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RESEARCH ARTICLE

THE EXPERTS IN THE CROWD: THE ROLE OF EXPERIENCED INVESTORS IN A CROWDFUNDING MARKET

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Appendix

Additional Robustness Tests

In this section, we provide additional robustness checks to establish the validity of the results presented in the paper. These include the use of fixed effects Poisson models, the examination of social network effects as a confounding factor, the examination of source of influence of experienced investors, the use of different cutoff values for experienced investors, the potential for collusion, the inclusion of apps only up to December 2012, the log-transformation of two herding-related control variables, and the assessment of product- and market-related risk using text mining. In each case, we show that our central relationships of interest are robust.

Fixed Effects Poisson

Since the daily amount that a listing receives cannot be negative and not all listings get funded on a given day, we also estimate a fixed effects Poisson model to examine the effect of investors with experience on subsequent investors. We assume that the daily amount of funding (in dollars) in each listing can be drawn from a different Poisson distribution. As shown in Table A1, we find that our main findings are qualitatively similar. We note that we could not include time fixed effects in columns (2) and (3), because including them does not lead to converged results.

Table A1. Fixed Effects Poisson Models

	All	Concept	Live
DV: Amt of backing in day t	**(1)**	**(2)**	**(3)**
Ln(Overall experience of App Developer Investors)	0.732***	1.136**	0.259*
	(0.247)	(0.455)	(0.135)
Ln(Overall experience of Experienced Investors)	0.093	0.155	0.183*
	(0.086)	(0.134)	(0.096)
Controls	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	No	No
N	9688	4819	5379

Note: The table reports app-fixed effects regressions. Standard errors are clustered by apps. The influence is calculated as the sum of cumulative amounts of investments in prior projects made by investors with experience in a listing. ***significant at 1%; **significant at 5%; *significant at 10%.

Social Network Effect as a Confounding Factor

One could argue that the experienced investors, being active on the platform, also send a lot of referrals to invite subsequent investors to invest in that app. In that case, the subsequent investment may be driven by word of mouth, rather than signaling. We first note that there is no network of investors visible on the platform. Thus, it is not likely that an investor will invite her friends within the platform. Still, it is possible to invite friends from her other social networks such as Facebook friendship networks. To examine, this we gather data on investors' social networks. The data show that investors with experience do not have a significantly larger social network than the crowd. If any, the crowd has a larger social network than the investors with experience. The group mean-comparison tests between the crowd and either group for either Facebook or Twitter show that p-values are all greater than .5 (see Table A2). The results are based on a set of 243 investors (out of over 1,000 distinct investors) whose friendship network on either Facebook or Twitter is revealed publicly. Out of 243 investors, 40 investors are App Developer Investors and 7 investors are Experienced Investors.

In addition, our nuanced findings imply that this omitted variable will not drive our findings. For example, our falsification test suggests that App Developer Investors are influential mainly when their ownership of apps is publicly shared within the platform and so is visible to potential investors on the platform. If the friendship networks of investors with experience drive our findings, we should not have this nuanced finding, because the social network effect should be similar regardless of this information. Overall, we believe that this should not be a serious concern in our paper based on our additional analysis as well as the original set of analyses.

Table A2. Social Networks of Investors by Groups

		App Developer Investor	Experienced Investor	The Crowd
Twitter Followers	Mean	4781	1120	61594
	p-value for group mean-comparison test with the crowd	0.553	0.778	
	Median	499	488	281
Facebook friends	Mean	555	174	906
	p-value for group mean-comparison test with the crowd	0.627	0.639	
	Median	392	114	364

Source of Influence of Investors with Experience

We conduct an additional test to verify if the influence of investors with experience comes mainly from their activities within the platform, rather than from their activities outside the platform (e.g., their education background and experience). Some investors with experience in our sample make their relevant outside experiences or credentials available online. If potential investors access such information, those investors could be more influential than those not releasing the information. To examine this possibility, we first identified who among our investors with experience disclosed their outside activities based on various external sources including LinkedIn. For App Developer Investors, we then created a dummy for whether an App Developer Investor is reported to be an app/software developer or representing an app development firm. It is likely that those investors are more influential if their outside profile information is accessible. Finally, we generated and added a variable to represent the number of those App Developer Investors on a particular day for each project. If investors care primarily about outside expertise of these investors but dismiss their experiences accumulated within the platform, we should expect that our main overall experience variables become insignificant with the addition of this new variable. Similarly, for Experienced Investors we generated and added a variable to capture the number of Experienced Investors with relevant and significant outside experiences disclosed. As shown in Table A3, the coefficients for the new variables are not significant. Of greater interest, our main quality signals based on the activities within the platform are still significant and influential in our context.

Table A3. Controlling for the Relevant Outside Experience of Investors

DV: Ln (Amt of backing in day t)	Concept (1)	Live (2)	Concept (3)	Live (4)
Ln(Overall experience of App Developer Investors)	0.202***	0.059	0.183***	0.053
	(0.065)	(0.054)	(0.064)	(0.054)
Ln(Number of App Developer Investors with relevant outside experiences disclosed)	-0.296	0.020		
	(0.422)	(0.368)		
Ln(Overall experience of Experienced Investors)	0.033	0.054*	0.036	0.061**
	(0.043)	(0.029)	(0.042)	(0.030)
Ln(Number of Experienced Investors with relevant outside experiences disclosed)			0.143	-0.454
			(0.476)	(0.351)
Controls	Yes	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
N	4994	5444	4994	5444

Note: The table reports app-fixed effects regressions. Standard errors are clustered by apps. The influence is calculated as the sum of cumulative amounts of investments in prior projects made by reputable investors in a listing. ***significant at 1%; **significant at 5%; *significant at 10%.

Different Cutoff Values to Define Experienced Investors

Based on our main criteria, Experienced Investors invested more than $2,000 and had at least five investments. We report our results with different cutoff values in Table A4. As shown in the table, our main finding that App Developer Investors are more crucial in concept apps, while Experienced Investors in live apps is robust. The table also suggests that Experienced Investors with more experience are more influential. When we define Experienced Investors most strictly like in columns (3)–(4) and (7)–(8), the effects of Experienced Investors are strongest in magnitude, while with the least strict definition in columns (5)–(6), the effect becomes smaller in statistical significance and magnitude.

Table A4. Different Definition of Experienced Investors

DV: Ln (Amt of backing in day t)	$2,000 with 4 invs.		$2,000 with 7 invs.		$1,500 with 5 invs.		$2,500 with 5 invs.	
	Concept (1)	Live (2)	Concept (3)	Live (4)	Concept (5)	Live (6)	Concept (7)	Live (8)
Ln(Overall experience of App Developer Investors)	0.138**	0.059	0.140**	0.056	0.142**	0.066	0.140**	0.056
	(0.065)	(0.054)	(0.065)	(0.053)	(0.065)	(0.057)	(0.063)	(0.053)
Ln (Overall experience of Experienced Investors)	0.097*	0.054*	0.100**	0.059*	0.094*	0.041	0.100**	0.059*
	(0.050)	(0.028)	(0.050)	(0.031)	(0.048)	(0.028)	(0.045)	(0.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4994	5444	4994	5444	4994	5444	4994	5444

Note: The table reports app-fixed effects regressions. Standard errors are clustered by apps. The influence is calculated as the sum of cumulative amounts of investments in prior projects made by reputable investors in a listing. ***significant at 1%; **significant at 5%; *significant at 10%.

Apps Only up to December 2012

For apps that ended their funding cycle close to July 2013, the sales data may not be credible. An app that has been in the market for a shorter time will have fewer sales. To dampen this concern, we conducted the same set of analyses only with apps listed up to December 2012. As you see in Tables A4 and A5, all the significances in both the first and the second stages are almost the same.

Table A5. Selection Model Only with Listed Apps up to December 2012

DV: a dummy for whether an investor with experience invested in a focal app	App Developer Investor	Experienced Investor	Either
	(1)	(2)	(3)
Ln(Price)	0.141	0.088	0.070
	(0.123)	(0.110)	(0.110)
Apple	1.116***	0.837***	0.884***
	(0.358)	(0.236)	(0.235)
Company	0.276	0.123	0.176
	(0.236)	(0.182)	(0.182)
Concept	0.514*	0.942***	0.975***
	(0.268)	(0.223)	(0.225)
App age	-0.002	-0.004*	-0.004*
	(0.003)	(0.003)	(0.002)
Global Rank	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
App rating	0.009***	0.007***	0.007***
	(0.003)	(0.003)	(0.003)
Entertainment	0.065	0.129	0.231
	(0.318)	(0.245)	(0.243)
Life & Health	0.194	0.011	0.032
	(0.421)	(0.363)	(0.364)
Games	-0.183	-0.011	-0.001
	(0.294)	(0.213)	(0.213)
Log likelihood	-85.56	-156.28	-156.57
N	294	294	294

Note: The table reports Probit regressions at an app level. ***significant at 1%; **significant at 5%; *significant at 10%.

Table A6. Sales Outcomes Only with Listed Apps up to December 2012			
DV: Ln(Cumulative Num of App Downloads)	App Developer Investor	Experienced Investor	Either
	(1)	(2)	(3)
Ln(Price)	-0.175	-0.187	-0.184
	(0.136)	(0.158)	(0.146)
Apple	0.051	0.914	0.696
	(0.453)	(0.962)	(0.948)
Company	0.275	0.405	0.382
	(0.230)	(0.263)	(0.421)
Concept	0.351	1.981	1.412
	(0.402)	(1.498)	(1.423)
App age	0.006**	0.001	0.002
	(0.003)	(0.006)	(0.005)
Global Rank/1000	-0.008***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)
App rating	0.024***	0.033***	0.030***
	(0.004)	(0.009)	(0.009)
Entertainment	0.468*	0.638*	0.709*
	(0.273)	(0.354)	(0.395)
Life & Health	0.054	0.204	0.209
	(0.385)	(0.347)	(0.351)
Games	-0.021	-0.022	0.004
	(0.211)	(0.236)	(0.233)
Exp.	-8.703	-5.645	-4.753
	(5.084)	(5.371)	(5.020)
Ln(Price)*Exp.	0.100	0.337	0.200
	(0.249)	(0.233)	(0.230)
Apple*Exp.	4.270***	0.481	0.429
	(1.479)	(0.959)	(0.914)
Company*Exp.	1.854***	0.237	0.382
	(0.664)	(0.415)	(0.421)
Concept*Exp.	1.203	-0.121	0.232
	(0.793)	(0.662)	(0.615)
App age*Exp.	0.009	-0.001	0.004
	(0.009)	(0.007)	(0.006)
Global Rank/1000*Exp.	-0.016**	-0.006*	-0.007**
	(0.007)	(0.003)	(0.003)
App rating*Exp.	0.018	0.006	0.005
	(0.012)	(0.007)	(0.006)
Entertainment*Exp.	-0.727	-0.551	-0.487
	(0.951)	(0.633)	(0.647)
Life & Health*Exp.	-0.580	-1.280	-1.239
	(0.766)	(1.185)	(1.180)
Games*Exp.	-0.776	-0.124	-0.048
	(0.671)	(0.539)	(0.544)
Lambda(Exp.)	1.586	3.296	2.596
	(1.750)	(2.766)	(2.540)
Adjusted R^2	0.402	0.365	0.375
N	291	291	291

Note: The table reports OLS regressions at an app level using a Heckman-style selection correction. Exp. is a dummy variable which is equal to 1 if an app has at least one investor with experience and 0 otherwise. ***significant at 1%; **significant at 5%; *significant at 10%.

Two Herding-Related Control Variables Log-Transformed

The control variables for herding, "cumulative amount/1000" and "cumulative number of specific investments," are not log transformed, while the key independent variables are log transformed. As a robustness check, we also log transform the two control variables for herding. Table A6 shows that our main findings are qualitatively the same.

Table A7. Influence of Investors with Experience on the Crowd with Two Herding-Related Control Variables Log-Transformed

	All Subsequent Investors			Only the Subsequent Crowd		
	All	Concept	Live	All	Concept	Live
DV: Ln (Amt of backing in day t)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Ln(Overall experience of App Developer Investors)	0.167***	0.192***	0.098**	0.140***	0.171**	0.030
	(0.053)	(0.071)	(0.049)	(0.053)	(0.068)	(0.053)
Ln(Overall experience of Experienced Investors)	0.080***	0.097*	0.093***	0.042*	0.057	0.051*
	(0.027)	(0.051)	(0.033)	(0.024)	(0.046)	(0.030)
Ln(Cumulative amount/1000)	-0.381***	-0.517***	-0.244**	-0.308***	-0.396***	-0.189**
	(0.093)	(0.162)	(0.102)	(0.084)	(0.147)	(0.089)
Ln(Cumulative num. of specific investments)	0.128	0.177	-0.027	0.151*	0.153	-0.017
	(0.094)	(0.121)	(0.101)	(0.081)	(0.110)	(0.085)
Percentage needed	-0.000	0.001	-0.001	-0.002	-0.004	-0.002
	(0.003)	(0.001)	(0.003)	(0.003)	(0.006)	(0.003)
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.042	0.068	0.019	0.032	0.058	0.010
N	10438	4994	5444	10438	4994	5444

Note: The table reports app-fixed effects regressions. Standard errors are clustered by apps. The influence is calculated as the sum of cumulative amounts of investments in prior projects made by reputable investors in a listing. ***significant at 1%; **significant at 5%; *significant at 10%.

Assessment of Product- and Market-Related Risk Using Text Mining

We performed a text mining analysis of the textual descriptions of all the listings to see what terms dominate the descriptions of concept apps and live apps. We first extracted all the textual descriptions under the two sections, "Why should you back this app?" and "What will the money be used for?" We collected the descriptions of 181 concept apps and 171 live apps for the main analysis. After performing the typical text pre-processing including stemming and removal of stop words, we find that development-related words dominate the description of concept apps. A normalized comparison of the terms for live apps indicates that marketing related terms dominate the description of live apps.

Table A8 shows the top 20 words in terms of the cumulative number of mentions of words in the entire set of texts.

Table A8. Term Frequency of the Top 20 Most Popular Words by Type of Apps

	Concept		Live	
Rank	**Words**	**Frequency**	**Words**	**Frequency**
1	Game	269	Game	159
2	Develop	228	Develop	115
3	Marketing	166	Marketing	112
4	Design	103	Feature	77
5	Version	77	Version	73
6	Application	74	Market	49
7	Website	72	Update	48
8	Store	67	Create	43
9	Market	55	Improve	41
10	Success	55	Store	41
11	Feature	53	Advertise	40
12	Social	52	Promote	39
13	Android	51	Android	35
14	Release	48	Add	33
15	Create	47	Free	33
16	Advertise	46	Ipad	33
17	Promote	44	Review	32
18	Video	40	Potential	31
19	First	38	Support	30
20	Add	36	Iphone	29

For a deeper analysis, we chose three key product development-related words (i.e., develop, design, and create) and three marketing-related words (i.e., marketing, promotion, and advertise), and reported in Table A9 their frequency of usage. Overall, we observe that the product development-related words are used much more frequently in concept apps but marketing-related words are used slightly more frequently in live apps. This further implies that concept apps have more of a product-related focus, while live apps have more marketing and demand-related focus. In Table A10, we further show how many apps have at least one product development- or marketing-related word and find a qualitatively similar pattern.

Table A9. Term Frequency of Key Product Development and Marketing-related Words by Type of Apps

Product Development			**Marketing**		
	Concept	**Live**		**Concept**	**Live**
Develop	228	115	Marketing	166	112
Design	103	13	Promote	44	39
Create	47	43	Advertise	46	40
All	378	171	All	256	191
Average per app	2.088	1.000	Average per app	1.414	1.117

Table A10. Use of Key Product Development and Marketing-Related Words of Apps by Type of Apps

Product Development			**Marketing**		
	Concept	**Live**		**Concept**	**Live**
Develop	114	84	Marketing	102	81
Design	53	10	Promote	35	26
Create	34	33	Advertise	33	25
At least one	136	101	At least one	127	104
% of apps	75.1	59.1	% of apps	70.2	60.8

We have further used word pairs to better capture the nature of product development. We found that for concept apps, words indicating the development of new products are used frequently. These include application development, finish development, and create product. In contrast, for live apps, words relating to development refer to updates to exisiting products. These include add features, continue develop, add new, develop update, improve game, and further update. We further note that update, add, and improve are rarely used in concept apps as shown in Table A8.

Campaign and Investor Pages

Figure A1 shows a snapshot of a crowdfunding campaign page. As shown in Figure A1, investors can obtain several campaign-specific characteristics such as price, category, and platform. Moreover, the list of current investors is also very public to potential investors. Clicking on the "View All" button provides information on the list of 80 backers. Clicking on any particular investor leads to the investor profile page shown in Figure A2. The right-hand side provides information on which projects this investor has invested in thus far and whether this investor has also posted her own app on the platform. An investor can also describe their identity in more detail on the left-hand side. They can use this space to describe their education, job experiences, skills, etc. We manually verified the textual description of experienced investors. Out of 67 App Developer Investors in our data, 50 had provided some textual description. Interestingly, none of the 17 Experienced Investors provided any description on their profile page.

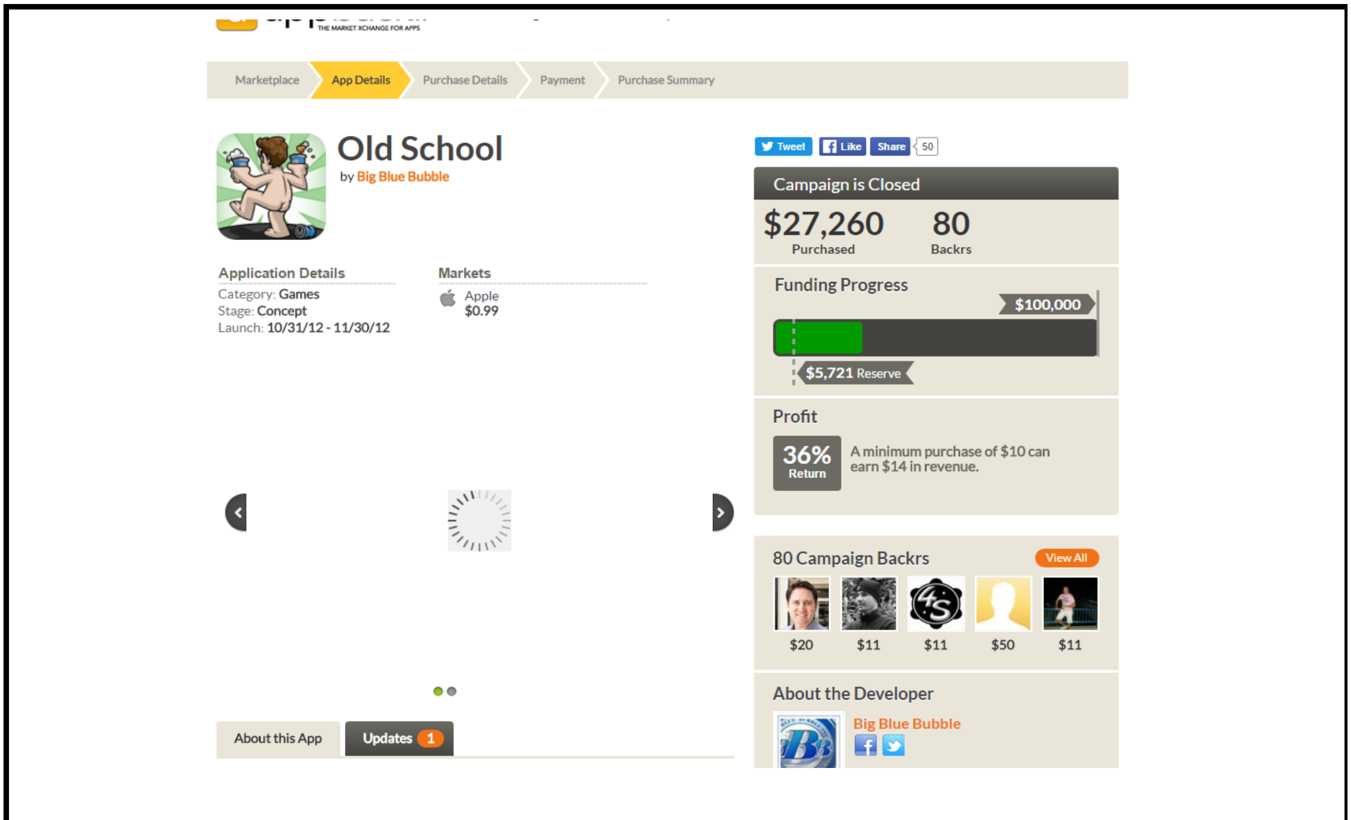

Figure A1. A Snapshot of a Crowdfunding Campaign Page

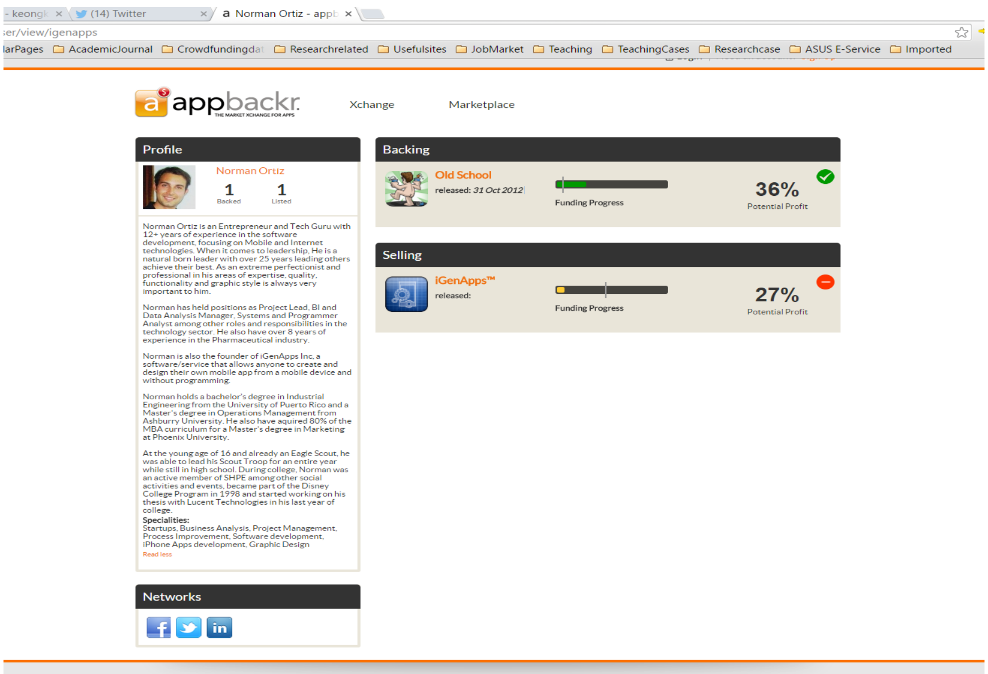

Figure A2. A Snapshot of an Investor Profile Page