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Promoting Platform Takeoff and Self-Fulfilling Expectations: Field Experimental Evidence

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Abstract. A platform might have the potential to bring enormous value to its users. However, without a well-orchestrated launch strategy that coordinates a sufficient number of users onto the platform, this potential will not be realized. The theoretical literature predicts that one approach to coordinating platform take-off is to influence the market's subjective focal expectations of the future installed base of users. This paper reports on a field experiment investigating the causal role of subjective expectations in the launch of a new platform venture, in which invitations to join a newly launched platform were sent to 16,349 individuals. The invitations included randomized statements regarding the size of the future expected installed base (along with disclosures of the current installed base). I find that simple, subjective, uncommitted, and relatively costless statements broadcasted by the platform with the goal of influencing market expectations were indeed able to influence platform takeoff and overcome an initial chicken-and-egg problem. These broadcasted subjective statements regarding future installed base had a larger influence on adoption rates than did disclosures of the true current installed base during early adoption. However, these subjective statements of expected future installed base ceased to have any effect once the true current installed base grew large. I discuss implications for the promotion, marketing, and evangelism of new platform ventures.

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1. Introduction

Society now relies on online platforms as basic 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 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 (Katz and Shapiro 1985). Shapiro and Varian (1999, p. 31) 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, p. 118) specify that "expectations about the ultimate size of a network are crucial." How or whether subjective market expectations might be practically influenced has yet received little empirical testing or investigation. This study tests the theory and investigates the influence of expectations using a large-scale field experiment.

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 strong network effects, a consumer's best decision is to do what others do. The theory implies a large-scale coordination problem (Schelling 1960),

Table 1. Simple Game Theoretic Illustration of Market Adoption with Network Effects

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

whereby potential adopters will be best off if they can coordinate on an equilibrium of each adopting the platform or, alternatively, an equilibrium of each *not* adopting the platform or each not doing so.

To illustrate this point with a simple example, consider a market with two potential adopters: A and B. Let the cost of adopting a platform be say \$1. If the benefits of adopting come from network effects (rather than stand-alone benefits), then consider that adopters might enjoy say \$2 worth of benefits in the case that everyone adopts, or \$0 otherwise. There are two equilibria: everyone adopts and nobody adopts (see Table 1). Therefore, platform adoption can involve more than usual marketing and promotion, it can require shifting or coordinating the multiple actors in a market from one equilibrium to another. (In cases of competing platforms, this idea extends to adopting one platform or another or none at all.)

Expectations are theorized to play a central role in shaping choices where adopters cannot explicitly coordinate or communicate with one another. The multiplicity of possible equilibria creates fundamental uncertainty about what others will do and which outcome will eventually emerge. Accordingly, adopters cannot "look forward and reason back" as in usual rational expectations, and therefore expectations about future adoption are necessarily subjective. Consequently, conventional means of influencing rational expectations—for example, economic signaling and precommitments—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 simply defined as the choice to which most people default and which individuals expect others will choose (Schelling 1960, Mehta et al. 1994). Therefore, focality and expectations are closely intertwined.

The platforms literature is silent on how focal expectations are formed or influenced. Instead, theorizing in this literature has proceeded by presuming consumers follow some focal rule. Most models presume, for example, that consumers choose the economically efficient outcome (Farrell and Klemperer 2007).[3] In contrast, discussions of chicken-and-egg problems often presume that consumers tend toward nonadoption, as a default. More recent advances have begun to consider the competitive implications of alternative focal rules, 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 modeling network effects have taken the approach of specifying adoption as a function of the current or lagged installed base within a static framework.[4] Several exceptional studies estimate models with perfectly forward-looking consumers (Dubé et al. 2005, Rysman et al. 2011, Ryan and Tucker 2012). Each of these approaches should be better suited to analyzing and modeling mature markets that have already begun to converge toward one equilibrium or another.

Therefore, the theorized role of subjective expectations in coordinating earliest adoption remains untested and many practical questions remain. How are early expectations of future installed base formed? Can they be shaped? Can they be shaped by the a platform venture, itself? This study makes progress on these questions.

The findings in this paper finally provide empirical support of prior theoretical characterizations of platform adoption with network effects and a chicken-and-egg adoption problem, where subjective focal expectations have been hypothesized to play a central role. The results here also show that the platform venture could itself influence expectations by broadcasting relatively costless statements to the market. Thus, the findings shed light on a new generation of marketing and promotion tactics used by platform ventures—and raise new research questions regarding how these tactics geared to shifting subjective expectations can be optimized.

2. Research Design

This study builds on a small stream of field experiments studying platform adoption (Tucker and Zhang 2010, Bapna and Umyarov 2015, Sun et al. 2019).[5] In the current study, I instead observe a known risk set of 16,349 individuals who are invited to join a newly launched product development platform focused on the Internet of Things (IoT). I study how experimentally varying statements regarding the *expected future* size of the installed base affect the likelihood of adoption (while controlling for any effects of disclosing the *current* installed base). The experimental strategy features an approach that implements experimental treatments while maintaining truth-telling to all subjects.

2.1. Context

The product development platform in this study was created to serve alumni and students of a large U.S. university.[6] The platform mimics key features of today's in-person hackathons where people meet, exchange ideas, and design prototypes—but with the

Table 2. Summary Statistics

Variable	No. observations	Mean	Standard deviation	Description
Participation	16,349	0.05	0.21	Indicator variable switched to one where the individual chooses to join the platform
ExpectationsStated	16,349	0.68	0.47	Indicator variable switched to one for individuals receiving an invitation that included some message of expectations
ExpectedNumUsers	16,349	11.30	10.41	The stated expected number of users [000's] contained in the invitation, for those invitations containing expectations
ExpectedNumCompanies	16,349	34.43	37.39	The stated expected number of numbers of companies contained in the invitation, for those invitations containing expectations
InstalledBaseDisclosed	16,349	0.44	0.50	Indicator variable switched to one for individuals receiving an invitation that included a disclosure of the current installed base
CurrentNumUsers	16,349	0.67	0.98	The number of users on the platform [000s] contained in the disclosure of installed base, for those invitations containing this disclosure
CurrentNumCompanies	16,349	8.08	13.12	The number of companies on the platform contained in the disclosure of installed base, for those invitations containing this disclosure
Engineering	16,349	0.62	0.49	Indicator for undergraduate degree in engineering
ComputerScience	16,349	0.11	0.31	Indicator for undergraduate degree in computer science
Sciences	16,349	0.27	0.44	Indicator for undergraduate degree in sciences
GraduationYear	16,349	2000	18	Year of graduation
Student	16,349	0.10	0.29	Not yet graduated
Female	16,012	0.29	0.46	Sex indicator variable
Day	16,349	30.37	17.26	Count variable from 1 to 60 for each of the days in which invitations were sent (not including weekends and holidays)
Month	16,349	1.91	0.80	Count variable from one to three corresponding to the three months over which the experiment took place
dow	16,349	2.98	1.41	Count variable from one to five corresponding to weekdays

goal of achieving larger scale and giving accessibility to a wide range of students and graduates. 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 the data collection and networking of those elements. Collaborators can develop their own ideas or respond to challenges issued by the platform or companies. The platform has grown to more than 5,500 participants.

Similar to the context studied by Tucker and Zhang (2010), users were not charged to participate on the platform but may experience nonpecuniary costs in the process of learning about the platform and signing up. Furthermore, within this context, signing up implies an 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 after launch. Ensuring many users was vital because the platform depends on interactions among users and the ability to form 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. The risk set of potential adopters to be studied was identified before executing the experiment, allowing both adoption and nonadoption to be recorded. 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).[7] Table 2 summarizes characteristics of this group. (Data on sex were available for 16,012 individuals rather than the entire 16,349.)

2.2.2. Invitations to Join the Platform. Each participant received an email invitation to join the platform (see appendix) 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 the platform to learn more and to consider joining.

2.2.3. Platform Sign-Up. Those clicking-through from the email to the platform encountered a brief description of the technical nature of IoT and a description of the collaborative development on the platform. Apart from fostering interactions, it was also mentioned that the platform supported learning new skills, networking within the university community, and the possibility of winning cash prizes. The platform also presented a prominent "join and participate" button and could sign-in to become a member using their LinkedIn credentials. LinkedIn Application Programming Interface–accessible information and photographs then auto-populated their platform member profiles.

2.3. Treatments and Random Assignment

Experimental treatments were implemented within the invitation to join (see appendix) by varying whether several statements appeared or not and the specific content of those statements:

1. Expectation statement: "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 forecasted scenarios of the platform developers. In related to users, these scenarios included: 2,500 (low scenario), 10,000 (medium scenario), and 25,000 (high scenario) users. For companies, these scenarios included: 10 (low scenario), 25 (medium scenario), 40 (high scenario), and 100 (very high scenario) companies.[8] Apart from either stating expectations or not within invitations, independent variation in numbers of expected users and expected companies was generated by combining different scenarios. Platform developers decided 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.

2.3.2. Disclosures of Current Installed Base. To avoid making misleading statements of current numbers of users, disclosures were based on the true numbers of users across the 60-day campaign. To acquire a nonarbitrary number of companies, users were asked whether their companies would likely sponsor a challenge. To generate independent variation in numbers of users and companies, these values were each intermittently and alternately updated from day to day to ensure multiple numbers of users for each number of companies and vice versa.

2.3.3. Random Assignment Procedure. Random assignments to treatments were performed by the platform developers based on the following principles. Individuals in the study group were first randomly assigned to receiving invitations across the 60 days of the campaign. For each day, individuals were randomly assigned to receive a statement of expectations of the future installed base (statement 1) or not and a disclosure of the current installed base (statement 2) or not. 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.

2.4. Randomization Check

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.

3. Results

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

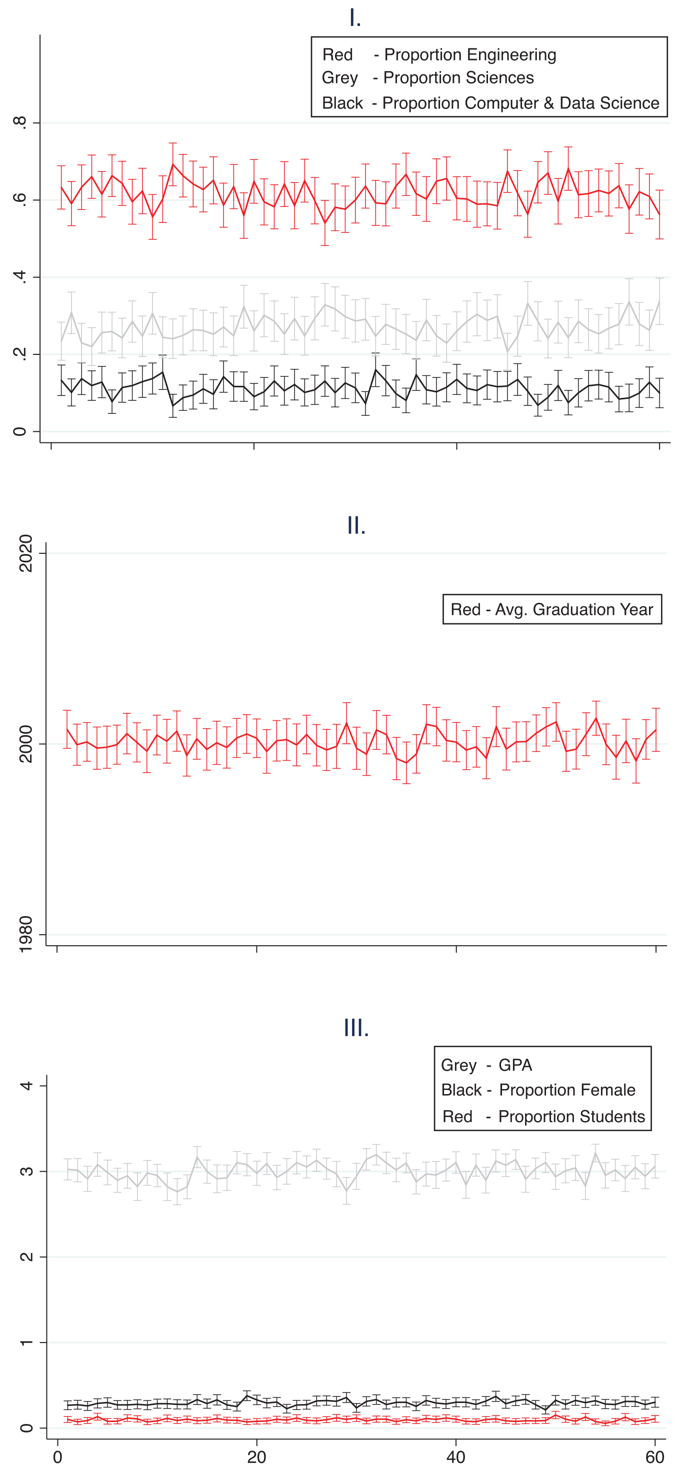
A probit model of the following form is estimated to relate the decision to adopt or participate on the platform and the experimental treatments[9]:

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

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 2). The model is estimated by maximum likelihood.

Model 1 of Table 3 reports model 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.

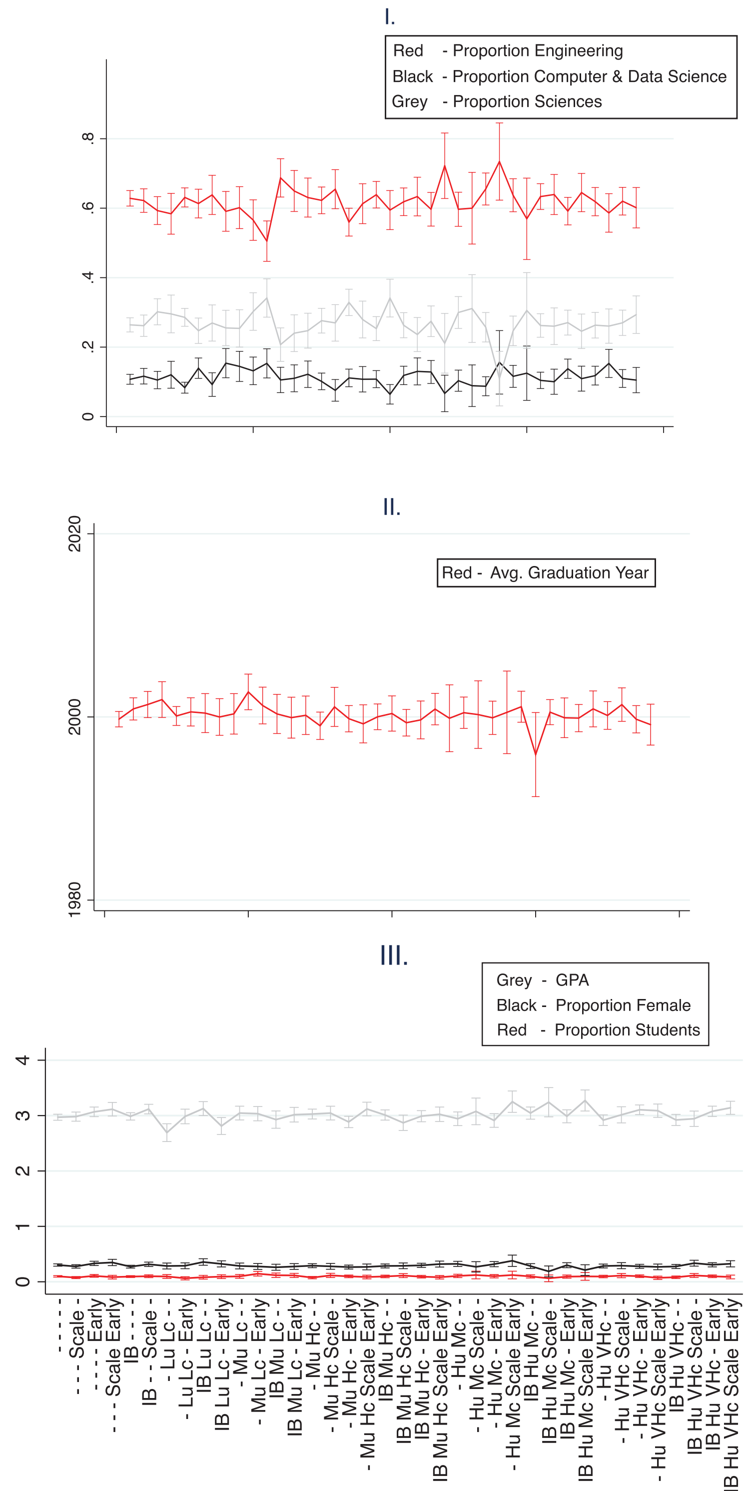
Figure 1. (Color online) Subject Characteristics Across Days of the Campaign



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

Figure 2. (Color online) Subject Characteristics Across Treatments



Note. The treatment codes in the *x* axis of (c) 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, and early adopter statement (Section 2.2).

in models 5 and 6, leads to the same coefficient estimates as when estimating them separately. These results confirm that statements about expectations had a causal effect on participation.

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.

Table 3. Probit Estimates of Effects of Stating Expectations

	Dependent variable: *Participation*					
	(1)	(2)	(3)	(4)	(5)	(6)
Installed base communications						
ExpectationsStated	−0.089**	−0.090**			−0.088**	−0.087**
	(0.036)	(0.038)			(0.036)	(0.039)
InstalledBaseDisclosed			−0.023	−0.025	−0.011	−0.014
			(0.034)	(0.036)	(0.035)	(0.037)
Individual characteristics						
Computer Science		0.336***		0.334***		0.336***
		(0.059)		(0.059)		(0.059)
Engineering		0.193***		0.194***		0.193***
		(0.046)		(0.046)		(0.046)
GraduationYear		0.023***		0.023***		0.023***
		(0.002)		(0.002)		(0.002)
Female		−0.020		−0.018		−0.020
		(0.041)		(0.041)		(0.041)
Other controls						
Day		−0.009		−0.009		−0.009
		(0.006)		(0.006)		(0.006)
Day^2		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)
Tuesday		−0.017		−0.016		−0.017
		(0.056)		(0.056)		(0.056)
Wednesday		0.059		0.059		0.059
		(0.054)		(0.054)		(0.054)
Thursday		−0.102*		−0.102*		−0.102*
		(0.060)		(0.060)		(0.060)
Friday		−0.085		−0.086		−0.085
		(0.057)		(0.057)		(0.057)
Month = Sept		0.111		0.116		0.112
		(0.083)		(0.083)		(0.083)
Month = Oct		0.051		0.055		0.051
		(0.138)		(0.138)		(0.138)
Constant	−1.634***		−1.683***		−1.630***	
	(0.029)		(0.023)		(0.031)	
Log-likelihood	−3007	−2787	−3010	−2790	−3007	−2787

Notes. Probit model coefficient estimates; standard errors are in parentheses. Number of observations = 16,349 (16,012 for models including *Female*).

Model 1 of Table 4 includes *ExpectationsStated* and adds first and second-order polynomial terms for numbers of expected users and expected companies. 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 inclusion of the current installed base, as in model 3. Consistent with Table 4 results, measures of the current installed base measures are insignificant, as in models 2 and 3.

To reveal effect magnitudes explicitly, Table 5 presents the relationship re-estimated with the different expectations scenarios specified as dummies in a linear probability model. Whether controlling for the current installed base measures or not, as in models 1 and 2, results are similar.[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.

3.3. Validation of Interpretation

To assess whether the significant expectations variables might simply be capturing adopters' responses to seeing large numbers associated with market potential—all prior models were re-estimated with a variable capturing an explicit indication of market scale. This is an indicator switched on for statement 3 mentioned in Section 2.3.1: "The university community comprises 20,000 students, 200,000 alumni, and 2,000 staff and professors. There are also 4,000 affiliated companies." I

Table 4. Probit Estimates of Effects of Different Levels of Expectations

	Dependent variable: *Participation*		
	(1)	(2)	(3)
Installed base communications			
ExpectationsStated	−0.091	−0.087**	−0.087
	(0.119)	(0.039)	(0.119)
ExpectedNumUsers [000s]	0.041**		0.041**
	(0.020)		(0.020)
ExpectedNumUsers^2	−0.001**		−0.001**
	(0.001)		(0.001)
ExpectedNumCompanies	−0.011**		−0.012***
	(0.004)		(0.004)
ExpectedNumCompanies^2	0.0001***		0.0001***
	(0.0000)		(0.0000)
InstalledBaseDisclosed	−0.012	−0.006	0.000
	(0.037)	(0.095)	(0.096)
CurrentNumUsers [000s]		−0.097	−0.125
		(0.254)	(0.255)
CurrentNumUsers^2		0.027	0.032
		(0.102)	(0.103)
CurrentNumCompanies		0.008	0.010
		(0.018)	(0.018)
CurrentNumCompanies^2		0.000	0.000
		(0.000)	(0.000)
Individual characteristics and other controls			
Field dummies	Yes	Yes	Yes
Graduation year trend	Yes	Yes	Yes
Female dummy	Yes	Yes	Yes
Time controls	Yes	Yes	Yes
Log-likelihood	−2783	−2787	−2783

Notes. Probit model coefficient estimates; standard errors are in parentheses. Number of observations = 16,012. Time controls include a quadratic day trend, days of the week dummies, and month dummies

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

find no statistical difference in likelihood of adoption for those subjects who were randomly assigned this statement. This result is consistent with statements of expectations not simply conveying a sense of the scale of the market; rather, these statements provoked a response by indicating what individuals in the market would *do*.

To assess whether individuals were well aware they were making adoption decisions in an earliest period following platform launch, I investigated whether adoption was related to random assignment of the statement, "This is an invitation for early adopters" (also see Section 2.3.1) As I find no statistical difference in likelihood of adoption for those subjects who were randomly assigned this statement, I conclude that individuals were already 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 discern whether there might be a more nuanced relationship, I re-estimate the adoption model with each level of *NumCurrentUsers* as a dummy within a linear framework, reported in Figure 4.

Table 5. Ordinary Least Squares Dummy Estimates of Effects of Levels of Expectations

	Dependent variable: *Participation*	
	(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		Yes
Adjusted R^2	0.046	0.046

Notes. Probit model coefficient estimates; standard errors are in parentheses. Number of observations = 16,349.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

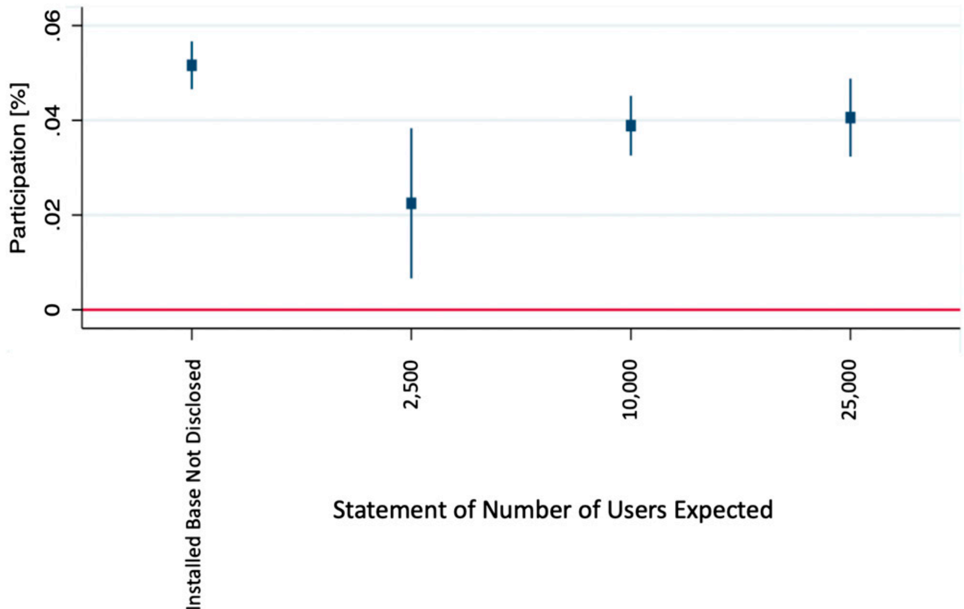
The individual coefficients estimated are mostly statistically insignificant; but, several statistical facts can be discerned. For example, participation is lower with lowest levels of disclosed installed base than when stating nothing at all (analogous to earlier results related to stating user expectations, as in Figure 3). 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 the true 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 $(1/2)^{21}$—or virtually zero. Therefore, I interpret adoption to be systematically higher after 1,000 users have already adopted.

Models 1 and 2 of Table 6 therefore compare model estimates for those cases in which the disclosed installed base exceeded 1,000 versus not. Consistent with the theory, statements of expectations have no effect on adoption after the installed base of users exceeds 1,000 users.

3.5. Does Stating Expectations Affect Heterogeneity of Responses?

Here, I investigate whether statements of the expected future or disclosed current installed base affected

Figure 3. (Color online) Effect of Messaging Expected Installed Base

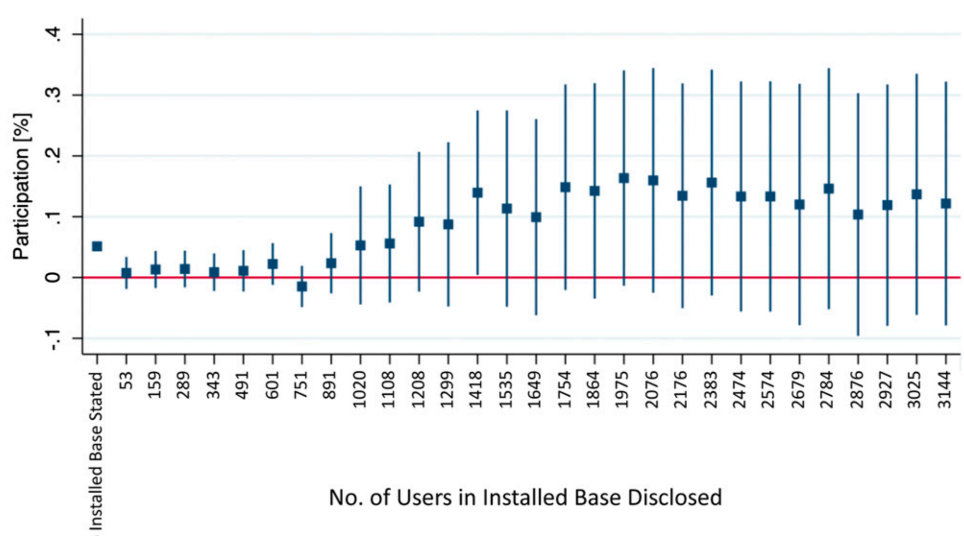


Notes. Estimates presented here are based on model 3 in Table 4, re-estimated with individual dummies for levels of the installed base of users, as a linear probability model to facilitate interpretation. The 95% confidence interval is based on robust standard error estimates.

variance in outcomes. I re-estimate the probit model, allowing for model variance to be parameterized as $\sigma_i^2 = \{\exp(\gamma_0 + \gamma_1 ExpectationsStated_i + \gamma_2 InstalledBaseDisclosed_i)\}^2$. The γ terms are variance model parameters. The variance parameters, along with main model, are estimated simultaneously using maximum likelihood.

Mean model estimates are statistically unaffected by this alternative specification. Variance model estimates are reported in Table 7. As reported 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.

Figure 4. (Color online) Effect of Disclosing Current Installed Base



Notes. 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.

Table 6. Effects of Influencing Expectations in Earliest vs. Later Periods

	Dependent variable: *Participation*	
	Current users < 1,000	Current users ≥ 1,000
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***	0.000
	(0.000)	(0.000)
Individual characteristics and other controls		
Field dummies	Yes	Yes
Graduation year trend	Yes	Yes
Female dummy	Yes	Yes
Time controls	Yes	Yes
Log-likelihood	−1,976	−796

Notes. Probit model coefficient estimates; standard errors are in parentheses. Number of observations = 16,012. Time controls include a quadratic day trend, days of the week dummies, and month dummies.
$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

4. Discussion of Results

4.1. Subjective Expectations and Early Platform Takeoff

The patterns shown in the analysis are each consistent with the theoretical prediction that subjective expectations play a crucial role in shaping early platform adoption with network effects (Section 1). Exposing individuals to statements of expectations concerning the future installed base shifted adoption rates by one-fifth relative to average baseline levels (Section 3.1). The effect of statements of expectations was more significant than the effect of disclosing the true actual installed base size in periods of early takeoff (Sections 3.1 and 3.2). The large causal effects of statements of expectations on adoption ceased to be significant once the disclosed installed base grew past 1,000 users

Table 7. Parametric Variance Estimates

	Dependent variable: *Participation*	
	Current users < 1,000 (1)	Current users ≥ 1,000 (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	Yes	Yes
× I{Current Users < 1,000}		Yes
Quadratic InstalledBaseDisclosed	Yes	Yes
× I{Current Users < 1,000}		Yes
Field dummies	Yes	Yes
Graduation year trend	Yes	Yes
Female dummy	Yes	Yes
Time controls	Yes	Yes
Log-likelihood	−2,780	−2,775

Notes. Probit model coefficient estimates; standard errors are in parentheses. Number of observations = 16,012. 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. Time controls include a quadratic day trend, days of the week dummies, and month dummies.
$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

(Section 3.4). This is, itself, consistent with the theoretical prediction that subjective focal expectations should play a role before the market coordinating on a particular equilibrium.

Underlining the subjectivity of expectations in the market, the statements of expectations to which adopters responded in a systematic manner (Section 3.2) were themselves highly subjective and uncertain. The statements of expectations of future installed base reflected a wide range of plausible scenarios; low and high scenarios differed by a factor of 10 times (Section 2.3.1). Also consistent with subjective and heterogeneous responses to these statements, exposing individuals to statements of expectations led to increased variance (Section 3.5). By contrast, disclosures of the true current installed base reduced variance.

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

The observed patterns 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 (Table 5; Figure 3), consistent with a reluctance to adopt when expectations are pessimistic and there are currently few adopters. Similarly, stating low numbers of current users in the installed base led to statistically lower adoption than stating nothing at all (Section 3.2 and Figure 4). Also consistent with self-fulfilling expectations, statements of more optimistic expectations of numbers of users or stating high numbers of current users in the installed base was associated with higher adoption rates than was stating lower numbers, albeit not always with statistical significance (Section 3.2). It remains a question whether, say, stating considerably higher or more optimistic expectations (or perhaps using differently designed statements or varying features of the context) could have resulted in still larger or more statistically significant differences.

Thus, these results lend support to heretofore untested claims of focal expectations shaping platform takeoff (Farrell and Saloner 1985, Katz and Shapiro 1985, Farrell and Klemperer 2007, Suleymanova and Wey 2012, Zhu and Iansiti 2012, Halaburda and Yehezkel 2019, Halaburda et al. 2020). These results reflect theory that generalizes to relatively typical platform conditions: user benefits come mostly from network effects (rather than stand-alone benefits), adoption is costly, and potential adopters are not able to explicitly coordinate their adoption decisions.

4.3. The Platform's Influence on Expectations

Although this study's main thrust was to test the role of expectations per se, the approach was to do so by *influencing* expectations. At least as notable as the results is the finding that market expectations and adoption behavior could be influenced by the platform, itself, by issuing simple, subjective, uncommitted, and relatively costless statements. The generalizability of this result and practical implications for platform policy should depend on the underlying mechanisms at work. Given the importance of these questions, in the following paragraphs, I speculate on possible explanations and implications for promoting platform growth.

4.3.1. Platform Statements of Expectations—As a Coordinating Device? A first possibility, closest to the theory, is that the platform's statements served as focal cues and coordinating devices (Schelling 1960, Mehta et al. 1994, Sitzia and Zheng 2019).[11] 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 requires that (i) the statements were deemed highly focal by adopters, and (ii) adopters engaged in some form of higher-order reasoning to anticipate and respond to others' choices.

This interpretation point to platforms playing a *leadership* role in a coordinating adoption across many actors (Gawer and Cusumano 2002, Boudreau and Hagiu 2009, Boudreau 2017). Here, efforts might be taken to establish the focalness or salience of statements and create a collective expectation of what others will do. The tangible means of establishing *focalness* of one's statements (either in terms of the design of the statements themselves, or the character and history and significance of those issuing statements) remain under-researched topics.

4.3.2. Platform Statements of Expectations—As Information? An alternative explanation for a platform's ability to influence expectations with its statements is that adopters might perceive the platform's statements to be genuinely informative. This interpretation requires that (i) the platform somehow possesses private information on future adoption (despite the fundamental uncertainty of market coordination) and (ii) potential users believe the platform's statements are credible.[12]

In this context, surely the second condition held, as the platform has a valuable reputation to uphold and this university-sponsored platform could be trusted to act in the interest of students and alumni. Indeed, strenuous efforts were taken to avoid deception (Section 2).

In the context studied here, the first condition less clearly held. Recall, for example, there were wide ranging scenarios for plausible expectations (Section 2.3.) One means of meeting the first condition would be for the platform to carry out meaningful market research. However, in early periods and under the fundamental uncertainty of market coordination, consumers might provide statements to market researchers that might not themselves be credible or committed, as they *wait and see* what others do before adopting.

Another possibility for meeting the first condition is if the platform, itself, be willing to take extraordinary actions to coax future adoption should this adoption not arise on its own. This could involve, for example, giving away platform access for free or creating powerful incentives for adoption among early influential adopters. In such an interpretation, a credible reputation for aggressively supporting growth at all costs could be helpful.

4.3.3. Platform Statements of Expectations—As Persuasion and "Moral Suasion"? A third explanation does not require the platform have private information about future adoption. This is a scenario in which boundedly rational adopters respond to statements by the platform at face value. Adopters might perhaps be influenced simply by a *plausible* characterization of the future. This might especially be true where belief in a plausible scenario can be self-fulfilling, and where adopters might not fully appreciate they are in a fundamentally uncertain context in which the equilibrium is not yet selected. In such an account, adopters might not require a fully rational and credible basis accepting statements.[13] It is plausible in the research context here, for example, that a university-sponsored platform could be deemed to be "legitimate" in a sociological sense, and thus statements could have been taken for granted rather than subject to rational evaluation. Outside of this context, one might imagine a possible role for persuasion on the basis of rhetoric, charisma, moral suasion and other tools of influence in ambiguous decision environments with boundedly rational adopters.

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

Apart from main findings, a secondary finding here is of a negative cross-side interaction between the expected numbers of companies and user adoption (Section 3.2). This result adds to prior findings of negative network effects (Church and Gandal 1992, Economides 1996, Augereau et al. 2006, Tucker and Zhang 2010, Boudreau, 2017). The result here, however, is notable as it relates to a platform designed around team-based contests issued by companies. The prior research tends to focus instead on platforms structured and organized a multisided markets.

A negative cross-platform network effect in this context is consistent with the institutional design around team-based contests. Greater numbers of companies have the effect of splitting-up users across multiple contests or challenges, reducing users' ability to find and collaborate with others. The negative cross-side effect is also consistent with users perhaps preferring that the platform not emphasize problem-solving for companies, but rather instead emphasize, say, learning, development, and community networking (Section 2).

5. Conclusion

The theoretical literature characterizes the initial takeoff of a platform venture very differently from the takeoff of traditional ventures selling regular goods and services. Where there are strong network effects, theory suggests that successful launch and takeoff of a platform can require coordinating sufficient numbers of consumers at once onto the platform to solve the chicken-and-egg adoption problem. The theory suggests this problem is tantamount to establishing or coordinating a new equilibrium in the market—a much greater challenge than simply marketing to and attracting "one customer at a time." The theoretical literature has also long suggested that one way of solving this problem is to influence the market's focal subjective expectations about how many users will eventually adopt the platform in the future. However, while the theory is able to keenly evaluate implications of a given set of market expectations, the theory and its formal models are not able to provide a basis for explaining how subjective focal expectations might form, whether or how they might possibly be influenced, and whether a platform venture can itself influence these expectations. This field experiment reported here was geared to finally bringing empirical evidence to bear on these questions.

In Section 3 (and summarized in Section 4), this paper reported a series patterns consistent with this long-time theoretical characterization of platform adoption and takeoff as a kind of coordination to overcome a chicken-and-egg adoption problem. The results reported here also went beyond the theory by revealing that subjective expectations could be significantly influenced, how they were influenced, and that they were indeed influenced by the platform venture in this instance. Remarkably, the platform venture influenced adoption by broadcasting relatively simple, subjective, uncommitted, and costless statements. I hypothesized three possible explanations for this influence (platform statements as coordination devices, as information, and as persuasion or "moral suasion"). These questions require further investigation and research.

The findings have important implications for managers, investors, entrepreneurs, and marketers seeking to successfully launch new platform ventures. In particular, the findings illuminate and provide results consistent with a new generation of marketing and promotion tactics by platform ventures. For example, platform marketers often actively use media and events to communicate subjective narratives of how the future will unfold (Kawasaki 1992, 2012, 2015; Maher 2015). Apart from conveying optimistic expectations of one's own platform, it has long been customary to convey negative expectations of one's competitors—including conveying fear, uncertainty, and doubt about their platforms (Pfaffenberger 2000, Raymond 2001, Egyedi and Hommels 2019).

Likewise, in contrast to traditional marketing based on bilateral communications, marketers of platforms are more likely to foster socialized and multilateral communications, building communities around a platform, including user and developer groups. These practices might be understood as means to better facilitate the communication of focal cues and ultimate coordination of the market around a platform. These practices may distinguish a new generation of promotion of platform ventures from traditional product promotion, perhaps explaining why platform marketers often describe themselves as platform *evangelists* (Kawasaki 2015). There are currently 2,330 Chief Evangelists listed on Linkedin (versus 121,155 listings of Chief Marketing Officers). The research here lends empirical support to the evolution of the marketing function to include the task of constructing, managing and socializing subjective beliefs and expectations. This may indeed be central to platform entrepreneurship and platform leadership (Gawer and Cusumano 2002) or platform governance and regulation (Boudreau and Hagiu 2009).

Many research questions remain–particularly regarding the mechanisms underlying influence of subjective expectations and how they can be best invoked. The statements used here to influence expectations in this context were designed for simplicity and clarity. There is no reason to believe the design of these statements was necessarily optimal in promoting adoption and takeoff. Likewise, the influence of expectations here was carried out by a particular platform with a particular set of attributes. It remains to be determined whether other sorts of platforms should expect greater or lesser ability to influence expectations relative to outcomes reported here.

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Appendix. Invitation to the Platform

Hi ,

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.)

Endnotes

[1] Rysman (2009) and Rietveld and Schilling (2020) provide surveys on research on platforms.

[2] See, for example, Caillaud and Jullien (2003), Fang et al. (2021), Fath and Sarvary (2003), Hagiu and Eisenmann (2007), Hagiu and Spulber (2013), Ochs and Park (2010), and Stummer et al. (2018).

[3] A related literature examines whether markets get locked in to inferior platforms (David 1985, Hossain and Morgan 2009, Hossain et al. 2011, Liebowitz and Margolis 2014).

[4] For example, Saloner and Shepard (1995), Gupta et al. (1999), Shankar and Bayus (2003), Nair et al. (2004), Ackerberg and Gowrisankaran (2006), Wilbur (2008), Corts and Lederman (2009), Tucker and Zhang (2010), Boudreau and Jeppesen (2015), and Chu and Manchanda (2016).

[5] Among the 3,314 instances of new listings of products initiated over three months, the authors found that in a control group that received no message regarding installed base that 84% of sellers failed to complete their new listings. In various treatment conditions providing randomized statements of numbers of buyers and/or sellers on the platform, the completion rate increased to 85%, with differences depending on the figures that were disclosed.

[6] 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 25th and 75th percentile SAT scores of admitted students are 690 and 790.

[7] The platform embedded other experiments and A/B tests and across different populations in its launch campaign in a way that was orthogonal to and had no effect on the current analysis.

[8] The additional scenario for companies reflected greater uncertainty regarding the number of companies and important differences in the operating model that would need to be implemented depending on which of these scenarios emerged. Nonetheless, the ratio between the lowest and very highest scenarios was 10 times for both users and companies.

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

[10] The full set of controls are not included, as doing so leads to less precise estimates and large standard errors.

[11] This interpretation is also closest to theory and experimental research from the more general literature on coordination games. For example, messaging and labeling of choices in laboratory-based coordination games has been shown to significantly increase the likelihood of players successfully coordinating (Mehta et al. 1994, Bacharach and Bernasconi 1997, Parravano and Poulsen 2015).

[12] This situation differs from situations studied in research on "cheap talk" in coordination games (Farrell and Rabin 1996) that 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—as long as players' interests are somewhat aligned. However, in this context, the platform is not a player in the market coordination game played by adopters; rather, the platform is effectively a third-party observer of this market coordination.

[13] Research on persuasion, beyond the scope of this study, points to a range of behavioral, cognitive, economic, and socio-psychological mechanisms that can generate influence.

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