post hoc analysis: effect of reputation advantages vis-à-vis competitors

I ran several post hoc tests to further explore the mechanisms underlying the attenuating effects of crowding on the relationships between PPQ/PP and sales. I reran all models to test whether the attenuating effect would also exist if I used the relative measures of

[7] In robustness tests, I included orthogonalized versions of these two variable pairs in the models to confirm that their exclusion does not affect the results. Adding these variables does not incur any meaningful changes to the coefficients and significance levels of the main variables and interactions.

Table 4
Main regressions models (models 1–5).

DV: Sales	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	p	β	p	β	p	β	p	β	p
Course Length	0.07***	(0.000)	0.05***	(0.000)	0.05***	(0.000)	0.05***	(0.000)	0.05***	(0.000)
Age Rank	−0.11	(0.098)	0.09	(0.094)	0.09	(0.100)	0.09	(0.081)	0.09	(0.086)
Course Price	0.01***	(0.000)	0.00***	(0.000)	0.00***	(0.000)	0.00***	(0.000)	0.00***	(0.000)
Beginner Level	0.07	(0.138)	0.09*	(0.015)	0.09*	(0.015)	0.09*	(0.012)	0.09*	(0.013)
Expert Level	0.32*	(0.041)	0.42***	(0.001)	0.41***	(0.001)	0.42***	(0.001)	0.42***	(0.001)
Intermediate Level	0.33***	(0.000)	0.42***	(0.000)	0.42***	(0.000)	0.42***	(0.000)	0.42***	(0.000)
Category Contrast	−0.33***	(0.000)	0.21***	(0.001)	0.20***	(0.001)	0.24***	(0.000)	0.24***	(0.000)
Courses	−0.01*	(0.014)	0.01***	(0.000)	0.01***	(0.000)	0.01***	(0.000)	0.01***	(0.000)
PPQ			0.13***	(0.000)	0.46	(0.005)	0.13***	(0.000)	0.42*	(0.012)
PP			0.97***	(0.000)	0.97***	(0.000)	1.46***	(0.000)	1.45***	(0.000)
Crowding			−0.27***	(0.000)	−0.00	(0.988)	−0.15***	(0.000)	0.08	(0.569)
PPQ × Crowding					−0.06*	(0.044)			−0.06	(0.078)
PP × Crowding							−0.09***	(0.000)	−0.09***	(0.000)
Constant	1.28***	(0.000)	2.02***	(0.000)	0.61	(0.398)	1.50***	(0.000)	0.28	(0.700)
Observations	10,949		10,949		10,949		10,949		10,949	
R^2	0.063		0.364		0.364		0.368		0.369	
Adjusted R^2	0.062		0.363		0.364		0.368		0.368	
p	0.000		0.000		0.000		0.000		0.000	

p-Values in parentheses.
** $p < 0.01$.
* $p < 0.05$.
*** $p < 0.001$.

Table 5
Post hoc models with categorical specification of crowding.

	Model 6		Model 7		Model 8		Model 9	
	β	p	β	p	β	β	p	β
Course Length	0.05***	(0.000)	0.05***	(0.000)	0.05***	(0.000)	0.05***	(0.000)
Age Rank	0.03	(0.627)	0.07	(0.189)	0.02	(0.677)	0.07	(0.202)
Course Price	0.00***	(0.000)	0.00***	(0.000)	0.00***	(0.000)	0.00***	(0.000)
Level	Included		Included		Included		Included	
Category Contrast	−0.21**	(0.002)	−0.42***	(0.000)	−0.14*	(0.031)	−0.42***	(0.000)
Courses	0.00	(0.478)	0.01***	(0.000)	0.00	(0.420)	0.01***	(0.000)
PPQ (std)	0.49***	(0.000)			0.25***	(0.000)		
PP (std)	1.01***	(0.000)			3.53***	(0.000)		
PPQ Advantage			0.18*	(0.013)			0.05***	(0.001)
PP Advantage			1.12***	(0.000)			1.49***	(0.000)
Low Crowding	Baseline		Baseline		Baseline		Baseline	
Medium Crowding	−0.67***	(0.000)	−0.52***	(0.000)	−1.34***	(0.000)	−0.52***	(0.000)
High Crowding	−1.02***	(0.000)	−0.77***	(0.000)	−1.74***	(0.000)	−0.77***	(0.000)
Low Crowding × PPQ (std)	Baseline							
Medium Crowding × PPQ (std)	−0.06	(0.438)						
High Crowding × PPQ (std)	−0.31***	(0.000)						
Low Crowding × PPQ Advantage			Baseline					
Medium Crowding × PPQ Advantage			−0.05	(0.518)				
High Crowding × PPQ Advantage			−0.16*	(0.037)				
Low Crowding × PP (std)					Baseline			
Medium Crowding × PP (std)					−2.14***	(0.000)		
High Crowding × PP (std)					−2.60***	(0.000)		
Low Crowding × PP Advantage							Baseline	
Medium Crowding × PP Advantage							−0.23**	(0.004)
High Crowding × PP Advantage							−0.45***	(0.000)
Constant	2.61***	(0.000)	2.05***	(0.000)	3.45***	(0.000)	2.04***	(0.000)
Observations	10,949		10,949		10,949		10,949	
R^2	0.303		0.382		0.325		0.387	
Adjusted R^2	0.302		0.382		0.324		0.387	
p	0.000		0.000		0.000		0.000	

p-Values in parentheses. std = values are standardized (z-scores) to the entire sample.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 6
Estimated marginal effects on sales.

	Estimated margins for…	High crowding[a]	Low crowding[a]	Relative difference between reputation effect at high and low crowding[a]
PPQ	3.0 stars	2.15	2.65	*23.1%*
	4.0 stars	2.20	2.88	*30.6%*
	5.0 stars	2.25	3.11	*37.7%*
	Δ 1.0 star	*2.4%*	*8.0%*	
PP	−1 SD	1.47	1.42	*−3.0%*
	Mean	2.32	2.95	*27.5%*
	+1 SD	3.17	4.48	*41.5%*
	Δ 1 SD	36.6%	*52.8%*	
PPQ Advantage	−1 SD	2.34	2.70	*15.3%*
	Mean	2.39	2.75	*14.9%*
	+1 SD	2.45	2.80	*14.5%*
	Δ 1 SD	*2.5%*	*1.8%*	
PP Advantage	−1 SD	1.38	1.46	*6.1%*
	Mean	2.39	2.76	*15.2%*
	+1 SD	3.41	4.05	*18.9%*
	Δ 1 SD	*42.7%*	*46.7%*	

Values in italics represent the relative differences between Sales predictions at different fixed levels of crowding or reputation.
[a] High/low crowding is based on the 10th and 90th percentile (3.78, 6.44) of the sample.

PPQ Advantage and *PP Advantage* instead of the absolute measures of *PPQ* and *PP*. The attenuating effect of crowding should be weaker with these measures as they account more strongly for the reputation heterogeneity between markets. Models 7 and 9 in Table 5 include these measures. For ease of comparison, the table includes models with the *PPQ* and *PP* measures (Models 6 and 8). In contrast to Models 1–5, the measures for *PPQ* and *PP* are transformed into z-scores based on the entire sample's distribution. For instance, a PPQ of zero in Table 5 indicates that the product's rating score matches the average rating score of the entire sample (across all markets). This allows for a more direct comparison of effect sizes. To directly represent the difference between reputation effects at low and high crowding, I transformed *Crowding* into a binary variable. To do so, I calculated the 25th percentile and the 75th percentile of *Crowding*. Products in markets with fewer than 26 products (i.e., the 25th percentile) are classified as members of *Low Crowding*, products in markets with >141 products (i.e., the 75th percentile) are classified as members of *High Crowding*, and those in between as *Medium Crowding*.

The findings in Table 5 further support Hypotheses 1a, 1b, 2a, and 2b. They additionally confirm the underlying assumption that the moderation effect partly depends on ventures' PPQ and PP relative to their direct competitors. As the variables are standardized ($\mu = 0$, $\sigma = 1$), I can directly infer that the effect of *PP* is more than twice as strong as the effect of *PPQ* and that the effect of *PP Advantage* is more than six times stronger than the effect of *PPQ Advantage*. The models further show that *Crowding* significantly attenuates reputation effects even after accounting for inter-market heterogeneity in firms' average reputation.

5.3. Estimation of effect sizes

How much do reputation effects differ between markets with low and high crowding? To provide a comparison, I estimated Model 5's margins at low and high levels of *Crowding*. Table 6 compares the estimated margins. The table presents predicted *Sales* values at fixed levels of reputation (specified in column 2) and at a fixed level of high (column 3) or low crowding (column 4). Percentage values in the table represent relative differences between Sales predictions at different levels of reputation and crowding. *Low Crowding* and *High Crowding* here correspond to the 10th and 90th percentile of the sample. As such, 3.78 log-products (i.e., 43 products) represent a market with *Low Crowding* and 6.44 log-products (i.e., 623 products) represent a market with *High Crowding*.[8]

The table provides predicted Sales for different levels of *PPQ* (unstandardized), *PP* (as z-scores), *PPQ Advantage*, and *PP Advantage*. I estimate the margins at one standard deviation above the respective sample means to represent *High PP*, *High PPQ Advantage*, and *High PP Advantage*. The table allows comparing of margins (1) between levels of crowding at a given level of reputation (horizontally), and (2) between different degrees of reputation at a given level of crowding (vertically). The effect of *High PPQ* on *Sales* is 38% lower at *High Crowding* compared to the same margin at *Low Crowding*. The positive effect of *High PP* on *Sales* is 42% weaker under the condition of *High Crowding*, compared to *Low Crowding*. A venture with *PP* of 5 (which corresponds to approximately 150 ratings) could expect 76% more unit sales in a market with low versus high crowding. The intra-market comparison (vertically) shows that an increase in one standard deviation in *PP* increases predicted *Sales* by 53% under the condition of *Low Crowding* and 37% under *High Crowding*. The margin comparison provides further weight to the study's main finding: the reputation effect – for both PPQ and PP – is substantially contingent on the level of market crowding.

I further estimated these margins for the variables of *PPQ Advantage* and *PP Advantage* to determine the effect of a superior PPQ and PP vis-à-vis other products in the same market. I estimated the effects at assumed values of one standard deviation below and

[8] In the sample, 31 markets consist of 43 or fewer products. The benchmark for *low crowding* thus represents a rather conservative measure. The difference between a market with very low crowding (e.g., 5 products) and high crowding would naturally be larger than the presented differences.

above the average *PPQ Advantage* and *PP Advantage*. *PPQ Advantage* leads to 15% less *Sales* at *High Crowding* versus *Low Crowding*. This difference does not deviate much from the corresponding value for *PPQ*. An increase in one standard deviation of *PP Advantage* increases estimated sales by nearly 50% and the positive effect of *PP Advantage* is 19% weaker under high (versus low) crowding. These estimations suggest that markets with high crowding exhibit higher average levels of PP than markets with low crowding, and that this difference explains a large share of the inter-market differences. Even after netting out the heterogeneity in markets' average levels of PP and PPQ, there still exists a substantial moderating effect of market crowding.

6. Discussion and conclusions

This study aimed to advance the literature on reputation as a driver of new venture performance. The study specifically aimed to explore how market crowding affects the theorized benefits of a favorable reputation. I focused my theorization and hypotheses on the context of online markets, in which rating scores and rating volume provide commonly observable reputation cues. To hypothesize about the moderating role of crowding in this context, I drew upon the two dominant theoretical perspectives on reputation – economic signaling theory and the RBV. I expected that the perceived quality and prominence of ventures' products in online markets would engender an uncertainty-reducing signaling effect as well as a competitive effect that would differentiate the venture from others in the market. I argued that crowding would decrease reputation benefits as favorable reputations will become increasingly ubiquitous in crowded markets. This is particularly evident for standardized, one-dimensional reputation cues like rating scores. While previous research has emphasized that rating scores and volume provide efficient mechanisms to reduce consumers' uncertainty (e.g., Dellarocas, 2003), I highlight that such standardized mechanisms limit the space for reputational diversity and therefore provide a relatively weak source of competitive advantage. I thus predicted that the benefit of reputation would decrease in crowded markets.

An empirical study of 119 online markets showed that (1) products' perceived quality (PPQ) and product prominence (PP) had a significantly positive effect on their sales performance; (2) the positive effect of PP on sales is at least twice as strong as the effect of PPQ; (3) crowding has a significantly negative effect on sales; and (4) crowding significantly attenuate the relationship between PPQ/PP and sales. Subsequent post hoc tests showed that PPQ has a 38% more positive effect in markets with low crowding compared to markets with high crowding. Ventures benefit 42% more from a high PP under low (versus high) crowding. The effect remains significant and practically relevant even when I accounted for inter-market heterogeneity in the distribution of reputation among firms. All else equal, a venture benefits less from a favorable reputation when it operates in a more crowded market.

My study contributes to research on platform entrepreneurship, i.e., the pursuit of entrepreneurial opportunities in platform-mediated online markets (Nambisan, 2017; Srinivasan and Venkatraman, 2017). Specifically, I add to the line of research that explores the role of ratings as critical reputation signals in such markets (Li and Hitt, 2008; Reuber and Fischer, 2009, 2011). In their study of software products, Reuber and Fischer (2009) found that a product's average rating (similar to this study's measure of PPQ) has a positive ($\beta = 0.2$) effect on the number of trial downloads (a proxy for product performance). Li and Hitt (2008) found a similar effect ($\beta = 0.18$) on estimated book sales in selected markets within the Amazon Marketplace. My study finds a similar average effect ($\beta = 0.14$) in the relevant model without interactions. Regarding the prominence dimension, Li and Hitt (2008) found a slightly lower effect of review volume on sales ($\beta = 0.71$) than I found in my study ($\beta = 0.97$). While previous platform entrepreneurship research has conceptualized rating scores and volume as reputation signals, I conceptually and empirically distinguished between the signaling and competitive effect of such reputation cues. Acknowledging the competitive effect of reputation allowed me to uncover the market-contingent nature of reputation. My theorizing and empirical study show that average reputation effects might not be particularly meaningful because they are contingent on competitive market conditions and may systematically decrease as a market becomes more crowded. This has high practical relevance for the study of platform entrepreneurship as it challenges the robustness of prior findings about the consequences of reputation in online markets.

The study's findings further contribute to the broader literature on new venture performance (Short et al., 2009). An important question is to what degree ventures' performance heterogeneity results from factors that are internal (e.g., resources) or external (industry or market) to the firm. This line of research extends a long-lasting discussion in strategic management (McGahan and Porter, 1997; Rumelt, 1991), which aims to locate the primary driver of superior firm performance. In the context of mature firms, internal factors explain between 31% and 44% of firms' performance variance, whereas environmental factors explain between 4% and 19% of performance variance (Misangyi et al., 2006). To date, Short et al. (2009) provide the only study that decomposes firm-level and market-level effects of new venture performance. Their study of new ventures in Sweden finds that firm-level effects explain 41% and environmental factors 15% of new ventures' performance variance. In my study, heterogeneity in ventures' PPQ and PP explain 29.6% of sales variance.[9] In comparison, heterogeneity at the market level only accounts for 6.2% of the variance in ventures' sales performance.[10] This suggests that reputation (i.e., an internal factor) is nearly five times as important for achieving superior sales performance than selecting the right market. My study thus underscores the critical relevance of reputation for new ventures, and hopefully incentivizes research on new venture performance to include this construct in further empirical studies.

This research further contributes to literature on new venture reputation in organizational theory. Research on the role of reputation for new ventures is scarce to date (Petkova, 2016), and existing studies have primarily focused on the antecedents and

[9] The added variance is estimated through differences in the total explained variance between a model with and without the respective variable of interest (based on Model 2).

[10] The market-level effect is based on a model that adds market dummies instead of the individual market-level variables.

formation of reputation for new ventures (Fischer and Reuber, 2007; Petkova et al., 2008; Rindova et al., 2007), ventures' benefits in associating themselves with reputable firms (Pollock and Rindova, 2003), and the role of founders' personal reputations (Ebbers and Wijnberg, 2012). For instance, Rindova et al. (2007) studied how new ventures initially build their reputations. Their exploratory analysis was instrumental in developing a multi-dimensional understanding of reputation and showed that different activity types, such as entering partnerships or symbolic actions, can affect different dimensions of reputation. In a notable exception, Pollock et al. (2015) explore new ventures' co-evolution of reputation and status, a different social approval asset. They argue and find that new ventures' reputation positively influences their acquisition of status. Their study further highlights that path-dependence of reputation but suggests that the relationship between ventures' past and future reputation is not contingent on their age. My study complements existing studies in this line of research in that it focuses on the performance consequences of new venture reputation.

My study further extends reputation research more broadly (Bergh et al., 2010; Boyd et al., 2009; Rindova et al., 2005; Rindova et al., 2010). Organizational theorists have long shown that reputation generally leads to positive performance outcomes. Reputation benefits include higher price premiums (Rindova et al., 2005), higher return on assets (Deephouse, 2000), lower penalization of negative events by stakeholders (Pfarrer et al., 2010), access to critical resources such as alliance partners (Hubbard et al., 2018) and human talent (Turban and Cable, 2003), and ultimately superior profitability (Greenwood et al., 2005). Rindova et al.'s (2005) seminal study on the reputation effects of business schools theoretically and empirically advanced the understanding of reputation as a driver of beneficial performance outcomes. Yet, the study's authors acknowledged the limitations of their survey-based, single-market research design. Most importantly, such a research design can rarely detect how environmental factors shape the reputation–performance relationship (Rindova et al., 2005). Rindova et al. (2005) thus encouraged reputation researchers to explore whether “the effects of perceived quality and prominence vary across contexts” (Rindova et al., 2010). My study addresses their call by suggesting that the effects of perceived quality and prominence substantially differ between markets and decrease as markets become more crowded. My theorization and empirical findings can allow future reputation research to make more accurate predictions about when and how firms will benefit from a favorable reputation.

Like all studies, this study is not without limitations. Empirically, the presented relationships may also depend on the legitimacy and reputation of the market-mediating platform. The legitimation of market-mediating platforms may potentially affect consumers' perception and evaluation of reputation cues. When a platform itself lacks legitimacy, stakeholders may pay more attention to signals about ventures' legitimacy rather than their reputation (Rindova et al., 2007). Further, I cannot fully isolate the theorized effects from a potential effect that results from the platform's proprietary search and filter algorithms. Such algorithms likely reinforce the benefits of reputation as they present highly reputable products most saliently to consumers (Taeuscher, 2019). By focusing on markets mediated by the same platform and by choosing a relatively short observation period, I aimed to reduce the likelihood that platform-level changes and unobservable algorithmic factors would affect the study's findings.

The context of online markets allowed me to overcome common empirical challenges in research on new venture reputation and performance, but there may exist some limits to the generalizability of my findings to other contexts. Management scholars have conceptualized reputation as a dynamic asset that can be lost within a short period (Lange et al., 2010; Pfarrer et al., 2010; Pollock et al., 2015), but its fragility may be particularly high in online markets. At the same time, however, the longevity of reputation cues in digital contexts might also smoothen reputation dynamics. Beyond the online context, my study's findings may be most generalizable to other contexts in which consumers perceive and evaluate reputation cues. Stakeholder groups differ in their evaluations of new ventures' legitimacy (Fisher et al., 2017), and they may also differ in how they evaluate and react to reputation cues. Given these minor limitations to the generalizability of my findings, I encourage future research to further test the hypothesized relationships in other contexts.

7. Summary

Entrepreneurship research has paid relatively little attention to the reputation of new ventures (Petkova, 2016). In this study, I show that reputation represents a highly important driver of new venture performance. I find that products' perceived quality and prominence – the two dimensions of reputation – explain 30% of sales variance in online markets. Previous entrepreneurship research suggested that favorable reputations allow new ventures to signal their quality and stand out in crowded markets (Reuber and Fischer, 2009). This paper challenges such an unconditional perspective and suggests that market crowding attenuates reputation benefits. My study in 119 markets for self-paced online courses offers strong and robust support for this hypothesis. Different post hoc tests underline the high practical significance of this contingency and show that market crowding attenuates the positive effects of perceived quality and prominence by 38% and 42%, respectively.

Declaration of Competing Interest

None.

Acknowledgments

I would like to thank Associate Editor Greg Fisher and three anonymous reviewers for their excellent remarks. I also want to thank Joseph Lampel for his insightful comments on earlier drafts of this manuscript.

Appendix 1. Overview of markets

Table A.1
Descriptive statistics for individual markets.

Market	Crowding (# of products)	Mean PPQ	Mean PP	Mean unit sales	Mean price
3D & animation	74	4.3	2.3	103.6	53.9
Advertising	14	4.4	2.4	115.5	85.4
Affiliate marketing	12	4.0	9.0	268.8	84.4
Analytics & automation	7	4.2	8.1	138.1	91.7
Apple	52	4.1	8.8	41.8	53.1
Arabic	4	4.0	1.0	156.8	65.3
Architectural design	4	4.3	2.5	399.3	116.8
Arts & crafts	117	4.5	2.0	93.0	36.6
Beauty & makeup	14	4.2	2.9	140.7	72.9
Branding	19	4.5	1.7	120.4	63.2
Business law	47	4.2	8.2	66.7	86.0
Career development	304	4.3	6.0	52.5	70.8
Chinese	8	4.5	0.6	56.4	26.1
College entry exam	15	4.3	0.6	90.5	47.1
Commercial photography	10	4.1	2.1	131.4	103.7
Communications	303	4.3	13.0	51.0	82.0
Content marketing	40	4.2	2.5	106.3	73.7
Creativity	73	4.4	9.3	50.7	72.2
Dance	18	4.5	1.6	82.6	57.8
Data & analytics	118	4.1	9.2	108.2	96.6
Databases	98	4.1	14.0	92.0	93.6
Design tools	165	4.4	2.2	96.4	55.2
Development tools	34	4.1	14.6	117.4	66.3
Dieting	29	4.5	2.6	135.8	65.1
Digital marketing	107	4.1	2.9	93.7	75.4
Digital photography	17	4.3	6.3	199.5	51.6
E-commerce	39	4.1	6.1	107.6	52.6
Educational development	32	4.6	2.4	128.4	72.6
English	73	4.4	3.0	106.6	52.0
Entrepreneurship	623	4.2	8.1	58.4	97.9
Fashion	6	4.5	1.8	162.0	69.3
Finance	548	4.1	9.5	90.9	82.7
Fitness	62	4.5	0.9	75.9	55.8
Food & beverage	50	4.5	2.0	87.9	47.1
French	8	4.0	3.5	101.1	71.5
Game design	24	4.6	5.7	103.0	52.4
Game development	186	4.2	12.1	53.9	76.2
Gaming	8	4.4	1.6	126.9	31.1
General health	102	4.5	2.1	99.6	51.2
German	8	4.5	4.5	205.6	49.5
Google	41	4.2	12.7	57.0	55.1
Grad entry exam	8	4.3	3.9	145.4	70.3
Graphic design	64	4.2	2.8	115.3	47.4
Growth hacking	5	4.7	1.0	58.4	92.2
Happiness	67	4.3	9.3	51.5	94.9
Hardware	71	4.0	10.9	121.4	83.8
Home business	383	4.2	11.8	60.4	108.3
Home improvement	12	4.6	2.7	170.6	39.8
Human resources	71	4.0	3.3	31.1	82.4
Humanities	42	4.7	2.2	72.6	58.6
Industry	78	4.1	7.8	46.8	76.7
Influence	55	4.3	11.4	56.1	81.7
Instructional design	16	4.7	3.8	203.6	61.5
Instruments	101	4.6	2.2	91.8	51.7
Interior design	4	4.3	3.0	52.3	42.3
Intuit	10	4.3	2.2	16.1	67.8
IT certification	187	3.9	11.3	80.2	84.7
Japanese	7	4.5	0.4	185.9	39.4
Leadership	49	4.3	3.4	36.9	77.4
Management	241	4.2	5.7	31.8	77.2
Marketing fundamentals	37	3.9	1.8	79.5	63.7
Math & science	191	4.3	1.0	65.5	36.2
Media	186	4.3	9.7	58.9	75.7
Meditation	18	4.0	2.6	126.9	33.5
Memory & study skills	57	4.1	10.4	57.3	110.8

(*continued on next page*)

Table A.1 (*continued*)

Market	Crowding (# of products)	Mean PPQ	Mean PP	Mean unit sales	Mean price
Mental health	32	4.4	6.7	115.9	57.7
Microsoft	568	4.2	8.7	49.3	66.4
Mobile apps	319	4.0	12.5	58.6	88.0
Motivation	36	4.4	4.5	27.0	84.3
Music fundamentals	26	4.7	3.9	123.2	70.1
Music software	12	4.3	1.2	199.8	42.1
Music techniques	13	3.8	1.8	106.4	85.2
Network & security	204	4.1	12.5	69.9	78.2
Nutrition	45	4.5	1.7	137.7	66.6
Operating systems	97	4.2	7.1	73.0	64.7
Operations	99	4.1	10.3	71.1	97.9
Oracle	35	3.8	6.8	46.6	121.8
Other	574	4.4	1.7	109.9	50.0
Parenting & relationships	172	4.3	3.3	32.1	64.3
Personal brand building	37	4.5	9.2	21.5	116.9
Personal finance	145	4.3	5.8	89.2	80.3
Personal transformation	326	4.3	6.0	57.3	77.7
Pet care & training	14	3.6	4.2	119.6	67.2
Photography fundamentals	26	4.2	2.7	93.3	52.8
Photography tools	10	3.9	1.5	159.8	59.0
Portraits	5	4.6	5.0	80.2	53.2
Product marketing	14	4.5	1.9	74.6	83.1
Production	27	4.1	3.0	57.8	66.0
Productivity	156	4.2	11.4	60.2	81.4
Programming languages	311	4.1	16.6	94.5	72.9
Project management	143	4.0	10.1	56.3	107.4
Public relations	11	3.0	2.3	131.7	59.5
Real estate	56	4.4	6.2	79.0	106.8
Religion & spirituality	91	4.5	5.9	59.7	58.5
Safety & first aid	12	4.5	1.2	70.9	48.0
Sales	197	4.3	6.7	57.1	109.8
Salesforce	9	4.4	27.1	69.7	108.9
SAP	92	3.6	12.3	64.2	137.6
Search engine optimization	45	4.1	5.0	129.9	104.4
Self defense	8	4.5	4.0	258.6	54.0
Self esteem	43	4.4	7.8	75.4	82.4
Social media marketing	137	4.1	2.4	83.2	75.7
Social science	32	4.6	1.1	61.7	58.3
Software engineering	61	3.9	10.5	79.6	81.2
Software testing	51	3.8	13.9	111.5	84.6
Spanish	8	4.5	3.6	80.3	36.3
Sports	34	4.4	2.4	157.8	60.9
Strategy	116	4.3	7.4	52.4	92.9
Stress management	56	4.6	6.8	43.7	63.3
Teaching tools	50	4.5	2.0	154.4	62.0
Test taking skills	14	4.3	1.3	24.3	55.0
Travel	21	4.7	2.0	132.8	53.3
User experience	13	3.9	7.5	111.2	83.9
Video & mobile marketing	45	4.5	4.5	66.0	69.2
Video design	32	4.3	2.3	91.6	67.8
Vocal	12	4.5	4.3	60.1	94.3
Web design	85	4.1	2.1	93.7	66.8
Web development	649	4.1	15.4	70.6	70.3
Yoga	51	4.5	1.8	131.0	46.2

Appendix 2. Zero-inflated negative binomial regression

The ZINB technique combines a logistic model that predicts a binary outcome of zero with a model that predicts the value for all nonzero outcomes. The model thus predicts both the likelihood that the course does not sell at all and the expected number of sales in case of nonzero outcomes separately (Cameron and Trivedi, 2013). The model coefficients then express the expected count as a combination of the two models (Cameron and Trivedi, 2013). The presented models add variables in the same way as presented in the robust regressions. The respective logit models contain all controls and PQ. Table A.1 presents the results of the zero-inflated binomial regression models. In ZINB models, chi-square values represent the model's predictive quality by comparing the full model to a model without any count predictors. The chi-square and *p*-values indicate that all models are statistically significant. The lower part of the table represents coefficients for the logistic model. The models support our main findings since all hypothesized relationships maintain their direction. The interaction between prominence and crowding is less significant in the combined Model 5.

Table A.2
Zero-inflated binomial regression (Models 1–5).

	Model 1		Model 2		Model 3		Model 4		Model 5	
Sales (units)										
Course Length	0.03***	(0.000)	0.02***	(0.000)	0.02***	(0.000)	0.02***	(0.000)	0.02***	(0.000)
Age Rank	−0.11	(0.063)	−0.03	(0.559)	−0.04	(0.423)	−0.03	(0.538)	−0.04	(0.428)
Course Price	0.00***	(0.000)	0.00	(0.503)	0.00	(0.576)	0.00	(0.530)	0.00	(0.588)
Beginner Level	0.03	(0.452)	0.05	(0.210)	0.05	(0.188)	0.05	(0.192)	0.05	(0.179)
Expert Level	−0.06	(0.675)	0.00	(0.976)	0.01	(0.950)	−0.00	(0.988)	0.00	(0.977)
Intermediate Level	0.12	(0.056)	0.20***	(0.001)	0.20***	(0.001)	0.20***	(0.001)	0.20***	(0.001)
Category Contrast	0.27***	(0.000)	0.62***	(0.000)	0.61***	(0.000)	0.62***	(0.000)	0.61***	(0.000)
Courses	−0.01***	(0.000)	0.00	(0.192)	0.00	(0.185)	0.00	(0.224)	0.00	(0.206)
PPQ			0.12***	(0.000)	0.50***	(0.000)	0.12***	(0.000)	0.45***	(0.000)
PP			0.66***	(0.000)	0.66***	(0.000)	0.89***	(0.000)	0.82***	(0.000)
Crowding			−0.23***	(0.000)	0.04	(0.575)	−0.18***	(0.000)	0.04	(0.580)
PPQ × crowding					−0.08***	(0.000)			−0.07**	(0.002)
PP × crowding							−0.04**	(0.006)	−0.03	(0.077)
Constant	4.47***	(0.000)	4.84***	(0.000)	3.43***	(0.000)	4.56***	(0.000)	3.44***	(0.000)
Zero sales (logistic model)										
Course Length	−8.55**	(0.010)	−9.07**	(0.008)	−9.03**	(0.007)	−9.12**	(0.008)	−9.06**	(0.007)
Age Rank	−0.55	(0.336)	−0.73	(0.321)	−0.75	(0.314)	−0.73	(0.324)	−0.75	(0.317)
Course Price	−0.03**	(0.010)	−0.03**	(0.009)	−0.03**	(0.009)	−0.03**	(0.009)	−0.03**	(0.009)
Course level	Included		Included		Included		Included		Included	
Category Contrast	−1.21*	(0.047)	−1.32	(0.077)	−1.36	(0.070)	−1.36	(0.071)	−1.38	(0.067)
Courses	−0.19	(0.077)	−0.19	(0.087)	−0.19	(0.085)	−0.19	(0.088)	−0.19	(0.086)
PPQ	−2.32***	(0.000)	−2.27***	(0.000)	−2.28***	(0.000)	−2.28***	(0.000)	−2.28***	(0.000)
Constant	12.63**	(0.002)	12.62**	(0.003)	12.53**	(0.003)	12.62**	(0.003)	12.54**	(0.003)
LnAlpha (constant)	1.17***	(0.000)	1.04***	(0.000)	1.04***	(0.000)	1.04***	(0.000)	1.04***	(0.000)
Likelihood ratio chi-square	181.33		2027.41		2041.53		2034.86		2044.67	
p	0.000		0.000		0.000		0.000		0.000	

p-Values in parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

References

Aldrich, H.E., 1999. Organizations Evolving, First published. ed. SAGE Publications, London (Thousand Oaks, New Delhi, 413 pp).
Anderson, E.W., Salisbury, L.C., 2003. The formation of market-level expectations and its covariates. J. Consum. Res. 30 (1), 115–124.
Anderson, E.T., Simester, D.I., 2014. Reviews without a purchase: low ratings, loyal customers, and deception. J. Mark. Res. 51 (3), 249–269.
Bakos, J.Y., 1997. Reducing buyer search costs: implications for electronic marketplaces. Manag. Sci. 43 (12), 1676–1692.
Bakos, Y., Brynjolfsson, E., 2000. Bundling and competition on the Internet. Mark. Sci. 19 (1), 63–82.
Barlow, M.A., Verhaal, J.C., Angus, R.W., 2019. Optimal distinctiveness, strategic categorization, and product market entry on the Google Play app platform. Strateg. Manag. J. 91 (3), 454.
Barnett, M.L., Pollock, T.G. (Eds.), 2012. The Oxford Handbook of Corporate Reputation. Oxford Univ. Press, Oxford (502 pp).
Barney, J., 1991. Firm resources and sustained competitive advantage. J. Manag. 17 (1), 99–120.
Bergh, D.D., Ketchen, D.J., Boyd, B.K., Bergh, J., 2010. New frontiers of the reputation—performance relationship: insights from multiple theories. J. Manag. 36 (3), 620–632.
Bitektine, A., 2011. Toward a theory of social judgments of organizations: the case of legitimacy, reputation, and status. Acad. Manag. Rev. 36 (1), 151–179.
Bowman, C., Ambrosini, V., 2000. Value creation versus value capture: towards a coherent definition of value in strategy. Br. J. Manag. 11.
Boyd, B.K., Bergh, D.D., Ketchen, D.J., 2009. Reconsidering the reputation—performance relationship: a resource-based view. J. Manag. 36 (3), 588–609.
Brynjolfsson, E., Hu, Y., Smith, M.D., 2010. Research commentary — long tails vs. superstars: the effect of information technology on product variety and sales concentration patterns. Inf. Syst. Res. 21 (4), 736–747.
Cameron, A.C., Trivedi, P.K., 2013. Regression analysis of count data. In: Econometric Society Monographs 53, Second edition ed. Cambridge University Press, Cambridge (566 pp).
Carlsson, H., Dasgupta, S., 1997. Noise-proof equilibria in two-action signaling games. J. Econ. Theory 77 (2), 432–460.
Chen, Y., Fay, S., Wang, Q., 2011. The role of marketing in social media: how online consumer reviews evolve. J. Interact. Mark. 25 (2), 85–94.
Chevalier, J.A., Mayzlin, D., 2006. The effect of word of mouth on sales: online book reviews. J. Mark. Res. 43 (3), 345–354.
Connelly, B.L., Certo, S.T., Ireland, R.D., Reutzel, C.R., 2010. Signaling theory: a review and assessment. J. Manag. 37 (1), 39–67.
Deephouse, D.L., 2000. Media reputation as a strategic resource: an integration of mass communication and resource-based theories. J. Manag. 26 (6), 1091–1112.
Dellarocas, C., 2003. The digitization of word of mouth: promise and challenges of online feedback mechanisms. Manag. Sci. 49 (10), 1407–1424.
Desmarais, B.A., Harden, J.J., 2013. Testing for zero inflation in count models: bias correction for the Vuong test. Stata J. 13 (4), 810–835 (26).
Dimov, D., Shepherd, D.A., Sutcliffe, K.M., 2007. Requisite expertise, firm reputation, and status in venture capital investment allocation decisions. J. Bus. Ventur. 22 (4), 481–502.
Duan, W., Gu, B., Whinston, A.B., 2008. Do online reviews matter?: — an empirical investigation of panel data. Decis. Support. Syst. 45 (4), 1007–1016.
Ebbers, J.J., Wijnberg, N.M., 2012. Nascent ventures competing for start-up capital: matching reputations and investors. J. Bus. Ventur. 27 (3), 372–384.
Fischer, E., Reuber, R., 2007. The good, the bad, and the unfamiliar: the challenges of reputation formation facing new firms. Entrep. Theory Pract. 31 (1), 53–75.
Fisher, G., Kuratko, D.F., Bloodgood, J.M., Hornsby, J.S., 2017. Legitimate to whom?: the challenge of audience diversity and new venture legitimacy. J. Bus. Ventur. 32 (1), 52–71.
Flanagan, D.J., O'Shaughnessy, K.C., 2005. The effect of layoffs on firm reputation. J. Manag. 31 (3), 445–463.

Floyd, K., Freling, R., Alhoqail, S., Cho, H.Y., Freling, T., 2014. How online product reviews affect retail sales: a meta-analysis. J. Retail. 90 (2), 217–232.
Fombrun, C., Shanley, M., 1990. What's in a name? Reputation building and corporate strategy. Acad. Manag. J. 33 (2), 233–258.
Godes, D., Mayzlin, D., 2004. Using online conversations to study word-of-mouth communication. Mark. Sci. 23 (4), 545–560.
Greenwood, R., Li, S.X., Prakash, R., Deephouse, D.L., 2005. Reputation, diversification, and organizational explanations of performance in professional service firms. Organ. Sci. 16 (6), 661–673.
Haan, T. de, Offerman, T., Sloof, R., 2011. Noisy signaling: theory and experiment. Games Econ. Behav. 73 (2), 402–428.
Hall, R., 1992. The strategic analysis of intangible resources. Strateg. Manag. J. 13 (2), 135–144.
Hoskisson, R.E., Hitt, M.A., 2016. Antecedents and performance outcomes of diversification: a review and critique of theoretical perspectives. J. Manag. 16 (2), 461–509.
Hsu, G., 2006. Jacks of all trades and masters of none: audiences' reactions to spanning genres in feature film production. Adm. Sci. Q. 51 (3), 420–450.
Hubbard, T.D., Pollock, T., Hubbard, T.D., Pollock, T., Pfarrer, M., Rindova, V.P., 2018. Safe Bets or Hot Hands?: How Status and Celebrity Influence Strategic Alliance Formations by Newly-Public Firms. Academy of Management Journal 61 (5), 1976–1999.
Jensen, M., Roy, A., 2008. Staging exchange partner choices: when do status and reputation matter? Acad. Manag. J. 51 (3), 495–516.
Ketchen, D.J., Snow, C.C., Hoover, V.L., 2004. Research on competitive dynamics: recent accomplishments and future challenges. J. Manag. 30 (6), 779–804.
Khare, A., Labrecque, L.I., Asare, A.K., 2011. The assimilative and contrastive effects of word-of-mouth volume: an experimental examination of online consumer ratings. J. Retail. 87 (1), 111–126.
Koh, N.S., Hu, N., Clemons, E.K., 2010. Do online reviews reflect a product's true perceived quality?: an investigation of online movie reviews across cultures. Electron. Commer. Res. Appl. 9 (5), 374–385.
Kovács, B., Hannan, M.T., 2010. Categories in markets: origins and evolution. In: Hsu, G. (Ed.), Categories in Markets. Origins and Evolution, 1. ed. ed. Research in the Sociology of Organizations Emerald, Bingley.
Lange, D., Lee, P.M., Dai, Y., 2010. Organizational reputation: a review. J. Manag. 37 (1), 153–184.
Langhe, B. de, Fernbach, P.M., Lichtenstein, D.R., 2016. Navigating by the stars: investigating the actual and perceived validity of online user ratings. J. Consum. Res. 42 (6), 817–833.
Li, X., Hitt, L.M., 2008. Self-selection and information role of online product reviews. Inf. Syst. Res. 19 (4), 456–474.
Loane, S., McNaughton, R.B., Bell, J., 2004. The internationalization of Internet-enabled entrepreneurial firms: evidence from Europe and North America. Can. J. Admin. Sci. Rev. Can. Sci. Admin. 21 (1), 79–96.
Mayzlin, D., Dover, Y., Chevalier, J., 2012. Promotional Reviews: An Empirical Investigation of Online Review Manipulation. National Bureau of Economic Research, Cambridge, MA.
McGahan, A.M., Porter, M.E., 1997. How much does industry matter, really? Strateg. Manag. J. 18 (S1), 15–30.
Milgrom, P., Roberts, J., 1986. Price and advertising signals of product quality. J. Polit. Econ. 94 (4), 796–821.
Mishina, Y., Block, E.S., Mannor, M.J., 2012. The path dependence of organizational reputation: how social judgment influences assessments of capability and character. Strategic Management Journal 33 (5), 459–477.
Misangyi, V.F., Elms, H., Greckhamer, T., Lepine, J.A., 2006. A new perspective on a fundamental debate: a multilevel approach to industry, corporate, and business unit effects. Strateg. Manag. J. 27 (6), 571–590.
Moreno, A., Terwiesch, C., 2014. Doing business with strangers: reputation in online service marketplaces. Inf. Syst. Res. 25 (4), 865–886.
Nambisan, S., 2017. Digital entrepreneurship: toward a digital technology perspective of entrepreneurship. Entrepreneurship Theory and Practice 41 (6), 1029–1055.
Navis, C., Glynn, M.A., 2010. How new market categories emerge: temporal dynamics of legitimacy, identity, and entrepreneurship in satellite radio, 1990–2005. Adm. Sci. Q. 55 (3), 439–471.
Negro, G., Leung, M.D., 2013. “Actual” and perceptual effects of category spanning. Organ. Sci. 24 (3), 684–696.
Newbert, S.L., 2007. Empirical research on the resource-based view of the firm: an assessment and suggestions for future research. Strateg. Manag. J. 28 (2), 121–146.
Parker, O., Krause, R., Devers, C.E., 2019. How Firm Reputation Shapes Managerial Discretion. Academy of Management Review 44 (2), 254–278.
Petkova, A.P., 2016. Standing out or blending in? The formation of new firms' legitimacy and reputation under different levels of market uncertainty. Corp. Reput. Rev. 19 (1), 22–34.
Petkova, A.P., Rindova, V.P., Gupta, A.K., 2008. How can new ventures build reputation? An exploratory study. Corp. Reput. Rev. 11 (4), 320–334.
Petkova, A.P., Rindova, V.P., Gupta, A.K., 2013. No news is bad news: sensegiving activities, media attention, and venture capital funding of new technology organizations. Organ. Sci. 24 (3), 865–888.
Pfarrer, M.D., Pollock, T.G., Rindova, V.P., 2010. A tale of two assets: the effects of firm reputation and celebrity on earnings surprises and investors' reactions. Acad. Manag. J. 53 (5), 1131–1152.
Podolny, J.M., 1994. Market uncertainty and the social character of economic exchange. Adm. Sci. Q. 39 (3), 458–483.
Pollock, T.G., Gulati, R., 2007. Standing out from the crowd: the visibility-enhancing effects of IPO-related signals on alliance formation by entrepreneurial firms. Strateg. Organ. 5 (4), 339–372.
Pollock, T.G., Rindova, V.P., 2003. Media legitimation effects in the market for initial public offerings. Acad. Manag. J. 46 (5), 631–642.
Pollock, T.G., Lee, P.M., Jin, K., Lashley, K., 2015. (Un)tangled: exploring the asymmetric coevolution of new venture capital firms' reputation and status. Adm. Sci. Q. 60 (3), 482–517.
Pontikes, E.G., 2012. Two sides of the same coin: how ambiguous classification affects multiple audiences' evaluations. Adm. Sci. Q. 57 (1), 81–118.
Proserpio, D., Zervas, G., 2017. Online reputation management: estimating the impact of management responses on consumer reviews. Mark. Sci. 36 (5), 645–665.
Reuber, A.R., Fischer, E., 2009. Signalling reputation in international online markets. Strateg. Entrep. J. 3 (4), 369–386.
Reuber, A.R., Fischer, E., 2011. International entrepreneurship in Internet-enabled markets. J. Bus. Ventur. 26 (6), 660–679.
Rindova, V.P., Martins, L.L., 2012. Show me the money: a multidimensional perspective on reputation as an intangible asset. In: Barnett, M.L., Pollock, T.G. (Eds.), The Oxford Handbook of Corporate Reputation. Oxford Univ. Press, Oxford, pp. 16–33.
Rindova, V.P., Williamson, I.O., Petkova, A.P., Sever, J.M., 2005. Being good or being known: an empirical examination of the dimensions, antecedents, and consequences of organizational reputation. Acad. Manag. J. 48 (6), 1033–1049.
Rindova, V.P., Petkova, A.P., Kotha, S., 2007. Standing out: how new firms in emerging markets build reputation. Strateg. Organ. 5 (1), 31–70.
Rindova, V.P., Williamson, I.O., Petkova, A.P., 2010. Reputation as an intangible asset: reflections on theory and methods in two empirical studies of business school reputations. J. Manag. 36 (3), 610–619.
Roberts, P.W., Dowling, G.R., 2002. Corporate reputation and sustained superior financial performance. Strateg. Manag. J. 23 (12), 1077–1093.
Ruef, M., Patterson, K., 2009. Credit and classification: the impact of industry boundaries in nineteenth-century America. Adm. Sci. Q. 54 (3), 486–520.
Rumelt, R.P., 1991. How much does industry matter? Strateg. Manag. J. 12 (3), 167–185.
Shapiro, C., 1982. Consumer information, product quality, and seller reputation. Bell J. Econ. 13 (1), 20–35.
Shapiro, C., 1983. Premiums for high quality products as returns to reputations. Q. J. Econ. 98 (4), 659.
Short, J.C., McKelvie, A., Ketchen, D.J., Chandler, G.N., 2009. Firm and industry effects on firm performance: a generalization and extension for new ventures. Strateg. Entrep. J. 3 (1), 47–65.
Simonson, I., Rosen, E., 2014. Absolute Value: What Really Influences Customers in the Age of (Nearly) Perfect Information, 1. ed. ed. Harper Business, New York, NY (232 pp).
Spence, M., 1973. Job Market Signaling. Quarterly Journal of Economics 87 (3), 355.
Srinivasan, A., Venkatraman, N., 2017. Entrepreneurship in digital platforms: a network-centric view. Strateg. Entrep. J. 45 (3), 425.
Statista, 2019. Number of Employees Employed by Businesses Selling on Amazon Marketplace in 2018. Feedvisor. https://www.statista.com/statistics/886904/amazon-seller-business-size-by-employees/, Accessed date: 21 May 2019.
Stuart, T.E., Hoang, H., Hybels, R.C., 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. Adm. Sci. Q. 44 (2), 315–349.

Sundararajan, A., 2004. Nonlinear pricing of information goods. Manag. Sci. 50 (12), 1660–1673.
Taeuscher, K., 2019. Uncertainty kills the long tail: demand concentration in peer-to-peer marketplaces. Electronic Markets. https://doi.org/10.1007/s12525-019-00339-w.
Turban, D.B., Cable, D.M., 2003. Firm reputation and applicant pool characteristics. J. Organ. Behav. 24 (6), 733–751.
Varian, H.R., 1999. Markets for Information Goods. IMES Discussion Paper Series Institute for Monetary and Economic Studies, Bank of Japan.
Wry, T., Lounsbury, M.D., Jennings, J.E., 2014. Hybrid vigor: securing venture capital by spanning categories in nanotechnology. Acad. Manag. J. 57 (5), 1309–1333.