When to Form an Alliance? Emergent Entrepreneurs in the Internet Video Industry

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Abstract
One way to overcome the liability of newness for start-ups is by forming an alliance. An alliance provides access to the partner’s resources, but we argue that it also could inhibit development of a start-up’s own resources. Hence the start-up faces a trade-off: it can seek help, but doing so may limit its potential. We study this trade-off using data on entrepreneurs on YouTube and the alliances they form with multi-channel networks. These entrepreneurs often begin with limited experience because of the low entry cost. We argue that inexperienced start-ups benefit less (than do more experienced start-ups) from forming alliances. In line with this expectation, we find that inexperienced start-ups incur performance penalties—on the order of 10%–40%—when forming an alliance compared to not forming an alliance. Hence, entrepreneurs need to carefully consider the timing of an alliance.
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11 November 2016

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Key words: alliance, entrepreneurship, emergent entrepreneur, timing, YouTube
1. Introduction

On 1 November 2005, Ian Hecox and Anthony Padilla uploaded their first video on YouTube with the title “Pokemon Theme Music Video.” In 2011 they formed an alliance with Alloy Digital, a so-called multi-channel network (MCN), for aid in the post-production and monetization of their video content. Over the next few years, Ian and Anthony’s YouTube channel—called Smosh—became one of the most widely subscribed on the Internet. By October 2016, they had more than 22 million subscribers with 5.9 billion video views (Smosh 2016).

Unlike Ian and Anthony, most YouTube entrepreneurs have no success at all. It is estimated that more than a million people on YouTube are trying to exploit their videos financially, but 99% of them will never make a single cent (Dickey 2014, Kaufman 2014). This high failure rate for entrepreneurs is common across industries (Decker et al. 2014) and is known as the liability of newness or of smallness (Stinchcombe 1965, Freeman et al. 1983). Entrepreneurs often seek to overcome these liabilities by allying with more established partners (Eisenhardt and Schoonhoven 1996, Baum et al. 2000). For example, YouTube entrepreneurs can turn to MCNs for assistance with product development, programming, funding, promotion, partner management, digital rights management, and monetization. An alliance enables the entrepreneur to access the partner’s resources (e.g., Khaire 2010, Vissa 2011, Nakos et al. 2014, Yang et al. 2014); however, we argue that an alliance may also hamper development of the start-up’s own resources.

Thus an entrepreneur faces a fundamental trade-off: she can seek help, but that help may end up limiting the start-up’s potential. We refer to this weakening of a start-up’s resource accumulation process as the crowding-out effect. We theorize that the strength of this effect depends on the start-up’s stage of development. In particular, we expect crowding out to be worse—that is, more pronounced—for less experienced start-ups. It follows that a start-up must decide not only whether to partner but also when to partner.

We study this trade-off using data on entrepreneurs launching new channels on YouTube and the alliances they form with MCNs. Our empirical analysis examines YouTube channels that were
launched between 2011 and 2014. We observe the decision to ally (or not) with MCNs—and, if so, at what stage of the start-up’s development—and track, on a monthly basis, channels’ performance (as measured by numbers of views and subscribers). Across a range of specifications, we find broad support for our hypotheses: inexperienced start-ups benefit less from forming alliances than do more experienced start-ups. Our data indicate that inexperienced start-ups incur performance penalties ranging from 10% to 40% when forming an alliance (as compared with not forming one).

This paper makes two main contributions. The first of which is empirical. Examining the new phenomenon of start-ups on the YouTube platform, we seek insights into emergent entrepreneurship. A planned entrepreneur is one who transitions deliberately into entrepreneurship by trading off costs and benefits (Gentry and Hubbard 2000, Hurst and Lusardi 2004); an emergent entrepreneur is one who stumbles into entrepreneurship—that is, without having a particular plan or explicitly considering cost–benefit trade-offs. The latter category has become increasingly prevalent with the dramatic reduction in entrepreneurial entry costs due to Internet platforms, which has reduced the role of planning. For example, setting up a channel on YouTube and signing up for monetization take only minutes and cost nothing. Hence it should come as no surprise that many of these entrepreneurs are ill prepared, a tendency that provides fertile ground in which study our key trade-off: the benefits and costs of seeking help.

The paper’s second (and perhaps more important) contribution is theoretical. First, an established stream of research has investigated how an alliance may help a start-up (Eisenhardt and Schoonhoven 1996, Mowery et al. 1996, Stuart et al. 1999, Baum et al. 2000); yet that body of work has not investigated what we call the crowding-out effect. Second, a more recent stream of research focuses on the potential downsides of alliances, in particular how a startup may reveal its resources to a partner through information leakage (Dushnitsky and Shaver 2009, Diestre and Rajagopalan 2012, Hernandez et al. 2015, Pahnke et al. 2015). In our case, the downside is not that a partner may appropriate value through learning about resources of a start-up but rather that the latter’s resource development could be hindered. Third, another stream of the literature
investigates the timing of alliances; that research focuses mainly on timing as a defense mechanism, whereby start-ups delay forming alliances until a resource is sufficiently protected from being copied (Katila and Mang 2003, Katila et al. 2008, Hallen et al. 2014). In our paper, timing is related not to the resource’s revelation but instead to its development.

Thus we highlight a key paradox of entrepreneurship. Most entrepreneurs have limited resources and thus require help to counter the liability of newness. Yet by accepting help, the entrepreneur may inhibit development of the start-up’s own resources. Our proposed solution to this paradox involves the timing of alliance formation.

2. Theory
2.1. Background

A lack of resources is one of the main reasons for the high failure rate of entrepreneurship (Baum and Oliver 1991), which has been referred to as the liability of newness or of smallness (Stinchcombe 1965, Freeman et al. 1983). An approach commonly taken to overcome these liabilities consists of allying with a stronger or more established partner (Eisenhardt and Schoonhoven 1996, Baum et al. 2000, Das and Teng 2000).

The potential benefits of that approach are threefold. First, the partner’s resources become available. Thus a start-up can rely on the partner’s resources (Baum et al. 2000, Lee et al. 2001, Nakos et al. 2014), which alleviates the need to develop one’s own (Eisenhardt and Schoonhoven 1996). Second, perceptions of the start-up’s resources are enhanced. A partner can provide legitimacy and status to the start-up and can signal its quality (Baum and Oliver 1991, Stuart et al. 1999, Gulati and Higgins 2003, Khaire 2010, Yang et al. 2014). Third, the start-up’s resources themselves may be enhanced. A startup can learn from the partner and copy its organizational routines, thereby strengthening its own set of resources (Mowery et al. 1996, Flatten et al. 2011).

1 Helfat et al. (2007, p. 4) define resource base as the “tangible, intangible, and human assets (or resources) as well as capabilities which the organization owns, controls, or has access to on a preferential basis”. Our theory applies to resources and also to capabilities, but we refer to both as “resources” to simplify the presentation.
However, this learning effect depends on the start-up’s absorptive capacity, or its “ability to recognize the value of new, external information, assimilate it, and apply it” (Cohen and Levinthal 1990, p. 128). Absorptive capacity is in turn a function of a start-up’s prior related knowledge (Cohen and Levinthal 1990), so that only those start-ups having sufficient “knowledge overlap” with their partners are able to learn through alliances (Mowery et al. 1996, Lane and Lubatkin 1998). In their meta-analysis of 18 samples, Van Wijk et al. (2008) find that absorptive capacity is indeed a significant driver of interorganizational knowledge transfer. Thus a start-up must already have some resources in order to learn from a partner, which implies that such learning will be difficult—if not impossible—for the least experienced start-ups (Almeida et al. 2003).

2.2. Crowding-out Effect

We argue that an alliance can also have a crowding-out effect—that is, a weakening of the start-up’s resource accumulation process. Dierickx and Cool (1989) conceptualize the stock of a resource as an accumulation of flows over a period of time. These authors offer a bathtub metaphor in which the water level amounts to the stock of water, where that stock is the cumulative result of inflows (e.g., running the tap) and outflows (e.g., draining the tub, leakage). Flows can be adjusted instantaneously, but that is seldom true of stocks. Take, for instance, an entrepreneur seeking to build strong technological know-how by continued investment in research and development. Although she can immediately change R&D spending (a flow), the effect of that change on the start-up’s technological know-how (a stock) will be delayed.

An important source of inflows in resource accumulation is “learning by doing” (Nelson and Winter 1982, Argote 2013). The beneficial effect of such experience on resources has been observed across a wide range of industries; these include banking (Zollo and Singh 2004), manufacturing (Balasubramanian and Lieberman 2010), petrochemicals (Henderson and Cool 2003), software services (Ethiraj et al. 2005), and steel (Figueiredo 2003). It is therefore possible for a start-up to develop resources through its own cumulative experience. An alliance reduces such learning by doing because the alliance partner takes over some activities for which the entrepreneur would otherwise be responsible. Hence the entrepreneur ends up doing less and so learns less.
Figure 1 is a stylized representation of the activities in a simplified value chain for a YouTube start-up (YouTube 2016). Idea generation comprises the planning of the shoot, including decisions about the content and location. Filming is the actual shooting of the material. Post-production includes editing of the video and incorporating additional sound. Promotion occurs primarily through cross-advertising on other channels. Finally, monetization mainly involves ensuring that advertisements are appropriately placed within the video and reach the target audience. The alliance partner is a MCN that offers YouTube start-ups help in various aspects of the process.

Most MCNs focus primarily on the later stages of the value chain: post-production, promotion, and/or monetization. Not surprisingly, those are the stages that new start-ups have the least experience. So a start-up can rely on an MCN for (say) video editing, but with the consequence that it will be slower to develop those necessary skills. Thus an alliance may lead to more learning by other-doing (the learning effect) even as it leads to less learning by self-doing (the crowding-out effect).

[Insert Figure 1 near here]

There are two reasons why we expect this crowding-out effect to be worse for inexperienced than for more experienced start-ups. For the purpose of this discussion, consider a start-up to be “inexperienced” if there are some activities for which it does not have the needed resources (e.g., a start-up with some basic experience in idea generation, filming, and post-production but not in promotion or monetization). An “experienced” start-up is then one with at least some of the resources required for all basic activities. As an example suppose each start-up forms an alliance with an MCN for promotion but only the more experienced start-up has any resources applicable to that stage.

The first reason that an inexperienced start-up suffers more from the crowding-out effect is interdependence. Interdependence is when the outcome of one activity depends (at least in part) on what happens in some other activity. For instance, promotional success depends on idea generation,
e.g., how well the idea fits with a target audience. It is easier to coordinate interdependent activities if a start-up has at least some resources for each of them. This is the case for a more experienced, but not for an inexperienced, start-up. Consequently, less learning-by-self-doing harms an inexperienced start-up more because an alliance will hinder the build up of the necessary resources to deal with interdependencies, while a more experienced start-up already has these resources.

To illustrate the role of interdependence, consider our example in which the more experienced start-up has some resources for promotion. Those resources enable this start-up to manage interdependencies with idea generation regardless of whether (or not) an alliance is formed. However, the inexperienced start-up has no resources for promotion. Absent an alliance, this start-up would eventually engage in and learn about promotion. Such a buildup of promotion resources would, in turn, help to coordinate that activity with idea generation. Yet under an alliance, the start-up will leave promotion to the partner; that approach makes it harder to build up promotion-related resources or to duly consider interdependencies with idea generation. As a result, the crowding-out effect is worse for inexperienced than for a more experienced start-ups.

The second reason, which amplifies the effect of interdependence, is division of labor. There is less learning by self-doing because the alliance partner takes over some activities from the start-up. The preceding account argued that, for a given reduction in learning by self-doing, the consequences are worse for an inexperienced start-up. Under this account, we say that the actual extent of that reduction is greater for an inexperienced start-up.

Past work on the division of labor in alliances has distinguished two basic forms. In the first, partners split responsibilities for value chain activities; partners work on different aspects, and each is responsible for her own activities. Such arrangements have been referred to as X alliances (Porter and Fuller 1986), sequential alliances (Park and Russo 1996), or link alliances (Dussauge et al. 2000). For instance, a start-up focuses on idea generation, which the MCN then promotes. In the second form, partners share responsibilities for value chain activities and so work on the same aspects. These partnerships are known as Y alliances (Porter and Fuller 1986), integrative
alliances (Park and Russo 1996), or scale alliances (Dussauge et al. 2000). One example would be a start-up and MCN working together to promote the video content.

The latter form—sharing responsibilities—requires that both parties have the necessary resources (Dussauge et al. 2000) and so is less often observed for inexperienced start-ups. It follows that an inexperienced start-up is more likely to do less than an experienced start-up and that it will suffer the consequences. Recall our earlier example in which the inexperienced start-up does not have resources for promotion but the experienced start-up does. When deciding whether to share or split up responsibilities, an MCN is more likely to prefer sharing with a more experienced than with an inexperienced start-up. Hence there is less learning by self-doing for inexperienced than for more experienced start-ups, from which it follows that the crowding-out effect is stronger for inexperienced start-ups.

We therefore argue that the benefit (i.e., the learning effect) of an alliance is less for inexperienced than for more experienced start-ups and that the cost (i.e., the crowding-out effect) is greater for inexperienced than for more experienced start-ups. Overall, we conclude that an alliance will result in the accumulation of fewer resources for an inexperienced than for a more experienced start-up.

2.3. A Graphical Illustration

Our arguments are formalized in the Appendix. Here we illustrate them graphically (using a functional form specified in the Appendix). Figure 2 plots the resource accumulation of four start-ups: one inexperienced without an alliance (solid black line), one inexperienced with an alliance (dashed black line), one more experienced without an alliance (solid gray line), and one more experienced with an alliance (dashed gray line). The inexperienced (resp. experienced) start-ups begin with a resource stock of 0.9 (resp. 3.0).

[Insert Figure 2 near here]

An alliance is better for a start-up’s resource accumulation if the start-up has more rather than fewer resources. For inexperienced start-ups (black lines in the figure), the resource stock is less
with than without an alliance; conversely, for more experienced start-ups (gray lines), the resource stock is greater with than without an alliance. As a stark illustration we choose an example in which an alliance hurts an inexperienced start-up yet benefits an experienced start-up. Depending on the empirical context, our moderation argument may manifest itself in different ways. For instance, it could be that both inexperienced and more experienced start-ups benefit from an alliance but that the latter benefit more—or that both start-up types suffer, but inexperienced ones more so, from an alliance. It is difficult to predict ex ante which scenario applies in a given context and so our hypotheses focus on interaction effects, which we anticipate to hold across contexts.

2.4. Hypotheses

We test our arguments by analyzing an alliance’s effect on a start-up’s performance, and whether this effect depends on the start-up’s resource accumulation at the time of alliance formation. Given the notorious difficulty of measuring resource accumulation, we use two proxies: the start-up’s age (younger start-ups have fewer resources) and its cumulative output (start-ups with less output have fewer resources). Formally, we hypothesize two interaction effects as follow.²

Hypothesis 1. A start-up benefits less from an alliance if formed when the start-up is younger (rather than older).

Hypothesis 2. A start-up benefits less from an alliance if formed when the start-up has less (rather than more) cumulative output.

² An alternative prediction (though not an alternative explanation) is that an alliance may be more beneficial to inexperienced than to experienced start-ups—by shielding the start-up from competition (Eisenhardt and Schoonhoven 1996) or allowing it to rely on the partner’s resources (Baum et al. 2000). Such assistance is especially useful for inexperienced start-ups. So even if an alliance negatively affects the start-up’s resources, the start-up might still be better-off with than without a partner. That possibility poses no threat to the validity of our conclusions, since it actually raises the bar for confirming our arguments on resource accumulation.
3. Methods
3.1. Empirical Setting

Entrepreneurs launching channels on YouTube is an attractive setting for our research purposes. First of all, evaluating the effect of an entrepreneurial strategy (i.e., whether to form an alliance) is not a straightforward undertaking. Entrepreneurs make alliance choices based, at least in part, on the entrepreneurial opportunities they are facing. In that event, performance differences between start-ups might be due to differences in entrepreneurial strategy or in entrepreneurial opportunities. YouTube provides a setting in which entrepreneurs face a common opportunity set.

In the second place, our key theoretical trade-off—the benefits and costs of seeking help—is especially critical for low-resource entrepreneurs. A lack of resources is common among YouTube entrepreneurs and can be attributed to their emergent transition into entrepreneurship. They may not have planned to become entrepreneurs but instead acquired that status accidentally through hobby or experimentation. Entrepreneurship on YouTube has low entry costs, allowing entrepreneurs to start without planning. The unprepared nature of such entrepreneurs helps capture the key theoretical trade-off that we seek to clarify.

As an instance of emergent entrepreneurship, consider the case of Jenna Mourey—or Jenna Marbles, as she became known. In the summer of 2010, she was juggling part-time jobs to make ends meet (O’Leary 2013). She uploaded a video, entitled “How to trick people into thinking you are good looking”, that was viewed more than 5.3 million times over the subsequent week. During the next few years, Jenna continued to make and upload videos. The result is more than a million views each week and an estimated income exceeding $1 million (US) annually (Pearson 2016). Jenna’s transition into entrepreneurship was emergent rather than planned. Her mother recalled Jenna’s surprise upon discovering the viral success of her video: “Mom, I made this video on the Internet and a lot of people are watching it and I swear in it!” (O’Leary 2013). Jenna’s transition into entrepreneurship was similar to that of many other entrepreneurs who likewise start without a plan.
3.1.1. The Internet Video Industry  The Internet video industry essentially began with the founding of YouTube in September 2005. YouTube was founded on the following technological idea: clever software coding by the founders allows users to upload and share, via the Internet, Adobe Flash–based videos; and anyone with Internet access can view them free of charge. YouTube became an Internet and cultural phenomenon. In November 2006, less than a year after its launch, YouTube was acquired by Google in exchange for $1.65 billion in stock.

YouTube began simply as a means whereby people could easily upload and share videos. However, the website’s viral appeal—when combined with the popularization of Internet-based video—made YouTube a venue on which firms could advertise. In 2008, YouTube collected an estimated $120 million in total advertising revenues. By 2015 that figure had swollen to $9 billion, fueled by more than a million different advertisers (Ingham 2016).

In April 2011, YouTube announced a revenue-sharing program that would allow content producers to share with YouTube the advertising revenue sourced from their videos. The company had allowed some forms of revenue sharing as early as 2007, but the simplicity of the new model set off an entrepreneurial gold rush: a content creator needed only to allow Google-placed advertising on her site in return for a share of the revenue. The astronomical rise of interest in YouTube precipitated a rush of would-be media entrepreneurs seeking to enter the market. By 2014, YouTube recognized more than a million channels as revenue-sharing content creators; thousands of them had annual revenues of $100,000 or more. These entrepreneurs create content, and the productions range from single person operations to full studio outfits with dozens of employees. The most successful of them have branched out into such areas as artist management and merchandising.

3.1.2. Multi-Channel Networks  The rise of YouTube and of the media entrepreneurs that use it was greatly facilitated by the emergence of multi-channel networks, which are entities that affiliate with multiple YouTube channels while offering assistance to entrepreneurs. In exchange, MCNs typically take a percentage of their channels’ advertising revenue and negotiate contractual arrangements granting exclusivity. Such contracts typically last a year or more.
MCNs operate by first setting up accounts with YouTube directly and then directing their affiliate channels to those accounts. This approach allows entrepreneurs to skip much of the marketing efforts and so leaves more time for their creative efforts. By bundling channels together, MCNs are also able to negotiate better deals with potential advertisers while providing technical support and advice to entrepreneurs.

In recent years, MCNs have attracted considerable attention from investors in response to the increasing importance of Internet-based media to advertisers. By serving as middlemen connecting entrepreneurs to advertisers, MCNs have become one of the fastest-growing classes of investment targets for venture capitalists. At the same time, several MCNs have been purchased by large corporations. In early 2014, for example, Disney acquired Maker Studios for $500 million—a deal swiftly followed by the acquisition of AwesomenessTV by DreamWorks Animation.

3.2. Sample

We assembled a novel data set based on newly started YouTube channels. Random sampling was not possible because YouTube offers no directory or list of all channels. Hence we used a list of relevant keywords (e.g., games, movie review, music) to search for channels. With the aid of two research assistants, we identified 7,950 channels created during the period April 2011 through December 2014; we then tracked the development of each channel over that period. To our set of 7,950 channels we applied a matching procedure that yielded a treatment group and a control group, as we shall explain.\(^3\)

We developed algorithms to extract YouTube information on a longitudinal basis. Web-scraping code was written in Python to collect information on each channel on a monthly basis; this information includes performance metrics, genre, and country of origin. We observe each channel every month that it is in operation, with a minimum of one month, and a maximum of 44 months, and an average of about 21 months. The data set is structured as an unbalanced channel-month panel.

\(^3\)Even if we had been able to assemble a random initial sample, a non-random set would have emerged after the matching procedure.
Our data consists of information obtained from YouTube. To broaden our understanding of the Internet video industry, we explored various archival sources. These included: venture news sites, such as TheVerge.com; investment news databases, such as VentureXpert; and free databases, such as Crunchbase.com.

3.3. Variables

Table 1 defines the variables used in our analyses.

[Insert Table 1 near here]

3.3.1. Dependent Variables

We employ two measures of performance. The first is the natural logarithm of the number of Subscribers (Huang et al. 2009). A subscriber is a user who chooses to subscribe to the channel and thus will receive regular updates whenever that channel is updated, as when new videos are uploaded. Our second performance measure is the natural logarithm of the number of Views, in a given month, of all videos of a channel (Huang et al. 2009). Each measure is a key indicator of the channel’s commercial performance, since both directly reflect the audience size—that is, the target of advertisers.4

3.3.2. Treatment Variable

The treatment variable Alliance is an indicator set to 1 if the channel is affiliated with a multi-channel network in a particular month (and to 0 otherwise). The treatment group consists of those channels that enter an alliance at some point; in our data, no channel exits an alliance. The control group consists of those channels that do not have an alliance during our entire period of observation.

3.3.3. Interaction Effects

To test the hypotheses, we interact the treatment variable with two variables that indicate whether the channel is inexperienced at the time of alliance formation. In the main analysis we use the 10th percentile as an “inexperience” threshold; so among the

4 Other measures (e.g., clicks per advertisement) may affect advertising rates. However, these measures are both internal to and closely guarded by YouTube, precluding public availability.
channels that formed an alliance, only 10% of them did so having been in existence for fewer months or having uploaded fewer videos. The first variable we use, \textit{Young age}, is an indicator variable set equal to 1 if the channel was in existence for fewer than four months at the time of alliance formation, and zero otherwise. Thus this four-month cut-off corresponds to the youngest decile. The second variable, \textit{Few uploads}, is an indicator variable set equal to 1 if the channel had uploaded fewer than 17 videos before alliance formation (and set to 0 otherwise). We also report results from sensitivity analyses conducted while using instead the 25th percentile as our threshold for inexperience. In that case, the respective cutoffs are six months for \textit{Young age} and 42 videos for \textit{Few uploads}.

After constructing the variables, we implement a matching procedure (as described below). The cutoff values just given for the unmatched sample correspond to the following percentages for the matched sample: 17\% \textit{Young age} and 12\% \textit{Few uploads} for the 10th-percentile cutoff; 37\% \textit{Young age} and 27\% \textit{Few uploads} for the 25th-percentile cutoff.

3.3.4. Control Variables

The variable \textit{Age} is the number of months since the channel’s first uploaded video (natural logarithm).\footnote{5} The \textit{Uploads} variable is the cumulative number of videos that a channel has uploaded since its founding (natural logarithm). We account for time-invariant differences among channels by including channel fixed effects; we also include time indicators at the month level.

3.4. Estimation Procedure

The \textit{Alliance} variable could be endogenous; in other words, an unmodeled factor may simultaneously affect both performance and the decision to form an alliance. If so, then our model would yield inconsistent estimates of an alliance’s causal effects. We take three steps to lessen this concern. First, we ensure that the entrepreneurial opportunity is similar across channels by choosing the

\footnote{5}YouTube channels are linked to Google user accounts. To distinguish between when people joined YouTube and when they started creating content, we define a channel’s starting date as the month in which a video is first uploaded.
video Internet industry as our setting. Second, as already mentioned, we cancel out time-invariant differences among channels by incorporating channel fixed effects. Third, we ensure similar ex ante performance for channels with and without alliance by matching treatment and control groups in terms of performance prior to alliance formation. So when a channel with an alliance is matched to one without an alliance, the two channels had exhibited similar performance for the three-month period preceding alliance formation. The channel with an alliance is our treatment (T) and the one without an alliance is our control (C). Under that setup, T’s counterfactual ex post performance is based on C’s ex post performance, and T and C had similar ex ante performance. If this is an appropriate counterfactual, then we obtain a consistent estimate of the average treatment effect for the treated channels (Morgan and Winship 2015). Thus we lessen endogeneity concerns but cannot eliminate them altogether. In particular, problems could arise from unobserved time-varying differences among channels.

The matching procedure is as follows. We employ the coarsened exact matching (CEM) procedure (Blackwell et al. 2009) to construct treatment and control samples that are balanced with respect to pre-treatment variables. CEM is part of a general class of monotonic imbalance bounding methods, whose properties are superior to those of such previous methods as propensity score matching (King et al. 2011). We match the channels by ex ante performance in terms of Subscribers and Views during the three-month period prior to alliance formation, and also by Uploads, Age, Genre of the videos, and channels Country of origin. The last three of these variables are matched exactly. Following recent work (Aggarwal and Hsu 2013, Ching 2016), for matching purposes we use the variables’ un-logged values. With this procedure we matched 1,027 treated channels, resulting in a total sample of 2,054 channels. Table 2 shows that the treatment and control group are well balanced across our variables. The mean differences between treatment and control group are statistically insignificant in a t-test.

[Insert Table 2 near here]
4. Results

Table 3 provides descriptive statistics and pairwise correlations. The correlation between Young age and Few uploads is low ($r = -0.05$).

Table 4 shows the regression results for the matched sample for the dependent variables Subscribers and Views. All models include channel fixed effects and month indicators in addition to the control variables Age and Uploads. Across the models, older channels have more subscribers and monthly views. The cumulative number of videos uploaded is associated with having fewer subscribers but not with having either more or fewer monthly views. This indicates that a high number of uploaded videos is not required to attract a high number of subscribers.

Because Subscribers, Views, Age, and Upload are logged, the coefficients can be (approximately) interpreted as percentage changes. Thus a 1% older age corresponds to about 0.49% more subscribers and about 0.65% more monthly views; a 1% increase in videos uploaded corresponds to about 0.36% fewer subscribers.

For the dependent variable Subscribers, model (2) adds the main effect Alliance; the coefficient is close to zero. Thus we do not find a main effect for Alliance, which means that channels with an alliance have (on average) similar numbers of subscribers as do channels without an alliance. There is a slight difference for Views, however: channels with an alliance have about 6% ($p = 0.09$; model (5)) more views than those without an alliance.\(^6\)

\(^6\)We use a log-linear specification for Alliance and its interaction effects. The coefficient for a continuous independent variable, when multiplied by 100, approximates the percentage change of the dependent variable for a small change in the independent variable. This approximation does not hold for a unit change in an indicator independent variable (Halvorsen and Palmquist 1980), as for Alliance, Alliance $\times$ Young age, or Alliance $\times$ Few uploads. The quoted percentages are from the estimator given in Kennedy (1981): $100 \times \left( \exp\{\hat{c} - \frac{1}{2}\text{Var}(\hat{c})\} - 1 \right)$, where $\hat{c}$ is the estimated coefficient.
To test the hypotheses—that inexperienced start-ups benefit less from alliances—we add interaction effects. The interaction effect $Alliance \times Young\ age$ is negative, both for $Subscribers$ ($p = 0.08$; model (3)) and for $Views$ ($p < 0.01$; model (6)). Therefore, Hypothesis 1 is (marginally) supported. Channels that form alliances early underperform channels that form alliances later by approximately 12% in terms of subscribers and 7% in terms of monthly views. Relative to channels that do not form alliances, those that form alliances early have about 19% fewer subscribers and 27% fewer views.

The interaction effect $Alliance \times Few\ uploads$ is also negative—both for $Subscribers$ ($p < 0.01$) and $Views$ ($p = 0.56$)—but it is significant only for the former. Thus Hypothesis 2 is supported for subscribers but not for views. The best estimate is that the channels that form alliances after having uploaded relatively few videos underperform channels that form alliances later: by approximately 36% in terms of subscribers and 10% in terms of monthly views. Relative to channels that do not form alliances, those that form alliances with few uploads have about 42% fewer subscribers and 6% fewer views.\(^7\)

These findings are broadly consistent with our arguments: inexperienced start-ups benefit less from alliances. In fact, not only do they benefit less, they may actually do worse than start-ups that do not enter alliances. Figure 3 plots point estimates and 95% confidence intervals for the difference between start-ups with alliances and those without.\(^8\) Start-ups that form alliances after accumulating some experience perform similarly or marginally better than their peers without alliances (right panel); in contrast, inexperienced start-ups that form alliances perform substantially worse than their peers without alliances (left panel). Point estimates range from (roughly) 10% to 40%.

\[^7\] Adding the interaction effects leads to only small changes in $R^2$ (within). $R^2$ is an indicator of explained variation relative to total variation. A small change in $R^2$ means that, even though effect sizes may be large in absolute terms, they are only modest relative to total variation in the data.

\[^8\] Estimates are derived from single-interaction models while controlling for the main effects of $Age$ and $Uploads$.\]
4.1. Additional Analyses

Our central contention is that inexperienced start-ups gain less from alliances than do more experienced start-ups. In other words, there should be an identifiable range of “inexperience” within which start-ups receive reduced alliance benefits. By implication, regression coefficients should tail off for lower levels of inexperience (or, equivalently, for higher levels of experience). As a first additional analysis, we therefore explore inexperience in greater depth. We use the 25th (instead of the 10th) percentile of Young age and Few uploads to generate the interaction effects. In line with our theory, the coefficients for both interaction effects with each dependent variable shrink toward zero (and so all of them lie between the respective original coefficients and zero); see Table 5.

[Insert Table 5 near here]

Second, we perform our analyses while using count models on untransformed variables. When convergence was possible, the results (not reported here) are qualitatively similar. As a third additional analysis, we estimate the basic model for Subscribers and Views on different samples. The results are reported in Table 6. Models (1) and (4) are estimated on the full sample, including unmatched channels (7,950 channels); models (2) and (5) are estimated on the matched sample (2,054 channels), as in our main results; and models (3) and (6) are estimated on only the treated portion of the matched sample (1,027 channels). The effect size of Alliance varies by sample: from about 11% to 16% higher performance for the unmatched sample (models (1) and (4)), 0%–9% similar to higher performance for the matched sample (models (2) and (5)), and 4%–9% lower performance for the treated portion of the matched sample (models (3) and (6)).

[Insert Table 6 near here]

These divergent findings illustrate the importance of matching. In models (3) and (6), the implicit control group is the channels themselves before forming any alliances. Model (3) indicates that
channels do worse once they form alliances, while accounting for increases in \textit{Age} and \textit{Upload}. In models (2) and (5), the explicit control group is the channels that never formed an alliance (while accounting for stable characteristics through channel fixed effects). According to model (2), channels that never form an alliance do equally well for similar increases in \textit{Age} and \textit{Upload}. Thus models (2) and (5) and models (3) and (6) provide different interpretations for the effect of alliances, and the interpretations provided by (2) and (5) are closest to our research question. Note that neither model (1) nor model (4) accounts for differences in ex ante performance. The difference in results suggests that the unmatched sample contains a higher proportion of better-performing channels, and that they are more likely to form an alliance.

The findings for our unmatched sample help reconcile our results with those reported in previous studies. For instance, the foundational study in this stream of literature is Baum et al. (2000). For an unmatched sample those authors find that, in general, start-ups benefit from alliances. That result accords with the specification and findings of models (1) and (4).

4.2. Alternative Explanations

We have argued that, because of a crowding-out effect the benefits from an alliance are less for inexperienced than for experienced start-ups. Here we consider two alternative explanations. First, a learning effect combined with a threshold after which learning “kicks in” (i.e., absorptive capacity) can also generate the prediction that inexperienced start-ups benefit less than more experienced ones. However, this argument is insufficient to explain that inexperienced start-ups actually suffer relative to similar start-ups without alliance.

Second, we noted earlier that a view of alliances as most benefiting the inexperienced yields predictions that directly oppose our hypotheses. Yet a view of alliances as complementary—in which case alliance benefits are greater for more experienced start-ups—would yield predictions consistent with our hypotheses. As with the previous alternative, however, this account offers no explanation for why, among inexperienced start-ups, those with an alliance do worse than those without an alliance.
5. Discussion

This paper seeks to explicate a fundamental trade-off faced by entrepreneurs. Early on, start-ups are vulnerable because of their limited resources and hence could benefit from an alliance; yet an alliance may hinder accumulation of the start-up’s own resources. We find that the timing of alliance formation is a key factor for entrepreneurs looking to manage this trade-off. Inexperienced start-ups incur performance penalties of 10%–40% by forming an alliance compared to not forming an alliance, whereas more experienced start-ups obtain a small performance bonus (0%–9%). Start-ups must therefore decide not only whether to partner but also when to partner.

5.1. Theoretical Implications

5.1.1. Paradox of Entrepreneurship We examine a key paradox of entrepreneurship. On the one hand, start-ups typically have limited resources, which makes them vulnerable. As a consequence, the literature has documented the high failure rate of startups (Decker et al. 2014), generally referred to as the liability of newness or smallness (Stinchcombe 1965, Freeman et al. 1983). Thus, entrepreneurs often try to overcome that liability by seeking the aid of an alliance partner. On the other hand, we argue that the very act of so alleviating its liabilities may weaken a start-up’s long-term prospects.

We propose a way to resolve that paradox through the timing of alliance formation. The focus is not on whether but rather on when entrepreneurs should seek an alliance. Future research must therefore consider not only the viability of an entrepreneurial strategy but also how that viability depends on the start-up’s stage of development.

For example, start-ups often face the dilemma of cooperating versus competing with incumbent parties. Much of the extant literature has approached this issue from the perspective of a strategic decision’s viability. But by shifting the focus to the decision’s timing, we broadly extend potential implications of the strategic decision-making process. This approach coheres with the work of scholars who have begun to examine how entrepreneurs may benefit from strategic pivoting (Marx and Hsu 2015, Ching 2016).
5.1.2. **Emergent Entrepreneurs** Ever since the field of entrepreneurship was defined in terms of an individual–opportunity nexus (Shane and Venkataraman 2000), scholars have discussed how opportunities are discovered (Shane 2000). At one end, opportunities are found through directed search (Bhide 2003). At the other end, opportunities are not searched for but instead are discovered accidentally discovered (Shah and Tripsas 2007, Shah et al. 2012).

Here we highlight the other part of that nexus: the individual. In particular, we examine the transition into entrepreneurship, or the process by which one becomes an entrepreneur. An individual might *plan* to become entrepreneur. The literature has documented how individuals trade off costs and benefits when deciding about entry into entrepreneurship (Gentry and Hubbard 2000, Hurst and Lusardi 2004). It follows that current employment characteristics (e.g., career opportunities) affect whether a person will start her own firm (Dobrev and Barnett 2005, Kacperczyk and Marx 2016). A planned entrepreneur could choose to rely either on directed search or on accidental discovery (see Figure 4). Mutual fund managers who spin off their own individual funds are examples of planned entrepreneurs who perform a directed search for opportunity (Kacperczyk 2012). Accidental discovery is exemplified by MBA students, taking an entrepreneurship class, who want to start a business but have no clear idea of just what business (Lazear 2004).

However, the transition into entrepreneurship could alternatively be *emergent* and arrived at through a process of use and experimentation. The trade-off between costs and benefits of the entry decision is absent or implicit. An emergent entrepreneur may either undertake a directed search or rely on accidental discovery. An example from the latter category is that of “user” entrepreneurs. For instance, in modifying the frame and other components of their bicycles, road-racing enthusiasts discovered an entrepreneurial opportunity now known as the mountain bike industry (Shah and Tripsas 2007). In the former category we place aspiring YouTube entrepreneurs. They are aware of others making money off the YouTube platform and so the opportunity is known; however, their transition to entrepreneurship may not well planned and hence better described as emergent.

[Insert Figure 4 near here]
It is this latter category that we have sought to highlight using YouTube entrepreneurs. YouTube has lowered the cost of entry into entrepreneurship, limiting potential downsides so that advance planning is no longer necessary, and the result is a proliferation of such emergent entrepreneurs. We observe this phenomenon also on other platforms, such as Instagram and Twitch.

The emergent nature of the process by which these individuals enter into entrepreneurship also implies that they are probably less well prepared and also lacking in the required resources. Many entrepreneurs are under-prepared, yet we argue that the emergent ones are likely even less prepared since they never planned on becoming entrepreneurs. In the absence of the required resources needed to succeed, emergent entrepreneurs are may seek help through alliances, although such help arguably comes at the cost of reduced long-term performance.

5.2. Managerial Implications

This study bears several implications for practicing managers of start-ups. Many entrepreneurs face the decision of whether to “go it alone” or to ally with a partner. We have shown that an equally critical question is that of just when to seek help. Our evidence suggests that entrepreneurs without some prior level of experience may not benefit from partnership. This finding helps to reconcile the nearly paradoxical views of the entrepreneurial process: it is by nature a lonely process, but the entrepreneur may well flounder without help. Our evidence suggests that while help can be beneficial, the best condition for receiving the help may come with a period of trial and error.
Appendix. Formalization

We formalize our arguments using the Knott et al. (2003) resource accumulation model, which is based on Dierickx and Cool (1989):

$$R_{t+1} = (1-d)R_t + f_i(R_t, R_{t}^p),$$  \(1\)

where \(R_t \geq 0\) denotes the resource stock at time \(t\) and where \(d\) (with \(0 < d < 1\)) is the per-period erosion of the resource stock (i.e., the outflow). The term \(I_t \geq 0\) denotes investment in the resource stock at time \(t\) (i.e., the inflow). Parameter \(a\) (with \(0 < a < 1\)) captures the diseconomies from time compression, or the diminishing marginal returns to current-period investment (i.e., the benefits from spreading a large investment over multiple time periods). The parameter \(b\) (with \(0 < b < 1\)) represents resource mass efficiencies, or economies of scale in resource accumulation (i.e., “success breeds success”).

An alliance influences the start-up’s learning by doing, which in our model is represented by a start-up’s investment or its inflow. Using \(R_t' \geq 0\) to indicate the alliance partner’s resource stock at time \(t\), we can write

$$R_{t+1} = (1-d)R_t + f_i(R_t, R_t')R_t^b.$$  \(2\)

Thus the start-up’s investment depends on its own resource stock and on that of its alliance partner. Our theoretical discussion leads us to assume as follows.

**Assumption 1.** **Learning effect:** \(\partial I_t / \partial R_t' > 0\) iff \(R_t > R^*\).

This statement reflects that a start-up learns from its partner \((\partial I_t / \partial R_t' > 0)\) but if and only if the start-up has sufficient absorptive capacity \((R_t > R^*)\. We further assume:

**Assumption 2.** **Crowding-out effect:** \(\partial I_t / \partial R_t' < 0\) and \(\partial^2 I_t / \partial R_t' \partial R_t > 0\).

This assumption captures the idea that a start-up’s resources are harmed by the reduced self-doing that results from an alliance \((\partial I_t / \partial R_t' < 0)\)—though the effect is less pronounced for more experienced start-ups \((\partial^2 I_t / \partial R_t' \partial R_t > 0)\).

Assumptions 1 and 2 together imply that an alliance is better for a start-up’s resource accumulation if the start-up already has strong \((R > R^*)\) rather than weak \((R \leq R^*)\) resources. This implication is the basis of our hypotheses.

**Example**

Figure 2 illustrates the effect of an alliance on a start-up’s resource accumulation. The figure’s plots are based on the following specific functional form, which satisfies equation (2) as well as Assumptions 1 and 2:

$$R_{t+1} = 0.9R_t + I_t^{0.1}R_t^{0.1},$$  \(3\)

$$I_t = R_t - R'_t + R_tR'_t.$$  \(4\)

To simplify matters, we hold the strength of an alliance partner’s resources constant \((R_t' = 10)\. Without an alliance it is \(R_t' = 0\).
References


Table 1  Measurement of Variables

<table>
<thead>
<tr>
<th>Variables</th>
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<td><strong>Dependent variables</strong></td>
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<td>Number of total subscribers of the channel each month (natural log)</td>
</tr>
<tr>
<td>Views</td>
<td>Number of new views of the channel each month (natural log)</td>
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<tr>
<td><strong>Treatment variable</strong></td>
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</tr>
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<tr>
<td><strong>Interaction variables</strong></td>
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<td>0 otherwise</td>
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<td>1 if channel joins an alliance before at least 17 uploaded videos,</td>
</tr>
<tr>
<td></td>
<td>0 otherwise</td>
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<td><strong>Control variables</strong></td>
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<td>Uploads</td>
<td>Cumulative number of videos uploaded by channel (natural log)</td>
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Table 2  Observations are Balanced after Matching

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<th>Control (mean)</th>
<th>(t)-test (p-value)</th>
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Note: Age, Genre, and Country are matched exactly.

Table 3  Summary Statistics and Correlations

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<th>(2) Views</th>
<th>(3) Alliance</th>
<th>(4) Young age</th>
<th>(5) Few uploads</th>
<th>(6) Age</th>
<th>(7) Uploads</th>
<th>(8) Mean</th>
<th>(9) Std. dev.</th>
<th>(10) Min.</th>
<th>(11) Max.</th>
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Table 4  OLS Regressions for Subscribers and Views: 10th-percentile Cutoff for Inexperienced

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<td>0.085**</td>
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<td>(0.049)</td>
<td>(0.049)</td>
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<tr>
<td>Alliance × Young age</td>
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<tr>
<td></td>
<td>(0.153)</td>
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Note: Standard errors clustered by channel in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed tests)

Table 5  OLS Regressions for Subscribers and Views: 25th-percentile Cutoff for Inexperienced

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<tr>
<td>n (channels)</td>
<td>2,054</td>
<td>2,054</td>
<td>2,054</td>
<td>2,054</td>
<td>2,054</td>
<td>2,054</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.158</td>
<td>0.158</td>
<td>0.161</td>
<td>0.084</td>
<td>0.085</td>
<td>0.085</td>
</tr>
<tr>
<td>$R^2$ (between)</td>
<td>0.066</td>
<td>0.066</td>
<td>0.052</td>
<td>0.040</td>
<td>0.040</td>
<td>0.046</td>
</tr>
</tbody>
</table>

Note: Standard errors clustered by channel in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed tests)
Table 6  OLS Regressions for Subscribers and Views Using Different Samples

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
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<tr>
<td></td>
<td>Subscribers</td>
<td>Subscribers</td>
<td>Subscribers</td>
<td>Views</td>
<td>Views</td>
<td>Views</td>
</tr>
<tr>
<td>Allia</td>
<td>0.107***</td>
<td>0.002</td>
<td>−0.088*</td>
<td>0.149***</td>
<td>0.085*</td>
<td>−0.039</td>
</tr>
<tr>
<td>nce</td>
<td>(0.022)</td>
<td>(0.045)</td>
<td>(0.045)</td>
<td>(0.023)</td>
<td>(0.048)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>Age</td>
<td>0.514***</td>
<td>0.494***</td>
<td>0.555***</td>
<td>0.618***</td>
<td>0.636***</td>
<td>0.707***</td>
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<tr>
<td></td>
<td>(0.025)</td>
<td>(0.050)</td>
<td>(0.075)</td>
<td>(0.027)</td>
<td>(0.054)</td>
<td>(0.086)</td>
</tr>
<tr>
<td>Uploads</td>
<td>−0.467***</td>
<td>−0.464***</td>
<td>−0.267</td>
<td>0.116</td>
<td>0.009</td>
<td>0.281</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.132)</td>
<td>(0.199)</td>
<td>(0.086)</td>
<td>(0.149)</td>
<td>(0.194)</td>
</tr>
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<td>Month indicators</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Channel FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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</table>

<table>
<thead>
<tr>
<th>Sample</th>
<th>Full</th>
<th>Matched</th>
<th>Treated of matched</th>
<th>Full</th>
<th>Matched</th>
<th>Treated of matched</th>
</tr>
</thead>
<tbody>
<tr>
<td>n (observations)</td>
<td>173,611</td>
<td>47,243</td>
<td>23,756</td>
<td>173,611</td>
<td>42,243</td>
<td>23,756</td>
</tr>
<tr>
<td>n (channels)</td>
<td>7,950</td>
<td>2,054</td>
<td>1,027</td>
<td>7,950</td>
<td>2,054</td>
<td>1,027</td>
</tr>
<tr>
<td>$R^2$ (within)</td>
<td>0.169</td>
<td>0.158</td>
<td>0.165</td>
<td>0.091</td>
<td>0.085</td>
<td>0.103</td>
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<tr>
<td>$R^2$ (between)</td>
<td>0.073</td>
<td>0.066</td>
<td>0.036</td>
<td>0.119</td>
<td>0.040</td>
<td>0.155</td>
</tr>
</tbody>
</table>

Note: Standard errors clustered by channel in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (two-tailed test)
Figure 1  Simplified Value Chain for a YouTube Start-up

![Figure 1](image1)

Figure 2  Relative Resource Accumulation from Alliance Formation

![Figure 2](image2)

Figure 3  An Alliance Benefits Somewhat a More Experienced Start-up but not an Inexperienced Start-up

![Figure 3](image3)
Figure 4 Types of Entrepreneurship