Information Disseminated with Technology Firms on Social Media

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Abstract— *Technology startups going public to build a sustainable company that is public, as we see hot technology initial public offerings (IPOs) – Twitter, Alibaba, and the like-went to public in past years. We examine the IT-Producing IPOs versus IT-Consuming IPOs on their first-day returns and long-run underperformance. We investigate the social media content on IT-Producing IPOs versus that on IT-Consuming IPOs and find that IT-Producing IPOs are actively using Twitter to inform consumers while IT-Consuming IPOs are tweeting to getting feedbacks and inputs from consumers. In addition, IT-Producing IPOs dominate over IT-Consuming IPOs in terms of the attention attracted from social media users as measured by the volume of the social media content posted on them*

Keywords— *social media content, initial public offering, technologies.*

I.　INTRODUCTION

Through years, we see technologies have changed the way we think, work, and connect with other people. Innovative technologies have provided solutions to people and played a huge role in our society. In the past years, new technologies bring people together through social media platforms and get connected with each other; new technologies provide platforms form people purchase and sell products beyond geographical and cultural boundaries; technologies make it possible for people to access to market information or news in seconds. Technology advances are making a real difference in every sector of our life.

Technology startups are going public to build a sustainable company that is public. Going public is the ultimate for most start-ups and it is the primary way for startup investors to cash out. In the past few years, technology firms such as Facebook, Twitter, and Alibaba went to public and made a big hit on their IPO day. Twitter closed its first trade day with the price 73% higher than the offer price. It raised 1.82 billion dollars in its initial public offering (IPO). Yelp! Soared 64% above its offer price on the first day. Technology IPOs are scarce, but they catch a lot of investors' attention. More than half of the tech firms that have gone public lately have posted double-digit stock gains. As noted in Dow Jones Venture Source, there are more than 130 technology startups valued at $1 billion and worth above $480 collectively. Technology companies that focus on new trends such as cloud computing, social network, network security, e-commence, data analytics have completed their IPOs successfully and their IPO attract the most investor interest and attention.

New technologies have brought people together through social media platform. When popular technology firms went to public, they cause a big buzz on social media. People tweet the IPOs and exchanged their opinions on the stock valuations. The chatters on Twitter share either positive or negative comments in the tweets. The IPOs catch more investor interest and attention. In this study, we investigate the technology IPOs and compare them with non-tech IPOs in terms of their first-day returns and long-run performance. We also examine the social media content about the technology IPOs. We study the topics embedded in the social media content mentioning IPOs.

II.　LITERATURE REVIEW

Research related to our study is found in the IPO literature. Liu et al. [4] study media coverage of IPOs. They examine conventional media coverage (press news) prior to an IPO to predict the IPO firm's long-run liquidity and its following analysts and institutional investors. They measure the pre-IPO news coverage of a company by the number of articles mentioning the company name during the 30 days prior to the IPO date, and find a positive correlation between the pre-IPO press coverage, the firm's long-run following analysts, institutional investors, and the stock's liquidity. Da et al. [2] use Google search trend as the index of retail investors' attention in predicting stock returns. Our paper differs from these studies in that we focus on the difference between IT-producing and IT-consuming companies and we study social media content rather than on conventional press news.

In the information systems (IS) literature, social media content has been examined. Bollen et al. [1] use the mood of daily Twitter feeds to predict the Dow Jones Industrial Average (DJIA) over time. Two mood-tracking tools, OpinionFinder and Google Profile of Mood States, are used to detect the mood of daily tweets. They find that the inclusion of public mood can improve the ability to predict stock prices. Yu et al. [9] use sentiment analysis to study the impact of the sentiment of social media content and of press media on firm equity value. The authors find that different social media, such as Google blogs, Google news, Twitter, and online forums, have different effects on stock performance, and those effects are stronger than the effects of press news. They examine the value of social media in finance and justify investments in social media and in new technology initiatives. Other studies of information value [1, 8, 10-14] examine the dissemination of information on social media, the adoption of new communication technologies of social media, and the value of social media content.

III. INDENTATIONS AND EQUATIONS

We separated companies into IT-Producing or IT-Consuming group following the literature [7]. IT-producing group includes industries with a NAICS code of 334, 5112, 517-519, and 5415. IT-consuming group consists of all remaining industries. We also tried with the classification SIC codes used in another study [5] for technology firms with the SIC code 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, etc., but found certain technology firms were left out with these SIC codes. The NAICS classification codes [7] provided a better identification of IT-Producing companies' vs IT-Consuming companies.

We used the IPOs in the year 2012 to 2015 as the sample IPOs and downloaded the accounting numbers from the Compustat database. The basic statistics of IT-Producing IPOs is provided in the Table 1, and the statistics of IT-Consuming IPOs is in Table 2.

TABLE 1
STATISTICS OF IT-PRODUCING IPOS

Variable	Mean	Std Dev	Minimum	Maximum	N	10th Pctl	90th Pctl
Offer Price	16.262	7.037	5	43	97	8	25
Opening Price	21.163	11.765	5	59.95	97	8.95	39
Close Price	21.077	11.671	4.28	56.1	97	8.8	37.16
Asset (million)	778.774	1810.31	7.5	15103	97	111.057	1981.09
Liability (million)	423.295	939.159	1.52	4633.62	96	25.52	1193.04

As shown in Table 1 and Table 2, 97 out of 447 IPO samples were IT-Producing companies and 350 IPOs were IT-Consuming firms. The average offer price of IT-Producing group and that of IT-Consuming group is not much different, with $16.262 for IT-Producing and $15.356 for IT-Consuming. However, in terms of asset, the IT-Producing firms are smaller on average than IT-Consuming group.

TABLE 2
STATISTICS OF IT-CONSUMING IPOS

Variable	Mean	Std Dev	Minimum	Maximum	N	10th Pctl	90th Pctl
Offer Price	15.356	6.867	5	91	350	8	22
Opening Price	17.149	8.183	4.4	91	350	9	27
Close Price	17.363	8.481	4.8	85	350	8.32	27.14
Asset (million)	3490.18	16903.45	6.588	221023.2	350	55.542	5249.48
Liability(million)	2776.79	15127.66	0.61	205509.2	350	4.845	4292

We downloaded the tweets over the IT-Producing and IT-Consuming IPOs from January 1, 2011 to December 31, 2015, using the firms' stock ticker symbols. On Twitter, users tweet stocks often with the dollar sign plus the stock ticker when mentioning a stock. We plot the number of the ticker tweets in Figure 1. The tweet age is the number of days between the tweet posted date and the tweeted stock's IPO date. The dark line represents for the average number of daily tweets of IT-producing group, and the dash line is for IT-consuming group. Figure 1 shows that IT-producing group dominates IT-consuming group in terms of number of ticker tweets. Users tweet IPOs actively 30 days prior to the IPO day, and the peak

of tweets is on the IPO day, with about 20 tweets on average and 15,000 tweets in total. Another smaller peak is on the 30th day after IPO. Afterwards, IPO stocks are frequently tweeted by users over time.
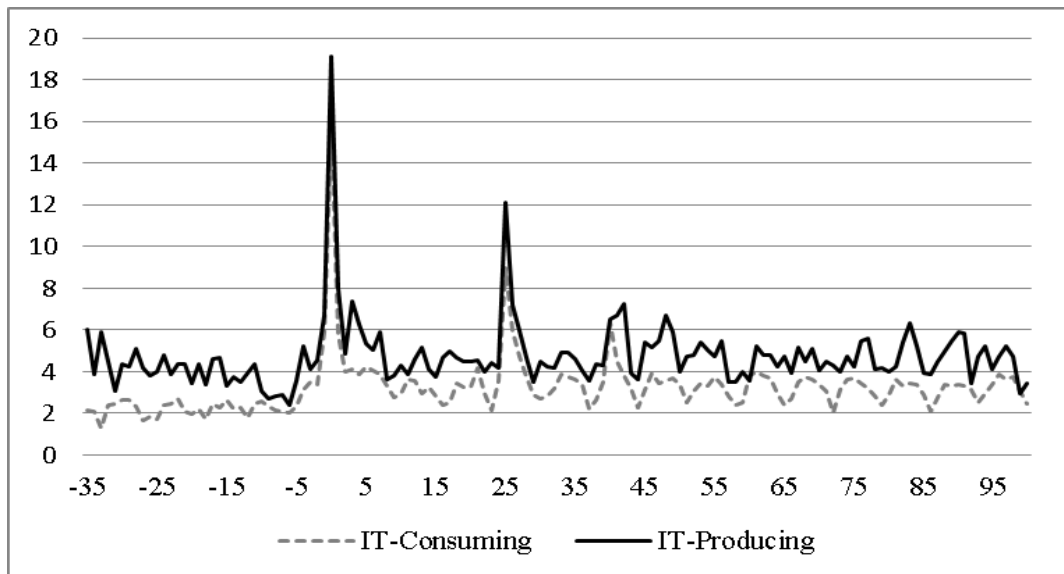

FIGURE 1: AVERAGE NUMBER OF DAILY TICKER TWEETS OVER TIME

In addition, the IPO firms also posted tweets on Twitter and disseminate products or service information to consumers. Most of them created a twitter account before the IPO day and actively communicated and interacted with users. We plot the number of the tweets posted by the IPO firm themselves in Figure 2 and call the tweets as "business tweets to separate them from the tweets searched by their ticker symbols and posted by Twitter users.
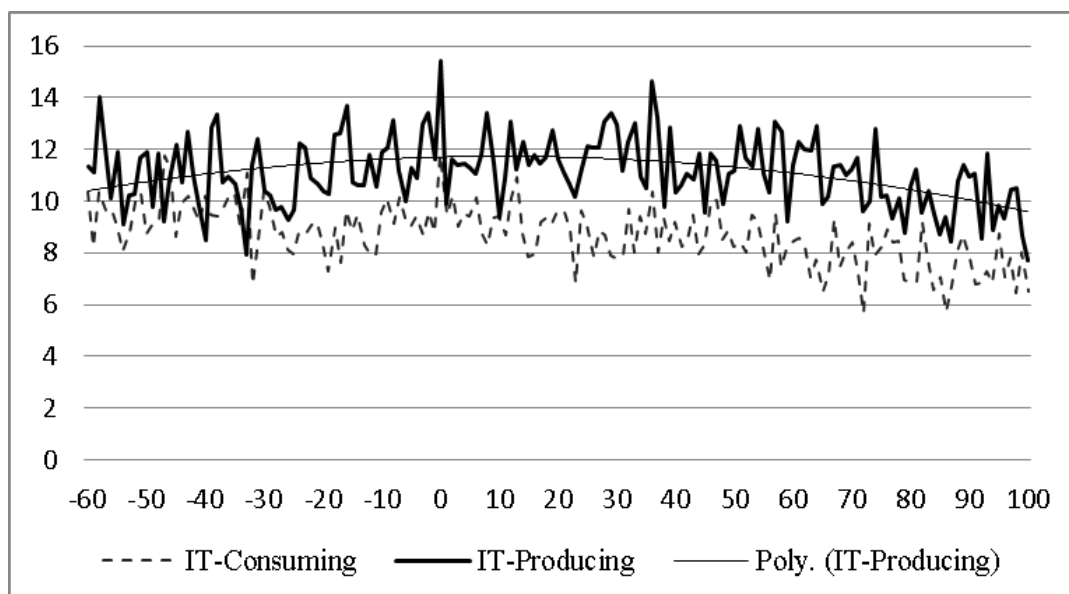

FIGURE 2: AVERAGE NUMBER OF DAILY BUSINESS TWEETS OVER TIME

We see that IT-producing companies dominate IT-consuming companies in terms of the number of business tweets, as shown Figure 2. The number of business tweets peaked on the IPO day but not as dramatic as in ticker tweets. Overall, the number of business tweets peaked on the IPO day. It increased before the IPO day and decreased after the IPO day.

IV.   EXPERIMENT RESULTS

Two characteristics of IPOs that are related to the behavior of retail investors are IPO underpricing and long-run underperformance [5, 6]. We first compare the first-day returns of IT-Producing IPOs with those of IT-Consuming IPOs and list the results in Table 3. We use "1" for IT-Producing IPOs and "0" for IT-Consuming IPOs. We see that IT-producing

IPOs have significantly higher first-day returns than IT-consuming IPOs. The average first-day return of IT-producing IPOs is 26% while that of IT-consuming IPOs is 13%. The long-run performance of the IT-Producing companies is still stronger than that of the IT-Consuming companies. The IT-Producing firms have 5% higher returns than the IT-Consuming firms do on average, but the difference is not significant any more. We used the Pooled t-test and Satterthwaite t-test. The Folded F test results show that the variance is unequal, so we use the Satterthwaite results. The results confirm that IT-Producing IPOs have significantly higher first-day returns than IT-Consuming IPOs.

TABLE 2
IT-PRODUCING VS IT-CONSUMING IPOS' FIRST-DAY RETURNS

		First-day Return			First-Year Return		
IT-Producing	Method	Mean	95% CL Mean		Mean	95% CL Mean	
0		0.13	0.10	0.15	0.34	0.26	0.43
1		0.26	0.19	0.32	0.39	0.23	0.54
Diff (1-2)	Pooled	-0.13	-0.19	-0.07	-0.04	-0.23	0.14
Diff (1-2)	Satterthwaite	-0.13	-0.20	-0.06	-0.04	-0.22	0.13
Method	Variances	DF	t Value	Pr>|t|	DF	t Value	Pr>|t|
Pooled	Equal	443	-4.23	<.0001	440	-0.49	0.63
Satterthwaite	Unequal	132	-3.78	0.0002	163	-0.51	0.61
Method	Num DF	Den DF	F Value	Pr>F	Den DF	F Value	Pr>F
Folded F	53	348	1.50	0.01	95	1.18	0.34

To conduct the analysis of variance on the first-day IPO returns, we include the prediction variables for the first-day returns as suggested in the IPO literature [e.g., 2, 3], such as the log of a firm's total assets, the age of firm, the reputation of underwriters. We also include the number of ticker tweets and their number of retweets and likes, and those of business tweets. Table 5 shows the variance using the stepwise selection of variables for the IT-Producing IPOs' first-day returns. The adjusted R-Square of the prediction model is 0.2816. We used the natural log of asset, age, and the number of tweets, retweets and likes. We see that the selected variables include the number of retweets, the log of number of business tweets in the quiet period, and the firm age.

TABLE 3
ANALYSIS OF VARIANCE ON THE FIRST-DAY RETURNS

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	2.66817	0.66704	8.92	<.0001
Error	91	6.808	0.07482		
Corrected Total	95	9.476			
Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	0.186	0.212	0.057	0.77	0.388
Ticker Retweets	0.092	0.056	0.204	2.73	0.101
Business tweets	0.035	0.013	0.519	6.94	0.009
Firm Age	-0.117	0.061	0.274	3.67	0.058

We plotted the Q-Q plot of residuals, the distribution of residuals, and other diagnostics for the regression model on the first-day IPO returns for the IT-Producing firms. The plots are included in Figure 3. As shown in these plots, the residuals follow normal distribution. The linearity of points in the Q-Q plot also suggests that the data are normally distributed.
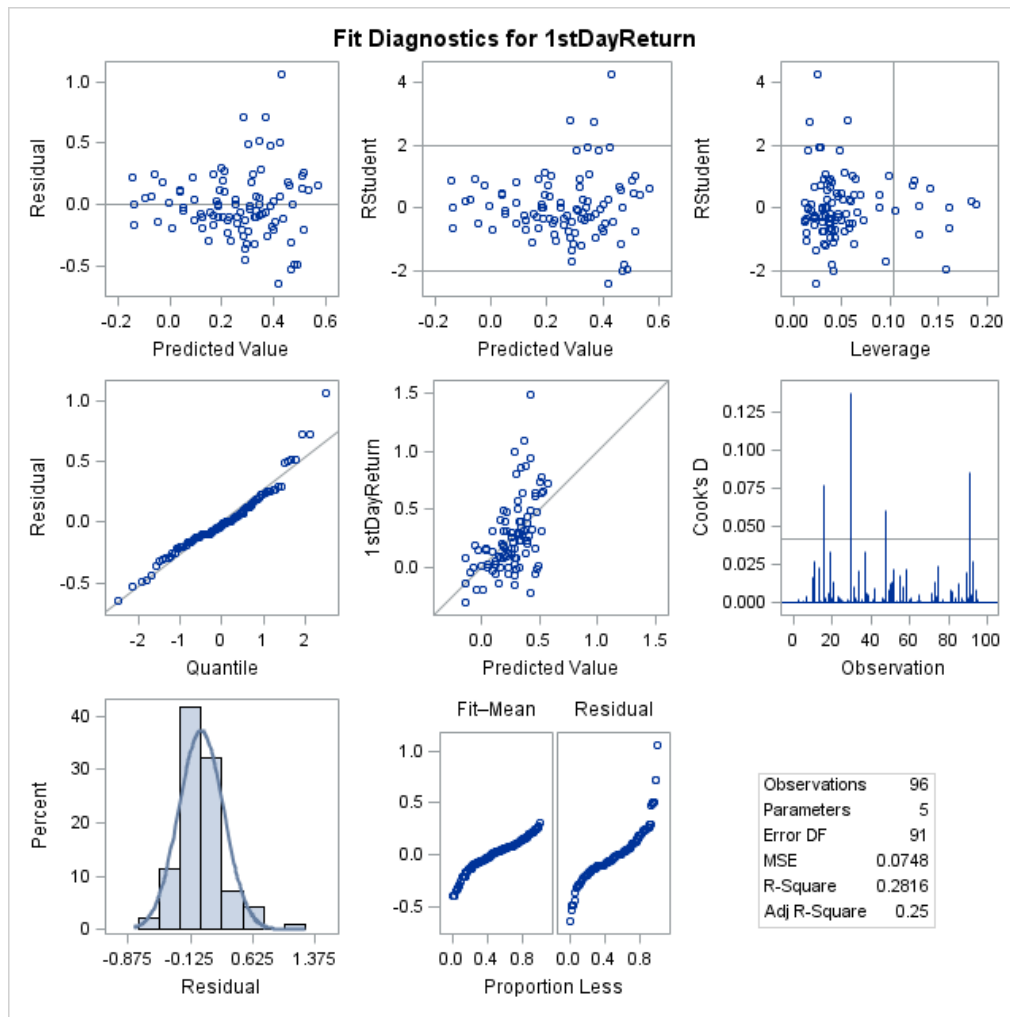
FIGURE 1: DIAGNOSTIC PLOTS ON THE FIRST-DAY IPO RETURNS

We examine the long-run performance of the IPO firms. The findings of the long-run performance are consistent with the IPO literature [5]. We provide the correlations of the accumulative raw returns in Table 5. The reversal in returns is observed as early as 30 days after the IPO. The first-day return is significantly negatively correlated with the 30-day return, with a coefficient of -0.19. It is also negatively correlated with the cumulative returns in the 45-day period, the 1-year period, and 1-year-after-30-day period.

TABLE 4
CORRELATION COEFFICIENTS OF RETURNS

	1st Day	30 Day	45 Day	1 Year	1 Year from 30th Day
1st Day	1	-0.191	-0.111	-0.136	-0.0471
		0.022	0.191	0.196	0.6571
30 Day	-0.191	1	0.861***	0.408***	0.0521
	0.022		<.0001	<.0001	0.6238
45 Day	-0.111	0.861***	1	0.464***	0.1302
	0.1916	<.0001		<.0001	0.2183
1 Year	-0.136	0.408***	0.464***	1	0.91***
	0.1968	<.0001	<.0001		<.0001
1 Year from	-0.0471	0.0521	0.1302	0.91***	1
the Day 30th	0.6571	0.6238	0.218	<.0001	
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					

To analyze the hidden information in the tweets content, we employed the LDA model to discover the topics in ticker tweets and those in business tweets in quiet period. We combined all the ticker tweets over the IT-Producing IPOs in a document and all the ticker tweets over the IT-Consuming IPOs in the other document. We list the topics in the ticker tweets in Table 6.

We found that the five top topics hidden in the tweets posted during the quiet period are "IPO", "IT", "Bio", "Entry", and "Comparable" as listed in Table 6. The keywords of each topic are listed under the topic. Comparing the topics in the ticker tweets over the IT-Producing IPOs and IT-Consuming IPOs, the probabilities of tweets on IT-Producing companies are 63.6% on "IPO" topic, 32.7% on "IT" topic, 1.53% on "Entry", 1.2% on "Comparable", and 0.97% on "Bio". The IT-consuming companies' tweets are first on the topic "IPO", followed by topic "Bio", "Entry", "Comparable", and "IT".

TABLE 5
TOPICS OF MICROBLOGGERS TWEETS IN QUIET PERIOD

Topics	"IPO"	"IT"	"Bio"	"Entry"	"Comparable"
Terms	ipo	tech	pharmaceutics	exhibit	alternative
	stock	data	therapeutic	genetic	disclosure
	buy	software	biotech	bag	primer
	initiate	network	initiate	enter	preclinical
	trade	hdp	hold	burger	overweight
	new	twitter	juno	wanna	Baird
	week	king	loco	known	Obama
	coverage	yelp	gpro	memory	volume
	analyst	cybr	rwlk	taken	probably
	market	facebook	capit	instead	bib
IT-Producing	63.60%	32.70%	0.97%	1.53%	1.20%
IT-Consuming	60.15%	0.80%	32.09%	3.54%	3.41%

The topics in business tweets are provided in Table 7. Business tweets are mainly used by IPO companies to communicate with consumers as shown in Table 7. IT-producing companies focus more on informing consumers while IT-consuming companies are about requesting inputs from consumers.

TABLE 6
TOPICS OF BUSINESS TWEETS IN QUIET PERIOD

Topic	"Communication"	"Informing"	"Requesting"	"Market"	"Events"
	thank	market	please	campaign	foodiechat
	help	blog	picture	consider	birthday
	hear	webinar	love	global	volcom
	know	mobile	great	practice	music
	see	chat	like	entrepreneur	skate
	get	data	theatre	yummy	race
	make	cloud	bank	clear	property
	happy	customer	favorite	higher	count
	glad	inbound	location	together	bright
	great	network	store	thrill	classroom
IT-Producing	56.42%	35.89%	0.16%	7.36%	0.17%
IT-Consuming	57.67%	0.30%	31.34%	0.20%	10.49%

The top five topics in business tweets in quiet period are "communication", "informing", "requesting", "market", and "events". The probabilities of IT-producing companies' tweets are 56.52% on the topic "communication", 35.89% on "informing", 7.36% on "market", 0.17% on "events', and 0.16% on "requesting". The probabilities of IT-consuming

companies' tweets are 57.67% on "communication", 31.34% on "requesting", 10.49% on "events, 0.3% on "informing", and 0.2% on "market.

V.   CONCLUSION

We compare IT-Producing IPOs and IT-Consuming IPOs in terms of their first-day returns and long-run underperformance in social media context. We find that IT-Producing IPOs have significantly higher returns on average than IT-Consuming IPOs, and higher long-run accumulative returns as well. The IT-Producing IPO firms dominate over IT-Consuming IPOs in terms of the number of their tweets posted by Twitter users and the number of business tweets tweeted by themselves. We also conduct a topic analysis on the tweets over the IPO firms, and find the IT-Producing firms are tweeting to inform consumers while IT-Consuming firms are tweeting to request feedbacks, inputs, or interactions from consumers. In addition, we find that IT-producing IPOs attract investors attention and technology IPOs is one the main topics in the tweets posted by Twitter users.

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