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# A Spanner in the Works: Category-Spanning Entrants and Audience Valuation of Incumbents

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**Abstract.** Previous work has examined how audiences evaluate category-spanning organizations, but little is known about how their entrance affects evaluations of other, proximate organizations. We posit that the emergence of category-spanning entrants signals the advent of an altered future state—and seeds doubt about incumbents' prospects in a reordered industry-categorization scheme. We test this hypothesis by treating announcements of funding for startups as an information shock to investors evaluating incumbent financial service providers between 2010 and 2017—a period marked by atypical category combinations at FinTech startups. We find that announcements by startups that embodied unusual combinations of categories resulted in lower cumulative average returns for incumbents, both in absolute terms and in comparison with typical startups. Our theory and results contribute to research on categorization in markets and to theories of disruptive innovation and industry evolution.

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**Keywords:** emerging industries • industry dynamics • organization and management theory • technology strategy • entrepreneurship • technology and innovation management

## Introduction

A group of LendingClub employees filed onto the New York Stock Exchange (NYSE) podium to collectively ring the June 21, 2019, opening bell. The company was celebrating its three millionth lender, the bell perhaps a vindication of claims that it was the future of finance (Alois 2019). Originally launched as a Facebook app, LendingClub paired borrowers and lenders through a seamless peer-to-peer online platform. Melding conventional personal loans with software-as-a-service elements and investor-friendly lending opportunities, the venture had come to originate more loans than most medium-sized banks (Iankov 2019). More than mere technological competition in the finance industry, LendingClub embodied the emergence of a new-to-the-world category: peer-to-peer (P2P) lending. Analysts warned that nascent categories like P2P lending could threaten profit pools long controlled by traditional financial service providers (Nash and Beardsley 2015).

LendingClub is not an isolated case. A growing body of research investigates the implications of enterprise models that span previously unrelated business categories. Early work emphasized the negative consequences of such spanning. The “categorical imperative” asserted that flouting an existing classification system projects

an incoherent identity and lack of legitimacy, causing organizations that do so to be overlooked or devalued (Zuckerman 1999). Studies documented the penalties that accrued to multigenre films (Hsu 2006), blended cuisines (Rao et al. 2005), and diversified corporations that did not fit analysts' industry classification schemes (Zuckerman 1999, 2000) or strayed from well-trodden technology domains (Benner 2007, 2010).

More recent work, however, has reported anomalies—instances in which category spanners avoided penalties or were even rewarded for their nonconformity. Studies of unconventional software companies (Pontikes 2012) and hybrid-technology ventures (Wry et al. 2014) have shown, for example, that atypical combinations' success depends on evaluating audiences' goals and on precisely how they span categories. Clever signaling strategies may enable firms to move into new technology spaces despite countervailing pressures from analysts (Rao et al. 2001, Benner and Ranganathan 2012, Hampel et al. 2020). Research has also demonstrated that in nascent markets, categorization involves a delicate balancing act between legitimation and differentiation (Lounsbury and Rao 2004, Lee et al. 2017, Pontikes and Kim 2017, McDonald and Eisenhardt 2020), and that ventures can actively shape emerging categories as a part of their

value-creating strategy (Lounsbury and Glynn 2001, David et al. 2013, Lee et al. 2018, Pontikes 2018). This work has paved the way for a more circumstance-contingent theory of market categorization (see Zuckerman 2017).

Yet existing perspectives remain largely silent about how category spanners impact other organizations—not just themselves—and rarely consider the extent to which audience evaluations of such spanners spill over to related sectors (see Sharkey and Bromley 2015). This oversight is surprising in light of recent work suggesting that *categorical innovations*, not just technological innovations (Christensen 1997, Christensen et al. 2015), pose challenges for established firms and can negatively impact their value (Rindova and Petkova 2007, Benner and Ranganathan 2013).<sup>1</sup> For example, the robo-advisor category, pioneered by ventures that meld algorithms with traditional wealth management services, emerged as “a potential replacement for human financial advisors” (e.g., private wealth management groups) (McDonald and Gao 2019, p. 1,292). Although robo-advisors had novel technological elements, their market impact was arguably more categorical than technological: they filled a new in-between category between the existing (quite distant) categories of high-touch money management and do-it-yourself budgeting software. Similarly, Under Armour adapted new synthetic materials from the lingerie industry to sportswear for football players. But its base layer was more than a technological innovation—it was a unique and innovative combination that spanned the previously distant categories of underwear and external athletic wear, transforming an athletic apparel industry dominated by Nike and Adidas (McDonald et al. 2018). Anecdotes like these highlight a crucial issue that has received little attention from theorists: Do category-spanning entrants affect audience valuation of incumbents?

This paper aims for a deeper understanding of the impact of category-spanning enterprises in markets. We focus on how audiences assess incumbents’ value in the wake of entrants pioneering unusual categorical combinations. Audiences may be expected to view such category spanners as illegitimate, and thus to devalue them or discount their impact (Zuckerman 1999, Rao et al. 2005, Hsu 2006, Sharkey 2014), but recombination is a hallmark of innovations that challenge the status quo (Hargadon and Sutton 1997, Fleming 2001, Rosenkopf and Nerkar 2001, Katila and Ahuja 2002, Schilling and Green 2011). While arguing that “conforming to audience expectations is generally wise,” Zuckerman (1999, pp. 1402–1403) nonetheless acknowledges that “the greatest returns likely flow to those who *innovate by creating new categories and corresponding interfaces*” (Schumpeter [1934] 1983) [emphasis added]. Might this principle imply that returns flow away from some other group? Building on research into category innovation and industry evolution (Bingham and Kahl 2013, Granqvist et al. 2013, Suarez et al. 2015), we posit that

the emergence of atypical categorical combinations signals an altered future state—and seeds doubt about certain incumbents’ future prospects given their old market identity within a reordered industry.

To understand these issues, we carried out an archival study of category innovation in the financial services sector. Combining capital-markets data on finance industry incumbents with data on the venture capital funding and category memberships of finance-related startups, we use an abnormal returns event study design to compare audience (stock market investors’) assessments of incumbents after startup entry (marked by their debut Series A funding announcements). Our analysis accounts for category spanning—that is, the degree to which an entrant combines previously unconnected categories. We argue and show that announcements by entrants that spanned unusual combinations of industry categories lead to lower cumulative average returns for incumbents, both in absolute terms, and also compared with announcements by more typical entrants (non-category spanners). Our theory and results contribute to research on category innovation in markets and to theories of industry evolution, disruptive innovation, and technology change.

## Theoretical Background and Hypothesis

### Category Spanners’ Potential to Transform Market Categories

Category spanners represent the potential emergence of new markets at the intersection of existing market categories. Prior research suggests that the most significant innovations arise from linking previously uncombined categories, such as new ventures that join disparate enterprise elements (Schumpeter [1934] 1983, Fleming 2001, Baker and Nelson 2005) or distinct business model components (Zott and Amit 2007) in unique ways; organizations that combine competing institutional logics (Battilana and Dorado 2010, Murray 2010, Dalpiaz et al. 2016); or firms that search in previously unexplored domains (March 1991). In keeping with this notion, Wry et al. (2014) showed that category-spanning ventures were evaluated more favorably by audiences and attracted more capital than single-category peers. In the software industry too, category spanners gained traction with audiences—a result that Pontikes (2012) attributed, in part, to their flexibility and readiness to successfully cultivate new market opportunities and adapt effectively to impending industry changes. The relevant audience in both of these cases was venture capitalists—a group Pontikes termed “market makers.” Such audiences did not devalue category spanners for inconsistency with the prevailing market identity. Instead, despite enormous uncertainty, they rewarded category spanners’ potential to capture value in a newly created hybrid market category.

## Internal and External Barriers for Incumbents Adapting to Categorical Change

Despite competitive pressure to adapt to newly emerging market categories, incumbents may find themselves bound to their old market identities by both internal and external pressures. Internally, incumbents' managerial cognition (Henderson and Clark 1990, Christensen 1997, Tripsas and Gavetti 2000, Raffaelli et al. 2019) or professional identity (Barley 1986, Barrett et al. 2012, Kellogg 2014, Truelove and Kellogg 2016) may keep them tied to the old market categories. Incumbents' superior resources and market positioning make it seemingly impossible for new entrants to break in if they play by the same rules. But incumbents with strong established market identities may have difficulty realizing when their fundamental assumptions about the market change, and adaptation requires competition on entirely new dimensions (Christensen and Bower 1996, Christensen 1997, Von Hippel et al. 1999, O'Reilly and Tushman 2016, Christensen et al. 2018). As categorical innovations such as the minivan emerged, for example, established automakers experienced inertia that resembled incumbents' classic (albeit maladaptive) responses to market and technological change (Rosa et al. 1999, Engler 2015).

External pressures also keep incumbents from adapting their identity in response to categorical change (McDonald and Gao 2019, Hampel et al. 2020). Specifically, Benner and colleagues proposed a novel explanation for incumbent inertia in the face of technological change that was rooted in institutional pressure from evaluators—in this case stock market analysts (Benner 2007, 2010; Benner and Ranganathan 2012). Perceiving an incumbent's response to industry change—an investment in a new technology or a newly commercialized product that incorporated that technology—as a departure from its accepted categorical identity, these investors and analysts would deem the move illegitimate and discount the company's stock price (Benner 2007). To avoid being penalized, incumbents needed to stay in their lane: they were encouraged to focus on preserving and extending an existing technological trajectory and were discouraged from pursuing new ones (Benner 2010). Taken together, the internal and external pressures for incumbent categorical coherence represent serious barriers to effective adaptation to the emergence of a new market category.

## Audience Evaluations of Incumbents Following Entry by Category Spanners

We have established that category-spanning entrants represent potential category transformation, and that there are internal and external barriers to incumbents' adaptation to such category transformation. Now, we turn our attention to how audiences value incumbents following entry by a category-spanner.

Given the many barriers incumbents face when adapting to market category transformation, audiences observing entry by new category spanners may doubt incumbents' future prospects in the established market category.<sup>2</sup> Though pinpointing the exact time of market entry can be difficult, our theory considers entry from the perspective of potential audiences who register it. Thus entry is the point in time of an early legitimation by an important evaluator: an early endorsement or major investment of resources by a relevant evaluator serves as a clear signal of an entrant's emergence as a potentially viable contender (Hsu 2007, Hallen and Eisenhardt 2012). Marking its debut in the public domain, legitimated entry often generates attention via other third-party evaluators (Rao et al. 2005), media, or word of mouth (Cohen et al. 2019). Thus in our conceptualization, entry serves as an information shock to external audiences—an informative signal even for an audience who may already be aware of the entrant's prior existence (e.g., its founding).

Although typical entrants (non-category spanners) may ultimately pose threats to incumbents, their entry is unlikely to immediately induce negative audience evaluations of incumbents' future prospects. Expert audiences recognize that incumbents can continue to compete effectively and hold their position within their established markets (Benner 2010), even if the entrant pioneers a new technology that competes along the same dimensions as previous products (Christensen and Bower 1996). Furthermore, given the high rate of failure of new entrants (Eisenmann 2006, Kerr and Nanda 2009, Artinger and Powell 2016, Furr and Kapoor 2018), the likelihood that any particular entrant will expand to challenge an established incumbent as a direct substitute is low.

But entry by category spanners may be quite different. Whether that particular atypical combination succeeds, its entry signals the potential propagation of a novel categorical combination that is inconsistent with the logic of the established market (a domain in which incumbents were thriving). Entry marks that specific entrant's emergence as a viable contender, but, more consequentially, it signals the expansion of a new-to-the-world category whose potential may trigger a broader reconfiguration of existing market structure and boundaries. Audiences recognize that should this happen, the incumbent may not have the luxury of staying in their lane. And even if audiences do not grasp the difficulty of incumbent adaptation to such a market transformation, they may still struggle to value the incumbent and its future prospects using their (preferred) existing market categorization scheme (Benner and Ranganathan 2013). These audiences may not see how the incumbent ought to respond because they are grounded in evaluation schemas designed around the previous market categorization (Chatterji et al. 2016).

Yet, market entry does not have the potential to influence evaluations of all incumbents equally. Entry into market categories unrelated to an incumbent's may not attract the attention of evaluating audiences, let alone signal an altered future state for the incumbent. Audience attention and adaptation perception depend on how closely related the entrant is to the incumbent. Only when an entrant's market categories connect to an incumbent does it get noticed and signal potential future change of those market categories.

In summary, to the audiences evaluating an incumbent, we posit that related entrants embodied by atypical categorical combinations portend an altered future state, seeding doubt among the audience about incumbents' future prospects. Such dimming future prospects are associated with an incumbent's inability to adapt their identity in a newly reconfigured market. Accordingly, we hypothesize:

**Hypothesis 1.** *The greater the category spanning of a market entrant, the lower the audience valuations for related incumbents.*

## Methods

### Research Context

Our research setting is the financial services industry from 2010 to 2017. During this time period, many non-traditional startups entered and began to push the boundaries of existing markets. Many of these startups were largely responsible for the growth of various new-to-the-world categories within the financial technology sector, collectively rolled together under the label "FinTech." According to our definition, FinTech refers to a collection of new technologies and market logics that seek to improve and automate the delivery and use of financial services. It helps companies and consumers manage their financial operations and processes, and utilizes specialized software and algorithms built for computers and, increasingly, smartphones (Gomber et al. 2018, Kagan 2019). Enabled by new digital technologies (Iansiti and Lakhani 2014), growth in data analytics, and increasingly automated and secure transactions, FinTech has emerged as a fertile domain for category-spanning startups that seized new opportunities to reimagine traditional finance.

To augment our archival research and triangulate our quantitative evidence (Jick 1979, Edmondson and McManus 2007), we undertook a qualitative content analysis of industry reports and news articles from the financial services sector. Consistent with similar multi-method investigations (Pollock and Rindova 2003, Petkova et al. 2013, Pahnke et al. 2015), we utilized a "snowball" technique to identify articles and reports related to our phenomenon. With a particular emphasis on the time period after the category-spanning startups entered, we collected popular press articles and analyst

reports about financial services and FinTech available from the LexisNexis database and ABI/Inform during our study period. Articles and reports that appeared under "industry news" were considered industry reports, and those that appeared under "magazines and journals" and "newspapers" were considered general media (Petkova et al. 2013). Aiming for illustration of our theoretical constructs rather than systematic data collection, we drew on 20 such articles to understand how audiences assess entry by category-spanning startups. Besides providing richness and identifying mechanisms that underlie our findings, the articles and industry reports helped pinpoint several foundational phenomena related to category spanning in our context. Our content analysis approach also provided contextual information about how audiences (investors) assess incumbents' value in the wake of category-spanning entry.

As we encountered anecdotal information related to the phenomenon that we aimed to investigate empirically, several themes emerged. Specifically, we saw evidence of audiences (investors, analysts, and the like) attending to category-spanning startups and keeping tabs on their early funding rounds. For example, in an article entitled, "A Busy Month for FinTech Funding," an analyst for American Banker commented on specific funding rounds: "Novo, a challenger institution in the field of small-business banking, and the no-code platform provider Unqork held Series A funding rounds" (DiCamillo 2019). Another acknowledged more generally that, "Yes, [traditional banks'] investors and managers get the appeal of digital banking. They know what FinTech firms have been up to . . ." (Cocheo 2019). Some of these audiences speculated about how entry by category-spanning startups could create problems for established service providers and shift the finance industry to a different future state. For instance, in a widely quoted equity research report entitled, "The Future of Finance: The Rise of the New Shadow Bank," Goldman Sachs analysts focused on "a new class of shadow banks that are emerging—new entrants such as LendingClub, Prosper, Kabbage that are changing the face of traditional activities" (Nash and Beardsley 2015, p. 3). An Ernst and Young report added, "The industry attracted over US\$13.1b in VC-backed investments in 2016" (Ernst and Young 2017, p. 3), while a Citibank report pointed out that incumbent financial services companies could be facing a 30% revenue hit as category-spanning challengers enter the market (Ghose et al. 2019, p. 22).

We also encountered explicit recognition of (and commentary about) the category-spanning nature of these FinTech startups (PwC 2019). One prominent industry report stated that "cutting-edge FinTech companies and new market activities are redrawing the competitive landscape, blurring the lines that define players

in the financial services sector” (PwC 2016, p. 3). A *Wall Street Journal* article on startup Lending Robot reported that the company, “combines three of the hottest trends in the financial technology sector: online lending, robo-advisory and the technology that underpins the digital currency bitcoin” (Rudegear 2016). Another commentator referred to startups like Chime as “enfant terribles”; the entrants represent “a sort of ‘different animal’, [incumbents] will not be able to understand them or compete with them properly” (Dans 2018). These anecdotal illustrations provide a compelling impetus for a more systematic investigation of category-spanning entry and investors’ assessments of incumbents.

## Research Design

Drawing on the financial services context, we examine how category-spanning entrants impact audiences’ assessment of incumbents. In theories of market categorization, audiences evaluate organizations whose identities are coherent (or not) with respect to some existing classification system. Empirically, this research has relied on several different audiences: critics in the film industry (Hsu 2006) and in cuisine (Rao et al. 2005), venture capitalists for startups (Pontikes 2012, Wry et al. 2014), and stock market investors and analysts for public companies (Zuckerman 1999, 2000; Benner 2007, 2010). Stock market investors are the relevant audience for our study. In our model, these investors assess and evaluate incumbents in the wake of entry (venture capital (VC) funding announcements) by category-spanning startups, and we measure their valuations using stock market reactions.

Over a long-term time horizon, measuring the impact of new entrants on investors’ valuations of incumbents poses two major empirical challenges. First, it is difficult to attribute changes to any single entrant since, over time, many factors could affect incumbent valuation. Although an entrant’s growth could potentially influence investor assessments of incumbents, that growth would be entangled with many other factors affecting the incumbent, including the growth of other competitors or macroeconomic trends. Second, the entry could be endogenous—that is, industries that are growing in value are apt to attract more startups and funding (Gompers and Lerner 2004). If this is the case, it would appear that category-spanning entry led to a positive effect on incumbent valuation even if there was no relationship.

To overcome the empirical challenges of a long-term time horizon, we focus on the short-term effects of startup funding announcements on incumbent valuation. We use Series A funding announcements for startups in the financial services industry from 2010 to 2017 as exogenous information shocks to investors’ evaluations of incumbents. Series A funding represents an early and clear milestone for a startup’s emergence as a potentially viable contender. Series A is often thought of as a

public debut that attracts attention via news stories, investor blog posts, and word of mouth (Hsu 2007, Cohen et al. 2019). The funding signifies capital for growth, but also an endorsement that is meaningful to a variety of audiences: investors, potential partners, and employees (Hallen and Eisenhardt 2012).

Using Series A funding as a clear entry allows us to compare the immediate stock reactions for each incumbent following funding announcements. To test our hypothesis, we compare these reactions for funding announcements by category-spanning startups versus non-category-spanning startups, and also related startups (i.e., those with many overlapping industry category labels) versus unrelated startups. According to our hypothesis, we expect to see a more negative effect on incumbent valuations for funding announcements of startups that are both related to the incumbent and span previously distinct and unconnected categories.

Using funding announcements as an information shock allows us to estimate the immediate impact of the new information on investors’ assessments of incumbents. Despite continuing uncertainty about the startup’s eventual success, Series A funding indicates a higher probability of the startup’s future expansion (Hallen and Eisenhardt 2012, Cohen et al. 2019)—and signifies a possible future state in which the current market is transformed. Although in the long run, a startup’s decision to enter a given industry may be a function of the attractiveness of that industry—such as the growth rate, media attention, or access to capital—we assume a Series A funding announcement for a startup is exogenous to incumbents’ returns on the actual day of the discrete announcement event. We elaborate on this assumption in the robustness section.

## Data

We collected data from two main sources: Crunchbase and the Center for Research in Security Prices (CRSP). Our sample of incumbents and startup announcements is drawn from Crunchbase, among the most comprehensive databases of startup funding (Ter Wal et al. 2016). Crunchbase’s granular list of industry categories characterizes each incumbent and startup; it also provides startup Series A funding announcement dates. Crunchbase relies on multiple sources, including 3,500+ global investment firms that submit monthly portfolio updates, and a cadre of executives and investors who serve as active contributors. Contributions are verified by Crunchbase at the time of any data edits. Algorithms scan for anomalies on an ongoing basis, and a data team performs manual data validation and curation.

The sample of incumbents comes from the population of all U.S. for-profit companies in the Crunchbase category groups financial services, lending and investments, and payments, identifiable via stock ticker in the

CRSP data and with founding dates of 1995 or earlier.<sup>3</sup> The CRSP database provides daily stock returns and other financial information to calculate abnormal returns for these incumbents. The sample of startup funding announcements includes Series A announcements between 2010<sup>4</sup> and 2017 of every finance-related (financial services, lending and investments, or payments) U.S. for-profit company in the Crunchbase database that raised \$1 million or more, an appropriate threshold for successful Series A rounds (see Hallen and Eisenhardt 2012).

Because it would be impossible to disentangle the effects of announcements that occurred simultaneously, we restricted our sample to only those announcements that did not overlap with any other announcement in a three-day (day of to two days after) window following the announcement. Due to the large number of announcements, there was considerable overlap, which led 37,759 observations to be dropped out of the 53,130 total observations. Since quarterly earnings announcements can also significantly impact investor evaluations, we avoid contamination by dropping any observations for which the incumbent's quarterly earnings announcement dates occurred in the three-day (day of to two days after) window after the startup funding announcement (dropping 295 out of the remaining 15,371 observations). This left us with a final sample of 15,076 observations, where each observation represents a startup announcement event for a particular incumbent. In the [online appendix](#), we compare descriptive statistics of the original sample ( $n = 53,054$ ) to the final sample ( $n = 15,076$ ), concluding that there was minimal selection bias (Table A1).

### Dependent Variable

We use stock reactions to capture investors' assessments of incumbents. As a forward-looking measure embodying investors' expectations of future earnings, the stock returns are not a measure of actual performance but rather investors' evaluations of the present value of the company based on estimated future cash flows. Thus stock returns can be sensitive to new information (such as a startup's funding announcement) in the short term—a necessary feature for our research design.

Our dependent variable *CAR* (cumulative abnormal returns) represents the market-adjusted firm returns on the three-day<sup>5</sup> window following a startup funding announcement. We chose the three-day window based on previous event studies in the economics and finance literature, which demonstrate that most of the increased trading volume following discrete events such as patent grants or earnings announcements occurs within that window (Lamont and Frazzini 2007, Kogan et al. 2017). Market-adjusted returns are calculated as the firm return (CRSP holding period return) minus the return on

the CRSP value-weighted index (Campbell et al. 1997, Kogan et al. 2017). These measures are an accepted method for evaluating firm returns with less noise, by adjusting for shocks common to the whole market.

As robustness checks, we also use a Fama-French 5 factor model (Fama and French 2015) and the CRSP S&P weighted index to calculate abnormal returns, which yield quantitatively similar results. We use the value-weighted index as the primary dependent variable because it does not require estimating a model, which introduces a potential source of measurement error. To minimize the impact of outliers, our models typically winsorize the dependent variable at the 1% level (Kogan et al. 2017). This is important in our study because it is unlikely that a startup funding announcement, which represents only a small probability of a potential future competitor, could influence the stock price of a large financial incumbent to a significant degree (e.g., the most extreme abnormal returns in our sample were over 30% changes in stock price). Nevertheless, in robustness checks, we verify that our choice of winsorization does not drive the results.

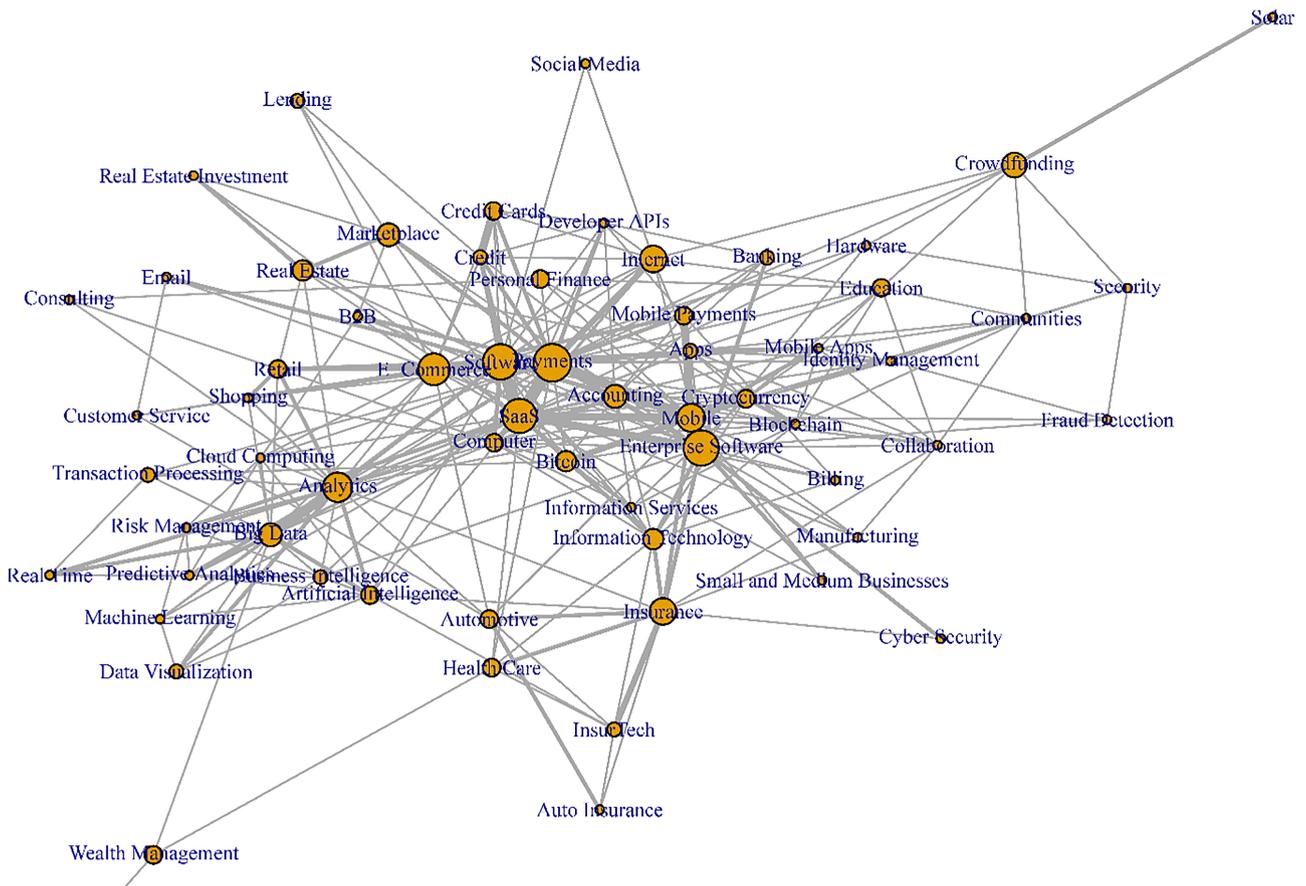
### Independent Variables

**Continuous Independent Variables.** To construct measures of *Relatedness* between incumbents and startups, and startups' *Category Spanning*, we use the categories labels in Crunchbase. At the time of writing, there were more than 700 categories in Crunchbase, nested within broader category groups. For example, the financial services category group (one of the three category groups used to filter our sample) contains the categories accounting, asset management, and banking, and about 30 other categories.

Figure 1 provides a network visualization of the prevalence and relatedness of categories in our final sample of startup funding announcements. The *Category* variable was used to determine whether each startup was related to each incumbent, and to create the measure of category spanning for each startup. In this network, the size of each node represents how frequently each category was used to characterize a startup. The thickness of each gray connecting line represents how many times each category labeled the same startup. The layout is calculated by placing nodes with strong shared connections and centrality in the center of the network using the Fruchterman Reingold force directed algorithm. For ease of visualization, we dropped any category that appeared in the data less than three times. We also dropped the top three categories: FinTech, finance, and financial services, which were by far the most common labels (essentially throwaway labels) and obstructed the view of other labels.

A startup's degree of relatedness to the incumbent is determined by the percentage of shared industry categories. Specifically, the relatedness between each

**Figure 1.** (Color online) Network Visualization of Startup Categories



incumbent and startup is calculated as a metric (ranged 0 to 1) that captures the percentage of shared categories between the incumbent and startup:

$$\text{Relatedness} = \frac{2 * \text{Shared Categories}}{(\text{Incumbent Categories} + \text{Startup Categories})}$$

A startup’s degree of category spanning is determined by how infrequently its own category labels have previously been used to simultaneously label any single organization. Unlike other databases, Crunchbase does not limit companies to one or two industry code classifications (e.g., Standard Industrial Classification (SIC) codes). On average, startups belong to 4.4 different categories, with a minimum of two and a maximum of 12. We exploit the fact that most companies belong to multiple categories by counting how frequently each category is coassigned with each other category to the same company. Intuitively, this measure of category spanning simply captures how frequently, on average, each pair of the startup’s categories have coincided at any finance company previous to the startup’s founding date (including previously founded startups

and established incumbents). Our approach is adapted from Lo and Kennedy’s (2014) measure of category blending in patents. They calculate proximity scores between each pair of patent classes that co-occur within the same patent, then take the average of the proximity of the class pairs within each patent to calculate a measure of typicality. We use the same process, using category labels for startups.

We first compute a proximity score  $P_{ij}$  for each pair of categories in the data, based on the frequency with which categories  $i$  and  $j$  coincide at any finance company prior to the startup’s founding:

$$P_{ij} = \frac{1}{2} \left( \frac{C_{ij}}{C_i} + \frac{C_{ij}}{C_j} \right),$$

where  $C_{ij}$  is the number of times that categories  $i$  and  $j$  coincide during the entire period of years before or during the year the startup entered, and  $C_i$  and  $C_j$  are, respectively, the number of times that categories  $i$  and  $j$  appear. These proximity scores and counts are obtained using all 2,220 Crunchbase-listed finance-related for-profit U.S. companies

that had cumulatively raised over \$1 million in any type of funding. Category spanning is calculated as one minus the average of the proximity scores of each pair of categories listed by the startup:

$$\text{CategorySpanning} = 1 - \frac{1}{N} \sum P_{ij},$$

where  $P_{ij}$  is the proximity of each pair of categories listed by the startup—how often the two categories previously coincided—and  $N$  is the total number of category pairs.<sup>6</sup> Intuitively, this measure will be higher for startups classified by many previously unrelated categories, and lower for startups assigned to categories that frequently coincide.

Note that this measure of spanning does not consider a startup to be category spanning just for being labeled by multiple categories. That is because many Crunchbase category labels appear together so frequently (e.g., financial services and accounting) that we do not consider them as representing true category spanning as perceived by audiences in the real world. We also point out that our category-spanning variable is merely a proxy for the underlying theoretical construct: the degree to which a startup is atypical because it spans previously distinct business categories. Rather than claiming that investors evaluating incumbent companies use Crunchbase categories to shape their perceptions of new entrants, we simply assume that the categories in Crunchbase map to the market categorizations as perceived by investors evaluating the incumbents. Because Crunchbase does not keep historical records of category labels, we take Crunchbase category labels at the time of download (December 2018) as mapping onto perceptions of the startup at the time of the Series A funding announcement.<sup>7</sup>

**Discrete Independent Variables.** For the main empirical analysis, we reformulate the continuous variables *Relatedness* and *Category Spanning* as combined discretized variables. That is, for each incumbent, each startup announcement is labeled as one of four possible classifications: *Not Related, Not Category Spanning*; *Not Related, Category Spanning*; *Related, Not Category Spanning*; or *Related, Category Spanning*.

Combining the two constructs into discrete categories has some advantages over two separate continuous measures. First, using these classifications facilitates interpretation, and allows us to demonstrate the results with plots of the raw data. Second, using discrete classifications does not require us to make as many modeling assumptions, such as the assumption that the interaction relationship between the two continuous variables (i.e., *Relatedness \* Category Spanning*) is linear (see Hainmueller et al. 2019).<sup>8</sup>

We considered a startup as related to an incumbent if the relatedness metric was  $\geq 0.4$ , which was the 90th

percentile of relatedness overall, but only the 70th percentile of relatedness for incumbent-startup pairs that had any overlapping categories. In the online appendix (Table A2), we show that the results are robust to alternative thresholds. For example, we adjust the threshold that divides related from not related for cutoffs between the 75th and 95th percentiles. In accordance with our hypothesis, we find that the treatment effect increases as the relatedness threshold increases. A startup is considered category spanning if its category-spanning score is above the median, and not category spanning otherwise. In the online appendix (Table A3), we show that whether we include interaction terms of the continuous variables (i.e., *Relatedness \* Category Spanning*) or the discrete classifications in our models, the results remain quantitatively similar.

## Controls

In order to isolate the effect of interest, our models include several controls, including the amount of *Money Raised* (in millions of dollars), the *Number of Categories* of the startup, and dummy variables to control for the most common industry categories (e.g., software).<sup>9</sup> We discuss the importance of these controls in more detail in the next section.

## Summary Statistics

The final sample used in the analysis is an imbalanced panel of 172 incumbents with on average 87.7 startup announcements each, for a total of 15,076 observations. Table 1 displays basic summary statistics for variables at the startup, incumbent, and observation levels. Table 2 displays a correlation matrix at the observation level.

## Model

To capture the effect of related category-spanning entry on investor valuation of incumbents, our research design attempts to address two main endogeneity concerns: (1) whether the timing of startup funding announcements are endogenous with respect to incumbent returns in the short term; and (2) whether a startup's level of category spanning is endogenous with respect to incumbent returns.

First, we consider whether the timing of startup funding announcements is endogenous with respect to incumbent returns. Over a longer time horizon, startups' decisions to enter a given industry may be a function of factors such as growth rate or market potential, but we argue the precise day of funding is exogenous to investors' valuations of incumbents. This is because the returns on a given day are a function only of new information entering the market, not existing information that has already been factored in to the value of the stock. Because securing funding is typically a long and arduous process (Hallen and Eisenhardt 2012), startups are unlikely to secure funding in response to new information within a

**Table 1.** Summary Statistics

Variable	N	Mean	St. Dev.	Min	Max
<b>Startup Series A announcement level</b>					
<i>Founded Year</i>	113	2011.2	2.114	2008	2016
<i>Series A Announcement Year</i>	113	2013.1	2.169	2010	2017
<i>Number of Categories</i>	113	4.381	1.789	2	12
<i>Category-Spanning Score</i>	113	0.857	0.074	0.621	1.000
<i>Funding Raised</i> (\$ millions)	113	5.98	6.49	1.00	50.00
<i>Covered by Media</i>	113	0.664	0.475	0	1
<b>Incumbent level</b>					
<i>Founded Year</i>	172	1942.0	47.771	1828	1995
<i>Number of Categories</i>	172	2.494	1.670	1	16
<b>Observation level</b>					
<i>CAR</i>	15,076	0.084	2.605	-8.604	8.732
<i>CAR (not winsorized)</i>	15,076	0.092	3.165	-34.347	67.795
<i>Not Related, Not Category Spanning</i>	15,076	0.416	0.493	0	1
<i>Not Related, Category Spanning</i>	15,076	0.464	0.499	0	1
<i>Related, Not Category Spanning</i>	15,076	0.098	0.297	0	1
<i>Related, Category Spanning</i>	15,076	0.022	0.145	0	1
<i>Relatedness Score</i> (% of shared categories)	15,076	0.121	0.178	0	1
<i>Shares at Least One Category</i>	15,076	0.360	0.480	0	1
<i>Day of Week</i>	15,076	3.853	1.401	1	7

single day. Of course, startups that have already secured funding may strategically choose when to announce it. But for strategic announcements to explain the patterns we observe, category-spanning startups must somehow systematically anticipate an event (which is unanticipated by the rest of the market) that causes negative stock reactions in related incumbents. Though unlikely, there are predictable external events, such as quarterly earnings announcements, around which startups might plan their funding announcements. This is one reason why we dropped any startup announcements that contained quarterly earnings announcements in a three-day window. The last possibility is that category-spanning startups with unannounced funding respond to an event earlier in the day that caused related incumbents' value to decrease. We believe this is unlikely—it is difficult to imagine why category-spanning startups would

systematically wait for events that cause negative incumbent stock reactions to announce their own funding. We cannot completely rule out this possibility, but have attempted to mitigate its potential effect by dropping any startup announcements whose three-day announcement windows overlapped with each other. This ensures that there is no clumping of startup announcements around potentially opportune announcement windows that could also correlate with negative incumbent stock reactions. In robustness checks, we will also ensure that there is no anticipatory lead effect of the funding announcement.

Second, we consider whether a startup's level of category spanning is endogenous with respect to incumbent returns. We argue that it is implausible that an incumbent firm's CAR following the startup's announcement could have any effect on the startup's choice of industry categories. However, a more relevant concern is the possibility

**Table 2.** Correlation Matrix

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 <i>CAR</i>	1													
2 <i>Category-Spanning Score</i>	0.01	1												
3 <i>Relatedness Score</i>	-0.01	-0.35	1											
4 <i>Not Related, Not Category Spanning</i>	0.01	-0.57	-0.12	1										
5 <i>Not Related, Category Spanning</i>	0	0.76	-0.36	-0.79	1									
6 <i>Related, Not Category Spanning</i>	0	-0.38	0.68	-0.28	-0.31	1								
7 <i>Related, Category Spanning</i>	-0.02	0.09	0.27	-0.13	-0.14	-0.05	1							
8 <i>Shares at Least One Category</i>	-0.01	-0.28	0.91	-0.03	-0.29	0.44	0.2	1						
9 <i>Funding Raised</i>	0.01	0	-0.06	0.12	-0.06	-0.08	-0.03	-0.03	1					
10 <i>Covered by Media</i>	0.03	-0.07	0	0.03	-0.02	-0.02	0.02	0.01	0.19	1				
11 <i>Startup Number of Categories</i>	0.03	0.28	-0.1	-0.09	0.2	-0.16	-0.05	0.04	0.11	0	1			
12 <i>Incumbent Number of Categories</i>	0	0	0.04	0.04	0.01	-0.07	-0.05	0.15	0	0	0	1		
13 <i>Series A Announcement Year</i>	0.03	0.06	-0.11	0.01	0.04	-0.07	-0.04	-0.08	0.22	0.18	0.06	0	1	
14 <i>Day of Week</i>	0	0	0.06	-0.04	0.03	0.03	-0.01	0.08	0.03	-0.01	0.07	0	-0.06	1

of omitted variables, which are both related to startup category spanning and incumbent stock reactions. It is possible that a high category-spanning score could be due to a correlation between the category-spanning variable and the presence of certain categories that actually represent the rise of a threatening technology. For example, perhaps category-spanning startups tend to be labeled with “software” or “cryptocurrency,” which could be categories that spook investors in traditional financial institutions. Or perhaps there is an unobservable factor about startups that list more categories that relates to both category spanning and their influence on incumbents. To alleviate these concerns, we include category controls, and the total number of startup categories in our models.

We use an event study design to capture the short-term effect of category-spanning entrants on valuation of incumbents. Our main model regresses incumbent three-day cumulative abnormal returns on our independent variables: *Not Related, Category Spanning*; *Related, Not Category Spanning*; or *Related, Category Spanning*, relative to the baseline of *Not Related, Not Category Spanning*. For this model, we estimate the effect of these funding announcements on incumbent CAR, denoted by  $R_{it}$ , for firm  $i$  at time  $t$ :

$$R_{it} = \beta_1 \text{Not Related, Category Spanning}_{it} + \beta_2 \text{Related, Not Category Spanning}_{it} + \beta_3 \text{Related, Category Spanning}_{it} + c Z_{it} + \epsilon_{it},$$

where each  $\beta$  measures the effect on  $R_{it}$  for each type of funding announcement relative to the omitted category “not related, not category spanning.” The model controls for variables in the matrix  $Z$ , including *Money Raised*, *Number of Categories*, and individual category fixed effects. The controls also include day of week and incumbent-year fixed effects. These fixed effects account for unobserved heterogeneity between announcement times and incumbents, and to account for the fact that incumbent heterogeneity may vary across years. Therefore, the estimated coefficients of interest represent within effects—the comparison of each incumbent’s stock reactions with its own reactions at different times to different announcements. We also run the models without fixed effects.

The overall objective is to compare the effects on incumbent CAR between startup funding announcements in each classification of relatedness and category spanning. If our hypothesis is correct, then we should observe a negative and significant effect for the *Related, Category Spanning* coefficient, and null effects for the other coefficients.

## Results

### Raw Data Visualizations

To observe the effect of category-spanning startup funding announcements on investor valuations of

incumbents, we first visualize the trends in incumbent stock returns before and after announcements. In order to view the raw effects, it is necessary to use the discretized version of the independent variables. Figure 2 plots the average raw cumulative abnormal returns of incumbents from five trading days before to five trading days after funding announcements for four types of startup events: not related, not category spanning; not related, category spanning; related, not category spanning; and related, category spanning. Each point on the figure represents the average cumulative abnormal returns of incumbents that were surrounding one of those four types of startup funding announcements.

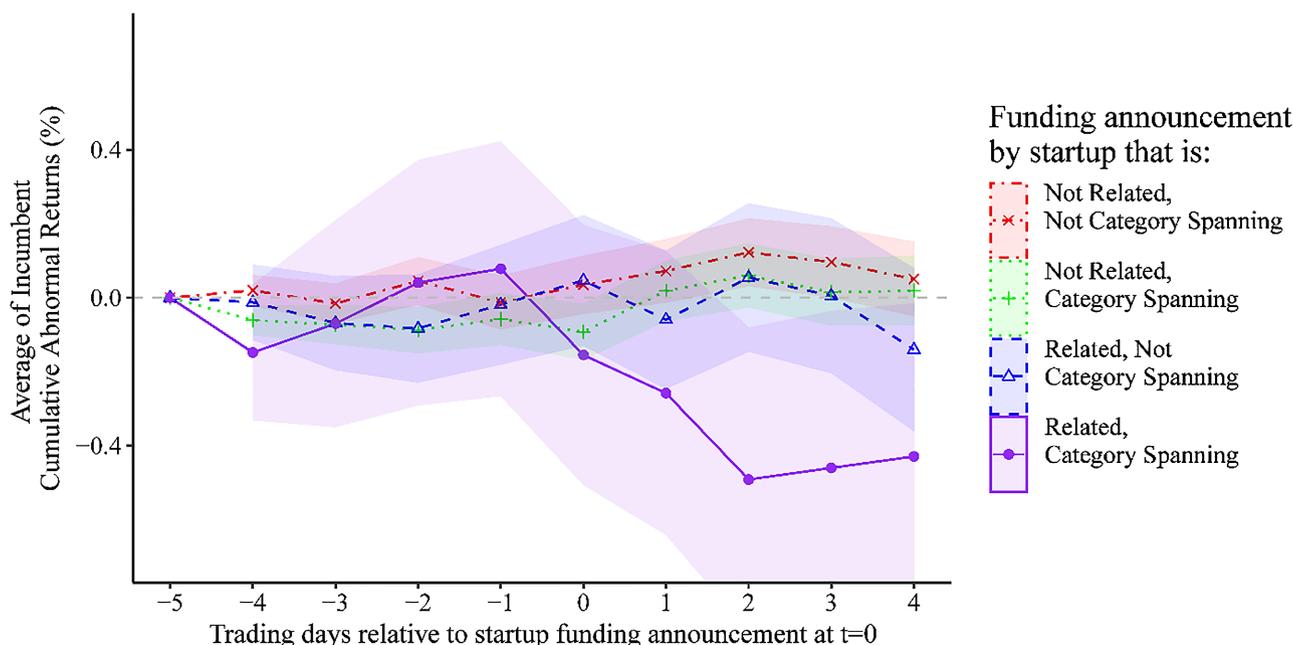
The figure shows that, on average, incumbents’ abnormal returns remain constant around zero before and after the startup announcement for every group except for the related, category-spanning announcements. As our theory predicts, following a funding announcement by a related, category-spanning startup, incumbents’ abnormal returns decrease, starting on the day of the announcement. Interestingly, the abnormal returns continue to fall the next two days, then level off—which coincides with previous literature that finds that the majority of trading activity following an information shock takes place in a three-day window after the event (Lamont and Frazzini 2007, Kogan et al. 2017).

Table 3 supplements Figure 2 by displaying a two-by-two table with two dimensions: related and category spanning. Each cell displays the number of observations, and the mean and standard error of three-day CAR for observations in the cell. The *Related, Category Spanning* cell has fewer observations because it was relatively rare for a startup to be both high on *Category Spanning* and highly *Related* to an incumbent. The relatively low number of observations explains why the confidence interval for related, category spanning in Figure 2 is wider in comparison with the other groups. Yet the CAR for this subgroup represents the only significantly negative effect among all the comparison groups.

Figure 3 illustrates the effect of startup announcements on incumbents using different threshold cutoffs for category spanning and not category spanning, as well as related and not related. The first panel shows that the more related the startup is to the incumbent, the lower the incumbent CAR—but only for category-spanning startups. The x-axis in this panel is the quartiles of the relatedness score—the percentage of shared categories between a startup and incumbent. Note that these quartiles only include nonzero values of the relatedness score, otherwise there are too many zero values so that quartiles do not produce unique breaks. In this panel, average incumbent CAR was calculated for two groups: announcements that were category spanning versus not category spanning (threshold at the median of the category-spanning score).

The second panel shows that for related startups, there is a sharp drop in incumbent CAR around the

**Figure 2.** (Color online) Average Incumbent Returns Five Trading Days Before and After Startup Funding Announcement



Note. Returns are adjusted by the CRSP value-weighted index and winsorized at the 1% level.

median category-spanning value. The x-axis is the quartiles of the category-spanning score—how much the startup spans previously unconnected categories. A high measure of category spanning represents that the categories that label the startup are infrequently seen together. In this panel, average incumbent CAR was calculated separately for announcements that were related versus not related (threshold at 0.4, which is the 90th percentile of the relatedness score).

**Ordinary Least Squares Regressions**

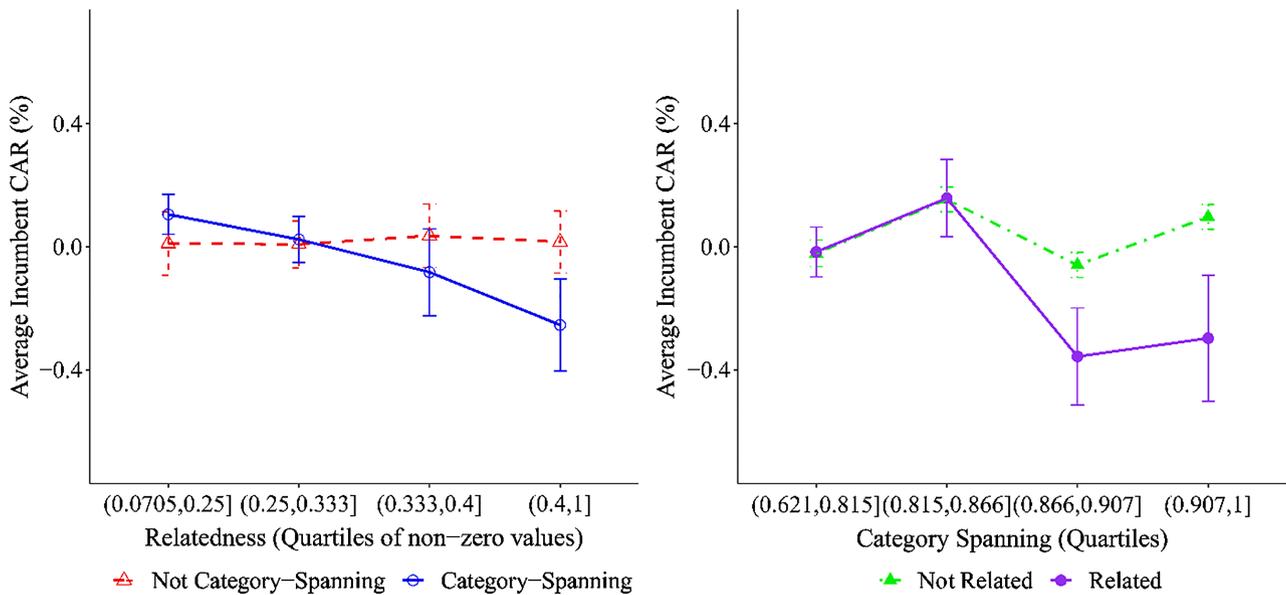
To formally test the effects displayed in the previous graphical visualizations, Table 4 displays ordinary least squares (OLS) estimates of the effect of related, category-spanning startup announcements on incumbent CAR. Columns (1)–(3) reports the main model with controls

and fixed effects, relative to each other discrete classification group in the independent variable. Column (4) reports the same model as column (1) without any controls or fixed effects and shows a quantitatively similar result. This suggests that unobserved heterogeneity between incumbent-years and other controls are not the primary driver of the results we observe. Columns (5) and (6) adjust the length of the time window following the announcement to calculate CAR to two days and one day (day of), respectively. The decreased magnitude of the coefficients corroborate the evidence in Figure 2 that a full three-day window is necessary to assess the full market reaction. Columns (7) and (8) report the same model as in (1) but use different methods of calculating CAR: the Fama-French five-factor model<sup>10</sup> and the S&P 500 index. These also yield quantitatively similar estimates to

**Table 3.** Three-Day Cumulative Abnormal Return Mean, Standard Error, and Sample Size for Each Discretized Independent Variable Category

	Not category spanning	Category spanning
<i>Not Related</i>	CAR mean: 0.127 (0.032) N = 6,134 Example: FactSet (incumbent) and RightCare Solutions (startup)	CAR mean: 0.085 (0.030) N = 7,137 Example: Prudential (incumbent) and Stripe (startup)
<i>Related</i>	CAR mean: 0.096 (0.072) N = 1,477 Example: Charles Schwab (incumbent) and Personal Capital (startup)	CAR mean: -0.482 (0.127) N = 328 Example: Berkshire Bank (incumbent) and NextSeed (startup)

Note. Each cell contains the raw three-day CAR sample mean (standard error in parentheses) and sample size (N) for incumbents following announcement events that correspond to the dimensions on the 2 × 2 table, and an example pairing of a startup and incumbent representative of each cell.

**Figure 3.** (Color online) Incumbent Cumulative Abnormal Returns by Relatedness and Category Spanning

Notes. The figure justifies the threshold cutoffs for related versus not related and category spanning versus not category panning used throughout the paper. The y-axis is the raw average of incumbent cumulative abnormal returns on a three-day window.

our main value-weighted index market-adjusted CAR in column (1). Overall, the results displayed in Table 4 are consistent with our hypothesis—entry by category-spanning startups decreases incumbent’s value, especially for market entrants that are more related to incumbents.

Each column shows that relative to the other types of announcements, only related, category spanning has a significantly different negative effect. The coefficient of  $-0.661$  indicates that, on average, when a related, category-spanning startup announced Series A funding, the incumbent’s return three days later was about half a percentage point lower than it would have been if the announcement had been made by a not related, not category-spanning startup. There are similar effects relative to the other categories: related, not category spanning and not related, category spanning. This effect is about 25% of the standard deviation of CAR in the sample (standard deviation of 2.6).

The discretized version of the independent variables facilitate interpretation, map onto the raw data visualizations (see Figure 2), and require fewer modeling assumptions. However, we also estimated models that included interaction terms between the continuous variables *Relatedness* and *Category Spanning* (online appendix, Table A3). As in Table 4, we run the main model, remove controls and fixed effects, adjust the time window, and use different dependent variables. The effect is robust to each specification. Finally, because interaction terms create challenges for interpretation, Figure A1 in the online appendix plots the marginal effects of the model in Table A3, column (1) for the interaction between *Relatedness* and *Category Spanning*.

### Robustness and Mechanisms

Our event study is designed to capture the short-term effect of category-spanning startup funding announcements on investor valuations of incumbents. The research design section of this paper highlighted several considerations to ensure that our results are not driven by simultaneous events unrelated to Series A announcements or other omitted variables. We include several additional robustness checks in Table 5.

First, to check the influence of outliers, we include models both without winsorizing the dependent variable (column (1)), and winsorizing at the 5% level (column (2)). The fact that the estimates do not significantly change either way suggests that our results are not driven by CAR outliers. Column (3) provides an additional check that simultaneous events are not driving our results. The coefficient estimates confirm that there is no lead effect in the week (five trading day) window leading up to the startup announcement. This suggests that the event was not anticipated, which is a necessary condition for an event study research design.

Next, we rule out the subtly different alternative explanation that the estimated incumbent discount effects are not from audience evaluations of individual startups, but rather are due to a cumulative growth of the overall umbrella of the FinTech sector. Column (4) interacts the continuous variable *Relatedness* with a dummy variable that indicates whether the startup had the FinTech label. This confirms that it was not merely being associated with FinTech that was driving the category-spanning effect. The same is true for other general

**Table 4.** Main Results: OLS Regressions of Incumbent Returns on Startup Funding Announcements Using Discretized Independent Variables

	Dependent variable: Cumulative Abnormal Returns (%)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
	Main model (relative to each omitted classification)		No fixed effects or controls		1-day window		Dependent variable: <i>Fama-French 5 Factor</i>		Dependent variable: <i>S&amp;P500 Index</i>
<i>Related, Category Spanning</i>	-0.661*** (0.140)	-0.607*** (0.140)	-0.707*** (0.147)	-0.619*** (0.124)	-0.439*** (0.129)	-0.198* (0.086)	-0.418** (0.135)	-0.603*** (0.139)	
<i>Related, Not Category Spanning</i>	0.046 (0.094)	0.099 (0.099)		-0.035 (0.080)	-0.039 (0.085)	0.052 (0.061)	0.105 (0.089)	0.023 (0.096)	
<i>Not Related, Category Spanning</i>	-0.054 (0.055)		-0.099 (0.099)	-0.045 (0.038)	-0.035 (0.045)	-0.031 (0.031)	0.056 (0.061)	-0.008 (0.055)	
<i>Not Related, Not Category Spanning</i>		0.054 (0.055)	-0.046 (0.094)						
<i>Funding Raised</i>	-0.003 (0.004)	-0.003 (0.004)	-0.003 (0.004)		-0.004 (0.003)	-0.011*** (0.003)	-0.011* (0.004)	0.002 (0.004)	
<i>Number of Categories</i>	-0.111*** (0.025)	-0.111*** (0.025)	-0.111*** (0.025)		-0.087*** (0.022)	-0.037* (0.016)	-0.088*** (0.026)	-0.123*** (0.025)	
Intercept				0.122*** (0.033)					
Individual category controls	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	
Incumbent-year fixed effects	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	
Day of week fixed effects	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	
R <sup>2</sup>	0.097	0.097	0.097	0.001	0.092	0.087	0.076	0.098	
Adjusted R <sup>2</sup>	0.021	0.021	0.021	0.001	0.015	0.011	-0.001	0.022	
Observations	15,076	15,076	15,076	15,076	15,077	15,082	15,076	15,076	

Notes. The dependent variable is cumulative market-adjusted abnormal returns of incumbent firms on a three-day window following the startup announcement date, with values winsorized at the 1% level. All models cluster standard errors at the incumbent level.

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

**Table 5.** Robustness and Mechanism Tests

	Dependent variable: Cumulative Abnormal Returns (%)					
	No winsorization (1)	5% winsorization (2)	Lead effect placebo (3)	FinTech label placebo (4)	Effect over time (5)	Media subsample (6)
<i>Related, Category Spanning</i>	−0.600* (0.279)	−0.611*** (0.120)	0.297 (0.207)		−0.665** (0.216)	−0.765*** (0.184)
<i>Related, Not Category Spanning</i>	−0.008 (0.109)	0.005 (0.076)	−0.119 (0.119)		0.264 (0.165)	0.021 (0.113)
<i>Not Related, Category Spanning</i>	−0.030 (0.074)	−0.075 (0.043)	−0.069 (0.088)		−0.141 (0.093)	−0.066 (0.080)
<i>Funding Raised</i>	−0.003 (0.005)	−0.005 (0.004)	−0.000*** (0.000)	−0.004 (0.004)	−0.003 (0.004)	0.000 (0.005)
<i>Number of Categories</i>	−0.102** (0.036)	−0.104*** (0.020)	0.048 (0.037)	−0.118*** (0.024)	−0.088*** (0.023)	−0.178*** (0.039)
<i>Relatedness</i>				−0.503* (0.196)		
<i>FinTech Label</i>				0.087 (0.078)		
<i>Relatedness * FinTech Label</i>				0.435 (0.280)		
<i>Announcement Year</i>					0.019 (0.017)	
<i>Announcement Year * Related, Category Spanning</i>					0.020 (0.056)	
<i>Announcement Year * Related, Not Category Spanning</i>					−0.074 (0.042)	
<i>Announcement Year * Not Related, Category Spanning</i>					0.014 (0.021)	
Individual category controls	Yes	Yes	Yes	Yes	Yes	Yes
Incumbent-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Day of week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R <sup>2</sup>	0.088	0.097	0.088	0.096	0.034	0.149
Adjusted R <sup>2</sup>	0.012	0.021	0.011	0.020	0.021	0.038
Observations	15,076	15,076	15,078	15,076	15,076	10,081

Notes. This table reports OLS regression results using the discretized independent variables. The dependent variable is cumulative market-adjusted abnormal returns of incumbent firms on a three-day window following the startup announcement date, with values winsorized at the 1% level (unless otherwise stated). All models cluster standard errors at the incumbent level.

\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ .

labels such as software (results available upon request). In a similar vein, we also consider whether the main estimated effect changed over time. That is, are we capturing the incumbent valuation discount due to individual startup announcements, or from a cumulative effect that changes over time? Column (5) confirms that the incumbent discount effect remained constant over the time period from 2010–2017.

We briefly turn our attention to exploring moderating factors that may influence the incumbent discount effect through our proposed mechanisms. If the results observed in the data are explained by our proposed theory, then startup funding announcements have influence on investors' assessments of the future state of the market. We would therefore expect that an important mechanism that moderates the relationship between a startup announcement and incumbent stock reaction would be the saliency of the information shock. We used Factiva and Crunchbase to identify the number of media articles before or during the

three-day announcement window for each startup. Although these databases do not form a complete picture of investors' level of awareness of each startup, they do roughly capture which startups received more attention. In column (6), we estimate the same model as column (1) but use only the subsample of startups that received mainstream media coverage before or within three days of the announcement event. In line with our theory, the effect of *Related, Category Spanning* is more negative for this subsample. Finally, in additional analyses not included in the paper, we found that incumbents that spent more on acquisitions (potentially a signal of dynamic capabilities; see Teece et al. 1997) experienced a smaller audience incumbent discount. This supplemental evidence is consistent with our proposed theory: it suggests that audience's discount of incumbents depends on their perception of the latter's inability to adapt their market identity (these results are available upon request).

## Discussion

Drawing inspiration from examples like LendingClub and Under Armour—new-to-the-world innovations that fundamentally reshaped and transformed the space between two categories—we sought a deeper understanding of category-spanning enterprises and their consequences in markets. Our theorizing focused on audience assessments of incumbents in the wake of startups pioneering unusual categorical combinations. Using an archival event study, we examined the impact of category-spanning entry by startups on investors' valuation of financial services incumbents. The analysis showed that announcements by startups that spanned unusual combinations of industry categories led to lower cumulative average returns for incumbents, compared with entry by typical startups. We pursue the theoretical and practical implications of our findings and discuss the paper's contributions for research on categorization in markets, disruptive innovation, and technological change.

### Implications for Theories of Categorization in Markets

Theories of market categorization present some intriguing opportunities. Since the categorical imperative was first introduced by Zuckerman (1999), the concept has gained significant currency among scholars, and the term has entered popular business discourse. Moreover, there have been extensive citations of the foundational work in fields such as organization theory, strategy, innovation, and entrepreneurship, as well as vibrant debate about the underlying mechanisms at play (see Zuckerman 2017 for an overview). Despite this progress, the core question under investigation has remained largely unchanged: when (i.e., under what conditions) do audiences punish (versus reward) organizations that flout convention by spanning categories? To be sure, this is an important question whose answer has clear implications for scholarship and prescriptive insights for managers in many industries. But there are other important considerations.

Our study contributes by expanding the scope of inquiry in several ways. First, whereas prior work typically investigates the consequences of category spanning for the spanners (Zuckerman 1999, 2000; Pontikes 2012; Sharkey 2014; Wry et al. 2014), we explored its implications for *other* organizations. Our results show that entry by category-spanning startups has a significant effect on related-sector incumbents. Thus, whereas prior research focuses on how various audiences (i.e., customers, the media, critics, and investors) assess and assign value to enterprises that span categories (Leung and Sharkey 2014), we join with recent work demonstrating that such evaluations can spill over to related parties. Sharkey and Bromley (2015) showed, for

instance, that even unrated firms tended to reduce emissions if they had many peer firms that were rated. In a similar vein, we find that the three-day CAR for incumbents is about half a percentage point lower following funding announcements by category-spanning startups (relative to unrelated, non-category-spanning startups).

At first glance, the magnitude of the effect may seem small, but that is expected based on our theorizing. It hinges on a low probability that the startup (e.g., LendingClub) or others in the new-to-the-world category changes the industry significantly enough to alter or detract from an incumbent's future prospects (e.g., lenders). If anything, it could be seen as surprising that nascent, unproven startups (those that just barely received Series A funding) have any consequences for incumbents' stock prices. But the negative effect appears robust—holding up under a variety of different specifications. The negative effect is also slightly more pronounced for startups that received mainstream media coverage. This latter result is consistent with the theoretical mechanism we posit: the emergence of atypical categorical combinations signals an altered future state—and seeds doubt among some investor-audiences about incumbents' future prospects within an industry given their existing market identity.

Our theory and results may also help reconcile conflicting empirical findings about the impact of entry on the stock price of incumbents. For example, in the finance literature, Hsu et al. (2010) found that incumbents experience negative stock price reactions to completed initial public offerings (IPOs) (entry) in their industry and positive stock price reactions to the withdrawal of those IPOs—implying that investors recognize the negative effects of competition from new entrants. On the other hand, Lee et al. (2011) showed that, in industries characterized by high uncertainty and growth, IPO announcements (entry) may be a signal of the potential and promise of the industry because it attracts investment. Given our study of the well-established finance industry, one possibility is that funding announcements of new startups simply represent increased competition (fixed pie) to investors more than the countervailing force of signaling expanding demand (growing pie). A more intriguing possibility is that whether entry negatively impacts incumbents' stock prices depends on the circumstances of the startup entering (category spanning versus not), not just the characteristics of the industry (uncertain, growing, etc.). Since many studies in this domain use IPO announcements as a proxy for entry, they cannot capture entry at the earlier point at which it actually occurs, nor can they account for the entering startup's degree of category spanning. Future research is needed to disentangle the relative importance of market characteristics and entry circumstances.

**Implications for Incumbent/Startup Dynamics, Disruptive Innovation, and Technology Change**  
**External Pressure Sparked by Category-Spanning Entrants.** Our study also has implications for research on the dynamics of industry evolution, reordering, and change. Across numerous industries, researchers have observed that leading firms failed to remain dominant in their respective markets—a decline often attributed to factors such as technological complexity, managerial cognition, or organizational inertia (Tushman and Anderson 1986, Henderson and Clark 1990, Henderson 1993, Tripsas and Gavetti 2000, Ahuja and Lampert 2001, Kapoor and Klueter 2015). One prominent theory, disruptive innovation, posits a specific pathway by which startups with few resources and limited market power are nonetheless able to successfully challenge leading incumbents (Christensen et al. 2018). Specifically, as incumbents focus on their best customers, they exceed the needs of some segments and ignore others. Startups that establish a foothold in these overlooked segments and then improve their offerings over time can eventually displace incumbents in the mainstream market (Marx et al. 2014, Christensen et al. 2015).

We extend this line of inquiry by proposing that even before incumbents experience substantive revenue threats in their product markets, category-spanning entrants may lead some external audiences to re-evaluate incumbents' value. Category-spanning entry by startups does not involve targeting overlooked customer segments (a hallmark of disruption), but it may still impact incumbents' prospects. For example, automated financial advisors or robo-advisors reshaped the wealth management industry and reconfigured the market for longstanding providers (McDonald and Gao 2019), and Under Armour's base layer altered the athletic apparel industry. Yet neither category-spanning innovation displaced incumbents; they simply reordered an existing market by adding a new, atypical category. The results in this paper suggest that such categorical innovations are perceived early by audiences who seem to take note of their implications. Such innovations may create a different kind of pressure or challenge for the incumbent firms even before they actually face revenue threats in the product markets.

**Organizational Inertia and Audience Penalties: Incumbents.** An insightful body of research has emerged at the intersection of market categorization in organization theory and research on technological change in strategy. In a series of papers, Benner and colleagues first proposed then empirically examined a novel explanation for incumbent inertia in the face of technological change—institutional pressure from stock market analysts (Benner 2007, 2010; Benner and Ranganathan 2012, 2017). According to their model, investors and analysts perceive an incumbent's response to technological

change (e.g., research and development investment in a new technology or entry into a new technological subfield) as an illegitimate departure from the firm's core identity in the stock market, leading them to discount its stock price (Benner 2007). Analysts' reactions thus encourage a continued focus on strategies meant to preserve and extend the old technology and discourage responding to new technologies (Benner 2010); some firms find clever ways to continue investments in new technologies without suffering a penalty (Benner and Ranganathan 2012).

We extend this important work in new directions. For instance, the institutional pressure model posits that audiences (analysts, stock market investors) will penalize incumbents for straying from their existing industry classification schemes (e.g., by investing in new technology) (Zuckerman 1999, Rao et al. 2001). This is because audiences' evaluation schemas rely on metrics of value that work well to evaluate profits in the traditional business but are less appropriate for evaluating the radical new technology. We investigate a similar phenomenon of category-spanning startups that do not fit into an existing industry classification scheme. However, given the startups' newness (and perhaps their ill fit in existing category schemas), it remains unclear whether investor-audiences even recognize the challenges they pose. Our results suggest that they do. Thus, even though investor-audiences punish incumbents for responding to radical and/or category-spanning change, the same audience seems to simultaneously recognize the challenge posed by entrants that defy the category and/or evaluation schema.

How can we reconcile Benner and colleagues' argument—investor-audiences punish incumbents that do not stay in their lane during technology change—with our theory that investors punish incumbents when category-spanning startups enter? (Benner 2007, 2010; Benner and Ranganathan 2012, 2017). One possibility is that investor-audiences are aware of the altered future state made possible by these new entrants, but they do not (or cannot) see how the incumbent ought to respond because they are rooted in their preferred evaluation schemas (based on quantitative analyses of discounted future profits). Therefore, incumbents may find themselves in a sort of Catch-22: in the context of a radical business model or technological change—one that may correspond to atypical category combinations—investor-audiences recognize incumbents may face an altered future state, but any actions to adapt are still evaluated negatively when compared against the metrics of incumbents' previous business. These negative external evaluations may be temporary, however, if incumbent managers carefully frame these strategic moves to analysts as necessary for future growth or survival (Benner and Ranganathan 2017).

Another possibility is that investor-audiences have learned from and incorporated the research on

incumbent inertia during technological change. Benner and colleagues studied older industries (digital photography, newspapers, etc.) in which incumbents were obviously challenged and, in some cases, displaced. Given the more recently emerging categories in financial technology, we posit that investors may be more likely to see and recognize the threat. More research is needed to determine which, if either, of these theoretical possibilities is more likely.

### Scope Conditions, Limitations, and Future Research

We expect our framework to be broadly applicable to established incumbents (not entrants) facing entry from category-spanning entrants (not from diversifying incumbents). However, we emphasize several important caveats to an event study like ours. First, we do not specifically examine radical technology change as industry evolution scholars might conceptualize it. Instead, we measure category spanning, an empirically related but conceptually distinct concept. Second, we explore the direct effect of category-spanning entry on the valuation of related incumbents. However, there may exist indirect pathways in which category-spanning entrants impact incumbents through their effects on the incumbent's primary competitors. Future research may be able to explore such a possibility. Third, with our data, we are not able to directly examine incumbents' strategies, which are a key component of the institutional pressure model that Benner and colleagues have proposed (Benner 2010, Benner and Ranganathan 2012). For example, we do not measure and therefore cannot account for other important factors that surely shape incumbents' future prospects (or audience-investors' assessments of those prospects) in the face of industry change, namely leveraging complementary assets (Teece 1986, Tripsas 1997) or a corporate venture capital arm (Dushnitsky and Lenox 2005). Future attempts to draw comparisons between our study and existing theory and research in strategy may prove fruitful, and we welcome efforts to generalize our framework to other contexts and circumstances.

### Conclusion

Competition from new categories is more intense than ever. If the past is any guide, then today's market categorizations will reorder and transform in the decades ahead. Existing theories provide useful insight into how audiences will perceive the pioneers of future market categories, but what of their evaluations of other, proximate organizations? Our study begins to unpack this issue by providing a window into the fate of these related incumbents. We hope it will inspire additional research in this area.

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### Endnotes

<sup>1</sup> Although categorical innovations may contain some novel technologies, their primary impact is how they create or recombine market categories.

<sup>2</sup> Studies investigating new entrants' effect on incumbent stock prices have reported mixed results. Hsu et al. (2010) found that incumbents experience negative stock price reactions to completed IPOs (entry) in their industry and positive stock price reactions to the withdrawal of those IPOs. But Lee et al. (2011) showed that IPO announcements (entry)—as a signal of the potential and promise of an industry—can lead to positive stock price reactions. We return to these conflicting findings from the finance literature in the Discussion section.

<sup>3</sup> Crunchbase files were downloaded on December 7, 2018, and CRSP files were downloaded October 24, 2018. The 1995 date was chosen to capture well-established companies.

<sup>4</sup> This period coincides with much of the growth in nontraditional financial services startups. We start the analysis in 2010 to avoid volatility from the financial crisis, and because Crunchbase did not even exist until 2008.

<sup>5</sup> The three days include the day of the announcement and the following two days. For example, if the announcement was on a Monday, the window would include Monday, Tuesday, and Wednesday.

<sup>6</sup> This is a notational simplification of Lo and Kennedy (2014), who use the form  $\frac{\sum P_{ij}}{(L(L-1))/2}$ , where  $L$  is the number of categories (rather than the number of category pairs).

<sup>7</sup> Although Crunchbase did not have historical records of category labels, we had previously downloaded Crunchbase data from more than a year earlier (July 2017). We merged that data set with 110 of the companies in our analysis, and found surprisingly little change in category labels. Specifically, 80% (86/110) of companies experienced no change in category labels. We manually examined the 24 startups whose categories did not perfectly match. Of these, 11 added a single label, four added two labels, two were blank in 2017, and six simply added more granular categories. Only two companies had meaningful changes to existing category labels. Based on this limited audit, we gained confidence that the labels as measured in December 2018 map well onto the startups' categories in 2010–2017.

<sup>8</sup> To visualize this assumption, consider plotting the predicted values from an interaction term between two continuous variables in a linear model (as in Figure A1 in the online appendix). Pushing the line to slope down on the right-hand side would necessarily cause that same line to rise on the left-hand side by the same amount—a mechanical consequence of a linear interaction assumption that is not necessarily reflected in the data.

<sup>9</sup> Controls are included for the top 25 most common categories, out of 154 total unique categories in the sample of final startups. Only the top categories are included because many categories appear only a small number of times, and paired with incumbent-year fixed effects, there is not enough variation. The results on the main coefficient of interest remain quantitatively similar whether 25, 30, or 50 top categories are used.

<sup>10</sup> We downloaded the five factors from Kenneth French's personal website, [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html#Developed](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Developed). We followed Flammer and Bansal (2017) by estimating the coefficients of the five factors on an estimation period of 200 trading days that starts 20 days prior to the startup announcement. To be included in the sample, the stock was required to have at least 15 nonmissing days during the 200-day estimation period (all of the observations fulfilled this requirement).

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