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The authenticity premium: Balancing conformity and innovation in high technology industries

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ABSTRACT

Research on categories and markets suggests that audiences rely on categorical distinctions to make sense of market offerings. Market offerings that deviate from category norms risk devaluation. Although literature in this area has led to valuable insights, scholars have begun to question whether there has been an overemphasis on conformity, leaving existing theories ill-equipped to account for innovation. Within this context, we argue that research on authenticity in cultural sociology offers a useful platform for theorizing. We draw on the work of Peterson (1997), who underscores the importance of signals in evaluation. Objective features of market offerings (e.g., quality) matter, but particularly for innovations, these features are not readily visible. Because authentic producers are typically thought to be more committed, capable, and intrinsically motivated, when visibility of such objective features is lacking, authenticity may serve as an alternative indicator of value. Appearing authentic requires signaling believability with respect to category norms, while also being distinctive. Using data on 684 firms from five high technology sectors, we explore the relationship between authenticity and investor perceptions of value. Focusing on three different proxies for signals of authenticity—networks, governance, and narratives—we find a curvilinear association between conformity/distinctiveness and Tobin's q. Consistent with our view of authenticity as a signal, we also find that this relationship flattens as firms gain better track records and face stiffer competition.

1. Introduction

Audiences rely on categories to make sense of market offerings (Benner, 2007; Jonsson et al., 2009). When market offerings deviate from category norms, they face an “illegitimacy discount.” Stimulated by Zuckerman (1999), research has studied the costs of failure to conform in settings ranging from feature films (Zuckerman et al., 2003; Hsu, 2006) and gourmet cuisine (Rao et al., 2005) to online markets (Hsu et al., 2009; Leung and Sharkey, 2013) and corporate securities (Zuckerman, 1999). Some scholars, however, have questioned whether the pendulum has swung too far, such that there has been an overemphasis on conformity, thereby leaving existing theories ill-equipped to account for innovation (Smith, 2011; Pontikes, 2012; Trapido, 2015). By definition, innovation entails nonconformity, precisely what should activate the illegitimacy discount; yet innovation is rewarded (even demanded) in many markets.

Existing efforts to address theoretical tensions surrounding market categories and innovation have devoted little attention to considering whether and how the features of market actors may potentially influence audience perceptions of innovation. Instead, recent work has focused on audience heterogeneity. For example, one approach has been to account for innovation by pointing to variation in audience preferences. This work argues market actors engage in innovation because different audiences have different tastes for conformity or nonconformity (Pontikes, 2012; Leahey et al., 2017; Zuckerman, 2017). Studies also suggest that *within* audience heterogeneity may matter. For example, Zuckerman (1999, 2017) argues that the strength of the “categorical imperative”—i.e., pressure for conformity—is a function of audiences’ objectives, their theories of value, and the codes that underpin those theories. Along these lines, research finds that when more concrete indicators of value are available, audiences are more tolerant of nonconformity (Smith, 2011; Trapido, 2015). Finally, some research

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considers how the nature of the categories influence audience evaluations. Scholars observe that audiences are more accepting of nonconformity when the boundaries of the categories themselves are less established (Lounsbury and Rao, 2004; Hannan et al., 2007; Ruef and Patterson, 2009; Negro et al., 2010; Kovács and Hannan, 2015).

Although valuable, we suggest that the audience-based approach taken by existing work is incomplete. Consider the divergent audience reactions to two offerings in the single-serve beverage industry, Keurig (coffee) and Juicero (juice). When introduced, both products appeared comparably "nonconformist," both entered mature markets (i.e., with established categories), and both targeted similar consumers. Yet when presenting their offerings, Keurig (which was successful) and Juicero (which was not) took different approaches. While Keurig focused on signaling parallels between K-Cups and tradition in the coffee industry (e.g., relating K-Cups to established brewing techniques, emphasizing its partnership with Green Mountain Coffee Roasters), Juicero used language (mocked by observers) more typically employed by software startups (e.g., emphasizing venture capital backing, mobile app support) than kitchen gadgets. Although no single factor accounts for the differential success of these two products (e.g., observers also criticized Juicero's overengineering), examples like these highlight the need for additional theorizing on categories and innovation.

With their focus on audiences, then, existing approaches are not equipped to account for the differential success of comparably nonconformist products that serve similar audiences (e.g., Keurig/Juicero). Nor do they readily account for cases (e.g., Uber/Taxi Magic)[1] where offerings with greater nonconformity beat out comparable, yet arguably less novel solutions that address similar needs. In particular, we suggest that attending to how the features of market actors may influence audience perceptions of innovation is likely to enrich efforts to account for successful nonconformity.

Within this context, we argue that the literature on authenticity in cultural sociology offers a useful platform for theorizing. We draw on the work of Peterson (1997), who studied authenticity in country music. According to Peterson (1997: 220), authenticity requires "being believable relative to a more or less explicit model, and at the same time being original, that is not being an imitation of the model." Peterson's account offers guideposts for developing deeper understanding of how the features of market actors may potentially influence audience perceptions of innovation, while also simultaneously attending to the conformity pressures of market categories. First, his account underscores the importance of signals in evaluation. Objective properties of market offerings (e.g., quality) matter, but these are often not visible due to information asymmetries, audiences' unfamiliarity with innovative offerings, and related factors (Akerlof, 1970; Podolny, 2010; Negro et al., 2015). Because authentic producers are typically thought to be more committed, capable, and intrinsically motivated (Beverland, 2005; Hahl, 2016), when visibility of such objective properties is lacking, signals of authenticity may serve as an alternative indicator of value (Frake, 2016).[2] Thus, offerings with similar properties but different signals may be given different valuations.

Second, beyond demonstrating that audiences rely on signals, Peterson shows that market actors, such as country performers, may use signals to influence audience perceptions. Finally, Peterson's work offers predictions about the signals that are likely to be most valuable for shaping audience perceptions of innovation. Consistent with research on categories and markets, innovative offerings benefit from signals of conformity, which help them appear recognizable and therefore temper the "illegitimacy discount." However, unlike work on categories and markets, Peterson's account underscores the importance of signals of distinctiveness. Offerings, even innovative ones, with signals *too* close to category norms appear inauthentic and, although Peterson does not use the term, may suffer from a "conformity discount."

Taken together with research on categories and markets, Peterson's work therefore suggests that signals that convey authenticity—i.e. that show conformity to the features of other category members, while also demonstrating distinctiveness from those members—may be particularly valuable for influencing audiences' perceptions of innovation. These considerations predict an "authenticity premium"—i.e., signals of moderate levels of conformity/distinctiveness associated with higher valuations—before the illegitimacy discount predominates.

We theorize that the magnitude of the authenticity premium depends in part on properties of market actors and categories. First, as noted above, status signaling theory suggests that audiences rely on signals when quality is unobservable (Podolny, 2010). Therefore, we propose that the authenticity premium will be flatter for market actors who have more tangible indicators of quality (i.e., track records). Second, signals of authenticity will be less valuable with increases in the number of competitors in a sector. Relative to underlying quality (which, as noted above, is often subject to information asymmetries), signals of authenticity (e.g., the stage appearance of a country music performer, the origin story of a high technology company) may be more readily perceptible. However, evaluating such signals still requires effort from audiences, particularly because such signals are often communicated via qualitative indicators (e.g., appearances, stories), which limits the number of offerings that may be considered. Consequently, as the number of competitors in a sector increases, we anticipate the relationship between authenticity and market value will be flatter.

Our approach builds on but also departs from the literatures on optimal distinctiveness and strategic balance theory (Brewer, 1991; Deephouse, 1999; Leonardelli et al., 2010; Zuckerman, 2016; Maldeniya et al., 2017). Specifically, our approach is consistent with findings from these literatures showing that social actors often face pressures to be both similar and different from their peers. Further, similar to existing work, we suggest that social actors may balance these dual pressures by striving for moderate distinctiveness (Uzzi et al., 2013; Askin and Mauskapf, 2017).

Notwithstanding these similarities, we also depart from research on optimal distinctiveness. As noted in a recent review (Zhao et al., 2017), previous organizational research on optimal distinctiveness has focused on theorizing the strategy-performance relationship. Put differently, prior work has largely considered how distinctiveness on core strategic attributes (e.g., product offerings, market position) relate to objective performance outcomes (e.g., revenue) (see, for example, McNamara et al., 2003; Roberts and Amit, 2003; Haans, 2019). Although helpful, studies using this approach have also produced conflicting findings, with some work observing, for example, lower performance levels at intermediate positioning (e.g., Cennamo and Santalo, 2013; Zott and Amit, 2007). Similarly, the strategy-performance approach taken by existing work is limited in its ability to account for the differential performance of firms with seemingly similar core strategies (e.g., consider our discussion of Keurig and Juicero above). Our study offers a potential way forward. Leveraging research on authenticity—a literature with different conceptual foundations from work on optimal distinctiveness and strategic balance—we theorize that beyond core strategic attributes, the distinctiveness of market actors' signals—which are often more readily observable than core strategic attributes and that may therefore help to communicate them—is critical for shaping more subjectively determined performance outcomes, specifically audience perceptions. To that end—although not our primary intended contribution—our paper adds to

[1] Taxi Magic and Uber were founded in 2008 and 2009, respectively, as on-demand, app-based ride hailing services. However, while Taxi Magic connected users with taxi drivers, Uber took a more distinctive approach, connecting users with other app users.

[2] As this description suggests, we are primarily interested in authenticity as an indicator of a market offering's underlying (but difficult to observe) quality (c.f., Frake, 2016). However, we note that prior work also observes that people attend to authenticity for other reasons, including as a reaction against mass production, as a means of self-expression or status signaling, and as something that is inherently valuable in a market offering (Carroll and Wheaton, 2009).

the literature by responding directly to recent criticisms of existing work on optimal distinctiveness and strategic balance theory for "neglecting the role of stakeholder perceptions" (Zhao et al., 2017: 94).

We examine these ideas using data on 684 firms that realized an initial public offering (IPO) in five high technology sectors—drugs, hardware, medical devices, software, and analytical services—between 1993 and 2005. We chose this setting for its potential value for developing insight on successful nonconformity. Virtually all firms in these sectors must innovate on a constant basis. In addition, because the firms we study are new to public markets, they are relatively unfamiliar to audiences (i.e., investors). Moreover, many firms in this setting, even those that will eventually become quite successful, are yet to establish revenue, customers, or even products. Taken together, these factors suggest that investors will attend closely to intangible indicators of value (e.g., authenticity).

The precise signals to which audiences attend in making assessments of authenticity are likely to depend on the context. For example, as Peterson (1997) suggests, in country music, audiences attend to things like the performer's biography, accent, hat, boots, and dress. To identify relevant signals in high technology, our strategy was to turn to existing literature on signaling among high technology firms. Prior work suggested that networks (i.e., firms' alliances) (Podolny, 1993; Zuckerman, 1999), governance (i.e., firms' top management) (Hannan et al., 2006; Davis and Robbins, 2004) and narratives (i.e., firms' self-descriptions) (Kennedy, 2008; Pontikes, 2012) were among the most important signals to which audiences in this domain attend, and therefore we focus on these three signals as proxies that firms use to signal authenticity.

Our theoretical arguments suggest that the tradeoff between conformity and distinctiveness should be associated with a curvilinear (inverted-U) relationship with market value, but with important contingencies that differ from the predictions that would be made using alternative theories. Empirically, we observe evidence consistent with our predictions across sectors whose typical network, governance, and narrative signals vary dramatically. Although the nature of our data limits our ability to conclusively distinguish our proposed authenticity mechanism from related mechanisms on strategic balance and optimal distinctiveness, we underscore in our hypotheses section how the predictions made by our approach differ from these established perspectives. In closing, we offer a discussion of the implications of our results and future directions for research, including the development of alternative, more refined measures of authenticity.

2. Authenticity and the conformity-distinctiveness tradeoff

Authenticity is an increasingly important consideration in the decisions of market audiences. Most scholars see authenticity as centering on sincerity—whether a producer is what it claims to be (Trilling, 2009). Organizational theorists have concentrated on *type* (or *genre*) authenticity, which concerns whether and how producers signal sincerity with respect to market categories (Peterson, 1997; Carroll and Wheaton, 2009; Hahl, 2016). Views of authenticity within this literature emphasize its socially constructed nature. Rather than being based on objective properties, "certain specific aspects of a product, performance, place, or producer somehow get defined and treated as authentic by audiences in a particular social context" (Carroll and Wheaton, 2009: 256). To theorize how organizations claim authenticity, researchers have turned to cultural industries. This work shows the importance of connecting to tradition. When restaurants connect more closely with the traditions of a particular ethnic cuisine, diners view those restaurants as more authentic (Lehman et al., 2014). Adherence to tradition helps organizations convey that their motivations are more than instrumental.

Like research on categories, this work emphasizes the demands (and benefits) of conformity. In addition to conformity, however, authenticity requires innovation (Peterson, 1997). Particularly in domains like science and technology, producers who copy what others have done are seen negatively. Instead, authenticity requires *simultaneously* conforming to category norms (i.e., type or genre authenticity) and doing something novel, the latter of which Carroll and Wheaton (2009) label *idiosyncratic* authenticity. Thus, Peterson suggests that market offerings appear most authentic when they signal a balance between genre/type authenticity on the one hand and idiosyncratic authenticity on the other.

In the early years of country music, record executives struggled to understand the appeal of artists like Fiddlin' John Carson, who "seemed to break all the conventions of what made for success in the world of urbane, sophisticated commercial popular music of the time" (Peterson, 1997: 3). Sensing that audiences valued Carson's authenticity, studios descended on southern communities in search of musicians who played traditional songs in traditional ways. This strategy was unsuccessful. Authenticity required more than historical accuracy. In addition to conveying the image of a country musician—through dress, accent, or personal story—successful musicians did something novel. "Prospective performers had to have the marks of tradition to make them *credible*, and the songs that would make them successful had to be original enough to show that their singers were not *in*authentic copies of what had gone before, that its, that they were *real*" (Peterson, 1997: 209; emphasis in original). Jimmie Rogers is another telling example. Although perhaps the most popular performer of his era, "Rogers was not a good musician, he could not read music, and he couldn't keep time." Instead, "His-gift was the ability to take a song and by bending the melody, breaking meter, finding guitar work that fit, and adding his signature yodel…to make his music seem an expression of his own personal feelings" (Peterson, 1997: 48). Rogers was authentic not only because of his novel style, but also because, by injecting his feelings, there was something unique even in his renditions of traditional songs.

As these examples illustrate, producers have agency in their efforts to appear authentic, what Peterson (1997) calls "fabricating authenticity."[3] Audiences ultimately decide whether they believe a producer is authentic, but producers may work to help their chances. In country, "music and performance are vital…but signifiers are also vital. The boots, the hat, the outfit, a soft rural Southern accent, as well as the sound and subjects of the songs, all help" (Peterson, 1997: 218).

Peterson's view of authenticity is useful for resolving theoretical tension surrounding the demands of market categories for conformity and observations of successful nonconformity (i.e., innovation). Claims of membership and their evaluation are relative to other category members. But participants need not completely adopt the conventions of their categories. The challenge, whether in country music, cuisine, or technology "centers on being *believable* relative to a more or less explicit model and at the same time being *original*, that is not being an imitation of the model" (Peterson, 1997: 220). Conforming perfectly to category norms might be sufficient to grant membership, but without innovation there is little reason for evaluators to perceive value in an offering. Success depends on conforming with norms of the category but is also a matter of distinguishing oneself from what has come before.

3. Authenticity in high technology

Our study focuses on high technology. As the previous discussion shows, however, existing research on authenticity has largely considered cultural industries. Nevertheless, audiences in high technology, like those in cultural industries, consider authenticity in their evaluations.

[3] Notwithstanding Peterson's (1997) use of the term "fabricating," efforts of market actors to signal a balance between conformity and distinctiveness may stem from genuine commitments (Frankfurt, 1988; Varga, 2011). Put differently, efforts to signal such a balance should not necessarily be taken as evidence of "made up" or "fake" authenticity.

Authenticity considerations are often visible when there is concern over copying. In 2013, Facebook attempted to acquire Snapchat for $3 billion, but the offer was rejected. Subsequently, Facebook began cloning Snapchat features (e.g., stories that disappear after 24 h). Although from a strategic perspective, some applauded Facebook's moves, overall, reactions were negative, as seen in headlines like "Facebook copied Snapchat for a fourth time, and now all its apps look the same" (Wagner, 2017), "Here are all the times Facebook has copied Snapchat so far" (Heath, 2016) and "Facebook's new feature is yet another Snapchat ripoff" (Kelly, 2016) and "This is getting ridiculous. Facebook just ripped off Snapchat's navigation" (Ryall, 2016).

Authenticity concerns are also visible when copying is less blatant. In 2018, when smartphone maker OnePlus added a larger screen to its flagship device, the company was criticized for including a notch in the display to accommodate the phone's earpiece, a camera, and sensors. Observers felt the notch lacked authenticity, arguing that "the definitive 'notch phone' for the vast majority of people is and will forever be the iPhone X…And that's what has irked a lot of Android fans: Apple has taken ownership of the notch look and any subsequent device that resembles it feels derivative" (Savov, 2018).

Consistent with Peterson's views, authenticity concerns are also common in high technology when offerings fail to demonstrate believability relative to a model. Consider the "Great Bodega Fiasco of 2017." Founded by two ex-Google employees, Bodega (now Stockwell) produces web-connected vending machines, which it installs in communal areas like dorm and apartment lobbies, offices, and gyms. The company drew ire for several reasons, but most centered on its name. Critics were angered by the name "Bodega" when neither of the founders were Hispanic. Others were upset that the vending machines would not have many traditional offerings of bodegas, noting "Real bodegas are all about human relationships within a community, having someone you know greet you and make the sandwich you like" (Segran, 2017) and asking more pointedly, "Where am I supposed to get my egg and cheese?" (Capps, 2017). Still another community of observers questioned Bodega's grandiose rhetoric about its "autonomous stores" rendering centralized shopping obsolete, noting that "outside Silicon Valley, we call them vending machines" (Capps, 2017). Thus, much of the criticism of Bodega can be interpreted as frustration over the offering not being believable with respect to what its name suggested it intended to be.

The examples so far suggest that audiences in high technology are critical of offerings that lack authenticity. Conversely, audiences also ascribe value to offerings that appear authentic. This behavior is clear in the case of Theranos, a company that claimed to have developed novel blood testing technology that required only a few drops of blood (Carreyrou, 2019). Founded by Elizabeth Holmes, a 19-year-old Stanford dropout, at its peak, Theranos was valued at $9 billion, had signed a major partnership with Walgreens, and touted a board that included two former U.S. Secretaries of State and two U.S. Senators. In late 2015, however, an investigation by the *Wall Street Journal* found that the company's technology was an elaborate fraud. Holmes was subsequently charged by the U.S. Securities and Exchange Commission (SEC), and Theranos ceased operations on August 31, 2018.

In the wake of the scandal, commentators have suggested that Holmes's authentic image led many to overlook the limitations of Theranos's technology. In addition to her background (e.g., as a young entrepreneur and Stanford dropout), Holmes added to Theranos's authenticity by frequently relating her motivation to start the company to her uncle, who died from skin cancer (Ginsberg and Huddleston, 2019). Before the scandal broke, observers also frequently commented on Holmes's dedication to Theranos (which was founded in 2003 but gained little recognition until 2013). Discussing perceptions of Holmes's among entrepreneurs, one article observed, "dyed-in-the-wool founders recognize Holmes as genuine, like-minded, and one of their own. She is no imposter…there's an authenticity in Holmes's lack of polish that other founders respect" (Mochari, 2015). Holmes's authentic image was so strong that it held even in the months after the scandal broke, with observers praising Holmes's for her ability to "[deliver] her message authentically" (Civiello, 2016).

Finally, consistent with expectations from the broader literature on authenticity, observers often attend to the authenticity of high technology companies whose business models have a strong geographic or place-based component. As an illustration, consider Zoku, a company that has been described as "WeWork combined with Airbnb" (Garfield, 2015). Founded in 2016, Zoku is a combination between a hotel and a coworking space. For business travelers, the coworking space is attractive because it allows them a comfortable place to work and collaborate while away from home. Interestingly, Zoku has also leveraged its coworking spaces to develop unique partnerships with local residents (who use the facilities), which help to make Zoku distinctive from similar offerings. As one industry observer noted, these partnerships add to Zoku's authenticity: "The more locals you attract to your lobby, the more genuine if feels" (Minsberg, 2018). WeWork itself offers another useful illustration. Among its various businesses, WeWork offers an incubator program that connects entrepreneurs with investors. In 2018, when WeWork opened a location in Portland, Oregon, authenticity was identified as a key challenge. As local entrepreneur Stephen Green noted, "Investors from outside Portland find it hard to access the network here in an authentic way" (Spencer, 2018). To overcome this challenge, WeWork developed partnerships in the community, including with investors who use coworking spaces. The company then leverages these connections to partner with outside investors who, through their partnership with WeWork, appear more distinctive relative to other outsiders, in a way that supports their authenticity. As Green further noted, "Being able to bring investors from outside who have Portland on the roadmap but don't have an authentic connection; [WeWork] can be the connector" (Spencer, 2018). In more general terms, the example of WeWork highlights a technology firm's use of networks to signal authenticity to an important audience.

4. Signals of authenticity in high-technology

The signals audiences use to infer authenticity likely differ according to the setting. In country music, signals include dress, associates, artistic style, and life story (Peterson, 1997). To identify relevant signals for our study, we draw on literature on high technology. Although this literature has not specifically addressed authenticity, researchers have identified many signals to which audiences attend.

We focus on three categories of signals—networks (i.e., alliances), governance (i.e., top management), and narratives (i.e., self-descriptions). Just as dress, associates, artistic style, and life story do not encompass all possible signals of authenticity in country music, we do not claim that networks, governance, and narratives encompass all relevant signals in high technology. However, given the prominence of these three signals in prior work, we believe they are a useful starting point for theorizing. Networks, governance, and narratives are also attractive for our purposes because they allow organizations opportunities to demonstrate both conformity and distinctiveness. First, patterns of networks, governance, and narratives vary across sectors, which allows them to serve as signals of conformity. Part of what makes country different from rap is the dress (e.g., cowboy hat versus baseball cap).

Likewise, part of what makes a software firm distinct from a biotechnology firm is its alliances—the types of activities it undertakes and the partners with which it pursues them (Gulati and Higgins, 2003; Ingram and Lifschitz, 2006; Stuart et al., 2007). Second, there is little given about an industry *a priori* that determines the nature of signals that must be sent to audiences. A rap song sounds similar whether the artist is wearing a cowboy hat or baseball cap. Similarly, with networks, governance, and narratives, there are norms that vary by sector, and within sectors, most firms conform with these norms. But there are also firms that depart from these norms, which shows the potential to use such signals to demonstrate distinctiveness.

4.1. Networks

Alliances are common in high technology. In addition to providing firms with access to resources, alliances are signals (Pollack and Gulati, 2007) that allow audiences to make inferences about unobservable characteristics of firms. As Dacin et al. (2007: 170) note, "the social, symbolic, and signaling characteristics of alliances may serve as a source of legitimacy…and this legitimacy itself is a strategic resource with the potential to yield significant economic and competitive advantages for firms." Alliances therefore influence outcomes directly by moving valuable resources between partners and indirectly by allowing firms to communicate with outside observers. Consequently, investors, analysts, and other market participants follow alliance announcements closely in biotechnology (Powell et al., 1996), software and semiconductors (Jensen, 2004), and high technology generally (Ozcan and Overby, 2008).

When evaluating alliances, prior work suggests observers assess signals on multiple dimensions (Gulati and Higgins, 2003; Ingram and Lifschitz, 2006; Stuart et al., 2007; Ozmel et al., 2013). In particular, the meaning of the alliances held by a firm depend on features of the partner organizations and the activities encompassed by the alliances. First, observers likely attend to *types of partners*. An activity undertaken with one partner may signal something different if undertaken with a partner of a different form. For example, Gulati and Higgins (2003) found that when equity markets were cold, endorsements from venture capitalists were important for IPO value. However, in hotter markets, the same kind of endorsements were more valuable if they came from investment banks. Ingram and Lifschitz (2006) came to similar conclusions on the importance of partner type. They found that in the interorganizational network of Clyde River ship builders, the benefits connections were contingent on the ownership of firms and their partners.

Second, different *types of activities*—conducted with the same types of partners—send varied signals. Although Gulati and Higgins (2003) found contingent effects of endorsements from venture capital firms and investment banks, another type of interorganizational connection—strategic alliances with pharmaceutical firms—did not show contingencies. This finding suggests that the type of activity might offer salient signals. Within high technology, for example, it is common for firms to establish connections with universities. The implications of those connections, however, depends on the types of activities. Upstream connections (e.g., intellectual property, R&D) may signal the potential of less established firms that lack strong product portfolios, while downstream connections (e.g., OEM, supplier relationships) may better signal the relative quality of more established firms' products or services.

Firms in different sectors organize their networks differently (Rosenkopf and Schilling, 2007). In biotechnology, alliances are essential (Powell et al., 1996; Stuart et al., 1999). They are less common in software, where they are used for different purposes (e.g., less for R&D). Therefore, a biotechnology firm with the standard alliances of other biotechnology companies will look more like a biotechnology than a software firm. By conforming with sector norms, firms signal membership. But alliances also allow firms to signal distinctiveness. Both Amazon and Google were Internet pioneers. Both leveraged information technology to improve existing business models, and both undertook massive efforts to make books searchable online (Levy, 2011). However, the firms used different types of alliances with different types of partners. Amazon formed partnerships with publishers, who supplied the company with digital versions of books, which they granted Amazon permission to use. Google partnered with academic libraries, which made their holdings available for scanning. Given its academic origins, this approach was natural. Thus, similar firms, pursuing similar objectives, formed different types of partnerships (i.e., licensing, development) with different types of organizations (i.e., publishers, academic libraries).

Connecting to authenticity, consider once again the examples of Zoku and WeWork, discussed above. Both companies were similar in that they were grappling with the challenge of how to convey authenticity in the context of local, place-based communities. Moreover, both Zoku and WeWork addressed that challenge by developing partnerships with local community actors, which helped the companies appear more distinctive relative to other related offerings (e.g., competing hotel chains). At the same time, further underscoring the potential flexibility of networks as signals, the partnership strategies pursued by both companies also differed in some respects, particularly according to activity type, with Zoku enrolling local community actors as customers (i.e., for communal work space) and WeWork enrolling them as marketers and information brokers.

4.2. Governance

Although researchers have considered various signaling dimensions of governance, we focus on leadership, particularly the connections of top management (Mizruchi, 1996). Existing work suggests that these connections are important for how evaluators make sense of young high technology firms, which are often yet to establish revenue, customers, or products. Without traditional viability indicators, evaluators turn to social cues. Executives and directors signal important information because, "as a fundamental driver of organizational norms, values, decision-making and action, [they] can convey legitimacy on the organization" (Cohen and Dean, 2005: 684). Recall the example of Theranos, which no doubt benefited from the legitimacy conveyed by its exceptionally high profile board members. Relative to other indicators, the extern connections a firm's leadership brings to the venture are difficult to manipulate and may better reflect the firm's potential.

Audiences attend to multiple dimensions of top management's connections. Paralleling our discussion of networks, we focus on the *type of organization* and the *type of connection*. First, audiences often monitor the types of organizations with which top management has connections. For example, firms are more vulnerable to negative spillover when their top management serves on boards accused of malfeasance (Kang, 2008). Research also shows that observers attend to top management's university connections, which may confer legitimacy, particularly when these connections are to elite institutions (Cohen and Dean, 2005). Second, observers evaluate the type of connections top managers have to other organizations. Like interorganizational networks, such connections mean something different depending on their nature. Consider an executive at a biotechnology firm who has a university connection. That connection will mean different things depending on whether the connection is a degree in business or a faculty appointment. Both connections confer value, but the nature of that value is different.

Like networks, governance allows firms to signal conformity and distinctiveness. The backgrounds of executives and directors differ across industries. In software, low entry barriers make it common for entrepreneurs to have no formal training, experience, or even a college degree, and therefore to have few connections to prominent organizations. Although often accepted in software, leaders with this background would be unusual in medical devices. At the same time, governance is also flexible, and therefore allows firms to signal their distinctiveness. Consider once again Elizabeth Holmes. Unlike most medical device entrepreneurs, Holmes was an undergraduate when she established Theranos. Thus, for observers of the company, Holmes's biography is an indicator that Theranos is unlike a typical medical device firm. Bodega offers a further illustration. Recall that Bodega's cofounders were ex-Google employees, a point that was often mentioned in profiles of the company. Notwithstanding the prestige offered by such a work history, the backgrounds of Bodega's leaders appears to have done little to help the company convey its distinctiveness, perhaps in part because they were so similar to those of many other recent startups (and so different from the businesses the company was trying to displace). Had Bodega's founders had more distinctive backgrounds (e.g., with at least one founder having a career trajectory more typical of entrepreneurs in the ethnic food industry), it seems plausible that assessments of the company may have been more positive.

Like networks, then, governance allows firms to signal conformity while also offering opportunities for them to convey their distinctiveness.

4.3. Narratives

Research on signaling has also considered how firms use stories to present themselves (Lounsbury and Glynn, 2001; Navis and Glynn, 2011; King et al., 2011). Narratives are important for nascent organizations, which are unable to address concerns about their viability through traditional benchmarks. As Aldrich and Fiol (1994: 652) explain, "Entrepreneurs…have no external source of validation from which to argue. Given the lack of externally validated arguments, they must draw on alternative forms of communication, such as narratives, to make a case."

Most commonly, firms rely on media (e.g., press releases, regulatory filings) communicate their narratives. Studying press releases, Kennedy (2008) finds that for firms with unclear category membership, mentioning competitors is useful for garnering attention. Audiences are willing to devote limited cognitive energy to understanding what makes a producer unique. Narratives ease cognitive burdens on audiences by allowing them to "abductively grasp new market concepts by reflecting on what they learn about firms mentioned together in news stories" (Kennedy, 2008: 273).

Narratives may serve as signals of conformity. All genres have conventions. Being seen as a genre member requires adhering to expectations. For example, audiences generally expect the Food and Drug Administration (FDA) to be a character in the narratives of biotechnology firms, whose viability depends on being able to develop therapies that have a chance at regulatory approval. Omitting reference to the FDA may raise suspicion, leading evaluators to question a firm's legitimacy as a biotechnology company. But narratives give firms opportunities to signal distinctiveness from competitors. For example, in Google's 2004 S-1, Larry Page and Sergey Brin shared their "Don't be evil" corporate motto with potential investors. This motto signaled Google's distinctiveness from other search engines by conveying its unwillingness to bias its search results for financial gain. Facebook's copying of Snapchat's features, discussed above, offers a further example. As the company develops more features that are similar (or identical) to those of its competitor, the stories that Facebook tells—for example, about the kinds of experiences it wants its users to have, and how those experiences support its broader mission—also become less distinctive.

5. Hypotheses

As previously discussed, market actors use categories to make sense of market offerings. Because they deviate from category norms, innovative offerings are more difficult for audiences to evaluate and consequently are at risk for devaluation. This observation does not presume that audiences are opposed to innovation. As Zuckerman (2017: 56) notes, “the fact that conventional practices increase the likelihood of *minimal* performance is not inconsistent with the possibility that unconventional methods increase the likelihood of *high* performance.” Put differently, audiences are aware that innovative offerings may be superior. The challenge lies in the difficulty of evaluation. Nonconforming offerings are likely to entail higher risks, thereby leading to devaluation.

Our core argument is that innovative offerings may be less subject such devaluation when they signal authenticity—i.e., following Peterson, carefully balance conformity and distinctiveness—which may serve as an alternative indicator of value when more objective indicators (e.g., quality) are unobservable. Although other signals (e.g., status) may also be beneficial, authenticity is particularly powerful because audiences often associate authenticity with other desirable qualities—e.g., competence, intrinsic motivation—which may serve to offset the feelings of risk that accompany nonconformity. Thus, in settings where innovation makes evaluation difficult and where alternative indicators of value are less available, authenticity may figure prominently in audiences’ assessments.

Our discussion in the previous section suggests that firms use signals like networks, governance, and narratives to simultaneously show conformity and distinctiveness. Achieving the right balance between signals of conformity and distinctiveness is precisely what Peterson (1997) describes as authenticity. Signals of conformity help to convey authenticity by connecting a market offering to valued traditions. With too much conformity, however, an offering runs the risk of appearing generic, like a copycat of other offerings (see the examples of Facebook versus Snapchat and OnePlus versus the iPhone above); authenticity also requires signals of distinctiveness. As Peterson (1997; 209, emphasis in original) explains in a discussion of successful country artists, “prospective performers had to have the marks of tradition to make them *credible*, and the songs that would make them successful had to be original enough to show that their singers were not *in*authentic copies of what had gone before, that is, that they were *real*.”

Thus, we suggest investors will view high technology firms that achieve this balance as more authentic. Like works of art or music, firms must conform to the categories within which they claim membership enough to be recognizable; market actors that are too distinctive are therefore likely to be overlooked and therefore devalued. But too much conformity is also likely to be problematic; market actors must also signal that they are distinctive from competitors to claim value. Thus,

Hypothesis 1. (H1): A firm's signals of distinctiveness (conformity) relative to others in its sector will have a curvilinear (inverted-U shaped) relationship with its market value.

Put differently, we predict that the highest valuations ascribed by investors will be observed at moderate levels of conformity/distinctiveness; by contrast, the lowest (potentially even negative) valuations will be observed at very high levels of conformity and at very high levels of distinctiveness.

5.1. Track record

The relationship outlined in H1 is based on the idea that when quality is difficult to judge (e.g., due to innovation) audiences will rely on signals (Podolny, 1993, 2010). The correlate of this argument is that as more direct indicators of quality become available, signals diminish in importance. We therefore expect that as a firm's economic performance improves, audiences will attend less to authenticity. Consequently, we expect the inverted-U shaped curve proposed in H1 to be flatter for firms with better track records.

Hypothesis 2A. (H2A): The curvilinear association between a firm's signals of distinctiveness (conformity) and its market value will become flatter as the firm's economic performance improves.

Facebook's copying of Snapchat offers a useful illustration. Observers were critical of the company's blatant stealing of its competitors features. However, even critics acknowledge that Facebook's moves made sense strategically, and there is little evidence that investors reacted negatively to the company's behavior. The logic underpinning H2A suggests that negative assessments were likely offset by the fact that at the time it began copying Snapchat, Facebook was earning billions, thereby making signals of authenticity less consequential. For a firm with a less robust track record, however, similar behavior may be associated with worse outcomes.

Note that the prediction made by Hypothesis 2A differs from that which would most likely be made using the lens of strategic balance theory. As formulated by Deephouse (1999), the core implication of strategic balance theory is that "firms seeking competitive advantage should be as different as legitimately possible." Strategic differentiation is helpful because it allows a firm to alleviate competitive pressures (a point we return to in greater detail following the next hypothesis). However, strategic balance theory also suggests that too much differentiation may be harmful because highly differentiated firms are often perceived by potential exchange partners as posing greater risks (Deephouse, 1999: 152–153). As a firm gains a better track record, however, concerns over such risks should lessen (e.g., firms with stronger revenues are probably seen as less likely at risk of failure). Thus, a stronger track record should allow a firm greater possibility to be different. Following this logic, together with the observation from strategic balance theory that firms "should be as different as legitimately possible," then, one may predict that for firms with better track records, the shape of the curvilinear relationship between conformity/distinctiveness will likely resemble an upside-down hockey stick or upside-down fish hook, such that there remains a substantively meaningful positive association between distinctiveness and value up to a point, after which there are more modest penalties for too much distinctiveness. This prediction differs from Hypothesis 2A, under which we anticipate that the curvilinear relationship between conformity/distinctiveness will flatten, becoming more dominated by the horizontal dimension, such that there are *both* smaller benefits and penalties associated with changes in conformity/distinctiveness (due to the value of authenticity as a signal should diminishing).

5.2. Competition

We also anticipate that the relationship between authenticity and value will depend on the difficulty audiences face in making assessments of authenticity. Although authenticity may be more readily perceptible than the quality of innovation, audiences have a finite capacity for evaluating authenticity. As noted above, among high technology firms, important signals include relationships with other organizations (i.e., networks), leaderships' experience and connections (i.e., governance), and self-presentations (i.e., narratives). Audience exposure to these signals will most likely come from qualitative sources—regulatory disclosures, press releases—which, by their nature, require time and attention to evaluate, and that therefore limit the number of candidates that can be considered.

Consequently, we anticipate that the relationship between authenticity and value will depend on the degree of competition within a sector. As the density of firms increases, so too will the costs of searching through and evaluating the information necessary to make assessments regarding the authenticity of candidate offerings. Instead, audiences are likely to turn to other means of assessment, including, for example, more quantifiable indicators or category signals (Negro et al., 2015). Country music once again offers a useful illustration. As Peterson notes, in country music, common signals of authenticity include not only visual ques (e.g., hat, boots, dress) but also the performer's biography. When evaluating a relatively smaller number of performers, collecting biographical information is likely feasible, but doing so becomes costlier as the number of performers increases, in which case, audiences are likely to make assessments on criteria other than authenticity (e.g., Billboard rank). Similarly, when there is relatively less competition in a sector, fuller assessments of networks, governance, narratives, or other signals are likely more feasible (from a search cost perspective) than when there are relatively more competitors; in the latter case, as noted above, audiences are likely to rely more on indicators like revenue, profitability, and related metrics that are likely allow for quicker and easier evaluations of candidates (again, from a search cost perspective) in more crowded sectors. Thus,

Hypothesis 2B. (H2B): The curvilinear association between a firm's signals of distinctiveness (conformity) and its market value will become flatter as the density of competitors in the firm's sector increases

Like Hypothesis 2A, the prediction we make in Hypothesis 2B differs from that which would most likely be made using strategic balance theory. Specifically, as noted previously, within strategic balance theory, competitive pressure provides the theoretical rationale for differentiation. As Deephouse (1999: 151) notes, "a firm that conforms to the strategies of others has many similar competitors that limit the performance of the firm and increase failure rates…rational differentiation reduces competition and increases performance." Thus, strategic balance theory provides a relatively clear prediction that as competition increases, greater differentiation should be associated with greater performance. This prediction differs from what we arrive at using the signaling based approach developed above. As just described, signals are typically qualitative in nature and therefore require cognitive effort to process. As competition increases, the value of differentiation is likely to flatten (due to the increasing difficulty of processing), and therefore we should anticipate fewer returns to distinctiveness.

6. Data and methods

6.1. Sample

We examine our hypotheses using a sample of 684 firms that were active between 1993 and 2005. We limit our focus to companies from five sectors—drugs, hardware, medical devices, software, and analytic services. We chose these sectors strategically, due to their heavy demands for innovation. Our sample was drawn from the population of 1302 companies that filed an S-1 form (described in greater detail below) with the SEC and realized an IPO during our study period. Our decision to analyze a sample of firms rather than the population of 1302 companies was informed by pragmatic considerations and sample sizes in prior work. As we discuss below, we gathered our data by hand coding information from narrative descriptions in sample firms' annual SEC filings. This labor-intensive approach allowed us to collect rich, detailed data but limited our ability to study the full population.

Our definition of high-technology sectors is based on the National Science Foundation's (NSF) survey of industrial research and development (R&D). The NSF categorizes industries using three-digit Standard Industrial Classification (SIC) codes. To identify sectors for our study, we began with firms in manufacturing SIC codes (i.e., two-digit SIC codes between 20 and 39 or 70 and 89). From these two-digit codes, we extracted constituent, three-digit codes. As noted previously, our interest is in sectors that place heavy demands on their members for innovation. We characterized a three-digit code as innovation intensive when the organizations that comprise that code accounted for more than 10% of the basic R&D spending of the larger, two-digit code in which the three-digit code was nested. Next, two of the authors independently clustered the resulting, innovation-intensive SIC codes into the five high-technology sectors—drugs, hardware, medical devices, software, and analytic services—mentioned above, by triangulating across NSF and US Patent and Trademark Office (USPTO) classifications (specifically, see the aggregation tables in Hall et al., 2001). A third coder resolved discrepancies. The resulting mapping between SIC codes and sectors is shown in the right two columns of Table 1. Collectively, organizations in these sectors performed 68.1% of basic industrial R&D ($15.5 billion) and 67.6% ($36.6 billion) of applied industrial R&D in the US in 1999.

After isolating relevant sectors, we used regulatory filings to identify firms. Before a company issues an IPO, it must file an S-1 form with the SEC. Legally, S-1 forms require that companies provide investors with a detailed look at virtually all aspects of their business, from their financial situation and strategic plans to competitive threats and director biographies. S-1 forms also report firms' self-identified SIC code. Therefore, S-1 forms are an important mechanism through which a

Table 1
Population and sample distribution of firms by four-digit industries.

SIC	Industry	Sector	Population	Sample
2833	Medicinal Chemicals and Botanical Products	Drugs	8	4
2834	Pharmaceutical Preparations	Drugs	115	59
2835	In Vitro and In Vivo Diagnostic Substances	Drugs	11	3
2836	Biological Products Except Diagnostic Substances	Drugs	37	19
3570	Computer & Office Equipment	Hardware	2	0
3571	Electronic Computers	Hardware	13	8
3572	Computer Storage Devices	Hardware	10	5
3575	Computer Terminals	Hardware	1	1
3577	Computer Peripheral Equipment	Hardware	34	15
3578	Calculating and Accounting Machines	Hardware	2	2
3661	Telephone and Telegraph Apparatus	Hardware	52	23
3663	Radio TV Broadcasting & Communications Equipment	Hardware	27	13
3669	Communications Equipment, NEC[†]	Hardware	15	6
3670	Electronic Components & Accessories	Hardware	14	8
3672	Printed Circuit Boards	Hardware	13	7
3674	Semiconductors & Related Devices	Hardware	98	60
3678	Electronic Connectors	Hardware	1	1
3679	Electronic Equipment, NEC[†]	Hardware	20	11
3823	Industrial Instruments for Measurement, Display, & Control	Medical Devices	10	7
3824	Totalizing Fluid Meters and Counting Devices	Medical Devices	1	1
3825	Instruments For Measuring and Testing of Electricity & Electric Signals	Medical Devices	16	6
3826	Laboratory Analytical Instruments	Medical Devices	22	11
3829	Measuring and Controlling Devices, NEC[†]	Medical Devices	6	3
3841	Surgical, Medical, and Dental Instruments	Medical Devices	53	26
3842	Orthopedic, Prosthetic, & Surgical Appliances & Supplies	Medical Devices	11	8
3844	X-Ray Apparatus & Tubes & Irradiation Apparatus	Medical Devices	5	1
3845	Electromedical & Electrotherapeutic Apparatus	Medical Devices	42	20
7370	Computer Programming Data Processing	Software	15	8
7371	Computer Programming Services	Software	79	37
7372	Prepackaged Software	Software	264	147
7373	Computer Integrated Systems Design	Software	76	44
7374	Computer Processing & Data Preparation Services	Software	29	10
7375	Information Retrieval Services	Software	57	29
7379	Computer Related Services, NEC[†]	Software	57	31
8711	Engineering Services	Analytic Services	4	0
8731	Commercial Physical and Biological Research	Analytic Services	69	41
8732	Commercial Economic, Sociological and Educational Research	Analytic Services	9	8
8733	Non-Commercial Research Organizations	Analytic Services	2	0
8734	Testing Laboratories	Analytic Services	2	1
		Total	1302	684

[†] Not elsewhere classified.

company claims industry membership. They signal, for the first time, to the community of market participants, the firm's industry identity. Subsequent to filing an S-1 form and issuing an IPO, publicly traded companies must file a 10-K report annually. Like the S-1 form, the 10-K requires that companies provide a detailed look at their business. For the purposes of our study, the main difference between an S-1 and 10-K is *when* they are filed (i.e., before issuing an IPO for the S-1; annually thereafter for the 10-K). Thus, the two forms provide us with the same data.

We identified—for all firms that issued an IPO between 1993 and 2005—primary four-digit SIC codes listed in S-1 forms. In cases where SIC codes were missing from the S-1, we consulted any amended S-1 s before turning to firms' subsequent annual 10-K reports. To implement these searches, we used Thompson Research and SEC EDGAR, with which we collected the names of all firms that listed any of the 44 four-digit SIC codes represented in our five sectors as a primary or secondary industry. Our searches were based on both S-1 and 10-K filings, and thus included companies that were publicly traded and those that realized an IPO in our study window. We excluded S-1 s for secondary offerings, or in which firms reported primary industries from outside our sampling frame. Table 1 presents four-digit SIC codes and sectors along with information on their constituent firms in our population and sample.

6.2. Dependent variable

To capture market value, we use the log of Tobin's q, defined as the ratio of a firm's market value to book value (Hall et al., 2005). Because it accounts for the value of tangible assets and liabilities, Tobin's q is useful for testing theories about intangible value. Our computation of Tobin's q is based on an approximation that can be estimated using the Compustat and CRSP databases (Chung and Pruitt, 1994), specifically

$$q = \frac{m + p + d}{a},$$

where m is the market value of the firm's outstanding common stock, p is the liquidating value of the firm's preferred stock, d is the value of short-terms liabilities minus the value of short-term assets, and a is the book value of the firm's total assets. For each year, we identified sample firms' closing market values using CRSP. We defined market value as the product of the share price and the number of outstanding common shares. Data on preferred stock, liabilities, and assets as of the end of the calendar year were collected from Compustat.[4] Missing values were collected from firms' annual reports.

[4] Specifically, we draw on Compustat, a database maintained by Wharton Research Data Services, for annual financial data on sample firms. The CRSP (Center for Research on Security Prices) data, maintained by the University of Chicago, provides stock prices for publicly traded firms, and allows us to capture annual closing market values.

6.3. Independent variables

We measure conformity/distinctiveness using SEC filings, which are uniquely valuable for our purposes. First, regulations require that firms file annual reports with the SEC and therefore we observe changes over time. Second, few firms failed to file relevant forms. Finally, firms are legally required to disclose all information of material interest to investors. Thus, our measures are based on information that firms deem important about their business.[5] Following our theory development, we consider three proxies for conformity/distinctiveness. Each proxy ranges from 0 to 1, with lower values indicating greater conformity, and higher values indicating greater distinctiveness. For shorthand, we refer to these proxies using the notation *ConfDist*.

6.3.1. Networks

Our first proxy uses formal relationships between organizations to evaluate how similar or different each firm is from others in its sector. To collect the data for this measure, we hand-coded, for each year, mentions of formal organizational partners in the "Prospectus Summary," "Business," and "Beneficial Owners" sections of relevant S-1, 10-K, and proxy filings. We code a relationship between a firm and a partner if the partner's proper name is mentioned and the form describes what is transferred through the tie (e.g. money, products) or the activities associated with the relationship (e.g. research, manufacturing). Our focus is on direct interactions. Organizational role models (e.g., "We aspire to be a leading vendor, like Microsoft…"), competitors, regulators, and industry bodies are therefore not included unless the form describes a transaction with one of these organizations, and the partner is named.

We classify relationships into six categories based on their content and activities. *Financial* ties are relationships that involve the movement of money, loans, or investments to or from the focal company. *Licensing* ties are agreements that entail sharing ideas, research materials, technologies, and IP. *R&D* ties involve collaborative discovery or joint development of new products or technologies. *Business-to-business* (B2B) ties are supply chain relationships in which materials, components or products are transferred. *Service* ties are relationships that involve intangible support, such as marketing agreements, distribution relationships, and consulting on organizational, technical, legal and financial issues. Finally, *Complex* ties span categories.

We classify formal partners into five categories. *Firms* are for-profit partners involved in non-financial markets. *Government* partners are public sector organizations or quasi-independent components of federal, state, or local governments, including funding and regulatory agencies. *Financial* organizations are banks and private equity investors (e.g., venture capitalists). We also identify *Nonprofit* partners that are not primarily engaged in research, such as professional associations and foundations. Finally, we reserve a category for *Research* partners, which includes the universities, research institutes, and hospitals that conduct basic R&D.[6]

After collecting these data, we operationalize network conformity/distinctiveness (*ConfDist*) by treating each of the thirty-possible tie × partner combinations as one dimension in a multidimensional space. This approach allows us to use the distribution of organizations' ties across dimensions to calculate a measure of pairwise distance. Formally, for each year *t*, we create an m × n matrix F, with rows that index firms, columns that index the thirty possible tie × partner combinations, and cells that record counts of tie × partner combinations. Next, we compare the network of each firm at time *t* to the networks of all others active in the sector. We calculate these comparisons using cosine distance, defined as

$$1-\frac{x\cdot y}{\|x\|\|y\|} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2}\sqrt{\sum_{i=1}^{n} y_i^2}}$$

where $x = (f_{x1}, f_{x2}, \ldots, f_{xn-1}, f_{xn})$ is a vector of tie × partner combinations for the focal firm x, $y = (f_{y1}, f_{y2}, \ldots, f_{yn-1}, f_{yn})$ is a vector of tie × partner combinations for a comparison firm y, and $x \neq y$. After computing pairwise, within-sector distances, we calculate, for each firm, for each year, the average distance to other firms, which yields our measure of network *ConfDist*.

Firms with low average network *ConfDist* values have networks that are generally similar to others. Average distance increases as an organization's network becomes more distinctive. The measure is not sensitive to network size—doubling the observed counts would change the magnitude of the vector, but the angle of separation would remain the same.

6.3.2. Governance

Our second proxy is governance conformity/distinctiveness. This measure shares features with network *ConfDist*. However, rather than alliances, we focus on the informal connections between firms and other organizations that are created by the mobility of top management. We collected the data to compute this measure by hand coding, for each study year, mentions of formal organizations in the biographies of managers and directors from Item 10, "Directors and Executive Officers of the Registrant," of the relevant S-1, 10-K, and proxy filings.

We classify governance ties into six categories, again based on content and activities. *Institutional* ties capture connections between a firm's top management and other organizations around political, nonprofit, cultural, or military activities. We label these ties "institutional" because we anticipate that most knowledge transferred will be institutional in nature. *Managerial* ties occur when a top manager reports managerial service at an external organization. *General* ties are similar, but capture service in employee or staff roles. We also include in this category training at the undergraduate level and certificate training. *Professional* ties capture connections between firms and external organizations with the potential for professional knowledge transfer. We record a professional tie when an officer or director reports legal, technical, medical, or financial training or service at an outside organization. *Science* ties record connections between firms and organizations around scientific activities. We record a scientific tie when officer or director reports research or advisory activities or training. Finally, *Strategy* ties are relationships to organizations that allow companies to access knowledge of organizational strategy. We include in this category connections that occur when a director or an officer serves as a founder, owner, executive, or director at an external organization.

For each year *t* in our study window, we measure governance *ConfDist* using the cosine distance approach discussed above. The measure ranges from 0 to 1. Firms with lower values have governance that is similar to others. Distance increases as an organization's governance becomes more distinctive.

6.3.3. Narratives

Our third proxy builds on the observation that social actors reveal their identities through language. Firms devote significant portions of their SEC filings to narrative descriptions of their history, strategy, and operations, which we leverage to compute this measure. Specifically, to compute narrative *ConfDist*, we represent firms' annual SEC filings as weighted vectors of words (i.e. we use a vector space model), separately for each year (Salton et al., 1975; Manning et al., 2008; Brown and Tucker, 2011; Hoberg and Phillips, 2010). We limit our focus to the "Prospectus Summary" (S-1 form) and "Business" (S-1 and 10-K) sections. To create the vectors, we split firms' narratives into tokens. After extracting these tokens, we remove stopwords (e.g., "the", "is", "an"). We also drop punctuation and convert strings to lowercase. We then create a vector, for each firm × year, with an entry for each word found in the

[5] For more details on our coding process, see Appendixes 1-4.

[6] We began by manually coding a small subsample of partner types, which we then used to train a naïve Bayes classifier for labeling the remaining cases.

Table 2
Descriptive statistics and correlations.

	Variable	Mean	SD	1	2	3	4	5	6
1	Tobin's *q* (logged)	1.33	0.58	1.00					
2	High status network partners†	0.07	0.13	0.13	1.00				
3	High status network partners†	0.16	0.33	0.17	0.37	1.00			
4	Indirect network partners†	1.46	3.23	0.12	0.85	0.41	1.00		
5	Indirect governance partners†	4.50	10.97	0.14	0.39	0.88	0.46	1.00	
6	Network degree centrality†	0.42	0.87	0.16	0.68	0.56	0.63	0.59	1.00
7	Governance degree centrality†	1.04	2.02	0.17	0.51	0.87	0.58	0.85	0.69
8	Patents	16.73	81.51	−0.02	−0.06	−0.06	−0.06	−0.05	−0.07
9	Board size	5.59	2.21	−0.03	−0.08	−0.02	−0.08	−0.07	−0.08
10	Competition	0.05	0.05	0.22	0.05	−0.05	0.04	−0.06	0.00
11	Track record†	0.72	0.66	−0.05	0.13	−0.03	0.16	0.01	0.06
12	Network *ConfDist*†	0.02	0.05	0.17	0.35	0.74	0.42	0.80	0.60
13	Governance *ConfDist*†	0.01	0.02	0.15	0.32	0.61	0.38	0.68	0.56
14	Narrative *ConfDist*†	0.02	0.03	0.16	0.40	0.75	0.49	0.83	0.63

	Variable	7	8	9	10	11	12	13	14
7	Governance degree centrality†	1.00							
8	Patents	−0.06	1.00						
9	Board size	−0.02	0.12	1.00					
10	Competition	−0.05	−0.08	−0.07	1.00				
11	Track record†	0.00	−0.03	−0.05	−0.01	1.00			
12	Network *ConfDist*†	0.79	−0.06	−0.13	−0.03	0.03	1.00		
13	Governance *ConfDist*†	0.65	−0.05	−0.14	−0.03	0.02	0.87	1.00	
14	Narrative *ConfDist*†	0.81	−0.06	−0.12	−0.02	0.04	0.96	0.86	1.00

N = 3970.
† Asset weighted.

corpus of narratives. Finally, we update the vectors to record the frequency of each token for the relevant firm × year.

Not all words convey the same amount of information. Therefore, we adjust term counts using word frequency-inverse document frequency weighting (wf-idf). For each word, we compute idf weights as

$$\mathrm{idf_w} = \log\frac{\mathrm{N}}{\mathrm{df_w}},$$

where N is the number of filings and $\mathrm{df_w}$ is the number of filings in which the word appears. After obtaining these weights, we apply them to the vectors as

$$\mathrm{wf_{w,d}} \times \mathrm{idf_w},$$

where $\mathrm{wf_{w,\,d}}$ is the raw of word w for some document d. Finally, with these weighted vectors, we obtain narrative *ConfDist* by calculating, separately for each year, the average cosine distance between focal companies and others in their sectors. Narrative *ConfDist* ranges from 0 to 1. Firms with lower values have narratives that are similar to others. As a firm becomes more distinctive, values of the measure increase.

6.3.4. Track record

H2A predicts that investors will attend less to authenticity when alternative indicators of value are available. We operationalize track record using a measure of revenues from Compustat.

6.3.5. Competition

We examine H2B using a measure that counts, for each firm i, the number of new, within-sector IPO filings in year t, weighted by the number of publicly traded firms in the sector.

6.4. Control variables

6.4.1. High status network partners

We include in our models a measure that indexes the number of high-status network partners to which each sample firm is connected at time t. Such connections may serve as an alternative indicator of value. We define high status partners as those with a degree centrality that is greater than three standard deviations above the mean for their type of organization.

6.4.2. High status governance partners

Following our logic for networks, we also control for counts of connections to high status governance partners at time t. We define high status governance partners as those with degree centralities that are over three standard deviations above the mean, conditional on the type of organization.

6.4.3. Indirect network partners

Firms that are more connected to central partners will likely have overlapping connections with competing firms, and therefore their networks may appear less distinctive. We account for this by controlling, for each sample firm at time t, the number of other sample firms to which the sample firm is connected indirectly through shared partners.

6.4.4. Indirect governance partners

Similarly, we also control for the number of other sample firms that focal firms are connected to via shared governance partners. Higher values on this measure indicate that a firm is closer to the structural center of their sector's network of governance ties.

6.4.5. Network degree centrality

Rather than the conformity/distinctiveness of a firm's network partners, investors may concern themselves more with the size of a firm's network. We therefore include in our models, for each firm at time t, a count of network partners.

6.4.6. Governance degree centrality

Following our logic for the previous control, we also include an analogous adjustment for governance.

6.4.7. Patents

We control for the number of patents (by application year) issued to each firm using data from the Harvard Patent Dataverse (Li et al., 2014). This control helps to adjust for the possibility that our results may be driven by changes in the size of firm's technology portfolios, which may be associated with both greater valuations and more complex (and therefore possibly more distinctive) networks, governance, and narratives.

6.4.8. Board size

Finally, we control for the size of firms' boards at time *t*.

Table 2 presents descriptive statistics and correlations.

6.5. Model estimation

Given the features of our data (e.g., a panel structure with a continuous outcome), we estimate fixed effects OLS regressions of the form

$$y_{it+1} = \alpha_i + x_{it}^{'}\beta + \epsilon_{it},\ i = 1, \cdots, N,\ t = 1, \cdots, T_i,$$

where y_{it+1} is the dependent variable for firm *i* at time $t+1$, x_{it} are the independent and control variables, β is a vector of coefficients, and α_i are time-invariant, unit (firm) specific effects (Cameron and Trivedi, 2005). To each model, we add year fixed effects with dummy variables. We report robust standard errors to adjust for multicollinearity in models that include multiple interactions between our *ConfDist* measures and their quadratic terms. To further aid with multicollinearity and facilitate interpretation, we mean center variables involved in interactions.[7] Following prior work (e.g., Hall et al., 2005; Ceccagnoli, 2008; Deng, 2008; Belenzon, 2012), we asset weight several firm-level variables (indicated in our results tables), to account for the tendency of Tobin's *q*—particularly during the window of our study—to capture investor's expectations about possibilities for growth rather than assessments of fundamentals.[8] This weighting procedure also helps to further adjust for the potential confounding effect of firm size (see also the *Patents* control above).

7. Results

7.1. Descriptive

One of the central claims in our theory development was that signals of authenticity are likely to vary across sectors. Just as part of what makes country music different from rap is the dress of the performer (e.g., cowboy hat versus baseball cap), part of what makes a software firm perceptible from a biotechnology firm is its alliances (e.g., the types of organizations it partners with and what it does with them). Thus, what audiences perceive as a highly conventional alliance portfolio versus one that departs substantially from the norm is likely to depend on whether the context is biotechnology, software, or a different sector. To evaluate our claim on cross-sector variation in signals, we conducted a series of descriptive analyses.

Beginning with networks, Fig. 1 uses rose plots to present observed sector × partner × activity combinations. Each flower shows, by sector, the distribution of alliances held by companies to partners of different types. Within flowers, each petal is proportional to the number of ties connecting a given type of activity to a given type of partner. To compare how firms across sectors interact with the same types of partners, pick a column and scan down. To compare how firms within sectors interact across partner types, pick a row and scan across.

Several patterns emerge. First, sector membership is associated with the types of activities firms pursue and the types of partners they favor. Second, common combinations of activities and partners vary by sector. Although firms in each sector collaborate on all activity types and with all partner types, they are distinguished by how they combine different types of relationships with different types of partners. Consider the first row of Fig. 1, which shows how drug firms connect with different partners. The flower in the second cell shows that these firms are relational generalists. Many drug firms have alliances with other corporations that span the product development cycle. Scanning down the second column, we see that although firm-to-firm ties are common across sectors, there are differences in emphasis. Hardware firms are less likely to forge R&D and license ties with other corporations, favoring instead B2B and service relationships. Medical device companies collaborate and license from other firms less than drug and more than software companies, but their focus on services and B2B with other firms is more akin to the latter than the former.

Column three of Fig. 1 tracks connections to government partners. Here drug companies emphasize upstream connections, commonly receiving funding and conducting R&D with the public sector. Hardware firms interact with government through B2B relationships. Perhaps unsurprisingly, medical device companies—which share a regulatory and financial environment with drug companies and a technology base with hardware firms—have a government profile that looks like a hybrid of the two. Finally, software firms overwhelmingly connect with public sector partners through B2B. Similar patterns hold across the odd numbered rows of the final column, which track connections to research organizations. R&D connections to those institutions are important in drugs and medical devices, as are license ties. Hardware and software organizations are less likely to do joint R&D with a research partner. Instead, they treat them as clients.

The first column of Fig. 1 tracks connections to finance partners. Finance partners are relational specialists. In drugs and medical devices, nearly all ties involve equity or debt. Hardware companies more frequently treat finance organizations as customers. Software firms provide products and services to finance partners, in addition to receiving funds. Where drug companies have the most balanced alliances with other firm and nonprofit organizations, software companies are diversely connected in finance. Organizations in drugs forge more upstream connections with government, nonprofit, and research organizations, while hardware and software firms connect to the same partners in more downstream alliances.

Fig. 2 is similar to Fig. 1 but for governance. Rows are sectors and columns are the type of organizations with which executives and directors have connections. Although differences across sectors are less pronounced than in Fig. 1, there are several noteworthy patterns. Column 3 captures executives and directors' government experience. Across sectors, executives and directors have diverse government backgrounds, with all six categories represented. Government experience in strategy is unusual among leaders of medical devices firms but common in hardware and software. Executives and directors of drugs, medical devices, and analytical services firms often have scientific experience with government organizations, which may reflect the importance of the NIH and related institutions. Similar patters hold for science experience with nonprofits, with the exception of medical devices, which is similar to software and hardware.

Finally, Fig. 3 illustrates narrative *ConfDist*. The dimensionality of this measure is extremely large and we are unable to show comprehensive distributions. Instead, Fig. 3 plots bar graphs of the top 25 most common terms by sector. For each term, bar size corresponds to the term's frequency, weighted by counts of forms coded for sector firms. Plots capture all terms (except stopwords) used by sample firms. This large set of terms includes many that will be used when describing any generic business activity (e.g., "products", "company"). Although this works against finding differences across sectors, Fig. 3 shows some interesting variation. Scientific and regulatory concerns are paramount for drug firms, with terms like "clinical", "drug", "fda", "trials",

[7] In our fully specified models (Table 3, Model 7; Table 4, Model 7; Table 5, Model 7), which include measures of *ConfDist*, their respective quadratic terms, and interactions between both measures and our two moderators, the quadratic interactions introduce modest multicollinearity. Nevertheless, the average VIF/Tolerance for these models are well within acceptable ranges (Table 3, Model 7, VIF = 6.22; Table 4, Model 7, VIF = 4.89; Table 5, Model 7, VIF = 5.93). Similarly, in models that include only one set of interactions, VIFs are within acceptable ranges.

[8] Appendix 5 visualizes the relationship between assets and Tobin's q.

Fig. 1. Networks across five high technology sectors. Rows correspond to sectors, columns correspond to partner types, colors correspond to tie types.

"approval", "patent", "research", and "regulatory" appearing dozens of times, on average, per form. In software, common terms include "business", "customers", "sales", "market", "financial", and "marketing", which suggest that these firms are focused on marketing and financial issues.

7.2. Inferential

Tables 3–5 present models that examine our hypotheses using networks, governance, and narratives, respectively, as proxies for conformity/distinctiveness. Within each table, Model 1 shows the controls only, Model 6 shows the independent variables only, and Model 7 is the fully-specified model.

Models 2 (linear term only for *ConfDist*) and 3 (quadratic term for *ConfDist*) of Tables 3 (networks), 4 (governance), and 5 (narratives) examine H1. Beginning with Model 2 (linear term only for *ConfDist*), we observe positive associations between *ConfDist* and Tobin's q; however, the relationship is only statistically significant for networks (i.e., not governance and narratives). Overall, this pattern suggests that modeling the relationship between *ConfDist* and Tobin's q with a linear term alone may not provide the best description of the data, a possibility that we explore more in the next paragraph. Turning to Model 3 of Tables 3 (networks), 4 (governance), and 5 (narratives), which adds quadratic terms for *ConfDist*, we find significant positive associations between *ConfDist* and Tobin's q. Moreover, consistent with our prediction of a curvilinear relationship (i.e., inverted-U shaped) between *ConfDist* and investor valuations, the quadratic terms are negative and significant. Both lower and higher values of *ConfDist* are associated with lower values of Tobin's q; the highest values of Tobin's q are observed at moderate values of *ConfDist*. The turning point for each proxy appears well within the range of the observed data (see Figs. 4 and 5, which plots both the regression lines and raw values), meaning that we see not just diminishing returns to higher levels of distinctiveness, but actually lower predicted valuations. These patterns of association are consistent with our predictions of Hypothesis 1 that the highest valuations ascribed by investors would be observed at moderate levels of conformity/distinctiveness, while the lowest valuations would be observed at very high levels of conformity and at very high levels of distinctiveness.

Comparisons of R2 values across Models 2 and 3 in Tables 3 (networks), 4 (governance), and 5 (narratives) suggest that the addition of the quadratic term improves model fit. To evaluate further, we ran likelihood ratio tests to compare the fit of models with and without the quadratic term, for networks, governance, and narratives. Comparisons of models with and without the quadratic term yielded chi-square values of 67.28 (p < 0.001; 1 degree of freedom), 59.09 (p < 0.001; 1

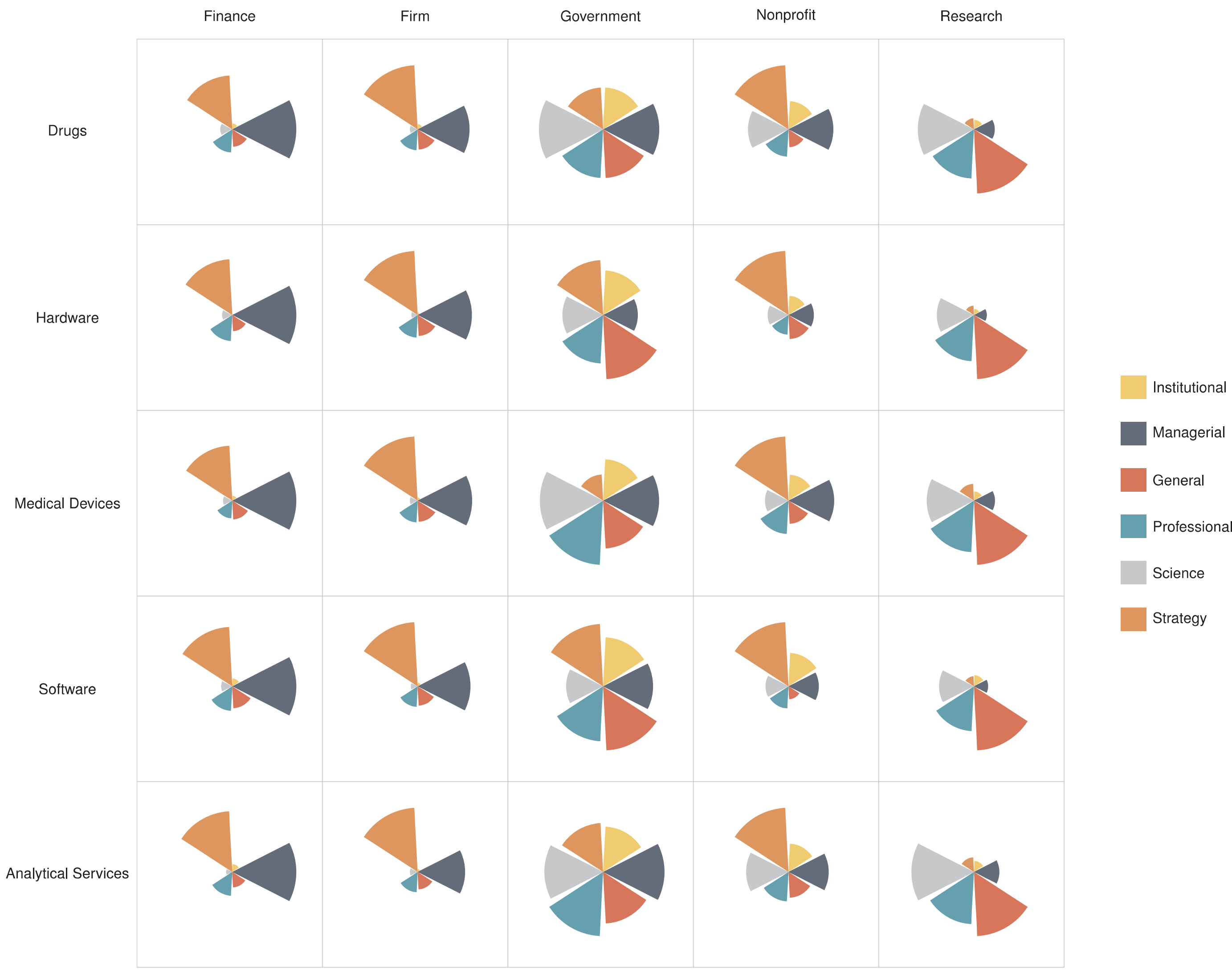

Fig. 2. Governance across five high technology sectors. Rows correspond to sectors, columns correspond to partner types, colors correspond to tie types. .

degree of freedom), and 67.49 ($p < 0.001$; 1 degree of freedom) for networks, governance, and narratives, respectively. The results of these tests suggest a significantly better fit to the data for models that include the quadratic term than those that do not.

H2A predicts that track record will moderate the association between conformity/distinctiveness and Tobin's q. Model 5 in Tables 3 (networks), 4 (governance), and 5 (narratives) examines this prediction by introducing interactions between our three proxies, their quadratic terms, and track record. These models support our hypothesis. Across proxies, coefficients for the interactions of *ConfDist* and track record are negative and significant. By contrast, with the exception of narratives, the coefficients for the interactions of the quadratic effects of *ConfDist* and track record are positive and significant. Thus, as a firm's track record improves, the association between conformity/distinctiveness and Tobin's q flattens.

A similar pattern is seen in Model 4 of Tables 3 (networks), 4 (governance), and 5 (narratives), which examines H2B using interactions between our *ConfDist* proxies, their quadratic terms, and competition. Recall that H2B predicts that as competition increases, so does the difficulty of processing signals of authenticity. Supporting this prediction, we find significant negative associations between our proxies and Tobin's q and significant positive associations between the corresponding quadratic terms and competition, again with the exception of narratives. As competition increases, the conformity/distinctiveness curve flattens.

Figs. 4 and 5 graph predicted Tobin's q for track record and competition, separately for networks, governance, and narratives. Better track records (higher competition) represent the top ventile; worse track records (lower competition) represent the bottom ventile. Other values are set to their means.

The subplots in Fig. 5 are calculated from Model 5 of Tables 3 (networks), 4 (governance), and 5 (narratives). Across proxies, the association between *ConfDist* and Tobin's q becomes flatter as firms improve their track records. Thus, where more direct evidence of offering quality is present, signals of authenticity are less helpful. Although there is evidence of diminishing returns to distinctiveness, the illegitimacy discount (i.e., decreasing valuations with increasing distinctiveness) predominates only at high levels of distinctiveness. These patterns are more pronounced in the governance panel of Fig. 5. As with networks, the illegitimacy discount predominates at high levels of distinctiveness, but the discount is larger. Finally, the right panel of Fig. 5 shows the narrative *ConfDist* and Tobin's q by track record. Relative to networks and governance, the curves are flatter. Across track records, there is less to be gained from moderate distinctiveness, but the punishment associated with being exceptionally different is also less severe.

Fig. 4 uses coefficients from Model 4 in Tables 3 (networks), 4 (governance), and 5 (narratives) to explore the association between

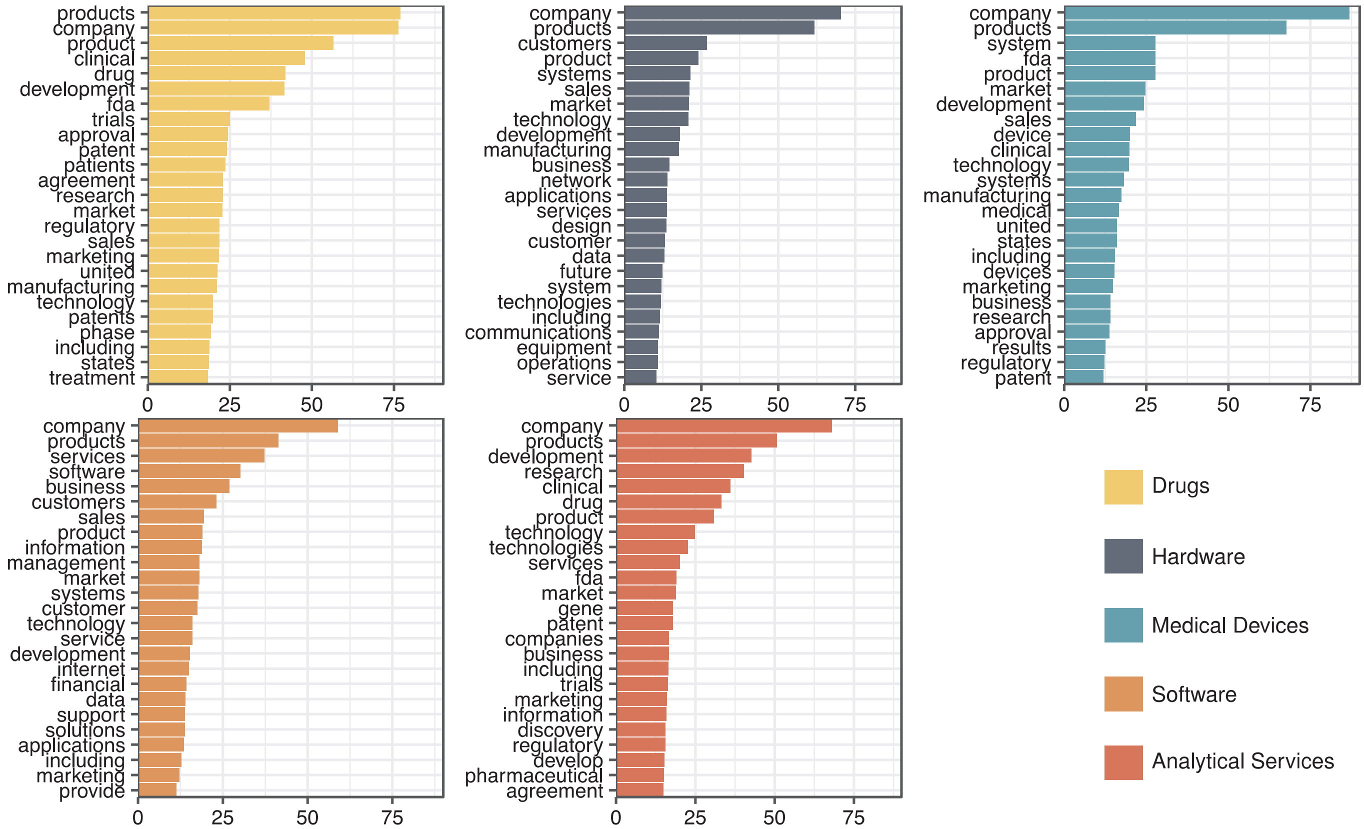

Fig. 3. Narratives across five high technology sectors.

ConfDist and valuations among firms at low, mean, and high competition. Similar to track record, we see flatter *ConfDist* curves as competition increases, an observation that is consistent with H2B. Signals of authenticity pay the highest premium when competition is lower. At mean and high levels of competition, the benefits of distinctiveness are lower. Moreover, as distinctiveness increases, the illegitimacy discount is much steeper than for firms facing less competition.

7.3. Robustness

We examined the robustness of our findings to alternative specifications.

First, we estimated models that adjust for firm age. Older firms may appear more authentic and less derivative of other firms. In our main models, firm and year fixed effects preclude us for controlling for age. Therefore, in Model 1 of Appendix 6 (networks), 7 (governance), and 8 (narratives), we estimated regressions that include year and sector fixed effects and firm random effects. Model 2 of Tables 6 (networks), 7 (governance), and 8 (narratives) adds age and its quadratic term to these models. We do not find age to be associated with Tobin's q.

Second, rather than authenticity, networks and governances may capture simpler features of firms' connections. For example, the fluctuations in Tobin's q associated with networks and governance signals may reflect investors' appreciation of young firms that can attract more connections or concerns about firms that take on too many partners. Alternatively, given findings about the difficulty individuals have perceiving network structure (e.g., Freeman and Romney, 1987; Freeman et al., 1987), investors may simply be responding to aggregate changes, such as increases or decreases in the number of alliances. To examine these possibilities, Models 3 of Appendix 6 (networks) and 7 (governance) introduce quadratic terms for network and governance degree centrality. Although addition of these terms introduces multicollinearity to our models, the results remain consistent with our core findings.

Third, rather than valuing networks or governance as signals of authenticity, investors may care about particular connections. For example, investors may expect biotechnology companies to license patents from universities and to have venture capital funding (Powell et al., 2005). To explore this possibility, we ran models—see Appendix 6 (networks) and 7 (governance)—that control for counts of networks and governance connections, by category. To eliminate redundant information, we drop our controls for network and governance centrality. Similar to our previous robustness check, addition of these counts (six new variables) introduces multicollinearity. Perhaps unsurprisingly, then, we find that the interaction of network *ConfDist* and its quadratic term with competition is no longer significant. Results for governance remain similar to our core models, however. Taken together, then, we believe these results offer support for our findings.

Fourth, following work in economics (e.g., Hall et al., 2005; Ceccagnoli, 2006; Deng, 2008; Belenzon, 2012), our core models asset weight several firm-level variables. To ensure our findings are not driven by this decision, Appendix 9 reports models of Tobin's q without asset weights. Although the results for governance are weaker, they are qualitatively similar to our core network models, and stronger than our core narrative models. Considering that these models completely eliminate one of the most important financial controls for publicly traded firms, we believe that these results add further support to our findings.

Fifth, our *ConfDist* measures are based on separation between sparse, high-dimensional vectors. Rather than reflecting a social process, the levels of *ConfDist* we observe may be driven by underlying features of the distributions from which the vectors are drawn (e.g., word frequencies). Thus, any vector—even one from a random distribution—with similar properties may result in similar *ConfDist* values. We therefore conducted simulations in which we randomly generated portfolios of formal partners (networks), executives and directors

Table 3
OLS regression models of associations between network *ConfDist* and Tobin's q.

	M1	M2	M3	M4	M5	M6	M7
High status network partners†	-0.03	-0.02	-0.04	-0.03	-0.04		-0.02
	(0.12)	(0.12)	(0.11)	(0.11)	(0.10)		(0.11)
High status governance partners†	0.07	0.08	0.03	0.03	0.03		0.03
	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)		(0.08)
Indirect network partners†	0.02*	0.02*	0.01	0.01	0.01*		0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)		(0.01)
Indirect governance partners†	0.00*	0.00	0.00	0.00	0.00		0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
Network degree centrality†	-0.03	-0.03	-0.03	-0.03	-0.02		-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)		(0.02)
Governance degree centrality†	0.00	-0.01	-0.02	-0.02	-0.03*		-0.03*
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)		(0.02)
Patents	-0.00	-0.00	-0.00	-0.00	-0.00		-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
Board size	-0.02*	-0.01*	-0.01*	-0.01	-0.01		-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)		(0.01)
Competition	-0.09	-0.15	-0.05	-0.17	-0.04	-0.06	-0.15
	(0.30)	(0.30)	(0.30)	(0.31)	(0.30)	(0.32)	(0.31)
Track record†	0.16***	0.15****	0.13	0.13***	0.18***	0.20***	0.19***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Network *ConfDist*†,¶		1.22*	4.13***	5.01***	5.63***	6.41***	6.57***
		(0.63)	(0.90)	(0.99)	(1.02)	(0.94)	(1.15)
Network *ConfDist2*†,¶			-6.66***	-9.05***	-7.86***	-9.83***	-10.31***
			(1.22)	(1.90)	(1.45)	(2.60)	(2.32)
Network *ConfDist*†,¶ × Competition				-14.48*		-13.69	-15.26**
				(9.28)		(9.60)	(8.82)
Network *ConfDist2*†,¶ × Competition				40.87**		20.13	38.47**
				(19.94)		(22.38)	(20.86)
Network *ConfDist*†,¶ × Track record†					-1.23***	-1.21***	-1.31***
					(0.37)	(0.36)	(0.38)
Network *ConfDist2*†,¶ × Track record†					1.30*	1.03	1.62*
					(0.90)	(1.07)	(1.02)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.32***	1.36***	1.35***	1.36***	1.30***	1.16***	1.31***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)
Observations	3264	3238	3238	3238	3238	3238	3238
R2	0.22	0.23	0.24	0.24	0.24	0.024	0.24

Two tailed tests are reported for control variables and one tailed tests for directional hypotheses.
† Asset weighted.
¶ Mean centered.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

(governance), and SEC filing text (narratives), which we compared to the observed values. The approach and findings are described in Appendixes 10 and 11. In brief, results offer strong evidence that our findings are not driven by mechanical features.

Finally, building on Peterson's (1997) work on country music, a key claim of our study is that audiences in high technology attend to signals of authenticity and moreover, that firms appear most authentic to audiences when they carefully balance signals of conformity and distinctiveness. Earlier, we gave evidence from case studies of high technology firms that support these claims. However, we also conducted a more systematic validation using textual analysis of news articles and trade publications.

While we reserve full methodological details for Appendix 12, our approach involved acquiring the full text of news articles and trade publications discussing sample firms. We limited our focus to a 5% random sample of companies, which yielded approximately 20,000 articles. We then used natural language processing techniques to extract words appearing in close proximity to mentions of sample firm names. With this list in hand, we drew on prior work (Kovács et al., 2014, hereafter KCL) to develop a lexicon of authenticity related terms (e.g., “pure,” “new,” “unorthodox,” “traditional,” “legitimate”). Using this lexicon, we counted the frequency with which mentions of authenticity related words appeared in discussion of sample companies. Our presumption is that use of authenticity related words in close proximity to mentions of sample companies will represent assessments of authenticity by an important audience.

Fig. 6 shows bar graphs of the distribution of authenticity words appearing in news articles in discussion of sample firms by network, governance, and narrative *ConfDist*. Each bar spans a decile on the corresponding *ConfDist* measure. Consistent with our expectation, we observe an inverted-U shaped pattern to the distribution, with the greatest frequency of authenticity words appearing in the middle bars. Fig. 7 offers a different view of the same data, showing the relationship between authenticity words appearing in news articles in discussion of sample firms by network, governance, and narrative *ConfDist* using a scatterplot. For reference, we fit a second order polynomial to the points. Once again, the pattern is consistent with our expectations, such that use of authenticity keywords is most common in discussion of firms with moderate *ConfDist* values.

Table 6 (main manuscript) shows some illustrative examples of discussion windows from the underlying data (e.g., “…Intel also faces pressure from smaller ‘**clone**’ companies like Advanced Micro Devices Inc. and Cyrix Corp., which have stepped up production of **imitations** of earlier Intel chips. Intel says…”, “…Ascend originally was seen as a **look-alike** competitor to remote-access specialist Shiva Corp., but…”). We highlight words from the KCL lexicon in red. When reviewing these

Table 4
OLS regression models of associations between governance *ConfDist* and Tobin's q.

	M1	M2	M3	M4	M5	M6	M7
High status network partners[†]	-0.02	-0.02	-0.01	-0.01	-0.01		-0.01
	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)		(0.11)
High status governance partners[†]	0.07	0.07	0.03	0.04	0.02		0.04
	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)		(0.08)
Indirect network partners[†]	0.02*	0.02+	0.01	0.01	0.01		0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)		(0.01)
Indirect governance partners[†]	0.00*	0.00+	0.00*	0.01	0.01		0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
Network degree centrality[†]	-0.03	-0.03	-0.03	-0.02	-0.02		-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)		(0.02)
Governance degree centrality[†]	0.00	0.00	-0.01	-0.02	-0.02		-0.02
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)		(0.02)
Patents	-0.00	-0.00	-0.00	-0.00	-0.00		-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
Board size	-0.02***	-0.02*	-0.01*	-0.01*	-0.01		-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)		(0.01)
Competition	-0.11	-0.11	-0.10	-0.29	-0.07	-0.26	-0.27
	(0.29)	(0.30)	(0.29)	(0.33)	(0.29)	(0.34)	(0.32)
Track record[†]	0.16***	0.16***	0.13***	0.13***	0.18***	0.20***	0.19***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Governance *ConfDist*[†,¶]		0.12	7.64	10.26***	11.01***	15.49***	13.65***
		(0.18)	(2.47)	(2.74)	(2.58)	(2.21)	(2.87)
Governance *ConfDist2*[†,¶]			-26.98***	-42.00***	-38.76***	-53.90***	-51.90***
			(8.19)	(8.93)	(9.49)	(10.02)	(10.32)
Governance *ConfDist*[†,¶] × Competition				-45.83**		-52.64**	-48.41
				(25.44)		(24.37)	(24.90)
Governance *ConfDist2*[†,¶] × Competition				264.88***		253.40**	278.49***
				(96.95)		(106.77)	(101.45)
Governance *ConfDist*[†,¶] × Track record[†]					-3.07***	-3.06***	-2.95***
					(0.91)	(0.86)	(0.92)
Governance *ConfDist2*[†,¶] × Track record[†]					11.71***	8.37*	9.24**
					(3.60)	(4.91)	(4.60)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.35***	1.34***	1.34***	1.36***	1.29***	1.16***	1.31***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)
Observations	3243	3243	3243	3243	3243	3243	3243
R2	0.22	0.22	0.23	0.23	0.24	0.23	0.24

Two tailed tests are reported for control variables and one tailed tests for directional hypotheses.
† Asset weighted.
¶ Mean centered.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

examples, we also frequently observed the use of other authenticity related words that were not in the KCL lexicon, which we highlight in blue (e.g., “clone,” “look-alike,” “rare”). These illustrations add further confidence to our claims that authenticity is important how audiences evaluate high technology firms.

8. Discussion

Researchers have used categories as a lens for understanding market dynamics. Although this work has led to important insights, existing literature has largely focused on the negative consequences of deviating from category norms. Audiences expect market offerings to look and behave according to templates. Market offerings that depart from these expectations risk devaluation. A consequence of this emphasis on conformity is that it is difficult to reconcile research on categories with the observation that in many markets, innovation is both expected and rewarded. Several studies have begun addressing this tension in the literature, with the goal of better understanding the conditions that enable successful deviation from category norms.

Notwithstanding this progress, efforts to reconcile conformity and innovation have focused on audience heterogeneity—some audiences have greater tolerance for innovation than others, thereby creating an opening for successful nonconformity. Perhaps due to this audience focus, research has devoted little attention to the market actors themselves. Thus, existing theory offers few tools for understanding how the features of market actors may potentially influence audience perceptions of innovation. Yet, reconciling the tension over conformity and innovation in the literature on categories is likely to prove challenging without attending to market actors. Understanding how features of market actors may potentially influence audience perceptions seems important, for example, for understanding how and why offerings with greater nonconformity sometimes beat out comparable but less novel solutions that target similar audiences (e.g., Uber/Taxi Magic). Similarly, attention to the features of market actors is likely valuable for understanding the differential success of comparably nonconformist products targeted at similar audiences (e.g., Keuring/Juicero).

Within this context, we drew on studies of authenticity in cultural sociology—particularly Peterson (1997)—as a foundation for theory development. In Peterson's (1997: 220) view, authenticity requires “being believable relative to a more or less explicit model, and at the same time being original, that is not being an imitation of the model.” Actors may potentially navigate these dual pressures and convey authenticity through the use of signals—for example, in country music, hats, clothes, accents—that simultaneously convey a balance between conformity with and distinctiveness from category norms. Peterson's work—when considered together with findings from research on

Table 5
OLS regression models of associations between narrative *ConfDist* and Tobin's q.

	M1	M2	M3	M4	M5	M6	M7
High status network partners†	-0.03	-0.02	-0.03	-0.02	-0.04		-0.02
	(0.12)	(0.12)	(0.11)	(0.11)	(0.11)		(0.11)
High status governance partners†	0.07	0.07	-0.02	-0.02	-0.02		-0.02
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)		(0.09)
Indirect network partners†	0.02*	0.02+	0.01	0.01	0.01		0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)		(0.01)
Indirect governance partners†	0.00	0.00	0.01*	0.01	0.00		0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
Network degree centrality†	-0.03	-0.03	-0.02	-0.02	-0.02		-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)		(0.02)
Governance degree centrality†	0.00	-0.00	-0.00	-0.01	-0.01		-0.01
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)		(0.02)
Patents	-0.00	-0.00	-0.00	-0.00	-0.00		-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
Board size	-0.02**	-0.02*	-0.01**	-0.01*	-0.01*		-0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)		(0.01)
Competition	-0.09	-0.08	-0.01	-0.10	0.04	0.03	-0.04
	(0.30)	(0.30)	(0.30)	(0.32)	(0.30)	(0.32)	(0.31)
Track record†	0.16***	0.16***	0.13***	0.13***	0.18***	0.19***	0.18***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Narrative *ConfDist*†,¶		0.26	3.71***	4.65***	5.07***	6.60	6.04***
		(0.85)	(1.25)	(1.50)	(1.35)	(1.23)	(1.59)
Narrative *ConfDist2*†,¶			-8.63***	-11.19	-9.66***	-11.88***	-12.39***
			(1.91)	(3.31)	(1.99)	(4.40)	(3.83)
Narrative *ConfDist*†,¶ × Competition				-15.15		-13.70	-15.45
				(12.46)		(12.79)	(12.10)
Narrative *ConfDist2*†,¶ × Competition				44.53*		20.42	43.28
				(31.60)		(39.10)	(34.18)
Narrative *ConfDist*†,¶ × Track record†					-1.14***	-1.11**	-1.21***
					(0.45)	(0.43)	(0.46)
Narrative *ConfDist2*†,¶ × Track record†					1.06	0.35	1.48
					(1.42)	(1.54)	(1.65)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.33***	1.33***	1.28***	1.29***	1.24***	1.10***	1.25***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)
Observations	3263	3263	3263	3263	3263	3263	3263
R2	0.22	0.22	0.23	0.23	0.23	0.23	0.24

Two tailed tests are reported for control variables and one tailed tests for directional hypotheses.
† Asset weighted.
¶ Mean centered.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

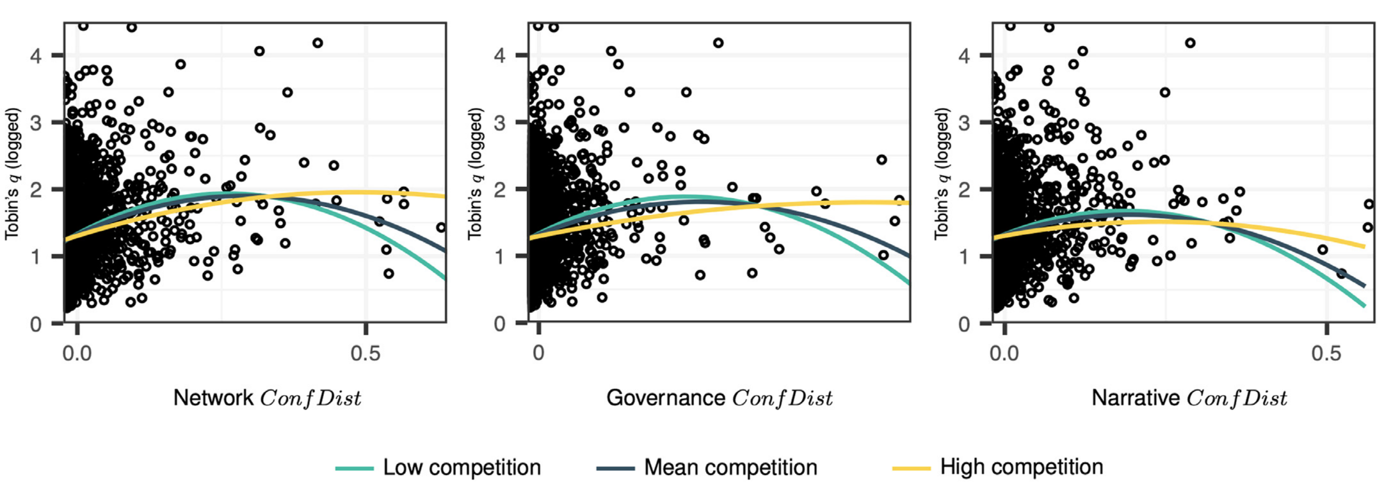

Fig. 4. Predicted values of Tobin's q (logged) at different levels of competition for three *ConfDist* proxies. Estimates are from Model 4 of Tables 3, 4, and 5 for network, governance, and narrative *ConfDist*, respectively. For each *ConfDist* measure, predictions are shown over the full range of observed values. Extreme levels of competition correspond to the 5th percentile (low competition) and the 95th percentile (high competition). Hollow points show the raw (unadjusted) data.

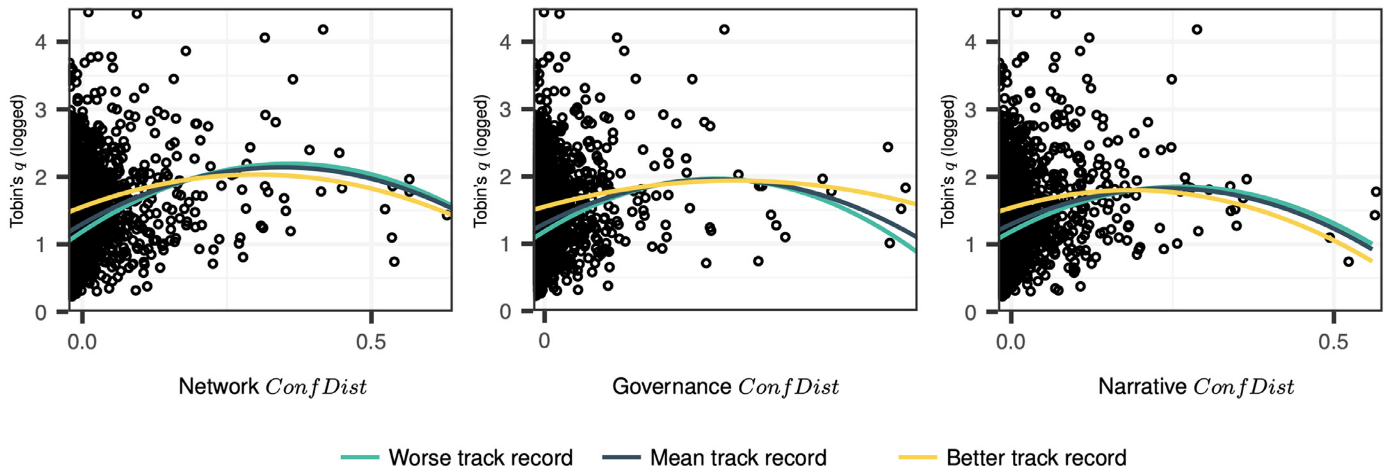

Fig. 5. Predicted values of Tobin's *q* (logged) for different track records across *ConfDist* proxies. Estimates are from Model 5 of Tables 3, 4, and 5 for network, governance, and narrative *ConfDist*, respectively. For each *ConfDist* measure, predictions are shown over the full range of observed values. Track records correspond to the 5th percentile (worse track records) and the 95th percentile (better track records). Hollow points show the raw (unadjusted) data.

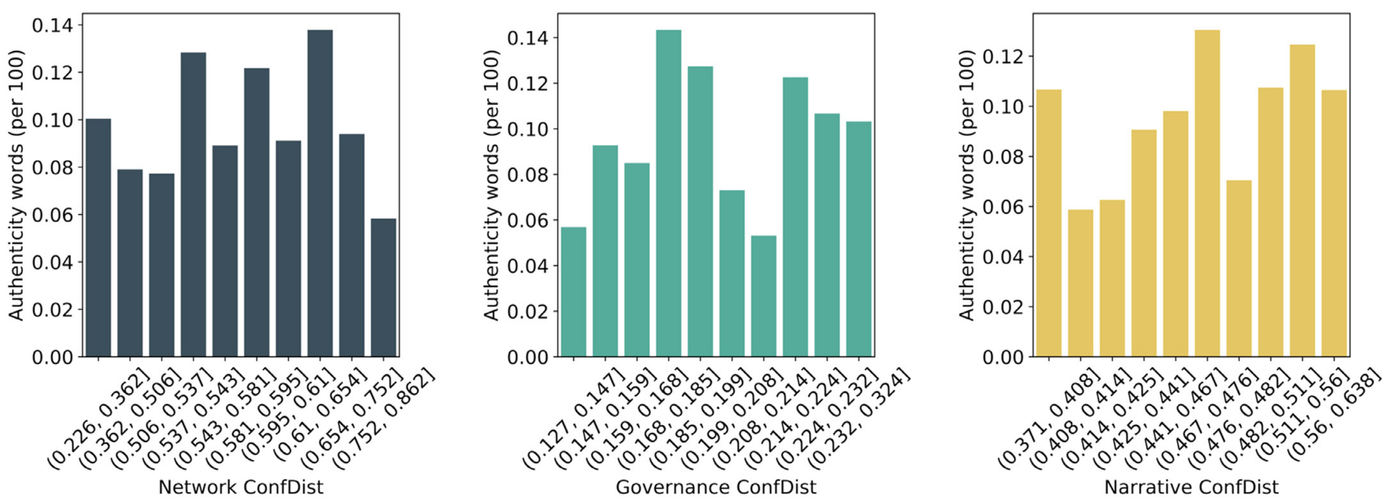

Fig. 6. Distribution of authenticity words (by decile) appearing in news articles in discussion of sample firms by network, governance, and narrative *ConfDist* .

categories and markets—suggests that signals that convey authenticity—by departing some, but not too much, from other category members—may be particularly effective for influencing audiences' perceptions of innovation.

We evaluated this idea by examining 684 high technology firms that went public between 1993 and 2005 in the drug, hardware, medical device, software, and analytical services sectors, all of which demand innovation. Considering three signals—networks, governance, and narratives—we find that audiences ascribe greater value to firms that signal departure from category norms. However, consistent with Peterson's views on authenticity, we also find that beyond a point, increasing distinctiveness (i.e., decreasing conformity) is associated with lower valuations.

Based on our conceptualization of authenticity as a signal for unobservable quality, we also examined conditions under which audiences are most likely responsive to such signals. First, we proposed that the authenticity premium (i.e., the curvilinear relationship between conformity/distinctiveness and market value) would be flatter for producers with more tangible indicators of quality (e.g., track records). Second, we suggested that signals of authenticity would be less valuable

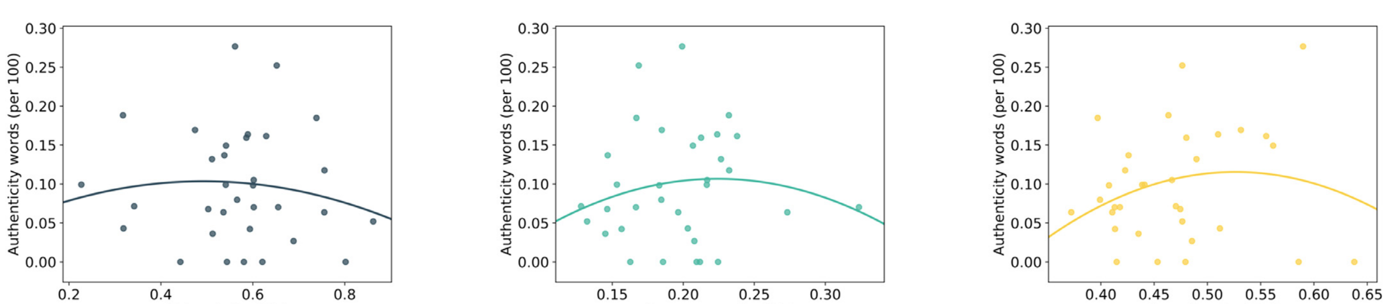

Fig. 7. Curvilinear relationship between authenticity words appearing in news articles in discussion of sample firms by network, governance, and narrative *ConfDist* .

Table 6
Illustrative windows of text around mentions of focal company names showing discussions of authenticity.

"…Bam Entertainment introduces a **unique** puzzle game for the Game Boy Advance starring, **oddly** enough, alien potato…"
"…nucleic acid hybridizations and amplification, antibody and antigen reactions, and more. Nanogen's **unique** approach of integrating **sophisticated** microelectronics and molecular biology made the…"
"…a Denver- based solution provider, said Veritas is well-positioned to realize its vision. 'Since Veritas is a **pure** software company, they are vendor-agnostic, as opposed to the other vendors that act…"
"…Intel also faces pressure from smaller **'clone'** companies like Advanced Micro Devices Inc. and Cyrix Corp., which have stepped up production of **imitations** of earlier Intel chips. Intel says…"
"…prefer to make products that result in incremental improvements over previous technology. 'Biosite can have **real** blockbusters and first-mover advantage,' Hamill said. To develop potential…"
"In an **unusual** commercial transaction between Cuba and the U.S., CancerVax Corporation, a Californian biotechnology company, received a **rare** U.S. government approval to…"
"…the **traditional** computer/telephony integration (CTI) market represented by the likes of Dialogic, Mitel and Natural Microsystems Inc. remained an analog-circuit aggregation business. Vendors…"
"…But in that instance, many of these **unorthodox** bases turned into screaming winners. One was Veritas Software, which made software for data storage management, primarily in the Unix environment…"
"…and Natural Microsystems, and the Signal Computing Systems Architecture (SCSA), promoted by Dialogic Corp. and its partners. While TDM architectures are considered **old-fashioned** in the client…"
"…companies didn't have separately," said Mike Wertheimer, president of Solunet Inc., a Lucent, Ascend and Cisco VAR in Palm Bay, Fla. "It [the deal] makes Lucent a **legitimate** data networking player…"
"…Navis software, which manages the core ATM and IP devices. Industry analysts were upbeat about Ascend's **ambitious** plans. 'In the end, it will mean more choices in services and competitive pricing for…"
"…group has to focus on architecture, not implementation-and the most **interesting** things about the Cyrix development are in implementation, not architecture. And I think Cyrix would not want to…"
"…lead programs that are successful. Bredy admitted a vendor can be a good source of leads. 'Veritas Software has **decent** leads," he said. "But that's not from their lead-generation program, per…"
"…copy-once functionality, security and cost. By teaming with Philips, the Macrovision/Digimarc group has come up with a 'very **creative** copy-once scheme that does not require the addition of…"
"…intelligent switches and directors from Cisco Systems Inc., Brocade Communications Inc. and McData Corp. The switches are among a **new** breed of storage technology that uses application-specific…"
"…Ascend originally was seen as a **look-alike** competitor to remote-access specialist Shiva Corp., but…"
"…'get the full story and have access to all of the details as soon as they are available.' Though Transmeta may be **unconventional**, its investors are anything but. Among those who have banked on the company…"
"…people, since the two companies are in what are **usually** regarded as entirely separate markets. Ascend, based in Alameda, California, makes communications gear used by telephone carriers and Internet…"

*__Note:__ Words that appear in the KCL lexicon are shown in red; new probable authenticity-related keywords found in our article search (not incorporated into our quantitative measures) are shown in blue.

as competition increases. Because signals of authenticity are largely conveyed through qualitative data (e.g., regulatory filings, press releases), audiences are limited in their capacity to consider such signals as the number of offerings increases. We found empirical patterns that were consistent with the predictions made in both moderating hypotheses.

Our study has several limitations. When measuring conformity/distinctiveness, we use averages to establish how much organizations depart from their category. However, investors may attend more closely to exemplars. How similar/different a firm is to Google, for instance, may be more important to establishing its category membership than its overall similarity to other competitors.

From a theoretical point of view, we suggested that greater attention to the features of market actors may be helpful for addressing tension in the categories literature over successful nonconformity. To that end, we focused on signals, which—consistent with work by Peterson (1997) and research in organizational theory—are potentially more readily subject to the agency of market actors than other attributes. Empirically, however, although we are able to observe and characterize different signals of market actors in our setting, our ability to determine strategic intent is limited. Relative to our quantitative approach, qualitative methodologies (e.g., interviews, ethnographies) are more capable of capturing such intents, and therefore studies using such approaches would be particularly valuable as a next step.

We treated networks, governance, and narratives separate proxies for signals of authenticity. However, as noted previously, networks, governance, and narratives do not encompass a logically exhaustive set of potential signals. Therefore, it is possible that some firms convey authenticity using signals that are not captured by our measures. In addition, networks, governance, narratives, (and other signals) may work together to influence audiences' perceptions. For example, firms may be able to balance high conformity on one signal by being highly distinctive on another. Future work may therefore help by studying connections among different signals.

Our approach does not account for the possibility that when signals place a firm far from sector norms, it may come closer to the profile of a different industry. Thus, future work may benefit from attending to the possibility of hybrid identities (Hsu, 2006) or multiple category membership (Hsu et al., 2009). Relatedly, our study did not examine heterogeneity across sectors. Nevertheless, our descriptive analysis of interindustry differences suggests that different signals of authenticity may matter more in some industries than others. More broadly, the perceived value of authenticity itself may vary. We have suggested that audiences are likely to attend to authenticity in settings where underlying quality of innovations is difficult to evaluate. But clearly, authenticity also matters in other contexts (i.e., where innovation is less important). Future work that examines sector-level determinants of attention to authenticity would be valuable.

Although we focused on the contemporary US, perceptions of authenticity are likely culturally contingent. Some observers suggest that contemporary attention to authenticity stems from disillusion with mass society. Thus, where such disillusion does not exist, audiences may value authenticity less. Even across cultures that do value authenticity, there will be variation in the signals to which audiences attend. Just as there are, for example, regional differences in the style of dress expected of country musicians (e.g., southeast/southwest), there may be differences across cultures in the weight given to, for example, narratives relative to other signals. Thus, caution should be used in generalizing our results to other cultural settings.

Our empirical analyses rely on observational data. Although we have attempted to minimize unobserved heterogeneity using statistical techniques, our estimates should not be seen as causal. Our primary empirical objective has been to demonstrate the plausibility of authenticity as way of reconciling the competing pressures of conformity and innovation in the category literature. Our data, which cover firms from five institutionally diverse sectors, are suited for these demonstrations. Future work, however, will be valuable for establishing causal relationships.

Finally, appropriate care should be used when interpreting our measures of conformity/distinctiveness as signals of authenticity. Although our case studies, theoretical arguments, and supplemental analyses offer assurances on the appropriateness of our measures, our data do not allow us to definitively rule out alternative interpretations, including, for example, the possibility (and likelihood) that dimensions of strategic balance are also reflected in firms' networks, governance, and narrative signals. Measurement of authenticity is an active area of research (Lehman et al., 2019), and there are exciting opportunities for future work that evaluates how to best capture this important phenomenon in settings—like high technology—that fall outside traditional cultural domains (e.g., food, music). Future work may benefit from linking signals of authenticity (e.g., networks, governance, and narratives) to more direct measures of audience perceptions. In this respect, the growing availability of text data (e.g., conference call transcripts, message board postings) will be helpful. Using these data, it may be feasible to expand on the text-based validation exercise we described above to more systematically evaluate, for instance, whether firms that more evenly balance signals of conformity/distinctiveness are described using language that is indicative of authenticity (e.g., using mediation and/or moderation analyses). Experimental approaches may also be feasible. One may imagine a study that provided subjects with descriptions of firms' networks, governance, narratives, or other signals that were experimentally manipulated on their conformity/distinctiveness and asking subjects to rate those firms on their sincerity or authenticity (c.f., Hahl and Zuckerman, 2014). The success of such an approach would of course depend heavily on finding the right subject pool (i.e., with the appropriate background and expertise) given the research question at hand.

Despite these limitations, we believe our study has several noteworthy implications. Our findings suggest that there is a flip side to Zuckerman (1999)'s "illegitimacy" discount in the form of an "authenticity" premium. Although producers are punished for too much distinctiveness, the illegitimacy discount appears to only predominate at high levels of nonconformity. Before that point, producers—at least in high technology sectors—are rewarded for showing distinctiveness from other category members.

This article also contributes to research on authenticity. We offer a quantitative approach to measuring the construct described by Peterson (1997) in his work on country music. Although our measures sacrifice nuance that is only possible with qualitative methods, they facilitate comparisons across producers and categories. To the literature on authenticity, we also add two contingencies—track record and competition—that describe when authenticity is likely to matter for audience evaluations.

These contingencies offer insight into the illegitimacy discount. Our findings suggest that cases—including those studied by Zuckerman (1999)—that focus on competitive industries populated by mature firms, there might be little benefit to authenticity. Under such conditions, we would expect precisely what has been found in that work—i.e., that the illegitimacy discount will predominate. By contrast, where a category is young and sparsely populated with organizations that lack established track records, the categorical imperative highlighted by Zuckerman (1999) might be understood not as a true discount but rather in terms of diminishing returns to distinctiveness.

CRediT authorship contribution statement

Helena Buhr: Conceptualization, Investigation, Methodology. **Russell J. Funk:** Conceptualization, Investigation, Methodology. **Jason Owen-Smith:** Conceptualization, Investigation, Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.respol.2020.104085.

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