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Surviving the Commercialization Gap: Identities, Forms, and the Emergence of New Industries

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Existing research suggests that the first commercialization of a product or service in a new activity domain is a key turning point in the evolution of what we commonly refer to industries. An organization theory logic implies high failure rates among these pioneers: most new firms in most new activity domains will disappear, a phenomenon we call the commercialization gap. A first challenge in understanding this gap is created because the dynamics of new forms are complex. Specifically, the dynamics of building consensus about appropriate ways of organizing with small numbers of firms, limited support from stakeholders, and high rates of mortality are not well understood. Liabilities of newness, made worse because the organizations are in new activity domains, suggest that most attempts at new industries will fail. Given that many may disappear without a trace, possibilities for large sample, empirical study of early phases of industry evolution are limited. Accordingly, we use simulation methodology and begin with a simple organization theory model of the commercialization gap. To apply the model, we derive theoretical questions related to how social information exchange might affect consensus about organizational identity. After discussing the computational algorithms and demonstrating that they produce a consistent commercialization gap, we run simulation experiments to investigate these theoretical questions. Based on clear answers from these experiments, we develop five propositions and close with a discussion of both theoretical and practical implications.

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Introduction

In 1977, three different companies commercialized a complete personal computer (PC): Apple in California, Commodore, a manufacturer of electronic calculators, in Pennsylvania, and Tandy, then the largest mass retailer of electronic goods in the United States, in Texas. Two of these first PCs, the Apple II and Commodore PET, were launched simultaneously at the West Coast Computer Faire, in the late spring; Tandy came to market with the TRS-80 in August (Chandler, 2005: 134). This group of firms and their novel products, which the 20th anniversary issue of the now defunct *Byte* magazine called the 1977 Trinity, launched a revolution in how computers were used in the US and globally. The slogan of the founder of Commodore wrapped up the intent of the launch of this industry: 'Computers for the masses.' The Commodore PET, which included a built-in monitor and tape drive, became a best seller at the bargain price of US$795; the firm quickly followed with the VIC-20, the industry's first million seller.[1] Decades of empirical and theoretical work suggest that the launch of novel products by three different firms at roughly the same time was likely no coincidence (Shah, 2003; Mody, 2006; Rothaermel and Thursby, 2007; Shah and Tripsas, 2007; Agarwal and Tripsas, 2008; Santos and Eisenhardt, 2009; Mowery, 2010; Fiol and Romanelli, 2012; Shah and Mody, 2014; Bogaert, et al., 2016; Klepper, 2016; Moeen and Agarwal, 2017; Aksaray and Thompson, 2018; Lee, Struben, and Bingham, 2018).

Summarizing and extending this work, Agarwal, Moeen, and Shah (2017: 288) observed the following: "It appears that although the triggers and actors may be different, the actions are similar: these efforts typically center around solving many technological problems to transform an innovative idea into a viable commercial product, as well as engaging potential adopters and stakeholders to gauge demand potential." This view is echoed by work from an organization theory perspective: Fiol and Romanelli (2012: 598) focused on the social negotiation of beliefs in similarity clusters: the communities of practice from which novel products and services emerge (McKendrick et al., 2003). A key venue for the incubation of the PC industry's similarity cluster was the Homebrew Computer Club. Founded in Silicon Valley in

[1] https://web.archive.org/web/20080618072507/http://www.byte.com/art/9509/sec7/art15.htm accessed 30 November 2020.

1975, its members included the two founders of Apple and Steve Leininger, who designed Tandy's TRS-80. During biweekly meetings and in its newsletter, this group encouraged open exchange of ideas and trading of devices among early PC hobbyists (McCracken, 2013). Steve Wozniak (1984), co-founder of Apple, described the club as focused on giving help to others and eschewing the bureaucracy of large firms and big money considerations. Social interactions among enthusiasts in similarity clusters provide a primal soup for new products and services, startups, and the emergence of new industries (Fiol and Romanelli, 2012: 599-600). This agreement about what precedes the first product commercialization between the industry evolution view and the organization theory view is striking, particularly given these scholars converge from distinct theoretical starting points.

Regarding what will happen after the first product or service launches, however, the disparate theoretical roots of these lines of scholarship focus the attention of researchers differently. Agarwal et al. (2017: 288) described a progression after the first products or services, which they labeled the generic industry life cycle model: "… an early quasi-monopoly period, followed by accelerated market entry of firms during the emergence or growth stage, sharp decline in the number of firms during the shakeout stage, and an eventual mature stage with low levels of firm entry and exit." These stages have been derived from cases where a recognizable new industry achieves a considerable level of success. Models of how industries grow from the earliest stages to a shakeout and maturity have provided valuable understanding of industry dynamics as a function of time (Abernathy and Utterback, 1978; Gort and Klepper, 1982; Carroll and Hannan, 1989; Aksaray and Thompson, 2018). By contrast, research in organization theory has focused on the difficulties of launching new kinds of firms in novel activity domains, yielding robust evidence that young organizations in new industries to die at a high rate (Wiklund, Baker, and Shepherd, 2010). This will be driven by both liabilities of newness (Stinchcombe, 1965; Freeman, Carroll, and Hannan, 1983; Hannan and Freeman, 1984) and what we call *liabilities of new activity domains* (Lounsbury and Glynn, 2001; Fiol and Romanelli, 2012). This combination imposes extreme selection pressures on new firms in nascent activity domains with the result that most disappear, a phenomenon we call the commercialization gap. We develop an organization theory model of these stylized findings to enhance understanding and suggest implications for theory and practice.

The commercialization gap: An organization theory model

Aggarwal et al. (2017: 290) described the incubation phase, which precedes first product or service launches in a new activity domain. Product launches end this phase and signal the beginning of the next phase -- commercialization, which is the focus of our study. We use an organization theory lens to understand this phase by creating the *proto-industry model*. A first principle is that all new firms face liabilities of newness (Aldrich and Ruef, 2006: 62; Geroski, Mata, and Portugal, 2010: 511), making survival unlikely. Empirical evidence consistent with this principle has come from an ecological tradition that elaborated the population dynamics of new firms (Singh, Tucker, and House, 1986) and forms. A second principle arises from a more recent ecological emphasis on social agreement about organizational identities (Pólos, Hannan, and Carroll, 2002; McKendrick et al., 2003; Baron, 2004; Hsu and Hannan, 2005; Hannan, Pólos, and Carroll, 2007). We interpret this work to suggest that the absence of consensus about appropriate identities imposes what we call *liabilities of new activity domains*. Simply put, we expect a lack of social consensus (Stuart, Hoang, and Hybels, 1999) and related legitimacy challenges (Dobrev and Gotsopoulos, 2010) to decrease both the number of firms that will enter new activity domains and the survival of those that do. This combination of liabilities means that the lives of struggling young firms that populate proto-industries will be, in the famous words of The Leviathan by Hobbes, solitary, poor, nasty, brutish, and short. The resulting disappearances of most proto-industries, which we call *the commercialization gap*, means that many (if not most) attempts to launch new activity domains may be unobservable (Winship and Mare, 1992; Denrell and Kovács, 2008). For those few domains that persist long enough to be observed, we expect the dynamics of social approval that lead to the emergence of legitimated forms to be a complex, history-dependent process (Hannan, et al., 2019). Reviewing the considerable work by organization scholars that has employed simulation methods, Davis, Eisenhardt, and Bingham (2007: 481) argued that this approach is particularly useful "… when the theoretical focus is longitudinal, nonlinear, or processual, or when empirical data are challenging to obtain." Accordingly, we build a simulation model of a proto-industry based on an organization theory logic to understand the dynamics of proto-industries.

Following the advice of Davis, et al. (2007: 1982), we start with a clear question; what organization theory mechanisms might be sufficient to explain the commercialization gap? The answer we develop begins with severe resource constraints and high levels of mortality as well as deficits of both knowledge and consensus (Dobrev and Gotsopoulos, 2010) that further reduce available resources. To give shape to this theoretical logic, we build a model of individual organizations that launch new products and services based on organization theory constructs. We begin, following Hannan and Freeman (1984: 156), by characterizing these organizations in terms of four core dimensions: stated goals, forms of authority, core technology, and marketing strategy. We refer to organizations that launch products and services in new activity domains as *producers* and assume that the core dimensions of these producers can be represented by a vector of four *codes*. The use of the word code is an intentional signal of both expectations about behavior, as in a code of conduct, and expectations about structure, as in a genetic code. Enthusiasts who want to promote these identities face the challenge of moving them towards the taken for granted status that distinguishes them from forms for which there is widespread consensus that they are legitimate (Pólos, Hannan, and Carroll, 2002: 88-9). In Figure 1, we provide examples of producer identities as a vector of four codes, one for each core feature, with two choices for each feature, indicated by 0 or 1 (Lant and Mezias, 1990, 1992; Mezias and Glynn, 1993). We see from these examples that producers P1, P3, and P4 have the same codes across all four dimensions, indicating they share the same identity. The social ecologies of these producers include specific groups, called *audiences*, who allocate the resources needed to survive in these difficult selection environments. Audiences have preferences among identities that can be represented by the same codes as for producers. When the identity of a producer matches the preferences of an audience, the audience supports the producer with its available resources. In Figure 1, the preferences of audience A3 and the identity of producer P2 match; given this, A3 will support P2 by transferring some resources.

Insert Figure 1 about here.

We build our theoretical model of the proto-industry by aggregating these producers and audiences into populations. Consistent with the advice of Gavetti and Warglien (2015: 1266), we focus on a set of parameters that govern the foundational processes to ". establish the precise role these variables play." Figure 2 displays the theoretical model visually, beginning at step 1 where a small number of producers, with initial endowments and identities, launch products and services and attract the attention of a small number of audiences, with initial resources and preferences among identities. We regard the initial stock of resources of a new producer as a single endowment (Fichman and Levinthal, 1991), and survival depends on getting subsequent resource allocations from audiences (Pólos, Hannan, and Carroll., 2002). In step 2, audiences search for producers with identities that match their preferences, but matches are rare when there is a lack of consensus about appropriate identities, and if they find no matches they eventually stop attending to the proto-industry. In the rare cases where they find a match, the audience transfers resources to support the producer, a process they repeat until they distribute all resources allocated to the new activity domain to producers with identities that match their preferences. In step 3, producers spend the resources on hand to survive the current period, but they often come up short. Consistent with the commercialization gap, most producers go bankrupt, making an ignominious exit from the proto-industry in step 4. The initial low levels of density among producers and these exits signal low levels of legitimacy, so there no replacement with new producers (Aksaray and Thompson, 2018; Carroll and Hannan, 2000). The proto-industry model is iterative; surviving producers and audiences who continue to attend to the proto-industry proceed along path 5A to repeat the cycle. Consistent with this continued attention, audiences allocate that same amount of resources to support the proto-industry in each subsequent period as in the initial period. This iterative cycle continues until one of two terminal events occur. Path 5B, where all producers become bankrupt and the proto-industry disappears, is the most frequent terminal event. Infrequently, the proto-industry phase ends along Path 5C where survival and growth allow newly recognized forms to cohere into a recognized new industry.

Insert Figure 2 about here.

Casting the story of the PC industry in these terms reveals a parsimonious representation of mechanisms consistent with an organization theory perspective. The proto-industry phase began with the release of the first products by three producers in 1977. Consistent with the commercialization gap, two of the initial three producers exited the industry. Both Tandy and Commodore discontinued production of PCs and ultimately ceased operations. This industry also represents a rare case where a producer, Apple, survived and grew during the proto-industry phase, crossing the commercialization gap. Two central assumptions drive our model: high rates of mortality, consistent with liabilities of newness, and low agreement on identity among producers and audiences, consistent with a liability of new activity domains: we discuss each in more detail. Regarding mortality, Aldrich (2010) reported that although about 12 million people were involved with startups in the US each year, only 240,000, roughly two percent, grew beyond the initial team. Although we took this as a starting point, we assumed that start-ups that have reached product launch would have a higher survival rate, which we set at five percent. Regarding identity, a growing literature linking codes, rewards, sanctions, and survival (Hannan, et al., 2019) demonstrates the robustness of the claim that consensus about identity is key to audience support for producers. We assume, following Koçak, Hannan, and Hsu (2014: 765), that the proto-industry phase is a time of "… minimal consensus about how a good is defined, who can trade it, and how trading is conducted." Consistent with this, we assumed low levels of agreement about appropriate identities in proto-industries, which impacted our model in several ways.

First, the framework of scarcity that drives most proto-industries to extinction is premised on a general lack of attention (Ocasio, 1997), which has important effects. Lack of knowledge about new activity domains limits the number of potential founders, so initial counts of producers in proto-industries will be small and no new producers jump into the fray when existing ones go bankrupt. Audiences will tend to be unaware of the sector, and producers will face challenges getting the resources necessary to survive. The subsistence producers that populate proto-industries face continuing problems finding the resources to sustain operations, hindering survival and growth, not just at the producer level but also at the population level. The founders of Apple sold a treasured high-end calculator and a Volkswagen minibus to finance purchase orders (Isaacson, 2011). Employee number three, Mike Markkula, bought equity (USD$80K) and provided a loan (USD$170K) as he joined Apple (Livingston, 2007). Although angel investing (Huang and Pearce, 2015) and venture capital, including private equity (Rider, 2012) and corporate venturing (Gaba and Dokko, 2016), have evolved significantly since 1977, we expect that capital during the proto-industry phase remains scarce. Relatedly, we assume the visible hand of coercive isomorphism is unlikely to have much effect on population dynamics in proto-industries, largely because important regulatory actors are not yet paying attention. In the case of the PC industry, regulatory action did not occur until the Federal Communications Commission requested data regarding interference with radio and television transmissions[2] more than two years after the first PC came to market.

Second, sources of coordination of identity expectations in the larger social infrastructure remain undeveloped. Thus, we expect institutional entrepreneurs specialized in the new sector to be infrequent during the proto-industry phase. In the PC example, Seymour Merrin, who founded the first industry association, the Association of Better Computer Dealers, did not do so until 1982, five years after the first products. A similar delay between commercialization and first industry associations has been observed in the automobile (Rao, 1994), American film (Mezias and Boyle, 2005), and Dutch audit (Bogaert, Boone, and Carroll, 2006) industries. Third, while there may be exceptional cases (Bruderl and Preisendörfer, 1998; Dencker and Gruber, 2015), we assume that founders and firms developing new identities face challenges deploying their contacts or knowledge assets to enhance survival. Returning to the PC example, the founders of Apple repeatedly failed in attempts to get funding, access to materials, and financing of orders from a broad group of friends and colleagues (Isaacson, 2011). Fourth and finally, we assume several effects from the lack of consensus about identity, not least that no dominant design has emerged. As a result, producers generally are unable to achieve economies by moving down the learning curve or creating value from experience (Argote and Epple, 1990; Kapoor and Adner, 2012; Adner and Kapoor, 2016) during the proto-industry phase. Relatedly, we do not expect mergers or acquisitions to be important

[2] https://transition.fcc.gov/Daily_Releases/Daily_Business/2017/db0111/FCC-87-300A1.pdf accessed 25 September 2020.

to proto-industry population dynamics as consolidation is considered subsequent to this phase. In the PC case, none of the three companies that developed the first personal computer were acquired by or merged with another producer. In 2001, more than two decades after the first product launches, Fortune Magazine declared the pending merger of Compaq and Hewlett Packard to be the signal of a 'long-awaited' consolidation.[3] Similarly, we assume that neither pre-industry experience nor prior history of interactions are important factors in proto-industry dynamics; thus, we do not differentiate *de alio* and *de novo* producers (Carroll et al., 1996; Khessina and Carroll, 2008; York and Lenox, 2014; Block, et al., 2016; Withers, Ireland, Miller, and Harrison, 2018). In the PC example, Apple, the *de novo* producer, was the ultimate winner; the two *de alio* entrants exited PC production before going bankrupt.

To summarize, we have developed an organization theory model of the proto-industry that includes basic theoretical mechanisms to govern the interactions of the producers and audiences in new activity domain. We have discussed theory and evidence consistent with the claim that extreme liabilities of newness will limit both survival and growth. As a result, most producers go bankrupt, and most proto-industries disappear. We also discussed theory and evidence consistent with our expectation that these producers will face liabilities of new activity domains. Specifically, we expect that obtaining support from key audiences given minimal consensus about identity will be challenging. The absence of mechanisms that produce identity consensus in more established sectors makes matches between audiences and producers less likely, reducing survival and growth. In the next section, we develop some theoretical questions about the population level processes suggested by this model. The focus of these questions will be on producer survival and total resources, which are key outcomes to distinguish between proto-industries that disappear and those that persist and emerge as new industries.

Social information exchange during the proto-industry phase

In this section, we build theory by demonstrating how the proto-industry model can accommodate informal information exchange among and between producers and audiences. The lack of consensus about

[3] https://www.forbes.com/2001/09/04/0904specsf.html#1f8ebe56f169 accessed on 25 September 2020.

the core features of a PC or the firms that would produce them was evident at the time of the first product launches. Apple co-founder Steve Wozniak (1984: 76) characterized the era this way: "We couldn't look back and say, 'Here's how computers earned a lot of money in the sixties and seventies, that's the style to do.' … If there was a known formula for what would make a successful product, and what would make a billion dollars, all the big companies would have jumped on it. All these companies were a lot smarter than us." Three years after the Apple II, however, an editorial in Byte magazine (Helmers, 1980) declared consensus: "A desirable contemporary personal computer has 64 K bytes of memory, about 500 K bytes of mass storage on line, any old competently designed computer architecture, upper and lowercase video terminal, printer, and high-level languages such as that provided by the UCSD Pascal software system. This is the state of the art in small computing." The genesis of shared beliefs and agreement about core features that shape identities, not just of products but of forms more generally, is at the heart of a gap in the current literature concerning the evolution of new industries. To develop theory to address this gap, we review relevant literature to generate some experimental questions about the role of social information exchange (SIE) during the proto-industry phase.

Prior work in organizational theory has used simulation experiments to investigate the antecedents and consequences of SIE. For example, Harrison and Carroll (1991; 2006) described a simple model of cultural transmission that was robust to high turnover and rapid growth. Lazer and Friedman (2007) examined how the structure of communication networks among actors can affect system-level performance. Tatarynowicz, Sytch, and Gulati (2016) found an association between the environmental characteristics and the structure of technology partnerships among producers. Following Carroll and Hannan (2000: 164–167), we conceptualize communication among producers and audiences as the means by which producers and audiences construct shared beliefs about organizational identity codes. While they focused on public discourse, we focus on SIE, which includes any private or public discourse addressing the new activity domain. This avoids assuming that specialty, business, or national press attend to proto-industries during the earliest days (Mezias, et al., 2010). As Fiol and Romanelli (2012: 607) noted, the interaction "…of internal processes of identification and external recognition stands as a next important arena for research."

Making a similar point, Hansen, Mors, and Løvås (2005) stressed the importance of distinguishing between information exchange within groups and between groups in organizations. The proto-industry model offers a clear distinction between two groups, producers and audiences, allowing us to distinguish within-group SIE, that is among only producers or among only audiences, and between-group SIE, that is between audiences and producers. Organization theory suggests that the viability of new industries is enhanced when shared beliefs about appropriate identities facilitate the exchange of resources between audiences and producers. Hannan, Pólos, and Carroll (2007: 41) discussed this process in terms of the concept of clustering and argued that these clusters might form on the basis of "… relational properties, such as network ties." This reference to networks and our use of the network literature to derive some questions about the value of SIE come with two important caveats. First, we do not assume the small numbers of audience and producers in proto-industries are known to one another: where SIE occurs it begins as unordered and bi-directional. Second, the SIE process we propose is simple: limited exchange of information with specific other producers and audiences about producer identity codes and audience preferences among them. To investigate how this minimal communication mechanism (Ziegler, 2008) might affect identity consensus, we suggest three experimental questions about SIE, producer survival, and total proto-industry resources.

We begin by considering the effects of SIE within-groups, that is, only among producers or only among audiences. One mechanism by which within group SIE might enhance survival and total industry resources would be to create consensus about identity, particularly proto-industries where we do not assume that either producers or audiences are aware of others. There is prior research to suggest that SIE could enhance agreement about identity; for example, by enhancing social cohesion (Reagans and McEvily, 2003), providing greater social support and solidarity (Ibarra, 1993), or helping to create a consistent basis of normative support (Podolny and Baron 1997; Fiol and Romanelli, 2012). More SIE about identities can enhance information sharing, a sense of accountability, and agreement on expectations (Sparrowe et al., 2001: 318). We interpret the models developed by Gould (1993) to suggest that when SIE provides consistent information about appropriate identities, it will facilitate mutual identification among members of a collectivity (Reagans, Zuckerman, and McEvily, 2004). The social action engendered by higher levels of within group SIE (Reagans and Zuckerman, 2001) may offer opportunities for advocacy of preferred codes and identities. Closure within groups may enhance social mobilization (Gibbons, 2004: 101) in a way that encourages innovation, (Nicolaou and Birley, 2003; Fleming, King III, and Juda, 2007; Lovejoy and Sinha, 2010) including new identity codes. Closure may enable monitoring that facilitates informal reputation-based arrangements, which may be a particularly effective source of social order in small, homogenous groups (Hillmann and Aven, 2011). Consistent with these mechanisms, Mehra et al. (2006: 67) found that more connections at the individual level resulted in higher group performance. That these generally positive effects of within group SIE may hold in the context of new industries again is suggested by anecdotes from the PC industry. The Home Brew Computer club drew from a technologically savvy community of practice to provide feedback about prototypes and products to would-be entrepreneurs. Computer shows, although still focused on mainframes, attracted PC enthusiasts, and configured the field (Lampel and Meyer, 2008), not least the 1977 event that launched the first two products (Isaacson, 2011). On the audience side, the co-founder of Apple has claimed that computer magazines and lists of the products represented important flows of social information among stakeholders (Wozniak, 1984).

The fundamental consistency with mechanisms to communicate identity, such as shared narratives in similarity clusters (Fiol and Romanelli, 2012; Garud, Lant, and Schildt, 2018), is striking, but would we necessarily expect that more within group SIE will increase support for new activity domains? The prior literature also suggests an alternative possibility for the effect of SIE within groups; it may produce redundancy, reducing the value of the SIE (Uzzi, 1997). For example, Gould (1993: 190) showed that under some conditions networks where everyone was connected resulted in performance that was "… distinctly mediocre." Burt (2000: 30-31) found that network density and performance had a negative relationship, suggesting that more within group SIE could reduce the informational and control advantages associated with spanning structural holes. Gibbons (2004: 949) put this argument in the context of innovation, a key driver of the new activities that characterize proto-industries, finding that the absence of connections created "… an opportunity structure for generating new ideas." Despite hypothesizing to the contrary, Sparrowe et al. (2001) found negative relationships between the density of individual relations within groups and group performance. In their study of cooperation in evolving social networks, Hanaki, et al. (2007: 1038) argued that networks with less SIE "… tend to generate higher levels of cooperation than those in which ties are made easily and friends of friends interact with high probability." The findings of Grimes (2018) indicate that strong identities, associated with more within-group SIE, may cause resistance to feedback not consistent with that identity. If strong identities are a key trigger for enthusiasts to become entrepreneurs (Fiol and Romanelli, 2012), this suggests the possibility that more SIE among producers (or audiences) might create resistance to feedback.

Again, anecdotes from the emergence of the PC industry provide some facts that can be interpreted to suggest how this might occur. On the producer side, the high technical knowledge of most of the enthusiasts repeatedly caused them to underestimate the need to solve all technical requirements that would permit a PC to be used by relatively unsophisticated customers. When Wozniak and Jobs presented their newly printed circuit boards at the Homebrew Computer Club, their technically sophisticated compatriots were wowed at the ease of executing the assembly. Based on this they created a proto-type PC in the form of a kit the buyer had to assemble after purchase, which was quickly rejected by the market. Their first customer insisted that the only viable product was a fully assembled computer that customers could remove from the box and begin using immediately (Isaacson, 2011: 66). On the audience side, potential investors were caught up in their own businesses and a shared understanding about computers and gaming that excluded PCs, slowing recognition of the new sector's potential. Hewlett-Packard, which employed Steve Wozniak, turned down five different requests by him to manufacture PC designed with Steve Jobs and Ronald Wayne, another HP employee. Atari's CEO Bushnell had no interest in home computers and declined to invest in Apple despite being impressed with the genius of Steve Jobs, a former employee.[4] Consistent with some prior research, these anecdotes reveal the potential dark side of too much within group

[4] https://www.smh.com.au/technology/how-ataris-nolan-bushnell-turned-down-steve-jobs-offer-of-a-third-of-apple-at-50000-20150324-1m62cm.html accessed 30 November 2020.

SIE, either among audiences or producers. This diversity of prior findings regarding the effect of within group SIE yields this question:

Experimental Question 1: Does more within-group SIE among (a) audiences or (b) producers *increase or decrease* survival and total resources during the proto-industry phase?

The formal model by Hannan, et al. (2007) linked shared beliefs about organizational classes, categories, and forms with communication between the audience and producer segments. This is consistent with the finding of Hansen (1999) that SIE across internal firm boundaries fostered the transfer of more complex knowledge. Lounsbury and Glynn's (2001) discussion of shared narratives and Fiol and Romanelli's (2012) claims that similarity clusters can enhance the recognition of new activity domains by audiences suggest the importance of complex processes to transfer information and beliefs during the proto-industry phase. Two early developments signal the importance of such exchange during the launch of the PC industry (Isaacson, 2011: 84). The first illustrates the importance of information exchange with a key audience, potential investors, during the early days of the industry. Ben Rosen, an investment banker, became a self-anointed Wall Street evangelist of personal computers in general and Apple in particular. He even took the Apple II on visits to clients to show the product had far greater potential than its perception as a toy for hobbyists and gamesters. By the time of the 1980 Apple IPO, he had ensured that his employer, Morgan Stanley, was a lead underwriter in that offering.[5] The second highlights the importance of independent developers who wrote software that could run on PC in an era when operating systems did not have whole ecosystems built around them (Boudreau, 2012). As it happened, the developer of Visicalc, a spreadsheet and personal finance program, was at the 1977 West Coast Computer Faire, where the Apple II and Commodore PET were launched. Eventually, it became clear that the Apple II was the obvious complement for the software due to the ease of installing a floppy disc drive. As a result, this software was available only on the Apple II for a year before it became available on any other PC. It proved to be an important rationale for families and businesses to purchase a home computer, becoming the killer app that elevated the Apple II over its competitors. These examples illustrate how SIE between audiences and

[5] https://www.huffpost.com/entry/steve-jobs-remembered_b_1026789 accessed April 28, 2021

producers can enhance performance (Burt, 2000, 2005), not least when SIE that spans structural holes between audiences and producers replaces minimal consensus with shared information and beliefs (Burt, 1992, 1997).

As agreement on identities between audiences and producers increases, violations of identity codes occur less frequently, and audiences are more likely to support producers. For example, Cattani et al. (2008) studied the audience-producer network in the U.S. motion picture industry between 1912 and 1970, finding that increased connectivity reduced exit rates from the population. The results of Huang and Knight (2017) suggest that SIE between investors and entrepreneurs might communicate both affective and instrumental signals that could make investment more likely. Communication between entrepreneurs and investors, not least to assess business viability and take a measure of the entrepreneur (Huang and Pearce, 2015), helps to build the 'gut feel' associated with more effective early investment (Huang, 2018). Kacperczyk and Younkin (2017) found that communication between investors and artist entrepreneurs enhanced the willingness of those audiences to sponsor more innovative activities. In the context of university technology offices seeking revenues from licensing firms, Kotha, Crama, and Kim (2018) found that some uncertainties inherent in commercialization could be mitigated by signals exchanged during negotiations. Taken together, these findings illustrate how SIE between audiences and producers should enhance identity convergence and result in more resource transfers from audiences to producers. Whether higher levels of survival and total resources result is our second experimental question.

Experimental Question 2: Does across-group SIE, that is, between audiences and producers, increase survival and total resources during the proto-industry phase?

Our final experimental question regarding the role of SIE in the emergence of new industries involves the interaction between across-group and within-group SIE. We begin with the recognition that the relationship between performance and within-group SIE may be contingent, rather than always positive or always negative (Oh, Chung, and Labianca, 2004; Lechner, Frankenberger, and Floyd, 2010). As Provan and Sebastian (1998: 454) argued "… network success is likely to be the result of effective interaction among small, overlapping subsets …" of larger networks. Extrapolating this argument to proto-industries suggests that SIE between audiences and producers may be a key contingency that determines whether SIE *within* the two groups enhances survival and growth. Reagans and McEvily (2003) theorized and found empirical support for the claims that both density, that is, high closure within groups, and diversity, that is, SIE that bridged structural holes, improved knowledge transfer. Similar arguments made by Hansen, et al. (2005) are consistent with the claim that SIE both within and across groups would have positive effects on knowledge sharing outcomes. In a study of the convergence of telephony and computer networking, Lee (2007) found significant positive effects for both closure, high density of within-group SIE, and brokerage, a greater amount of SIE between groups. Vedres and Stark (2010: 1172) argued that "… inter-cohesive business groups outperform their counterparts, who lack this ambitious yet recombinative advantage." Particularly when entrepreneurship is less about importing ideas than about generating new knowledge by re-combining resources, SIE between *and* within groups would produce the overlapping, cohesive group structures that may generate novel combinations. These arguments suggest a final experimental question about the interaction of between and within group SIE:

Experimental Question 3: Does the interaction of SIE between and within the producer and audience segments increase survival and total resources during the proto-industry phase?

Simulating proto-industries

Davis, et al. (2007: 486) characterize the stochastic process simulation approach in terms of three assumptions that match the proto-industry model. The first is that theoretical development requires understanding multiple system processes simultaneously. The proto-industry model focuses on the processes that generate the first producers and audiences, govern how audiences search among producers for matches with their preferred identities, and determine the resources of producers. The second is that these process elements can be modeled as sources of stochastic variation. For example, we generate the identities for the first producers and audiences consistent with examples in Figure 1. By assuming we can represent the four core features of identity with the values 0 or 1, for example, familiar and not familiar, we create an event space with sixteen unique identities. The third assumption of the stochastic processes calls for specific probability distributions for each stochastic source: continuing the same example, we operationalize minimal consensus as independent, random draws from this event space. Thus, identity matches between a single producer and a single audience are binomial with the probability of success at 1/16 = 0.0625. Reviewing recent simulation research, Chanda and Miller (2019) recommend a first step in verifying a simulation model: give the reader information necessary to recreate the model without any necessary reference to the original program code. To this end, our discussion of the model and the simulation algorithms in the following paragraphs follows the flow chart in Figure 2. Readers interested in the second step of the verification process discussed by Chanda and Miller (2019), comparing any recreation with the original model, can obtain the Visual Basic code for this study from the authors.

Insert Figure 2 about here.

We initialize the proto-industry simulation by setting the parameters as described in Table 1, which provides an *exhaustive* description of *all parameter distributions*. Wherever theoretically sensible, we used uniform distributions to maximize the variance of parameter values. We begin by generating producers and audiences with random identities according to initial counts of producers and audiences, which are separate draws from the integers uniform on [1,10]. The PC industry, with only 3 producers, falls below the mean of this distribution, which is 5.5 for both producers and audiences. In each run of the simulation, we generated uniform distributions to determine resources of audiences and producers separately but using the same process. We began with two draws from the integers uniform on [1, 20]: the larger value provided the upper bound, and the lesser value the lower bound of a uniform distribution. All producers and audiences during that run of the simulation obtain resources as a random draw from the integers distributed uniform across the range between the relevant upper and lower bound. As a cost of doing business, producers spend resources to survive at a rate determined by the parameter *producer spending rate*, which we define it as the *proportion* of resources on hand that a producer must consume to survive each period. We also used this parameter as the principal driver of liabilities of newness to achieve a survival of five percent. To do this, we varied values of this parameter, finding that setting the minimum value of this parameter at 0.9 produced a 95% mortality rate. Thus, the parameter *producer spending rate* was determined for each run of the simulation by a draw from the distribution uniform on [0.9, 1.0]. We treat it as a population parameter that is fixed for each run of the simulation, reflecting the assumption that there are no significant differences in costs among producers, for example, resulting from learning or network positions.. The parameter *audience transfer rate* determines the portion of resources an audience member transfers to each producer that matches its identity preferences. Since it must be greater than zero for transfers to occur, we set the lower bound on this parameter not at zero but at 0.05; in each run of the simulation the transfer rate is a draw from the distribution uniform on [0.05, 1]. The final set of parameters are those necessary to answer the experimental questions about SIE; these govern whether any specific producer or audience engages in SIE with others and are fixed for that run of the simulation. These values are set by three *independent* draws from distributions uniform on [0.01, 1] that determine the probabilities of within audience, within producer, and producer-audience SIE, respectively.

Insert Table 1 about here.

Once the parameters are set, populations proceed to step 2, which begins with any SIE that occurs during specific runs of the simulation and ends with search among producers by audiences to find any that match their preferred identities. We model all forms of SIE based on an algorithm for non-directed ties consistent with Erdös and Rényi (1960) graphs (Guimerà, Sales-Pardo, and Amaral, 2004). Whether a specific producer or audience, *ego*, engages in SIE with a relevant other, *alter*, is a draw from the distribution of the relevant parameter described in Table 1. These draws in the first period determine the patterns of SIE, which remain fixed for that run of the simulation. Only producers and audiences that have not exited are included in SIE in any period. Each actor who engages in SIE observes information about the value on each of the four dimensions of identity codes among alters, which are determined by the SIE condition. Based on this SIE, each actor calculates the absolute distance between its value on each dimension and those with whom it exchanged social information. The probability that an actor changes any component code of identity increases with the absolute difference between ego's code value and the average code value of alters with whom ego engages in SIE. For example, if within group SIE among producers occurred *only* with alters that have a *different* value for a specific component of the identity code, ego changes to that value with the probability of one. When all SIE and attendant changes to identity are finished, populations complete step 2 as audiences search among producers for those with identities that match their preferences. For each audience we create a random sequence among all producers, and the audience follows this sequence until all producers have been considered. If audiences find at least one match, they transfer resources to the matching producer at the *audience transfer rate*. They continue searching among producers to find those with matching identities, repeating the same sequence until they have no more resources to transfer. If an audience finds no matches, it transfers no resources, and its search during step 2 ends. If this occurs for five periods, the audience exits the proto-industry, does not return, and is not replaced. Then all proto-industries proceed to step 3 where producers must spend resources at the *producer spending rate*. In the next step, any producers with resources that fall below one unit are considered bankrupt and exit the simulation, without replacement. Any surviving producers and remaining audiences proceed along step 5A and the simulation repeats itself. If all producers are bankrupt, the simulation ends as indicated in step 5B. Otherwise, the simulation ran for 50 periods, which would represent about four years if we imagine these units as months. Proto-industries like these represent rare cases like the PC industry that cross the commercialization gap along step 5C, and we assume that the identities of the surviving producers become accepted as forms.

We ran the proto-industry simulation 10,000 times for each of eight different conditions: (1) no SIE: the basic proto-industry model, (2) within-group SIE only among audiences, (3) within-group SIE only among producers, (4) within-group SIE among both audiences and producers, (5) SIE between audiences and producers, (6) SIE between audiences and producers and within-group SIE only among audiences, (7) SIE between audiences and producers and within-group SIE only among producers, and (8) SIE between audiences and producers and within-group SIE among both audiences and producers. We use these 80000 observations for analyses to verify the theoretical model and answer the experimental questions. In doing so, we will treat the data on the number of surviving producers and total industry resources as measures of the success of the proto-industry; that is, we assume that larger numbers of survivors and more total resources hasten the consensus about identity that distinguishes proto-industry disappearance from emergence as a recognized new industry. Consistent with this, we analyze the count of the number of surviving producers, a dependent variable that violates the assumptions of ordinary least squares regression. As is standard, we began our consideration of estimators more suited to count data with Poisson regression and examined its fit with these data. The many cases where there were no surviving producers led us to test whether we needed to use a zero inflated technique, but the relevant test statistic suggested this was not necessary. However, the test statistic for the assumption of equal mean and variance necessary indicated that we should use the negative binomial regression, which we did to estimate all coefficients for the count of survivors (Hoffman, 2016). Because the second dependent variable, total industry resources, cannot go below zero, we use Tobit regression to account for this constraint (Enami and Mullahy, 2009). Additionally, this variable had a considerable right skew, so we used the natural logarithm transformation of these values (after adding one resource unit to avoid values of zero) as the dependent variable in the Tobit estimation,

The first set of independent measures in our analyses are those that measure stochastic processes in the theoretical model without SIE, which we regard as measures of environmental munificence. The initial audience count, mean initial resources of audiences, and the audience transfer rate are key measures of support for the proto-industry, and we expect higher values to increase both the number of survivors and total resources. Similarly, we expect larger values of both the initial producer count and the mean initial resources of producers to increase both the number of survivors and total industry resources. The producer spending rate is a negative measure of support: higher values decrease both the number of survivors and total industry resources. These results provide a baseline against which to compare our analysis of several variables to answer the experimental questions. Results for the first three SIE variables, the probabilities that governed SIE within audiences, within producers, and between producers and audiences, allow us to answer the first two experimental questions. To answer the third experimental question, we created two indicator variables to estimate interactions between within group SIE, audience and producer, and across group SIE. This mix of independent measures allows us to verify the model by demonstrating predicted theoretical effects and answer the experimental questions.

We report descriptive statistics and correlations in Table 2, which reveals that observed values are as expected given parameter distributions; for example, the mean initial numbers of producers and audiences are both about 5.5, and the mean resources of both are about 10.5. Mean producer spending rate is 0.95 while the mean audience transfer rate is 0.52. The three SIE probability variables are each centered at 0.5 in four of eight conditions, yielding means of 0.25 for all. The two interaction variables are true in two of eight conditions and interacted with variables with a mean of 0.5, yielding a mean of about 1/8, rounded to 0.13. The values of the two dependent variables at the bottom of the table are consistent with a commercialization gap. The average number of surviving producers per simulation trial was 0.34; compared with the average of 5.50 producers that were generated in each simulation, this represents a survival rate of just over 6%, elevated from our 5% base rate by conditions with SIE. The mean log of total industry resources was 0.37, which implies an average of about 1.7 resource units. Given that audiences bring 57.5 units on average (5.5 audiences each with 10.5 units), this average indicates that only 3% of the resources allocated to audiences at the beginning of the simulation are preserved at the. Correlations among the independent variables are quite low, which is not unusual with simulated data. To check the effect of these correlations among the components of the interaction variables, we estimated variance inflation factors, which suggested no multicollinearity issues.

Insert Table 2 about here.

We use regression analyses of these variables to estimate the coefficients that allow us to verify the proto-industry simulation and answer the experimental questions about SIE. To do this, we assume that the number of surviving producers and total industry resources from each run of the simulation are observations from an infinite population of simulation results (Levitt et al., 1994). We report estimated coefficients in Table 3 for all negative binomial regressions of the number of survivors and in Table 4 for all Tobit regressions of the log of total industry resources. In both tables, we begin with a model that includes only environmental munificence variables in the first column. As expected, initial audience count, the mean initial resources of audiences, the initial producer count, and mean initial resources of producers had positive, significant effects on the number of surviving producers, and the producer spending rate had a significant and substantial negative effect on the number of surviving producers. Contrary to our naïve expectation, the audience transfer rate decreased the number of surviving firms. The results of Tobit regression on total industry resources in Table 4 also show expected patterns of direction and significance of the environmental munificence variables, including audience transfer rate, which has a significant positive effect in this model. Across the two models, the negative effect of audience transfer rate on the count of surviving producers, which we review in the discussion, is the only anomalous result for the environmental munificence variables. We conclude that the proto-industry simulation produces *prima facie* sensible outcomes as severe resource constraints and minimal consensus produce a significant commercialization gap during the proto-industry phase. Having verified the basic theoretical model, we added variables to answer the experimental questions about SIE.

Insert Tables 3 and 4 about here.

Model 2 in Tables 3 and 4 introduces the variables that measure the probability of within group SIE with the definitive result that they *decrease* survival and growth. Proto-industries *without* SIE will have more survivors and higher average resources than those that have *only* within group SIE. In the third column of **Error! Reference source not found.**, we add the variable that measures the probability of audience-producer SIE to answer the second experimental question. Once again, we get a clear answer: SIE between audiences and producers significantly *increases* both the number of surviving producers and total industry resources. In the fourth column of Tables 3 and 4, we add the interaction variables that answer to the final experimental question with the finding that the interaction of within and across groups SIE *increases* survival and total resources. To summarize, we have several clear theoretical findings about SIE from these simulation experiments. Our first experimental question differentiated opposing logics in the context of the proto-industry: would within-group SIE (either among producers or audiences) increase or decrease survival and total industry resources? The answer is unambiguous, within-group SIE, either among audiences or among producers, decreases the number of surviving producers and total industry resources. Our findings about across-group SIE, that is between audiences and producers, are similarly unambiguous: it increases survival and total industry resources. The last of our experimental questions concerned the interaction of across- and within-group SIE among audiences and producers. The results again provide an unambiguous answer: the interaction of across- and within-group SIE increases both the number of surviving producers and total industry resources, which closes our discussion of answers to the theoretical questions.

The last columns of both tables report standardized coefficients (Long and Freese, 2003) for the theorized independent variables, expressed as the proportion of a one standard deviation increase in the simulated dependent variable we would expect given a one standard deviation increase in the theorized independent variables. Comparisons among these variables offers some interesting observations. First, despite its very limited range, the producer spending has very systematic effects on both dependent variables, with a more systematic effect on total resources. Second, not all environmental munificence is created equal. Although the variables determining the counts and resources of audiences and producers were generated independently from identical distributions, the effects of these variables for audiences are far more systematic. This follows directly from the organization theory logic (Hsu and Hannan, 2005: 476), which gives audiences "…control over material and symbolic resources that affect the success and failure … in the domain." Interestingly, the variables measuring the interaction of within audience and within producer SIE with across group SIE, also generated independently using the identical distributions, revealed an *opposite* pattern. The interaction of between and within SIE for producers was more systematic than the interaction of between and within SIE for audiences in both models. Once again, this effect is more pronounced for resources than for survivors. Of course, some of these differences, e.g., the more systematic effects of audience count and resources, result directly from theoretical assumptions; others emerged from the dynamics of the proto-industry model without any direct intention to ensure the model had these consequences. This reveals another value of simulation in this setting -- our precise description of the parameter distributions and clear models of the processes help to reveal and comprehend these differences. In that regard, our use of uniform distributions, which ensured that parameter values are as likely from the 'tails' as from the center, provides an important illustration. Although we made this choice of parameter values to ensure our results held across the range of theoretically sensible values, high variance in the parameter values likely helped to reveal subtle theoretical relationships obscured by the relative frequency of observations with no survivors and zero total resources. We also did three explicit robustness checks. First, we modeled SIE, which occurred randomly in the models reported above, as more likely between actors with similar identity codes. Second, instead of identity change at the level of a single identity code, we modeled change at the level of the identity, i.e., the four identity codes jointly. Third, instead of determining fixed patterns of SIE at the beginning of each run of the simulation, we varied patterns of SIE in each period. Despite some changes in significance levels, the results for all these robustness checks were generally similar to those discussed above, with identical answers to all experimental questions.

Five Propositions

A key purpose of this study was to develop theory with a simulation model to overcome the empirical difficulties of collecting data and the theoretical difficulties of modeling the dynamics of new activity domains. We began by asking if within-group SIE, that is only among audiences or only among producers, enhances or reduces survival and growth. We discussed some prior literature suggesting that within-group SIE might enhance survival and growth as well as other literature that suggested within-group SIE might decrease survival and growth. The simulated data provided an unambiguous answer: within-group SIE reduces both survival and total industry resources. To eliminate the possibility that this finding was an artifact of including conditions that allowed within-group SIE but not across-group SIE, we ran additional analyses focused only on the condition with all forms of SIE, within and between producers and audiences. Even here, the direct effects of *within-group* SIE, whether among audiences or producers, were negative, indicating the result is not an artifact of any single condition, and we conclude that this result must follow from the theoretical logic of the model. Specifically, within group SIE leads to convergence on an identity without reference to the preferences of the other group, reducing the chances of matches between the preferences of audiences and the identities of producers. The negative effects on survival and growth hold across all combinations of SIE, although it is more systematic for within group search among producers. It seems clear that SIE within groups reduces the number of survivors and total industry resources whether it is among producers or audiences -- our first proposition:

Proposition 1: Under conditions of minimal consensus, more SIE among audiences or producers *decreases* survival and total resources during the proto-industry phase.

In addition to examining the effects of SIE within groups, that is among audiences and among producers, we ran simulation experiments that introduced SIE between audiences and producers. Again, the implications of the theory are unambiguous: SIE between audiences and producers increases the likelihood of producer survival and total industry resources. The value of this SIE may be particularly important during the proto-industry phase, which is characterized by an absence of a prior history of interaction and fraught with difficulties of audience attention and understanding (Mezias, et al., 2010). Indeed, the 11% rate of successful exit reported by a recent survey of angel investors represents more than twice the rate of survival we incorporated in the proto-industry simulation (Huang, et al., 2017). Given evidence that investors can structure relations with producers to facilitate financial success (Dobbin and Dowd, 1997), there may be a variety of ways that financiers fill the void of minimal consensus. For example, angel investors may promote the belief that star engineering talent enhances the likelihood that a new business model can succeed. Our second proposition formalizes the claim that the survival and growth will be enhanced by SIE between audiences and producers:

Proposition 2: Under conditions of minimal consensus SIE between audiences and producers increases survival and total resources during the proto-industry phase.

The next set of simulation experiments allowed us to show that SIE among producers or audiences enhances survival and growth when there is also SIE between producers and audiences. It is worth noting that we did not build this relationship into the simulation by creating specific mechanisms; rather, this contingent relationship emerges as an implication of the theoretical logic. The juxtaposition of this finding with the negative effect of within group SIE suggests that the lessons producers learn from experience may convey mixed messages. Despite small numbers of producers and audiences in a typical proto-industry, selection may be a strong mechanism to reveal the positive effect of SIE across audience and producer groups. An organization theory perspective, emphasizing the survival and growth benefits of consensus about key features of identity, suggests that proto-industries that cross the commercialization gap will often have mechanisms that allow producers and audiences to share information and enact common beliefs. At the same time, it may be far more difficult to learn from experience that there is a positive interaction between within-group and across-group SIE. The direct negative effect may hinder discovery of the larger positive interaction, a point to which we return as we discuss the research and practical implications of our study. For now, we state the positive interaction as our third proposition:

> **Proposition 3: Under conditions of minimal consensus, the interaction of SIE between and within producers and audiences increases survival and total resources during the proto-industry phase.**

Two substantively interesting theoretical implications emerged from our study that were neither direct tests of our experimental questions nor by the design of our simulation; we summarize these as the two final propositions from our framework. First, our results show that the effects on survival and total industry resources of the SIE variables are comparable to the effects of the environmental munificence variables. To draw this conclusion, we compared the theorized effects of SIE and variables measuring environmental munificence using the standardized coefficients (Long and Freese, 2003) reported in the last columns of Tables 3 and 4. For both models, the three most systematic absolute effects, mean initial resources of audiences, producer spending rate, and initial audience count, are all munificence variables. However, also for both models, the SIE variables dominate the middle rankings to the point where the mean rank between the two sets of variables is not distinguishable. For the model of survival, the mean rank of the standardized coefficients for both environmental munificence and SIE variables is exactly six. For the model of total resources, the mean rank of the environmental munificence variables is 6.2 while that for SIE variables is 5.8. Across both models, it seems clear that the absolute effects of variables related to SIE and environment munificence are comparable. Of course, it is important to keep in mind that these are theoretical, not empirical, findings, but we are confident that these comparisons of the relative importance of SIE and environmental munificence is robust under a general set of conditions. Our results provide a theoretical rationale to expect that the effects of SIE, which increases consensus, will be systematic even compared to the substantial resource effects that contribute to the commercialization gap.

> **Proposition 4: Under conditions of minimal consensus, SIE among producers and audiences in proto-industries will have effects on survival and growth similar in importance to those of environmental munificence.**

The second unanticipated finding is related to the results for the parameter audience transfer rate. We had anticipated that as the proportion of resources transferred when an audience found a producer with an identity that matched its preference increased, so too would survival and total industry resources. However, the estimated models reveal that higher levels of the parameter audience transfer rate decrease the number of surviving producers but increase total industry resources. The greater the proportion of resources an audience transfers each time it encounters a matching producer has paradoxical theoretical implications: there are fewer surviving firms, but the total industry resources tend to be larger. The converse is also true; despite the larger average number of surviving firms, values of total industry resources tend to be lower with lower values of the parameter audience transfer rate. In **Error! Reference source not found.**, we vary the audience transfer rate across its theoretical range [0.05, 1] and graph this against the predicted number of surviving producers (the left Y axis) and predicted total industry resources (the right Y axis). The depicted estimates include all other variables at mean values multiplied by their coefficients in the full models in Tables 3 and 4. Although the lines of estimated points appear almost as straight linear relationships, all estimates are shallowly curvilinear from negative binomial or Tobit. As the crossing of the lines in the middle of the figure demonstrates, varying the magnitude of the audience transfer rate reveals a trade-off between the number of surviving producers and the total resources of the population. Audience members, such as policy makers or investors, who tend to make many small allocations of resources, will push the emerging industry in the direction of more competitors but with lower average competitive intensity (Barnett, 1997). As such an industry structure does not create a core of large producers that control most of the industry production, there also may be less resource partitioning (Carroll, 1985), which may be important to the continued generation of innovation as the new industry stabilizes (Mezias and Mezias, 2000).

Insert Figure 3 about here.

By contrast, audience members who tend to make fewer large investments, by transferring larger percentages of their available resources to single producers, will push the emerging industry in opposite directions. The new industry will be much more concentrated with fewer, larger competitors, i.e., an oligopolistic or even monopolistic industry structure. These conditions would be more likely to result in resource partitioning processes much earlier in the life of the new industry. In the long run it is difficult to say which should be preferred by policy makers or investors. For example, if gaining much-needed legitimacy is driven by a density dependent process (e.g., Carroll and Hannan, 1989), then small bets are to be preferred. By contrast, if legitimacy is driven by a mass dependent process (Barnett and Amburgy, 1990), then larger bets should be made. In theoretical terms, this is a clear illustration of a situation where the relative importance of density and mass dependent competition could be driven by the choices of audiences. Larger allocations are, at least implicitly, an attempt to grow legitimacy with mass, while smaller allocations would represent an attempt to grow legitimacy with density. Thus, we predict that the observed outcomes of selection during the proto-industry phase will depend on whether resource transfers from audiences to producers are relatively large or small, which is our fifth proposition.

> **Proposition 5: Under conditions of minimal consensus, smaller transfers of resources from audiences to producers increase the number of surviving producers but decrease total industry resources; larger transfers decrease the number of surviving producers but increase total industry resources.**

Taken together, these propositions set forth a complex selection environment. In particular, the first three highlight contingencies in the effects of SIE within and across groups on survival and growth during the proto-industry phase. To illustrate how difficult it may be to learn from experience, we depict in Figure 4 the theoretical relationships between the probability of producer-producer SIE across its range (horizontal axis) and the number of surviving producers (vertical axis). The lower and lighter line shows the direct effect: as the propensity of producers to engage in SIE moves from zero to one, the number of surviving producers *decreases* by about one. The gravity of this shift is most clearly seen by comparison the mean number of surviving producers, which was 0.34 in the full sample -- this direct negative effect is almost three times the average. The upper and darker line tracks the interaction of within producer SIE with SIE between producers and audiences, revealing a positive and considerably larger effect. This line tracks the predicted effect of the interaction between within and across group search as the probability of within group search among producers increases. Indeed, the predicted number of surviving producers increases by about 4.5 as the probability of SIE among producers goes from zero to one, which is considerably larger than the direct negative effect of SIE among producers. As within group SIE among producers becomes more likely *in the presence of SIE with audiences*, the number of surviving firms may increase by as much as a factor of ten, from 0.38 to 4.5. The speed of response to the direct and indirect effects of within group search among producers may be crucial. Any reduction in SIE among producers in response to the direct negative effect on survival must also reduce the larger positive survival effect of the interaction between SIE among producers and across group SIE with audiences.

Insert Figure 4 about here.

Conclusions and implications

The commercialization gap can be understood in terms of the distinct resource needs and social dynamics of the incubation and proto-industry phases. Experience, capabilities, and selection processes must adapt to dynamic resource constraints and system dependent selection (Lomi, Larsen, and Freeman, 2005) on the hazardous journey from similarity cluster to recognized new industry. The earlier incubation phase produces high levels of shared beliefs and agreement (Fiol and Romanelli, 2012) among potential producers as they consider the prospects for engaging potential stakeholders and adopters (Agarwal, et al., 2017). Situated in collectives like the Homebrew Computer Club, the enthusiasts of similarity clusters provide supportive communities of inventive practice to spawn innovative commercial identities, but only limited information about audiences. The pivot to survive the vicissitudes of the proto-industry phase (Grimes, 2018), as producers test prototypes against the harsh realities of finding customers in the market, is a difficult one. The more quickly a producer can make connections with audiences and ensure their continued support, the more likely they are to survive. The events that lead to an independent developer to launch VisiCalc only for the Apple II provides a great example (Isaacson 2011: 84). Members of the Homebrew Computer Club would have been inclined to consult one another for solutions to grow the market for PC. Independent developers unconnected with their similarity cluster were largely invisible, and the idea that one would launch an application of tantamount importance to the success of Apple and the PC proto-industry itself, was likely unimaginable. More generally, the commercialization gap is not the only selection discontinuity evolving industries must navigate. We predict that those few cases where a new activity domain proceeds beyond the proto-industry phase will require another pivot. Having survived a selection process where the direct effect of SIE with other producers is negative, producers may be disinclined to communicate and collaborate. Failure to pivot to more SIE among producers could delay collective efforts among producers to create industry associations and institutional infrastructure,

These findings have important practical implications for policy makers and entrepreneurs during the very early stages of industry emergence. A first implication results directly from a key theoretical finding: the contingent value of SIE set forth by the first three propositions. The organization theory logic dictates the mechanisms, which can inform the understanding of policy makers and practitioners. In a similarity cluster, communication among potential founders creates shared beliefs and understanding that are essential to the launch of first products or services. Simultaneously, this launch puts producers at high risk for mortality, what we have called the commercialization gap. At this point, the most important help to give any fledgling producer is to encourage communication with audiences, perhaps in a setting like networked incubators (Hansen, at al., 2000), but interventions that help them build their connections to key audiences are challenging (Clingingsmith and Shane, 2018). Interactions between start-up teams and audiences during competitions, for example, a shark tank, hardly seem adequate to promote consensus about appropriate identities. Producers and audiences linked by investments may find opportunities to enact consensus about identities, but it is not clear that funding competitions are the best way to determine which producers receive support from investors. At a minimum, some evidence that the most effective producers win these competitions or that these interventions yield higher levels of survival and growth at the population level would be useful. None of this is to suggest that effective interventions to enhance SIE between producers and audiences are easy, and our findings, e.g., the paradox of big bets, suggest the existence of trade-offs that may be difficult to track from experience. Yet the groundswell of energy to entrepreneurship has intensified experimentation and research and perhaps some learning in complex landscapes. For example, the traditional incubator experience, focused on SIE within the space and largely confining those who are not in the cohort to limited, structured interactions, is shifting. Policy makers, e.g., the ICORPS initiative,[6] practitioners, e.g., the ESHIP summit,[7] and researchers (e.g., Thompson, Purdy, and Ventresca, 2018) have come to recognize how larger ecosystems shape new forms and nascent activity domains (Adner, 2010). Second and related, the value of these new approaches will likely arise from developing more effective approaches to structuring within and across group SIE among key stakeholders. It is not immediately clear how to encourage SIE that links producers and audiences while maintaining SIE among producers to share what they have learned from audiences. The problem is not made easier when emerging producers face severe resource and time constraints or view themselves as competitors. Burt (2000: 410) summarized the dilemmas that can result when he noted that although "… brokerage across structural holes is the source of added value, closure can be critical to realizing the value buried in the holes."

When identities approved by audiences diffuse more rapidly among producers through SIE, more resources flow to the proto-industry, reducing mortality and increasing growth. While this is consistent with agglomeration arguments (Schoonhoven and Romanelli, 2001; Stuart and Sorenson, 2003; Saxenian, 2001), our result does not depend on geographical proximity, but only on SIE proximity (Robins and Pattison, 2005). Clearly, social capital interventions to enhance SIE between audiences and producers are crucial (Inkpen and Tsang, 2005). Dyadic relationships between audiences and producers have direct positive effects and enhance the value of within-group SIE among audiences and producers. Social mobilization in similarity clusters that generates shared information and beliefs are essential to the emergence of new activities and industries (Fiol and Romanelli, 2012), and producers emerging from these clusters may be much more oriented toward communication with other producers. Yet, our results show that during the proto-industry phase, SIE with audiences, many of which may not have been part of the similarity cluster, increase survival and growth. For those few proto-industries that cross the commercialization gap, selection may favor less within group communication. At the same time, the

[6] https://www.nsf.gov/news/special_reports/i-corps/
[7] https://www.kauffman.org/eship-summit/

consolidation that follows may reward collaborative efforts to promote the new industry, e.g., standards that enhance perceived quality. In light of repeated needs for pivots, policy sensitive to the need for SIE within and across groups to operate in the context of complex selection may prove valuable. For example, as regional governments become aware of emerging industries, which is more likely after the proto-industry phase, they can sponsor efforts to enhance collaboration among producers.

The second implication for policy makers and entrepreneurs directly results from our finding that the theoretical effects of environmental munificence and SIE on survival and growth are of similar magnitudes. Of course, we know from a long line of research that new firms face severe resource constraints, and direct policy subsidies often increase survival. At the same time, our results suggest that the value of enhancing SIE can produce survival benefits of similar magnitude to enhancing material support. This suggests policy makers and entrepreneurs might consider mitigating resource constraints by developing channels for functional SIE. The third implication directly results from the final proposition, which we call the paradox of big bets. Policy makers and investors can affect industry structure with actions to vary the magnitude of resource transfers to producers. Audiences that make more frequent, smaller resource transfers to producers are more likely to observe proto-industries with more but smaller producers. By contrast, audiences that make larger, less frequent resource transfers may observe industry structures with fewer larger producers. Coupling these possibilities with the notion of dynamic resource constraints (Lomi, Larsen, and Freeman, 2005) reinforces the complexity of processes that produce different structures in nascent industries.

One clear implication of this work for future research involves empirical verification of these propositions in the field. Of particular importance is finding data to distinguish between various mechanisms implied by our model of proto-industries under conditions of minimal consensus. The model implies simultaneous operation of all the propositions, which will be important to verify. In addition, finding support for the less 'obvious' propositions will be of particular interest. In this regard, verifying that the direct effect of SIE within-groups will be negative, that SIE produces effects that are large relative to resource effects even under severe selection pressures, and support for the paradox of big bets emerge as important findings to verify. Procuring appropriate samples and developing measures of the theoretical mechanisms that drive survival and growth in the model will be additional challenges. A second implication for research involves relaxing the assumptions of minimal consensus, and we have provided an example with our experiments involving SIE. The strength of simulation is that it eases the creation of experiments to answer theoretical questions, which was a key rationale for this study. To illustrate a variety of possibilities of interest to the literatures of strategy and organization theory, we will briefly review examples of how one might vary theoretical assumptions about proto-industries.

In the simulations reported here, there was no replacement for bankrupt firms based on a lack of awareness. Future research could allow replacement, perhaps based on the identities of largest firms (Mezias and Schloderer, 2016) or other characteristics, particularly within emerging clusters around key audiences (Cattani, et al., 2008). Because producers in proto-industries generally do not have the resources to perform Schumpeterian tasks and build market institutions, institutional entrepreneurs (Garud, Hardy, and Maguire, 2007) played no role in our model of the proto-industry. Extending the model to include active institutional entrepreneurs who promote specific forms (Tracey, Phillips, and Jarvis, 2011) or other mechanisms to overcome the lack of social infrastructure (Struben, Lee, and Bingham, 2020) during the proto-industry phase would represent a worthy experiment. Similarly, extending the model to investigate a more active role for state actors might help us understand top down attempts at creating new industries. For example, Navis and Glynn (2010: 441) observed that "…satellite radio was defined at its inception as a clearly bounded market category … due to a regulatory act." The model can accommodate a variety of mechanisms to test theoretical questions related to regulatory attention and the dynamics of proto-industries (Mezias and Schloderer, 2016; Yue, Qang, and Rao, 2020). Alternatives to the assumption that experience does not affect proto-industry outcomes might include theoretical experiments to understand presumed potential differences in producers based on their histories. For example, we might model dynamics between *de alio* and *de novo* producers (Kirchberger, 2019) or answer related theoretical questions. For example, what are the effects on survival and total industry resources when *de alio* producers get reliable resources from the mother company but are less likely to adopt identity changes not sanctioned from above? Future experiments could also relax the assumption that prior networks ties have no systematic value in the new activity domain, perhaps to allow theoretical questions related to prior investment, e.g., seed capital during the incubation period (Agarwal, et al., 2017). For example, what are the effects if audiences who supply seed capital in the incubation phase push producers to pursue business models that maximize chances for a profitable exit (Huang, et al., 2017)? Models of this process could be explored using the proto-industry simulation, perhaps linking prior capital allocations with population events like mergers and acquisitions (Dobbin and Dowd, 2000).

We suggest a final set of research implications based on the finding that producers engaging in SIE with audience members are favored by selection during the proto-industry phase. We have every expectation that this is a robust result, not least because we observed it for SIE generated using a simple algorithm for random bi-directional ties (Erdös and Rényi, 1960; Guimerà, et al., 2004). We endorse future research to explore the paths from this starting mechanism (Ziegler, 2008) during the proto-industry phases to considerably more complex networks that develop during the consolidation and later phases. Modeling the effects of this structuration on competitive dynamics during the industry life cycle (Agarwal et al., 2017: 288) could deepen our understanding of higher-order network properties frequently observed in more mature industries. In addition to comparing the statics of different network structures (Albert, Jeong, and Barabási, 1999; Watts and Strogatz, 1998), future research might also investigate dynamic mechanisms suggested by prior research. For example, experiments might model the interplay of social capital and structural holes in network evolution (Walker, Kogut, and Shan, 1997), vary patterns of SIE depending on how soon it occurs after founding (Hallen, 2008), vary the propensity to repeat connections (Amburgey and Miner, 1992), vary the propensity to cycle (Davis, 2016), or form SIE ties by accumulative advantage, follow-the-trend, or multi-connectivity (Powell, et al., 2005). Such research could help to reveal the mechanisms by which complex network structures emerge from unordered SIE among small numbers in proto-industries. Taken together these implications for research, along with the policy and practical implications, demonstrate the value of clear propositions as a starting point to understand complex realities. We close by highlighting our flowcharts as good null models (Schwab and Starbuck, 2012) to understand new industries: witness the propositions we develop by experimenting with them. Ultimately, the value of these propositions will be revealed by the role they play in subsequent work that advances understanding and tackles the empirical difficulties of studying new industries.

Figures and Tables

Figure 1: Representation of Identities in Proto-Industries

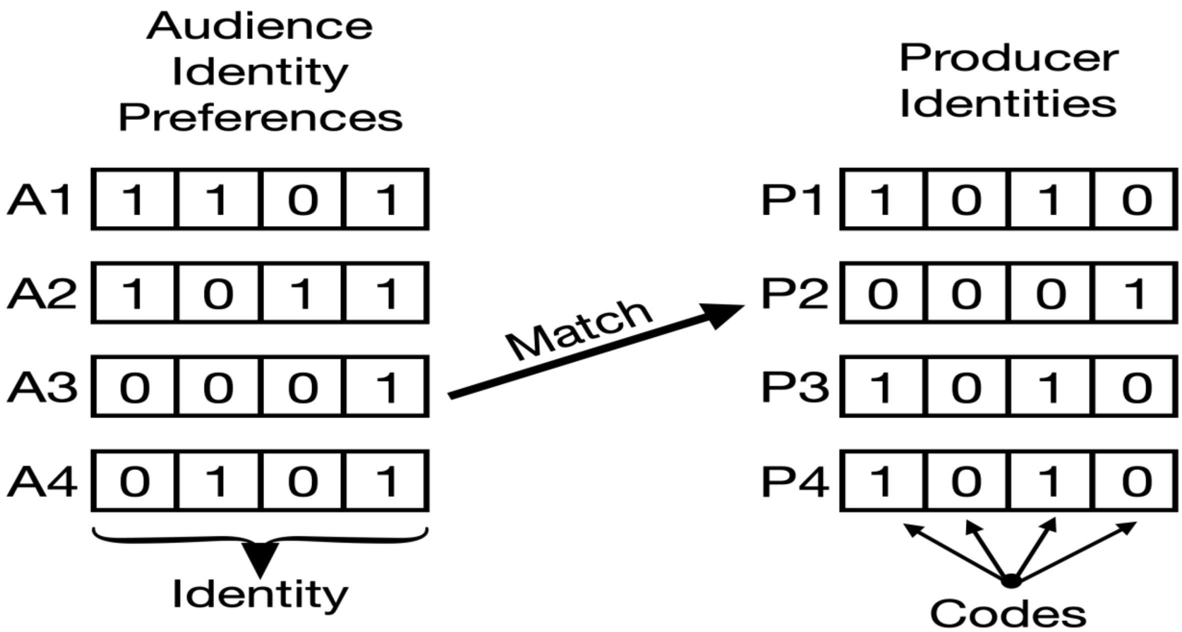

Figure 2: Theoretical Model of the Proto-Industry

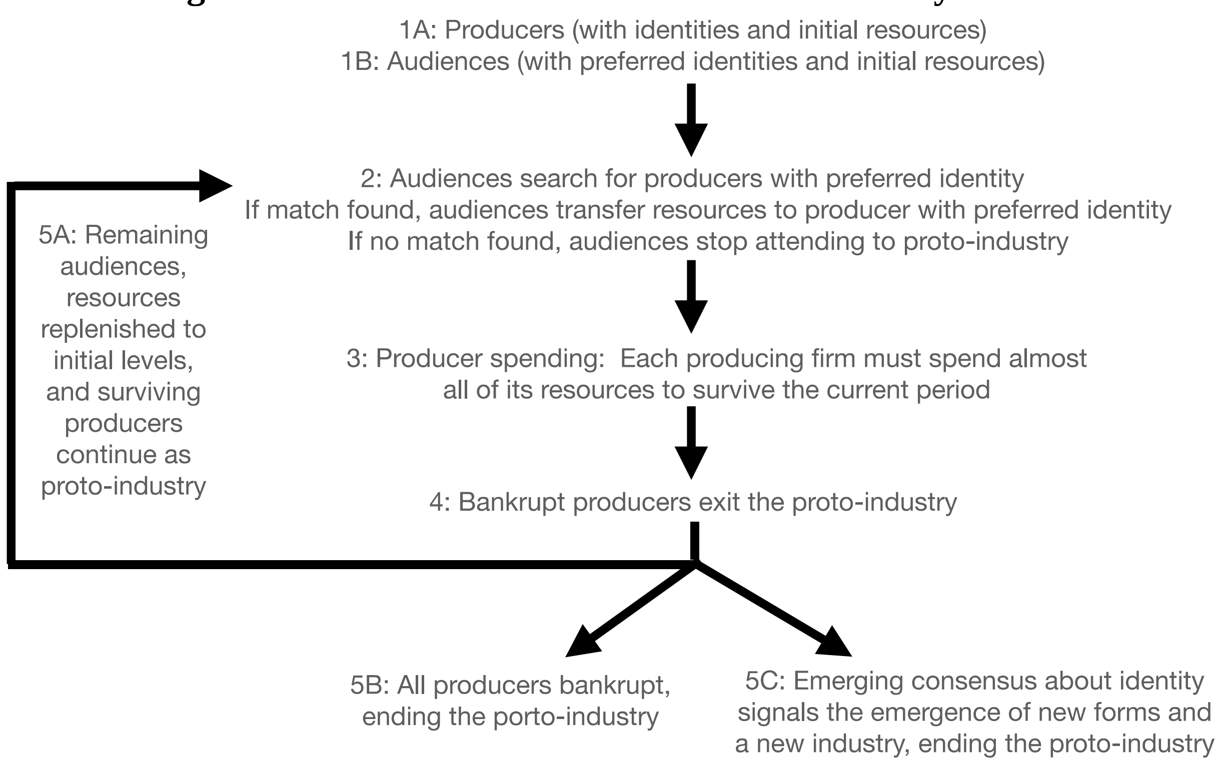

Figure 3: The paradox of big bets

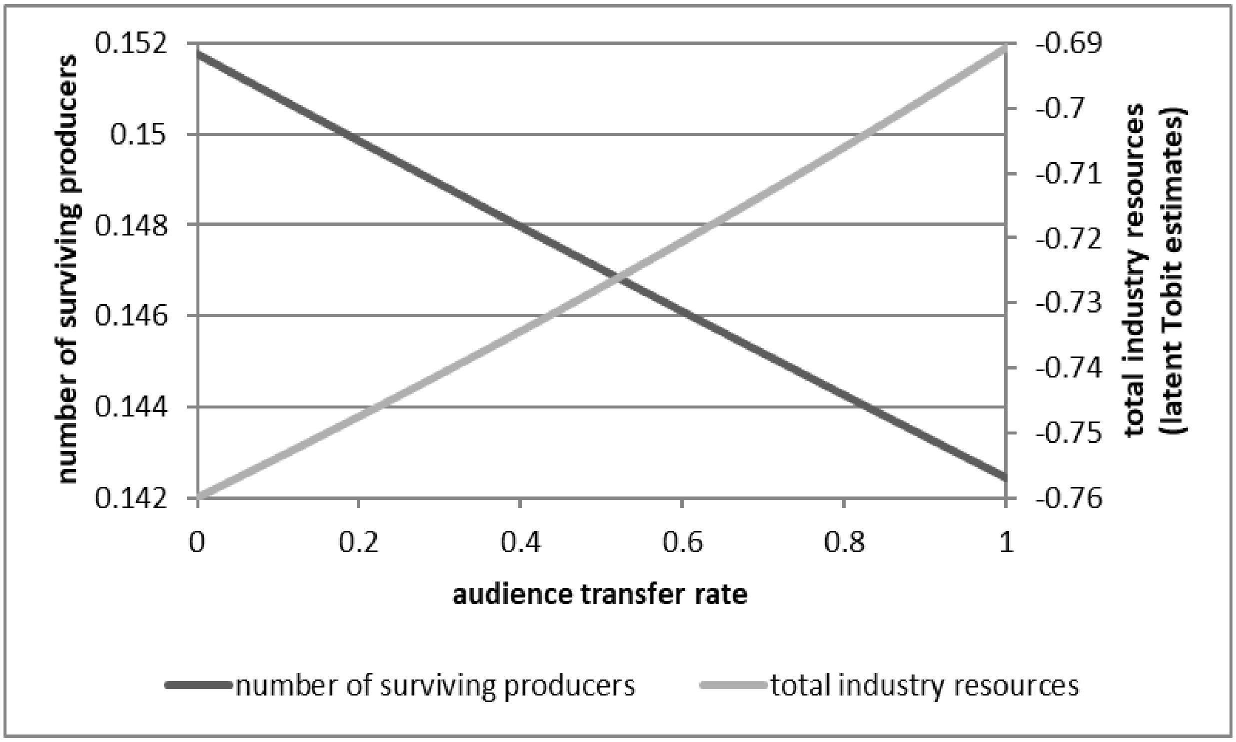

Figure 4: Within-producer SIE, effect on number of survivors

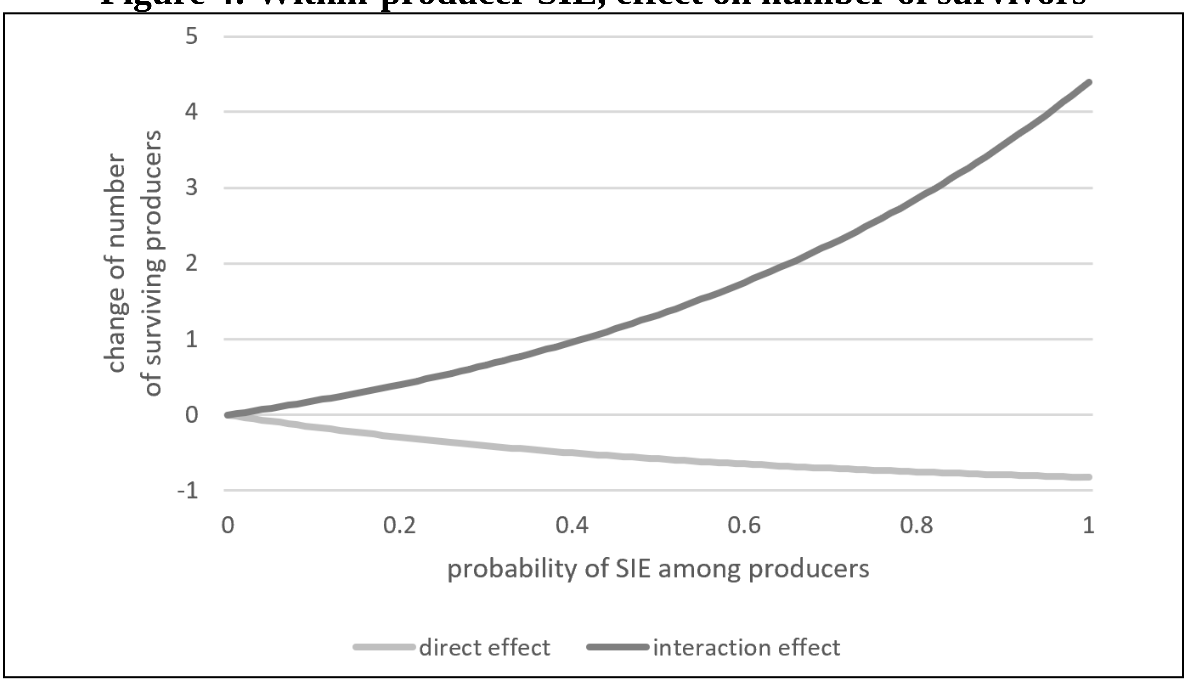

Table 1: Setting Simulation Parameters

1. Setting parameters. Verification variables in italics.	• *Initial audience count*: integer uniform on [1, 10]: random draws determine identity preferences • *Mean initial resources of audiences*: (*LARB* + *UARB)* / 2 • Lower and upper audience resource boundaries (*LARB*, *UARB*): integers uniform on [1, 20] • *Initial producer count*: integer uniform on [1, 10]: random draws determine identity preferences • *Mean initial resources of producers*: (*LPRB* + *UPRB)* / 2 • Lower and upper initial producer resource boundaries (*LPRB*, *UPRB*): integers uniform on [1, 20] • *Producer spending rate*: uniform on [.9, 1]. • *Audience transfer rate*: uniform on [.05, 1].
2. SIE Within & between groups	• Probability of SIE: discretely uniform on [.01, 1] increment .01, as required by experimental condition, zero otherwise • Each unique pair engaging in SIE gets a separate draw, requiring three parameters • *Probability of audience-audience SIE, Probability of producer-producer SIE, Probability of audience-producer SIE*

Table 2: Descriptive statistics and correlations for all simulation conditions

	Mean	Std.Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1 Initial audience count	5.50	2.87	1.00	10.00												
2 Mean initial resources of audiences	10.51	4.06	1.00	20.00	.00											
3 Audience transfer rate	.52	.27	.05	1.00	.00	.01										
4 Initial producer count	5.49	2.87	1.00	10.00	.00	.00	.00									
5 Mean initial resources of producers	10.49	4.08	1.00	20.00	.00	.00	.00	.00								
6 Producer spending rate	.95	.03	.90	1.00	-.01	.00	.00	.00	.00							
7 Probability of audience-audience SIE	.25	.32	.00	1.00	.00	-.01	.00	.00	.00	.01						
8 Probability of producer-producer SIE	.25	.32	.00	1.00	.00	.00	.00	.00	.00	.00	.00					
9 Probability of audience-producer SIE	.25	.32	.00	1.00	-.01	.01	.00	.00	.00	.00	.00	-.01				
10 Interaction within audience and between SIE	.13	.26	.00	1.00	.00	.00	.00	.00	.00	.01	.62	-.01	.37			
11 Interaction within producer and between SIE	.13	.26	.00	1.00	.00	.00	.00	.00	.00	.01	.00	.62	.37	.23		
12 Number of surviving producers	.34	.70	.00	9.00	.21	.25	-.01	.07	.01	-.39	-.09	-.07	.23	.04	.09	
13 Total industry resources*	.37	.70	.00	3.12	.25	.26	.03	.04	.01	-.41	-.04	-.06	.30	.10	.11	.90

n = 80,000   ** transformed by ln(x + 1)*

Table 3: Analysis of number of surviving producers

Number of surviving producers*	Model 1	Model 2	Model 3	Model 4	Std.Coef.**
Initial audience count	.159 •••	.157 •••	.157 •••	.157 •••	.570
	(.000)	(.000)	(.000)	(.000)	
Mean initial resources of audiences	.129 •••	.127 •••	.127 •••	.127 •••	.672
	(.000)	(.000)	(.000)	(.000)	
Audience transfer rate	-.056 •	-.058 ••	-.062 ••	-.063 ••	-.017
	(.012)	(.008)	(.004)	(.002)	
Initial producer count	.052 •••	.052 •••	.053 •••	.053 •••	.164
	(.000)	(.000)	(.000)	(.000)	
Mean initial resources of producers	.008 •••	.008 •••	.008 •••	.008 •••	.034
	(.000)	(.000)	(.000)	(.000)	
Producer spending rate	-32.181 •••	-31.833 •••	-31.855 •••	-31.847 •••	-.601
	(.000)	(.000)	(.000)	(.000)	
Probability of audience-audience SIE		-.616 •••	-.609 •••	-1.208 •••	-.324
		(.000)	(.000)	(.000)	
Probability of producer-producer SIE		-.457 •••	-.455 •••	-1.745 •••	-.433
		(.000)	(.000)	(.000)	
Probability of audience-producer SIE			1.260 •••	.832 •••	.310
			(.000)	(.000)	
Interaction within audience and between SIE				.814 •••	.237
				(.000)	
Interaction within producer and between SIE				1.686 •••	.553
				(.000)	
Constant	26.292 •••	26.243 •••	25.850 •••	26.021 •••	

• $p < .05$; •• $p < .01$; ••• $p < .001$; n = 80,000

** Model 1: negative binomial regression (because of overdispersion) with robust SE and BHHH algorithm; models 2-4: Poisson regression with robust SE*

*** x-standardization of exp-transformed coefficient (= change in expected count for SD increase in X)*

Table 4: Analysis of total industry resources

Total industry resources*	Model 1	Model 2	Model 3	Model 4	Std.Coef.**
Initial audience count	.216 •••	.214 •••	.207 •••	.207 •••	.287
	(.000)	(.000)	(.000)	(.000)	
Mean initial resources of audiences	.172 •••	.171 •••	.164 •••	.164 •••	.322
	(.000)	(.000)	(.000)	(.000)	
Audience transfer rate	.274 •••	.275 •••	.253 •••	.254 •••	.034
	(.000)	(.000)	(.000)	(.000)	
Initial producer count	.030 •••	.030 •••	.038 •••	.038 •••	.053
	(.000)	(.000)	(.000)	(.000)	
Mean initial resources of producers	.008 •••	.008 •••	.007 •••	.007 •••	.014
	(.000)	(.000)	(.000)	(.000)	
Producer spending rate	-40.870 •••	-40.733 •••	-39.217 •••	-39.087 •••	-.546
	(.000)	(.000)	(.000)	(.000)	
Probability of audience-audience SIE		-.386 •••	-.323 •••	-.499 •••	-.078
		(.000)	(.000)	(.000)	
Probability of producer-producer SIE		-.499 •••	-.505 •••	-1.522 •••	-.239
		(.000)	(.000)	(.000)	
Probability of audience-producer SIE			1.966 •••	1.531 •••	.240
			(.000)	(.000)	
Interaction within audience and between SIE				.292 •••	.037
				(.000)	
Interaction within producer and between SIE				1.527 •••	.193
				(.000)	
Constant	34.066 •••	34.178 •••	32.410 •••	32.460 •••	
	(.000)	(.000)	(.000)	(.000)	

• $p < .05$; •• $p < .01$; ••• $p < .001$; n=80,000

** Tobit regression model with robust standard errors; transformed by ln(x + 1)*

*** fully standardized coefficient (= SD change in Y for SD increase in X)*

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