Promoting Platform Takeoff and Self-Fulfilling Expectations:

Field Experimental Evidence

Kevin J. Boudreau*

Abstract. Many entrepreneurs and investors are attracted to platform businesses and the possibility of harnessing powerful network effects. But, network effects can be the very reason why platform businesses fail to takeoff, if users avoid platforms that do not already have a large installed base. The theoretical literature on platforms and network effects predicts that the initial growth and takeoff of a platform crucially depends on the market's expectations of the future installed base. This paper tests this claim, reporting on a field experiment in which invitations to join a newly launched platform were sent to 16,349 individuals and included randomized statements regarding the future expected installed base (along with disclosures of the current installed base). I find evidence consistent with subjective expectations playing a crucial role in shaping early adoption and platform takeoff. Statements regarding expectations of the future installed base more significantly affected adoption than did disclosures of the current installed base. Statements of larger numbers of expected users caused more adoption than did smaller numbers. Statements of a smaller installed base of users (whether current or expected) led to lower demand than did stating nothing at all. The effect of stating subjective expectations by the platform became insignificant once the current installed base grew larger. The response of adoption to expected numbers of users reveals patterns consistent with the long-theorized chicken-and-egg problem and self-fulfilling expectations. The findings have significant implications for the effective promotion, marketing, and "evangelism" of new platform ventures.

Keywords: Platforms, network effects, expectations, marketing, entrepreneurship, chicken-and-egg, coordination games, online distributed work.

* Northeastern University DMSB & NBER: 417 Interdisciplinary Science & Engineering Complex 805 Columbus Ave, Boston, MA 02120, tel: 617-373-3241, fax: 617-373-3241 (e-mail: kevin@northeastern.edu). I wish to especially thank crucial personnel of supporting organizations and advisors, including Paras Babbar, James Bean, Maria Costa De Sousa, Hugh Courtney, Mavez Dabas, Nicole Danuwidjaja, Rick Davis, Sylvain Demortier, Anthony Donaldson, Eric Doroski, Raj Echambadi, Koreen Geisler-Wagner, Austen Keene, Afan Khan, Atif Khan, Abhinav Kharbanda, Dyan Khor, Raghavi Kirouchenaradjou, Satish Kumar Anbalagan, Sreerag Sreenath Mandakathil, Patrick McGrath, Tucker Marion, Patrick McGrath, Marc Meyer, Robert Hughes, Michael Orr, Olga Ozhereleva, Kaushik Padmanabhan, Edwige Poinssot, Fernando Suarez, Prathamesh Tajane, Nikin Tharan, Emery Trahan, Maureen Underhill, Robert Whelan, and Katie Wilhoit. For especially useful comments in conversations on this topic, I thank Dónal Crilly and Andrei Hagiu. This research also benefitted from joint data collection, collaboration, and thinking on related topics with Nilam Kaushik. I would also like to acknowledge generous financial support from the Kauffman Foundation (grant G00005624) and Northeastern DMSB. This research was determined to be IRB exempt (NUIRB180419). All errors are my own.

1. Introduction

Society now relies on online platforms as essential infrastructure for many economic, social, scientific, health, education, and cultural activities (Evans and Gawer 2016, Parker et al. 2016, Ting et al. 2020).[1] Continued innovation and service expansion in this area will require ongoing successful launches of new platform ventures (Furman et al. 2019). Unfortunately, most platform ventures fail to take off (Noe and Parker 2005, Evans and Schmalensee 2010). Theory suggests that this is because potential users are reluctant to adopt platforms that do not already have a large installed base and network effects: the well-known chicken-and-egg problem.[2] The theory suggests that influencing consumers' expectations of *future* platform growth can help overcome this problem. Consumers who believe that a platform will eventually take off will join the platform and thereby catalyze network effects (e.g., Katz and Shapiro 1985). Shapiro and Varian (1999) write, "Managing consumer expectations is crucial in network markets. Your goal is to convince customers... you will emerge as the victor. Such expectations can easily become a self-fulfilling prophecy when network effects are strong." Besen and Farrell (1994) specify that "expectations about the ultimate size of a network are crucial." This study tests this theory.

The idea that expectations can be self-fulfilling has become standard in the theoretical literature on platforms (Hossain and Morgan 2009). When deciding whether to adopt a platform with network effects, a consumer's best decision is to do what others do.[3] The theory implies a large-scale coordination problem (e.g., Schelling 1960), whereby adopters should attempt to collectively adopt one platform, or another (if

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[1] The growing importance of platforms as a modern approach to organization is reflected in research attention from a growing number and variety of researchers and disciplines (e.g., Ghazawneh & Henfridsson, 2013; Iansiti & Lakhani, 2017; Suarez and Kirtley, 2012; Nambisan et al., 2017; Rietveld & Schilling, 2020; Rysman, 2009; Sundararajan, 2017; West, 2003).

[2] See: Caillaud and Jullien (2003), Fath and Sarvary (2003), Hagiu and Eisenmann (2007), Ochs and Park (2010), Stummer et al. (2018).

[3] Consider a market with two potential adopters, A and B. In this example, adoption costs are \$1, and benefits are \$2 if everyone adopts or \$0 otherwise. There are two possible equilibria: "nobody adopts" and "everyone adopts."

	Consumer B	
Consumer A	Not Adopt	Adopt
Adopt	(−1,0)	(1,1)
Not Adopt	(0,0)	(0,−1)

there are competitors), or none.[4] If adopters cannot explicitly coordinate or communicate, this multiplicity of possible equilibria creates fundamental uncertainty and ambiguity about which market outcome will emerge. Accordingly, adopters cannot "look forward and reason back" as in usual rational expectations (Hossain and Morgan, 2013) and expectations are subjective. Therefore, conventional means of influencing rational expectations—e.g., economic signaling and pre-commitments—should not work as usual.

Absent rational expectations, theorists instead appeal to "focality" as the concept determining the eventual market outcome. A focal equilibrium (or "focal point") is the choice to which most people default and which individuals expect others will choose (Schelling 1960, Mehta 1994). Therefore, focality and expectations are closely intertwined. The platforms literature is silent on how focal expectations are formed or influenced. Instead, theory has proceeded by presuming consumers follow some focal rule. Most models in the literature assume, for example, that consumers choose the economically efficient outcome (e.g., Farrell and Klemperer 2007).[5] In contrast, discussions of chicken-and-egg problems often implicitly presume that consumers tend towards non-adoption as a default. More recent advances have begun to consider alternative focal rules' competitive implications, such as adopting according to past market share (Suleymanova and Wey 2012, Hagiu and Spulber 2013, Hagiu and Halaburda 2014, Halaburda and Yehezkel 2019, Halaburda et al. 2020).

The empirical research does not yet study expectations in early platform growth. Instead, most empirical models specify adoption as a function of the current or lagged installed base within a static framework.[6] Several exceptional studies estimate models with perfectly-forward-looking consumers (Dubé et al. 2007, Rysman et al. 2011, Ryan and Tucker 2012). These approaches should be better suited to

[4] Market coordination problems are either explicit or implied throughout literature on platforms, standards, and network effects (Augereau et al., 2006; Fang et al., 2020; Farrell & Klemperer, 2007; Farrell & Saloner, 1988; Hagiu & Spulber, 2013; Simcoe, 2012)

[5] Related literatures examines whether markets get locked-in to inferior platforms (e.g., David 1985, Hossain and Morgan 2009, Hossain et al. 2011, Liebowitz and Margolis 2014) and when do markets tip (Cantillon & Yin, 2007; Ellison & Fudenberg, 2003; Hossain & Morgan, 2013).

[6] E.g., Ackerberg & Gowrisankaran, 2006; Boudreau & Jeppesen, 2015; Chu & Manchanda, 2016; Corts & Lederman, 2009; Gupta et al., 1999; Nair et al., 2004; Saloner & Shepard, 1992; Shankar & Bayus, 2003; Tucker & Zhang, 2011; Wilbur, 2008

studying mature markets when eventual outcomes are clear. Thus, the theorized role of expectations in coordinating earliest moments of adoption remains untested. This is the focus of this study.

2. Research Design

This study builds on a stream of field experiments studying platform adoption (e.g., Sun et al. 2019, Bapna and Umyarov 2015). I most closely build on Tucker and Zhang's (2010) field experimental framework for studying whether network effects exist on a large, mature Chinese B2B platform (Appendix A). Here I study whether exposing 16,349 individuals to experimentally assigned statements regarding future installed base (while controlling for the current installed base) affects adoption decisions in the context of an early platform launch campaign.

2.1. Context

The product development platform in this study was created to serve students and alumni of a large US university. This large R1 research-oriented university has approximately 20,000 undergraduate and 10,000 graduate students and has nationally ranked engineering, computer science, and business programs. The Princeton Review indicates that 25^{th} and 75^{th} percentile SAT scores of admitted students are 690 and 790.

The platform mimics today’s in-person hackathons’ essential features, where people meet, exchange ideas, and design prototypes. Distinct from usual hackathons, however, the platform was launched to achieve grander scale and wider access to greater numbers of participants than a typical hackathon. The platform now numbers over 5,500 participants. On the platform, individuals collaborate to design IoT-related products (“applications”). IoT refers to systems that connect machines, infrastructure, and consumer products and the intelligence created by those elements' data collection and networking. Collaborators can develop their own ideas or respond to challenges issued by the platform or companies. Users were not charged to participate on the platform but may have experienced non-pecuniary costs in the process of learning about the platform and signing up. Further, in this context, signing up also implied the opportunity cost of participating in a three-week part-time development project.

The experiment centered on the initial campaign to attract a critical mass of users within the first 60 business days following launch. Ensuring many users joined the platform was vital because the platform depends on interactions among users and forming teams to work on new projects. Platform developers also believed that adopters might respond to the number of companies on the platform.

2.2. Experimental Protocol and Treatments

2.2.1. Observable Potential Market

This experiment focused on a key risk set of potential adopters. This group included 16,349 students and past graduates of the university with backgrounds in engineering, computer science (including data science and information systems), and sciences (including natural sciences and mathematics). Table 1 summarizes the characteristics of this group. In identifying potential adopters before the launch of the platform, both adoption and non-adoption could be observed and recorded.[7]

<Table 1>

2.2.2. Invitations to Join the Platform

Each participant received an email invitation to join the platform (Appendix B) over the 60 business days. Those who did not initially open the invitation were sent a reminder seven days later. The emails included a brief description of the platform and invited the recipient to click-through to learn more and consider joining.

2.2.3. Platform Sign-Up

Clicking-through from the email to the platform provided a description of the Internet of Things and of the development activity that would take place on the platform. The description stated, too, that participating on the platform could foster interactions, support learning of new skills, and lead to cash prizes. The platform also presented a prominent "join and participate" button and could sign-in to become a member

[7] The platform embedded other experiments and A/B tests during its launch in a way that was entirely orthogonal to and had no effect on this analysis.

using their LinkedIn credentials. LinkedIn API-accessible information and photographs then auto-populated their platform member profiles.

2.3. Treatments and Random Assignment

The experimental treatments consisted of varying messages within the invitation to join (see Appendix B):

1. Expectation message: "We expect <#> users and <#> companies to join this year."
2. Installed base disclosure: "To date, <#> users and <#> companies have joined."
3. Total potential market scale statement: "The university community comprises 20,000 students, 200,000 alumni, and 2,000 staff and professors. There are also 4,000 affiliated companies."
4. Early adoption emphasis statement: "This is an invitation for early adopters."

Most central to the research question is statement (1) regarding the expected installed base. Statement (2) discloses the current installed base and provides a useful control and a basis for comparing the magnitude of effects with statement (1). Statements (3) and (4) provide further means of interpreting the effect of statement (1), as discussed in Section 3.3.

2.3.1. Messages of Expected Installed Base

To ensure that statements were neither arbitrary nor misleading, stated expectations corresponded to the platform developers' own forecasted scenarios. In relation to users, these scenarios included: 2,500 (low), 10,000 (medium), and 25,000 (high) users. For companies, these scenarios included: 10 (low), 25 (medium), 40 (high), and 100 (very high) companies.[8] Different scenarios were combined in different treatments to generate independent variation in numbers of expected users and expected companies (see Figure 2, panel III). Platform developers decided on possible combinations to avoid nonsensical combinations (e.g., combinations of very lowest with highest scenarios, expectations lower than current levels) and to limit the complexity of implementing the treatments.

[8] The additional scenario for companies reflected greater uncertainty regarding the number of companies and potentially important differences in the operating model to support these different numbers. Nonetheless, the ratio between the lowest and highest scenarios was 10X for both users and companies.

2.3.2. Disclosures of Current Installed Base

To avoid deception, disclosures of the current installed base were based on the true current number of users across the 60-day campaign. To acquire a nonarbitrary number of companies in the current installed base, users were asked whether their companies would likely sponsor a challenge.

To then generate independent variation in numbers of users and companies, these values were each intermittently and alternately updated from day to day (rather than tracking real-time values) to ensure multiple numbers of users for each number of companies and vice versa.

2.3.3. Random Assignment Procedure

Platform developers randomly assigned individuals to treatments based on the following principles. Individuals in the study group were first randomly assigned to receiving invitations across the campaign's 60 days. Each day, individuals were randomly assigned to receive a statement of expectations of the future installed base (statement 1) or not, and disclosure of the current installed base (statement 2). Those receiving statements of expectations were then randomly assigned to receive a particular combination of scenarios for particular numbers. Everyone was randomly assigned to receive statements (3) or (4), both, or neither. Panel III of Figure 2 summarized all possible combinations.

2.4. Randomization Checks

Randomization should ex-ante lead to equal treatment groups. Figures 1 and 2 explicitly check for balance ex-post. Figure 1 describes the observable characteristics of individuals assigned across the 60 days. Figure 2 describes the observable characteristics of individuals assigned across all treatment combinations. Characteristics are statistically identical in each case.

<Figure 1 >

<Figure 2>

3. Results

3.1. How does Stating Expectations of Installed Base Affect Adoption?

A probit model of the following form is estimated to relate the decision to adopt or participate on the platform and the experimental treatments:[9]

$$
\begin{gathered}
prob\{PARTICIPATION_i = 1\} \\
= \Phi(\beta_0 \cdot X_i + \beta_1 ExpectationsStated_i + \beta_2 InstalledBaseDisclosed_i \\
+\beta_3 ExpectedNumUsers_i + \beta_4 ExpectedNumCompanies_i \\
+\beta_5 CurrentNumUsers_i + \beta_6 CurrentNumCompanies_i)
\end{gathered}
$$

The function Φ is the cumulative standard normal distribution function. Individuals are indexed by i. The β terms are the coefficients to be estimated. X is a vector of individuals' characteristics and controls. The remaining variables relate to the treatments (Table 1). The model is estimated by maximum likelihood.

Model (1) of Table 2 reports estimates with just the *ExpectationsStated* indicator and a constant included in the model. The average effect of stating expectations on the probability of participation is statistically significant and negative. The effect translates to approximately a 1% drop in participation relative to a 5% average participation rate, or one-fifth impact. Model (2) adds time controls (quadratic time trend and day-of-week dummies), field of study (sciences omitted), gender, and graduation year. Adding these controls has no impact on the estimated effect of stating expectations.

Model (3) replaces *ExpectationsStated* with the *InstalledBaseDisclosed* indicator, and model (4) does the same while including all controls. The coefficient estimated on *InstalledBaseDisclosed* is statistically zero. Including *ExpectationsStated* and *InstalledBaseDisclosed* at once, as in models (5) and (6), leads to the same coefficient estimates as when estimating them separately. Therefore, these results confirm that statements about expectations had a causal effect on participation.

[9] All reported probit models generate similar patterns if estimated as linear probability models.

<Table 2>

3.2. How Does Stating Different Levels of Expectations Affect Adoption?

This section evaluates whether stating different scenarios for future installed base affected platform participation. Model (1) of Table 3 includes *ExpectationsStated* and adds first and second-order polynomial terms for numbers of expected users and expected companies stated. Coefficient estimates indicate a positive concave relationship between participation and *ExpectedNumUsers,* and a negative convex relationship between the participation and *ExpectedNumCompanies*. Estimates are insensitive to the inclusion of model controls or not, or inclusion of the current installed base, as in model (3). Consistent with Table 3 results, coefficients on the current installed base are insignificant, as in models (2) and (3).

Table 4 presents the relationship re-estimated with the different expectations scenarios specified as dummies in a linear probability model to reveal effect magnitudes explicitly. Controlling for the current installed base measures or not, as in models (1) and (2), finds similar results.[10] The negative convex relationship with *ExpectedCompanies* is driven by higher adoption in the lowest scenario (10 companies expected). The positive concave relationship with *ExpectedNumUsers*, also reported graphically in Figure 3, shows that stating the lowest scenario (2,500 users) leads to statistically lower participation than making no statement at all. Point estimates increase with higher scenarios, but with large confidence intervals.

<Table 3>

<Table 4>

<Figure 3>

[10] Controls are not included in this most flexible specification, as they lead to large standard errors.

3.3. Validation of Interpretation

The significant effects of statements of expectations might be capturing a response to a statement of large scale per se. To check this possibility, all prior models were re-estimated with a variable capturing an objective indication of market scale. This is an indicator switched on for statement (3): "The university community comprises 20,000 students, 200,000 alumni, and 2,000 staff and professors. There are also 4,000 affiliated companies." I find that being randomly assigned to receive this statement has statistically zero effect on participation rates and does not alter prior results. Therefore, the analysis of expectations does not appear to be capturing scale of the potential market, but rather expectations of what those in the potential market might choose to do.

Similarly, an indicator variable associated with the statement, "This is an invitation for early adopters," was found to be insignificant. This is consistent with subjects receiving these invitations already being well aware of the early stage of adoption without further prompting.

3.4. Is the Market More Susceptible to Focal Cues in Early Periods?

The theory suggests that subjective expectations are most important in early market coordination. To assess this possibility, I compare estimates when the stated installed base exceeds 1,000 users or not.

The breakpoint of 1,000 users first requires justification given that earlier models did not detect a relationship with *NumCurrentUsers*. To more closely scrutinize this relationship, I re-estimate the relationship with each level of *NumCurrentUsers* as a dummy in a linear framework, reported in Figure 4.

Individual coefficients are mostly insignificant. Nonetheless, statistical facts appear in the results. For example, participation is lower with the lowest levels of disclosed installed base than when stating nothing at all (analogous to earlier results, related to stating user expectations).

Most relevant to the breakpoint choice, each point estimate of coefficients for 1,000 users or greater has a higher value than the point estimate for not stating the installed base at all. If these values after 1,000 users were in fact the same as those when not stating the installed base, the likelihood of observing this pattern would be (½)^21—or virtually zero.

<Figure 4>

Models (1) and (2) of Table 5, therefore, compare model estimates for those cases in which the disclosed installed base exceeded 1,000 versus not. Consistent with the theory, expectations terms become insignificant, where the stated installed base exceeded 1,000 users.

<Table 5>

3.5. Does Stating Expectations Affect Heterogeneity of Responses?

Here I investigate whether statements of the expected future or disclosed current installed base affected variance in outcomes. I re-estimate the probit model, allowing for model variance to vary as $\sigma_i^2 = \{\exp\,(\gamma_0 + \gamma_1 ExpectationsStated_i + \gamma_2 InstalledBaseDisclosed_i)\}^2$, where γ terms are parameters. The variance parameters, along with main model, are estimated simultaneously using maximum likelihood.

Mean model estimates are unaffected by this alternative specification. Table 6 reports the variance model estimates. As in model (1), stating the current true installed base lowers variance, all else being equal. Stating subjective expectations increases variance. Similar results are found when allowing mean model terms to interact with an indicator for greater than 1,000 users, as in model (2), or when estimating each variance coefficient in separate models.

<Table 6>

4. Discussion of Results

This section discusses the findings reported in the preceding section.

4.1. Subjective Expectations are Crucial in Earliest Periods of Takeoff

The results include an array of patterns that are each consistent with the theory's predicted role of subjective expectations in the earliest periods of platform launch. Exposing individuals to statements of expectations of the future installed base shifted adoption rates by one-fifth relative to average levels (Section 3.1). The effect of expectations was more significant than disclosing the actual installed base size during early takeoff (Sections 3.1 and 3.2). The large causal effects of statements of expectations ceased to be significant once the disclosed installed base grew past 1,000 users (Section 3.4).

The statements of expectations to which adopters responded were themselves highly subjective and uncertain (varying between low and high scenarios by a factor of 10X) (Section 2.3.1). Nonetheless, adoption rates varied systematically according to the scenario to which individuals were exposed (Section 3.2).

Also consistent with subjective heterogeneous responses to these statements, exposing individuals to statements of expectations led to increased variance in the estimation model (Section 3.5). (By contrast, disclosures of the true current installed base reduced variance, consistent with converging expectations.)

4.2. Self-Fulfilling Expectations and the Chicken-and-Egg Problem

The shifts in adoption rates with expected future users' statements are also consistent with the long-theorized chicken-and-egg problem (see Section 1). Stating low expectations for future users caused lower adoption than stating nothing at all. Stating low current users caused lower adoption than stating nothing at all (Section 3.2 and Figure 4). It appears it is better for the platform to allow uncertainty to linger rather than to alleviate uncertainty in a way that confirms a platform has or expects few users. Also consistent with self-fulfilling expectations, stating either optimistic expectations of the number of users or stating high numbers of current users results in higher adoption than does stating lower numbers (Section 3.2).

When stating high user expectations, rates of adoption do not rise to a level of becoming statistically different from those when stating no expectations at all within the observed variation here. It remains a question whether stating still higher expectations or perhaps otherwise making more persuasive statement could have led adoption to become statistically higher. When stating high numbers of existing users, adoption rates statistically exceeded those when not stating anything.

Thus, these results lend support to longtime untested claims of focal expectations shaping platform takeoff (e.g., Farrell and Saloner 1985, Katz and Shapiro 1985, Farrell and Klemperer 2007, Hagiu and

Halaburda 2011, Suleymanova and Wey 2012, Zhu and Iansiti 2012, Halaburda and Yehezkel 2018, Halaburda et al. 2020).

These results, summarized in this subsection and the earlier subsection 4.1 reflect tests of general theory regarding platform adoption in a context of multiple equilibria and a market coordination problem. Therefore, these results should generalize to relatively typical platform conditions, i.e.: where user benefits come mostly from network effects (rather than stand-alone benefits), where adoption is costly, and potential adopters are not able to explicitly coordinate their adoption decisions.

4.3. Negative Cross-Side Interactions in a Collaborative Contest Platform

The analysis also found negative cross-side interactions between user adoption and expected numbers of companies (Section 3.2). This result adds to prior findings of negative network effects (e.g., Church and Gandal 1992, Economides 1996, Augereau et al. 2006, Tucker and Zhang 2010), and is notable for being consistent with the platform's institutional design, supporting collaborative challenges.

A negative cross-platform network effect in this context is consistent with the addition of more companies effectively splitting-up users across multiple challenges, with the effect of reducing users' ability to find and collaborate with others. This result is also consistent with users possibly preferring that the platform emphasize users' learning, development, and community networking (Section 2), rather than emphasizing problem-solving for companies.

4.4. The Ability of a Platform to Influence Expectations

While this study's primary thrust was to test the role and nature of expectations in shaping platform takeoff, the research design approach was to *influence* expectations. That expectations could be influenced—at all—much less by the platform, is a novel and consequential finding. Particularly, we find that simple, subjective, uncommitted, and costless ("cheap talk") statements broadcasted by the platform could influence market expectations in early platform takeoff. The generalizability of this result and the ability and means for other platforms to similarly influence expectations depends on the underlying mechanisms. Here, I speculate on three plausible explanations.

Statements Serve* as *Coordinating Devices? A first possibility, closest to the theory, is that the platform's statements served as focal cues and coordinating devices (Schelling, 1962; Mehta, 1994; Sitzia and Zheng, 2019). For example, adopters could have made adoption decisions under the expectation that some fraction of others would act in accordance with the broadcasted statements. This interpretation presumes that (i) the statements were deemed highly focal by adopters, and (ii) adopters engaged in higher-order reasoning to assess and respond to others' expected behavior.

This explanation of the salience of platform's statements leading to some measure of coordinated decisions is closest to the theory (Section 1). It is akin too to findings from coordination games in the lab, in which labels and language to describe alternative actions have been shown to significantly increase the likelihood of coordination (e.g., Mehta et al. 1994a, Bacharach and Bernasconi 1997, Parravano and Poulsen 2015). In this light, the current results might be likened to prior characterizations of platforms as a leader with a coordinating role within their "ecosystems" (Boudreau, 2017; Boudreau and Hagiu, 2009; Gawer and Cusumano, 2002).

Statements Serve* as *Information? An alternative explanation is that users perceived the platform's statements as genuinely informative, at least to some degree, and users respond accordingly. This interpretation requires that (i) the platform indeed had private information on future adoption (despite the fundamental uncertainty of market coordination) and (ii) potential users had some basis to believe the platform's statements were credible (otherwise users might expect a platform will always make optimistic statements).[11]

In this context, perhaps users believed the platform's central network position between alumni and students led adopters to think the platform was able to carry out meaningful market research.[12] (This was

[11] The long tradition of research on cheap talk and coordination games (e.g., Crawford and Sobel 1982, Farrell and Rabin 1996) shows that a player in a coordination game can send a no-cost, uncommitted, and unverifiable message to induce others to coordinate on a particular choice—so long as players' interests are somewhat aligned. However, in this context, the platform is not a player in the game, but effectively a third-party observer of market coordination.
[12] Strictly speaking, the communication of adopters' intent to a platform with market research involves a similar problem of sending a credible message regarding uncommitted future choices.

not true in this case, and the true high degree of uncertainty of platform developers was reflected in the wide-ranging scenarios described in Section 2.3.) In this context, users could also anticipate that the platform would disclose information truthfully. The platform both had a valuable reputation to uphold and, as a university, would act in the interest of students and alumni. Indeed, strenuous efforts were made to avoid deception (Section 2).

Statements Serve as Persuasion? A third explanation is that boundedly rational adopters responded to plausible statements at face value. They were persuadable and indeed persuaded, despite the absence of a fully rational basis for accepting the statements as truly informative. This interpretation might be especially relevant in early market coordination with (i) an ambiguous and uncertain decision environment, and in which (ii) potential adopters are perhaps boundedly rational and susceptible to persuasion.[13]

In this context, for example, the credulity of adopters could have been influenced by plausible statements coming from a sociologically legitimate authority—a university-sponsored platform. Outside of this context, this interpretation implies there could be considerable scope for talented and charismatic communicators and storytellers to deploy rhetoric and moral suasion to generate optimistic beliefs within an ambiguous decision environment.

5. Conclusion

Central to platform adoption theories is the idea that market expectations can play a role in determining whether a new platform venture takes off or not. This paper implemented a first systematic empirical investigation of the causal role of expectations in the launch of platform ventures. We investigated this question using a field experiment embedded in the launch campaign of a platform for a collaborative hackathon, during which the platform grew to several thousand users.

The study's results of Section 3 and summarized in Section 4 confirm a series of patterns that are consistent with subjective expectations playing a crucial role in the earliest platform growth and takeoff.

[13] Large literatures on persuasion point to a range of behavioral, cognitive, economic, and socio-psychological mechanisms that far exceed the scope of this study.

Also consistent with theory, the patterns are consistent with the existence of a chicken-and-egg problem in early adoption and that expectations can be self-fulfilling. Optimistic expectations of the future installed base of users might help overcome this problem and negative expectations will deter adoption. In this particular instance, the platform's stating nothing regarding the future installed base of users was more helpful to stimulating growth than stating low expectations

Perhaps most important of all, I found—in this context—that simple, subjective, uncommitted, and costless ("cheap talk") statements broadcasted by the platform could influence market expectations in early platform takeoff. In Section 4, I speculated on the mechanisms underlying this finding, suggesting that platform's statements could work as a coordinating device, as information, or as persuasion. Better understanding these mechanisms and the extent to which other platforms might influence expectations—and how—remains an area of much needed future research.

The findings here imply important implications for managers, investors, entrepreneurs, and marketers. Platform growth and takeoff involves more than just acquiring adopters one-at-a-time; to succeed in takeoff, a platform must coordinate multiple adopters to join the platform, at once, under most typical circumstances. Influencing the market's focal expectations of the future installed base's size is a means of getting this done. Consistent with the findings, leading platforms often use media and events to socialize optimistic commonly-shared narratives of the future (see, for example, Lucas-Conwell 2006, Kawasaki 2015) and pessimistic narratives about competitors (Pfaffenberger 2000, Raymond 2001, Egyedi and Hommels 2019). This emphasis on nuanced issues of shaping beliefs and expectations (Section 4.4) may explain why 2,330 chief marketers on Linkedin now describe themselves as "chief evangelists."

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Table 1. Summary Statistics

Variable	Mean	Std. Dev.	Description
Participation	0.05	0.21	Indicator variable switched to one where the individual chooses to join the platform
ExpectationsStated	0.68	0.47	Indicator variable switched to one for individuals receiving an invitation that included some message of expectations
ExpectedNumUsers	11,304	10,414	The number of users contained in the statement of expectations, for invitations containing expectations
ExpectedNumCompanies	34.43	37.39	The number of companies contained in the statement of expectations, for those invitations containing invitations
InstalledBaseDisclosed	0.44	0.50	Indicator variable switched to one for individuals receiving an invitation that included a disclosure of current installed base
CurrentNumUsers	674	981	The number of users on the platform contained in the disclosure of current installed base
CurrentNumCompanies	8.08	13.12	The number of companies on the platform contained in the disclosure of current installed base
Engineering	0.62	0.49	Undergraduate degree in engineering
ComputerScience	0.11	0.31	Undergraduate degree in computer science
Sciences	0.27	0.44	Undergraduate degree in sciences
GraduationYear	2000	18	Year of graduation
Student	0.10	0.29	Not yet graduated college
GraduationYear	0.33	0.47	Indicator switched on if field is computer science, engineering, or sciences
Female	0.29	0.46	Gender indicator switched to one for female

Note. Number of observations = 16,349.

Table 2. Probit Estimates of Effects of Stating Expectations

Dep. Var.:	*Participation*					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Installed Base Communications						
ExpectationsStated	−0.089**	−0.090**			−0.088**	−0.087**
	(0.04)	(0.04)			(0.04)	(0.04)
InstalledBaseDisclosed			−0.02	−0.03	−0.01	−0.01
			(0.03)	(0.04)	(0.04)	(0.04)
Individual Characteristics						
ComputerScience		0.336***		0.334***		0.336***
		(0.06)		(0.06)		(0.06)
Engineering		0.193***		0.194***		0.193***
		(0.05)		(0.05)		(0.05)
GraduationYear		0.023***		0.023***		0.023***
		(0.00)		(0.00)		(0.00)
Female		−(0.02)		−(0.02)		−(0.02)
		(0.04)		(0.04)		(0.04)
Other Controls						
Day		−0.01		−0.01		−0.01
		(0.01)		(0.01)		(0.01)
Day^2		0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)
Tuesday		−0.02		−0.02		−0.02
		(0.06)		(0.06)		(0.06)
Wednesday		0.06		0.06		0.06
		(0.05)		(0.05)		(0.05)
Thursday		−0.102*		−0.102*		−0.102*
		(0.06)		(0.06)		(0.06)
Friday		−0.09		−0.09		−0.09
		(0.06)		(0.06)		(0.06)
Month = Sept		0.11		0.12		0.11
		(0.08)		(0.08)		(0.08)
Month = Oct		0.05		0.06		0.05
		(0.14)		(0.14)		(0.14)
Constant	−1.634***		−1.683***		−1.630***	
	(0.03)		(0.02)		(0.03)	
Log-Likelihood	−3007	−2787	−3010	−2790	−3007	−2787

Note. Probit model coefficient estimates; standard errors are in parentheses.
Number of observations = 16,349.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 3. Probit Estimates of Effects of Different Levels of Expectations

Dep. Var.:	*Participation*		
Model:	(1)	(2)	(3)
Installed Base Communications			
ExpectationsStated	−0.09	−0.087**	−0.09
	(0.12)	(0.04)	(0.12)
ExpectedNumUsers [000s]	0.041**		0.041**
	(0.02)		(0.02)
ExpectedNumUsers^2	−0.001**		−0.001**
	(0.00)		(0.00)
ExpectedNumCompanies	−0.011**		−0.012***
	(0.00)		(0.00)
ExpectedNumCompanies^2	0.0001***		0.0001***
	(0.00004)		(0.00004)
InstalledBaseDisclosed	−0.01	−0.01	0.00
	(0.04)	(0.10)	(0.10)
CurrentNumUsers [000s]		−0.10	−0.13
		(0.25)	(0.26)
CurrentNumUsers^2		0.03	0.03
		(0.10)	(0.10)
CurrentNumCompanies		0.01	0.01
		(0.02)	(0.02)
CurrentNumCompanies^2		−0.0002	−0.0002
		(0.0005)	(0.0005)
Individual Characteristics & Other Controls			
Field Dummies	Y	Y	Y
GraduationYear Trend	Y	Y	Y
Female Dummy	Y	Y	Y
Time Controls	Y	Y	Y
Log-Likelihood	−2783	−2787	−2783

Note. Probit model coefficient estimates; standard errors are in parentheses.
Number of observations = 16,349.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 4. OLS Dummy Estimates of Effects of Levels of Expectations

Dep. Var.:	*Participation*	
Model:	(1)	(2)
Expected Installed Base = not stated	0.051***	0.051***
	(0.003)	(0.003)
ExpectedNumUsers = 2,500	0.022**	0.022**
	(0.010)	(0.010)
ExpectedNumUsers = 10,000	0.038***	0.039***
	(0.003)	(0.004)
ExpectedNumUsers = 25,000	0.043***	0.040***
	(0.004)	(0.005)
ExpectedNumCompanies = 10	0.021***	0.021***
	(0.007)	(0.007)
ExpectedNumCompanies = 25	-0.003	-0.003
	(0.006)	(0.006)
ExpectedNumCompanies = 100	Excluded	Excluded
Quadratic Installed Base Terms		Y
Adjusted-R^2	0.046	0.046

Note. OLS model coefficient estimates; standard errors are in parentheses.
Number of observations = 16,349.
Model (2) estimates are used in Figure 3.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 5. Effects of Influencing Expectations in Earliest vs. Later Periods

Dep. Var.:	*Participation*	
	Current Users <1,000	*Current Users ≥1,000*
Model:	(1)	(2)
Installed Base Communications		
ExpectationsStated	−0.055	−0.149
	0.128	0.336
ExpectedNumUsers [000s]	0.053**	−0.073
	(0.022)	(0.070)
ExpectedNumUsers^2	−0.002***	0.002
	(0.001)	(0.002)
ExpectedNumCompanies	−0.016***	0.019
	(0.005)	(0.015)
ExpectedNumCompanies^2	0.0001***	−0.0002
	(0.0000)	(0.0001)
Individual Characteristics & Other Controls		
Field Dummies	Y	Y
GraduationYear Trend	Y	Y
Female Dummy	Y	Y
Time Controls	Y	Y
Log-Likelihood	−1976	−796

Note. Probit model coefficient estimates; standard errors are in parentheses.
Number of observations = 16,349. Number of observations = 4,985 where current users ≥ 1,000. Cases of current users < 1,000 include observations in which the current installed base was not disclosed.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 6. Parametric Variance Estimates

Dep. Var.:	*Participation*	
Model:	(1)	(2)
Parameterized Variance Model		
ExpectationsStated	0.215*	0.255**
	(0.110)	(0.126)
InstalledBaseDisclosed	−0.187*	−0.251**
	(0.098)	(0.122)
Conditional Mean Probit Model		
Quadratic ExpectationsStated	Y	Y
× *I{Current Users <1,000}*		Y
Quadratic InstalledBaseDisclosed	Y	Y
× *I{Current Users <1,000}*		Y
Field Dummies	Y	Y
GraduationYear Trend	Y	Y
Female Dummy	Y	Y
Time Controls	Y	Y
Log-Likelihood	−2,780	−2,775

Note. Probit model coefficient estimates; standard errors are in parentheses.
Number of observations = 16,349. Number of observations = 4,985 where current users ≥ 1,000. Cases of current users < 1,000 include observations in which the current installed base was not disclosed.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Figure 1. Subject Characteristics Across Days of the Campaign

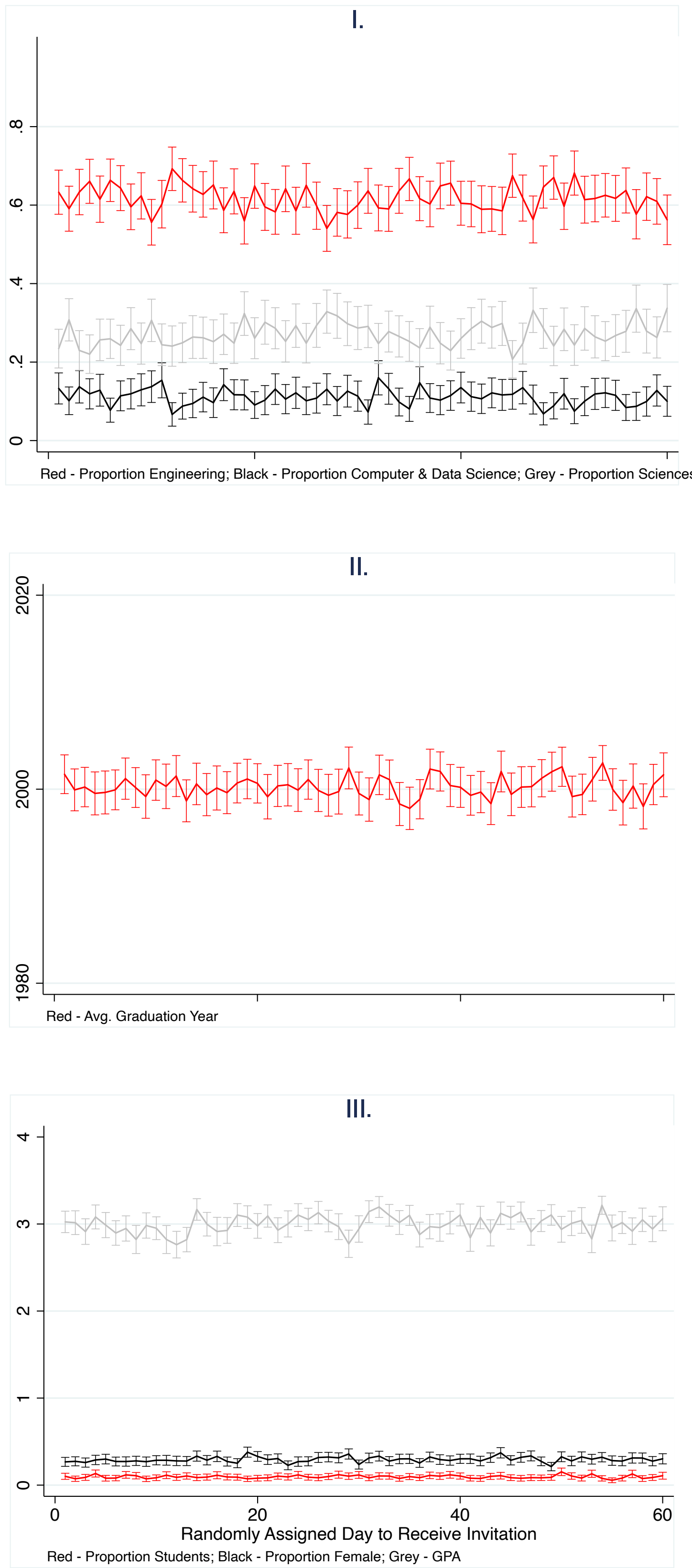
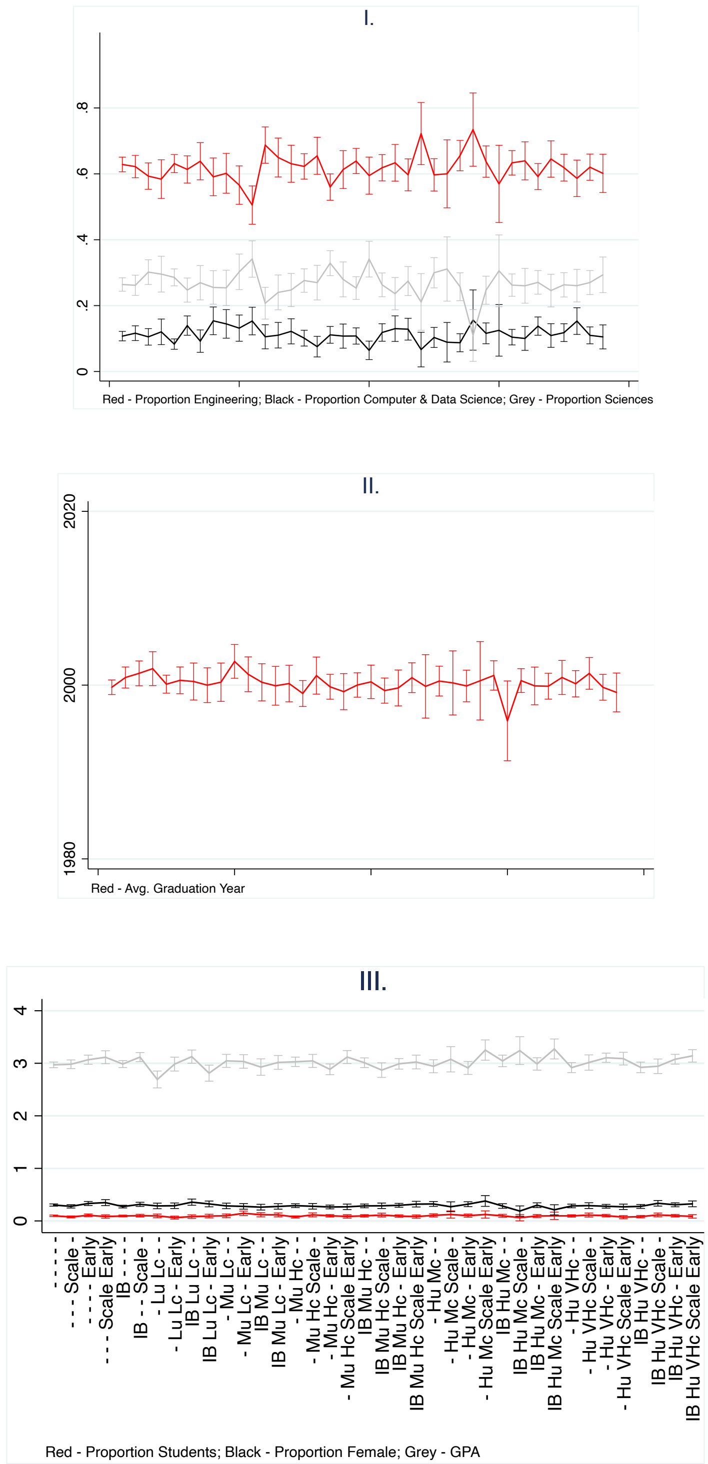
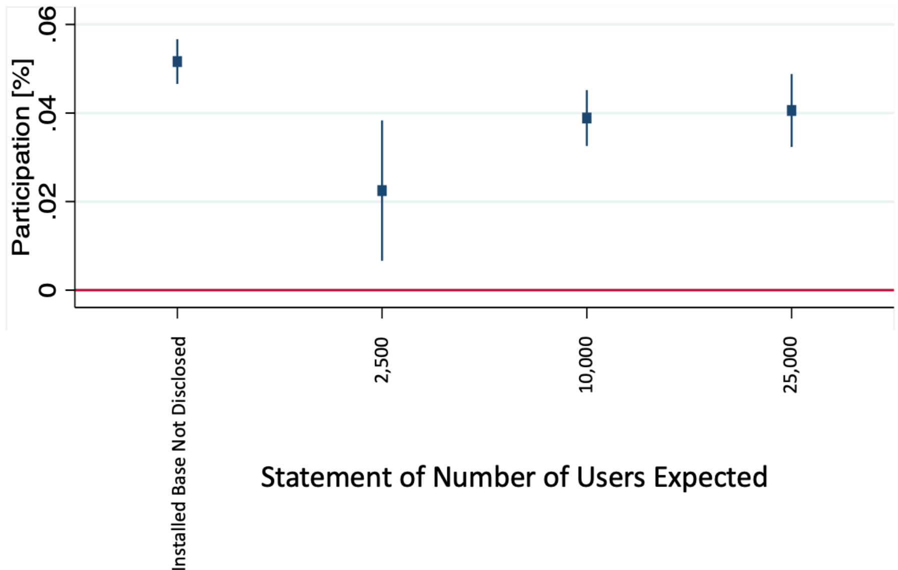


Figure 2. Subject Characteristics Across Treatments



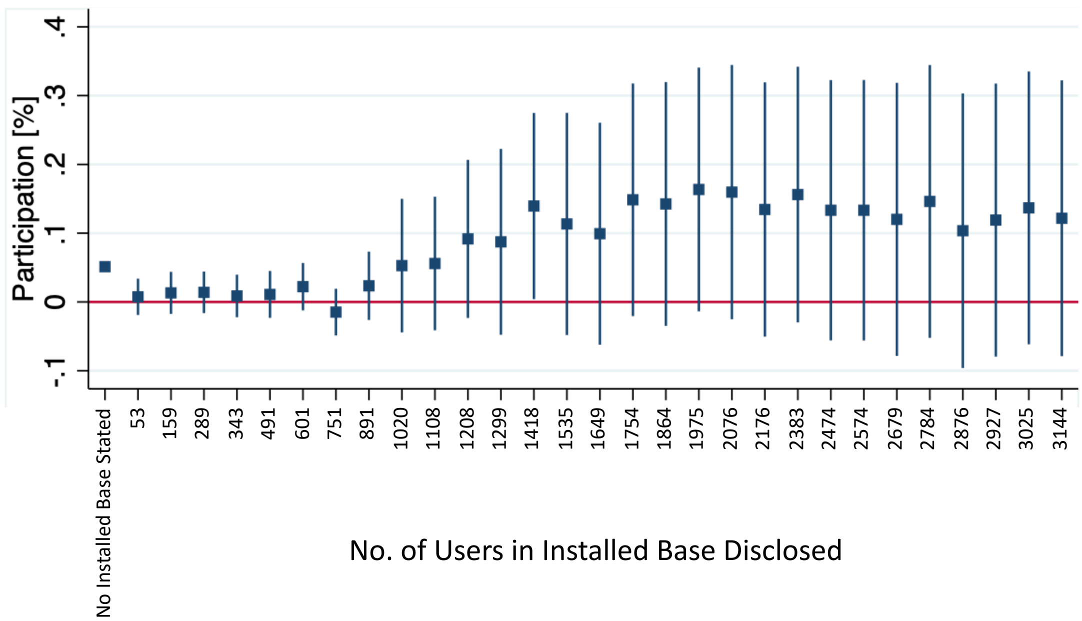
Note. The treatment codes in the x-axis of panel III correspond to the following order of codes: current installed base disclosed or not (level varies by day), user expectations scenario, company expectations scenario, scale statement, early adopter statement (Section 2.2).

Figure 3. Effect of Messaging Expected Installed Base



Note. Estimates presented here are based on model (3) in Table 3, re-estimated with individual dummies for levels of the installed base of users, as a linear probability model to facilitate interpretation. The 95% confidence interval is based on robust standard error estimates.

Figure 4. Effect of Disclosing Current Installed Base



Note. Estimates presented here are based on model (3) in Table 3, re-estimated with individual dummies for levels of the installed base of users, as a linear probability model to facilitate interpretation. The 95% confidence interval is based on robust standard error estimates.

APPENDIX A: Building on Tucker & Zhang (2010) Framework

	Tucker and Zhang (2010)	The Current Study
Research Question	• Effect of disclosing the current installed base on platform adoption in a mature platform	• Effect of stating expectations of future installed base during initial takeoff (Controlling for disclosing the current installed base)
Research Context	• Large, Chinese B2B intermediary platform, connecting B2B buyers and sellers (240,000 clicks per day); focus is on one city • Focus on sellers' decisions • Study 3,314 instances of sellers who initiate new listings (observe whether they complete the listing, after starting) • Zero charge to make a listing (costs include the non-pecuniary hassle and effort to list)	• Newly launched collaborative hackathon platform connecting users with companies; begins with zero users, grows to several thousand • Focus on users' decisions • Study a risk set of 16,349 potential users (observe whether they join or not) • Zero charge for participating (costs include non-pecuniary hassle and effort to list, plus 3-week participation)
Experimental Protocol	• Immediately after inbound seller chooses a product category to submit listing, platform discloses the current installed base • Randomize whether current installed base is disclosed (no. sellers, no. buyers, both, or neither) • Generate random number of sellers or buyers from 1–200 • Observe outcome of whether listers complete listing or not	• Platform invites targeted individuals to join; message includes expected future installed base (and disclosure of current installed base) • Randomize whether expectations of future installed base are stated • Randomize whether current installed base is disclosed • Generate numbers of expected and/or current users and companies according to procedure described in Section 2 • Observe outcome of whether potential users join (or not)
Data	• 3,314 instances of inbound listings over roughly 2 months • IP address, time stamp, good category, treatment, listing completed or not	• 16,349 invited individuals over roughly 2 months • Individual identifier, characteristics, time stamp, treatment, joined platform or not
Model	*Prob{Lister Completes the Listing} = f(Current Installed Base | Time, Listing Category, Number of Previous Listings)*	*Prob{New User Joins} = f(Expected Future Installed Base | Current Installed Base, Time, Individual Characteristics)*

APPENDIX B: Invitation to the Platform

Hi <NAME>,

We are reaching out to invite you to the university's new Internet of Things (IoT) Open Innovation platform linking our students, alumni, staff, faculty, and affiliated companies.

This is a two-sided **collaborative platform** to ideate and innovate "smart" IoT products and services using hardware, software, networking, data, and algorithms.

On one side of the platform, companies seek solutions to their IoT innovation challenges. On the other side, **you will work within a team to solve companies' IoT innovation problems** for cash and other benefits.

<Note: Treatments include subsets of the following points:>

- We expect <#> users and <#> companies to join this year.
- To date, <#> users and <#> companies have joined.
- This is an invitation to early adopters.
- The university community comprises 20,000 students, 200,000 alumni, and 2,000 staff and professors. There are also 4,000 affiliated companies.

Affiliated companies, including your employer, can request to launch new challenges, harnessing the network's diverse knowledge of industry and consumer use cases, technical skills (e.g., hardware, software, data, algorithms, network, cloud, and user interface), design thinking, and commercial planning capabilities. Interested in joining this platform? Click here to learn more and sign up.

(This invitation is not transferable and should not be forwarded.)