The customer knows best: The investment value of consumer opinions

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"Pollution and Performance: Do Investors Make Worse Trades on Hazy Days?" with Nianhang Xu and Honghai Yu, 2019, accepted for publication in MS.

"Internalizing Governance Externalities: The Role of Institutional Cross-ownership," with Jie (Jack) He and Shan Zhao, 2018, accepted for publication in JFE.

"Product Market Competition in a World of Cross-ownership: Evidence from Institutional Blockholdings," with Jie (Jack) He, RFS (2017).

ABSTRACT

- This paper investigates whether consumer opinions convey value-relevant information to financial markets.
- Using a data set of more than 14.5 million customer product reviews on Amazon.com from 2004 through 2015, I find evidence that consumer opinions contain information for stock pricing.
- A spread portfolio that is long on stocks with high abnormal customer ratings and short on stocks with low abnormal customer ratings delivers an abnormal return of around 55.7 to 73.0 basis points per month. There is no evidence of return reversals in the subsequent year.

ABSTRACT

- The return predictability of customer ratings continues to hold after controlling for firm characteristics such as gross profitability, advertising, research and development expenses, and trading volume. Furthermore, abnormal customer ratings positively predict revenues and earnings surprises.

- These results suggest that consumer opinions contain novel information about firms’ fundamentals and stock pricing.

1. Introduction

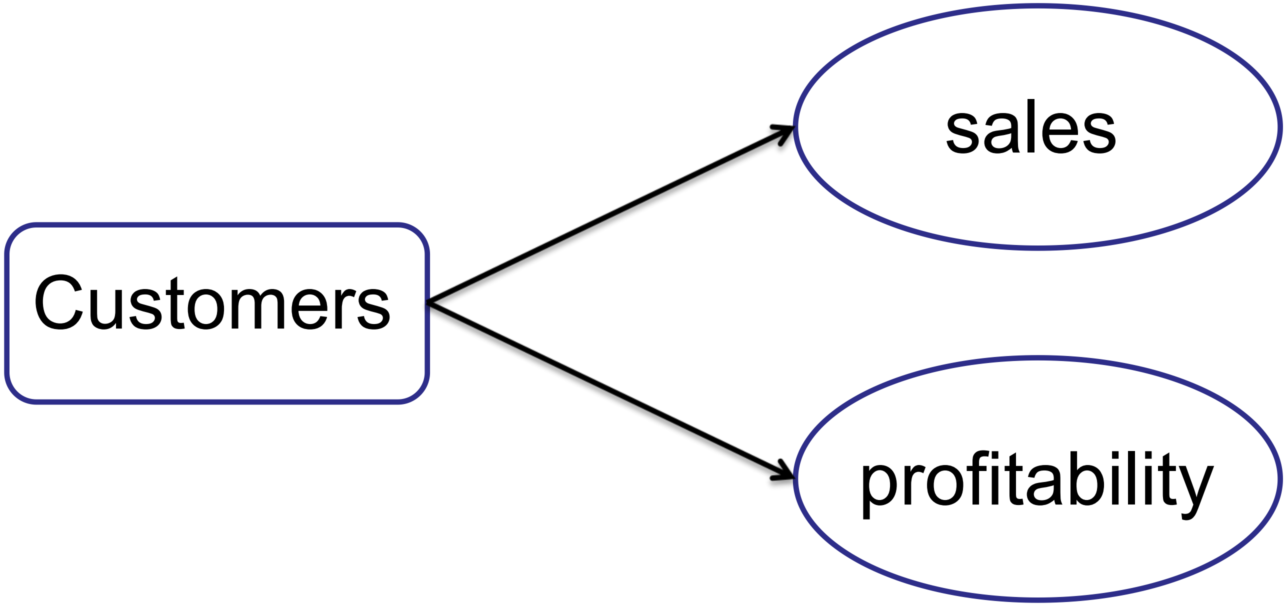
2. Literature review

3.Data and summary statistics

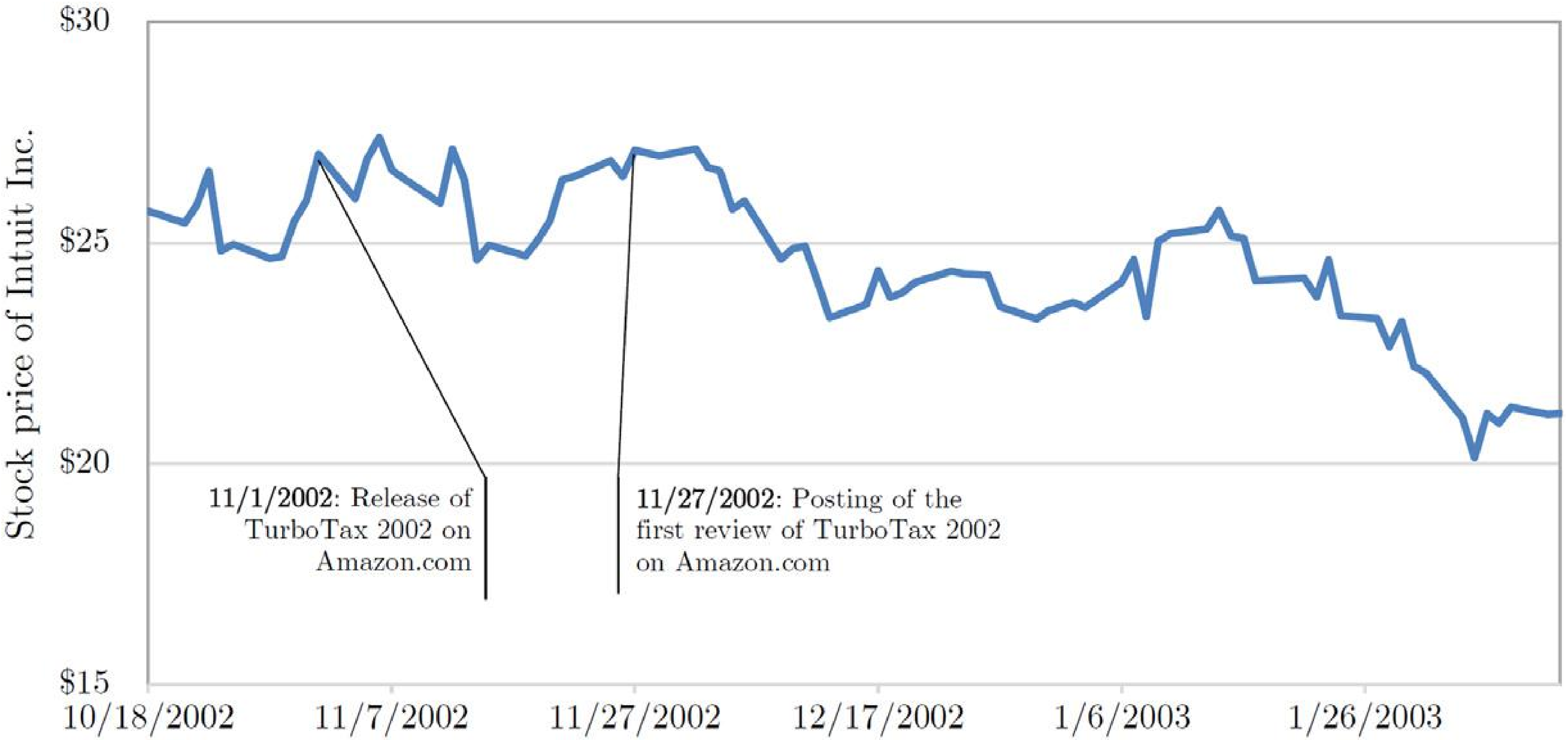
4.Empirical results

5. Conclusion

1. Introduction



Subrahmanyam and Titman (1999) coin the term “serendipitous information” for intelligence that investors gather in their everyday activities, such as information about product quality and demand. They argue that such information, while noisy, can provide useful signals of the underlying value of a firm when aggregated.


$30
$25
$20
$15
Stock price of Intuit Inc.
11/1/2002: Release of TurboTax 2002 on Amazon.com
11/27/2002: Posting of the first review of TurboTax 2002 on Amazon.com
10/18/2002
11/7/2002
11/27/2002
12/17/2002
1/6/2003
1/26/2003

consumer opinions may fail to provide new information beyond what has been incorporated in the stock price for at least three reasons

1. consumers may lack the incentive to provide truthful information about products. The sharing of information by consumers faces the free-rider problem.

2. consumers may lack the expertise to evaluate products. Also, consumer opinions may be influenced by product advertising and other attention-grabbing promotional activities, resulting in biased reviews.

3. even if consumer opinions are informative about fundamentals, the information could have already been incorporated into stock prices, which again makes such information useless in predicting future stock price movements.

there are several reasons to posit that the aggregated opinions of consumers contain information for the financial markets

1. consumer opinions not only provide signals about a company's products, but also affect purchase decisions of consumers.

2. consumer crowds are likely to satisfy the conditions required for the wisdom of crowds to hold true.

3. consumer opinions may have predictability for stock returns because of limited investor attention.

Contributions

- this study is among the first to test the information content of consumer opinions by distinguishing between an information story and an attention story.
- I construct a comprehensive sample of stocks with customer reviews on Amazon.com. The sample contains 346 distinct firms over a period of 12 years.
- by taking into account a number of known predictors in the cross section of stock returns as well as variables that are likely correlated with consumer opinions, my paper sheds light on the nature of the information conveyed by consumer opinions.
- by exploring whether the predictability is particularly pronounced for stocks with high arbitrage costs and more binding limits to investor attention, this paper illuminates the sources of the stock return predictability of consumer opinions.

2. Literature review

The first is the finance literature on the influence of product- related information on stock pricing

Subrahmanyam and Titman (1999) posit that such serendipitous information can have large aggregate effects on stock price efficiency.

Early empirical studies find evidence that product recall events are associated with significantly negative stock market reactions, suggesting that inferior product quality and, hence, poor customer perceptions negatively affect stock returns (Jarrell and Peltzman, 1985; Barber and Darrough, 1996).

More recently, Grullon et al. (2004) find that product market advertising increases the breadth of ownership and stock liquidity, suggesting that product advertisements influence investor decisions. Da et al. (2011b) show that Internet search volume for firms' products can serve as a leading indicator of a firm's earnings and stock prices.

The second literature this study contributes to is the marketing literature that examines the relation between online product reviews and stock returns

Tirunillai and Tellis (2012) examine relation between product reviews and stock market variables but find mixed results.

Using survey-based customer satisfaction scores observed at an annual frequency for a sample of about 300 firms over 15 years, Fornell et al. (2016) find that an investment strategy based on customer satisfaction scores delivers an abnormal return of 90 basis points per month.

The third literature that this paper is connected to is that on the informational role of large crowds (oftentimes nonprofessional investors) in financial markets

Da et al. (2011a) , Kelley and Tetlock (2013) , Chen et al. (2014) , and Lee et al. (2015) find evidence that the collective actions of large groups of financial market participants convey information about future stock returns and cash flows.

other studies suggest that some types of crowd activities provide little information about firm fundamentals (see, e.g., Tumarkin and Whitelaw, 2001; Antweiler and Frank, 2004; Das et al., 2005; Da et al., 2011a).

3.Data and summary statistics

Amazon.com review data

Amazon.com is the largest online retailer in the US, generating $107.01 billion in sales in 2015. Founded in July 1994, the company started letting customers post reviews of its products in 1995. Since then, more than ten million customers have posted more than 200 million reviews on the website, making it the largest single source of Internet consumer reviews.

According to Amazon.com’s review creation guidelines, “anyone who has purchased items from Amazon.com” can write a product review, and the review “should focus on specific features of the product and [the customer’s] experience with it.”

To minimize conflicts of interest, the guidelines prohibit paid reviews and manufacturers’ posting of reviews for their own products or negative reviews of competing products. The guidelines also stipulate that the reviews should be about the product, not about the seller, the shipping experience, packaging, or product availability.

Customers can rate a product on a scale of one to five stars, with five being the top rating, and enter a text review. All reviews are dated by the time it is first posted, which makes it possible to track consumer opinions over time. Amazon.com maintains all records of products and reviews on its website even when the products are discontinued.

identify public firms with customer product reviews on Amazon.com

I first retrieve the list of brands from Amazon.com under each product category and identify the companies that own these brands using various sources, including item- Master.com, Consumer Product Information Database, and Google and Wikipedia searches.

I identify firms that use Amazon.com to sell their products by searching for the term “Amazon” in 10-K filings of all publicly traded firms in the US. I then check whether the firm sells its products on Amazon.com by searching for the company’s brands and products on Amazon.com.

I cross-validate by searching on Amazon.com for the brands and products of rivals of the companies identified in the above two approaches.

Company Name	Industry	Start	End	# of months	Avg # of reviews
3M Co	Manuf	10/2004	12/2015	126	2,678
ABB Ltd	Manuf	6/2012	12/2014	31	31
Abbott Laboratories	Health	9/2005	12/2015	105	364
Abercrombie & Fitch	Shops	12/2012	12/2015	34	21
ACCO Brands Corp	BusEq	7/2006	12/2015	111	1,568
Accuride Corp	Durbl	8/2015	8/2015	1	10
Acme United Corp	Manuf	1/2009	12/2015	75	185
Activision Inc.	BusEq	7/2004	12/2015	126	1,217
Acura Pharmaceuticals Inc.	Health	11/2012	12/2015	35	57
Adobe Systems Inc.	BusEq	1/2005	12/2015	114	90
Aeropostale Inc.	Shops	5/2013	12/2015	30	26
Akorn Inc.	Health	1/2013	12/2015	23	21
Alberto-Culver Co	Chems	3/2010	4/2011	5	16
Alcon Inc.	Health	11/2010	3/2011	4	14
Alere Inc.	Health	1/2007	12/2014	58	149
Allergan Inc.	Health	7/2010	2/2015	44	76
Allison Transmission Holdings	Durbl	7/2015	10/2015	3	12
Alphabet Inc.	BusEq	2/2010	12/2015	80	778
AMC Networks Inc.	Telcm	11/2012	12/2015	35	100
American International Industries	Shops	1/2009	7/2010	12	15
Anheuser-Busch Inbev	NoDur	8/2012	12/2015	19	60
Annie's Inc.	NoDur	7/2012	9/2014	27	99
Apple Inc.	BusEq	7/2004	12/2015	134	2,247

To collect the reviews for the sample of public firms, I use a web-crawling program that inputs each brand owned by a public firm as a search term on Amazon.com and outputs all reviews for products whose brand name perfectly matches the search term

- The sample of reviews covers the period from July 2004 through December 2015.
  First, Amazon.com in June 2004 disallowed anonymous reviews and introduced a credit card requirement for posting product reviews, which could improve the informativeness of the reviews.
  Second, the number of reviews for products manufactured by public companies is relatively low before 2004.

- I remove duplicate reviews posted by the same reviewer account ID on the same day for the same product, which constitute less than 0.01% of the review sample

GoPro

GoPro HERO5 Black

217 customer reviews | 139 answered questions

#1 Best Seller in Sports & Action Video Cameras

Price: $394.99 Prime | **Fast, FREE Shipping** with Amazon Prime

In Stock.

Want it Wednesday, Jan. 4? Order within **54 hrs 15 mins** and choose **One-Day Shipping** at checkout.

Details

Ships from and sold by Amazon.com. Gift-wrap available.

Product Information

Style:**Only Camera**

Product Dimensions	1.8 x 2.4 x 1.3 inches
Item Weight	4.2 ounces
Shipping Weight	1.2 pounds (View shipping rates and policies)
ASIN	③ B01M14ATO0
Item model number	CHDHX-501
Batteries	1 Lithium Ion batteries required. (included)
Customer Reviews	217 customer reviews 4.2 out of 5 stars

Item model number	CHDHX-501
Batteries	1 Lithium ion batteries required. (included)
Customer Reviews	217 customer reviews 4.2 out of 5 stars
Best Sellers Rank	#3 in Camera & Photo #1 in Electronics > Camera & Photo > Video > Sports & Action Video Cameras
Date first available at Amazon.com	September 17, 2016

From first-time action camera owner: Great versatility, decent video quality

By Evan on November 26, 2016

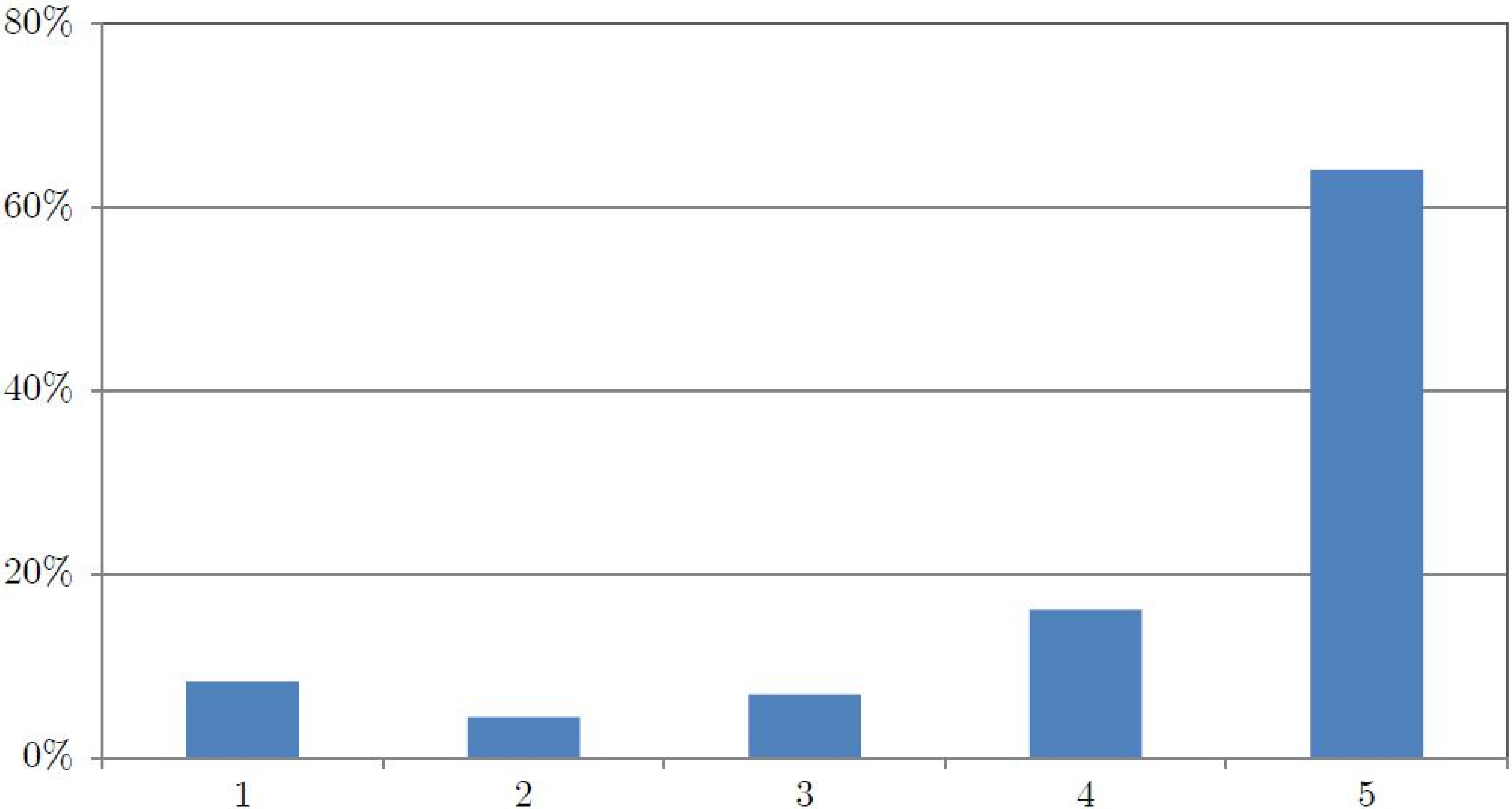
Style Name: Only Camera

This review is from my perspective as a freelance videographer and first-time action camera owner. I will keep the review short by going over the good, the bad, and the ugly of the GoPro Hero 5 Black.

Summary statistics on Amazon.com reviews for public firms

	Number of reviews	Number of products	Number of brands	Number of firms
Full sample	14,555,765	269,957	1931	346
By Fama and French 12 industries				
2. Consumer non-durables	2,583,822	66,008	798	80
Consumer durables	1,886,991	29,444	94	24
3. Manufacturing	2,036,257	48,719	170	46
Chemicals	1,248,339	29,779	384	21
1. Business equipment	4,652,443	47,571	176	68
Telecommunication	787,979	14,823	14	11
Shops	518,004	12,764	112	51
Healthcare	385,722	11,368	153	38
Others	456,208	9,481	30	7

I measure abnormal customer ratings as the difference between the average customer rating in a month and that in the prior 12 months.



The reviews are predominantly positive for two possible reasons

- a selection effect could exist in that products sold on Amazon.com may on average have (or be perceived to have) relatively high quality.
- products that receive low ratings could see their sales on Amazon.com decline and, in some cases, stop being offered, leading to fewer buyers and, hence, fewer negative reviews. On the other hand, favorable reviews and product sales could be mutually reinforcing, with favorable reviews attracting more buyers and these buyers in turn posting more favorable reviews to the extent that consumers have correlated opinions.

Data

I obtain stock return and volume data from the Center for Research on Stock Prices (CRSP), financial statement data from Standard and Poor’s (S&P) Compustat, and analysts’ earnings forecasts from the Institutional Brokers’ Estimate System (I/B/E/S).

I construct the F-score of Piotroski (2000) and gross profitability of Novy-Marx (2013) .
I also consider advertising and research and development (R&D) expenditures.
I consider the level and variation of dollar trading volume of Brennan et al. (1998) and Chordia et al. (2001).

I construct two measures to capture cash flow surprises

I use standardized unexpected revenue growth estimator (SURGE) as a measure of revenue surprises.

$$SURGE_{i,q} = \frac{REV_{i,q} - E(REV_{i,q})}{\sigma_{i,q}}$$

$$E(REV_{i,q}) = REV_{i,q-4} + \frac{1}{8}\sum_{j=1}^{8}(REV_{i,q-j} - REV_{i,q-j-4})$$

I obtain quarterly earnings forecasts for the sample of stocks from the I/B/E/S historical database. I use price-scaled forecast errors (SUE) as a measure for earnings surprises, defined as the difference between reported quarterly earnings per share (EPS) and the median of the most recent EPS forecasts of all analysts issued during the 90-day period prior to the earnings announcement date scaled by the stock price.

I construct measures for trading activities by hedge funds

I obtain the list of hedge funds from Gao and Huang (2016) , which contains 494 distinct hedge fund managers. I retrieve their quarterly holdings from Thomson Reuters CDA/Spectrum Institutional (13F) Holdings Database.

$$NetBuy_{i,q}^{HF} = \frac{ShrOwn_{i,q}^{HF}}{ShrOut_{i.q-1}} - \frac{ShrOwn_{i,q-1}^{HF}}{ShrOut_{i,q-1}}$$

Panel A: Summary statistics

Variable	N	Mean	Standard Deviation	25th percentile	Median	75th percentile
Customer reviews						
Average customer ratings	20,562	4.096	0.444	3.893	4.167	4.377
Abnormal customer ratings	20,562	0.014	0.309	−0.104	0.024	0.153
# of customer reviews	20,562	700.077	2048.420	33.000	109.000	449.000
Firm-level characteristics						
Market cap (millions of dollars)	20,562	25,723.300	56,088.990	997.479	5,533.220	21,868.000
Book-to-market	20,562	0.418	0.588	0.213	0.358	0.589
Stock return $_{m-12,m-1}$	20,562	0.170	1.034	−0.086	0.123	0.335
Advertising	20,562	0.040	0.053	0.004	0.022	0.054
R&D	20,562	0.009	0.015	0.000	0.000	0.014
Gross profitability	20,562	0.113	0.074	0.070	0.100	0.140
F-score	20,562	5.326	1.892	4.000	5.000	7.000
Dollar volume (millions of dollars)	20,562	3,701.090	11,572.960	117.757	944.920	3,228.530
CV of dollar volume	20,562	0.367	0.240	0.225	0.298	0.425
Book leverage	20,562	0.529	0.254	0.366	0.512	0.659
Asset tangibility	20,562	0.169	0.133	0.080	0.135	0.222
# of analysts	20,562	16.419	13.286	6.000	14.000	24.000
Institutional ownership	20,562	0.627	0.287	0.516	0.689	0.816
Analyst revisions (percent)	9,916	−0.108	2.157	−0.124	0.000	0.104
Cash flow surprises and institutional trades						
Revenue surprise (SURGE)	7,283	0.525	1.742	−0.215	0.292	1.095
Earnings surprise (SUE) (percent)	5,503	0.077	0.632	0.000	0.060	0.197
Net buying by HFs (percent)	7,886	0.009	2.140	−0.616	0.000	0.634
Net buying by non-HFs (percent)	7,886	0.056	4.407	−1.512	0.035	1.644

Panel B: Regression of one-month-ahead abnormal customer ratings on firm characteristics

	Dependent variable: One-month-ahead abnormal customer ratings			
	(1)	(2)	(3)	(4)
Advertising		−0.043	−0.037	0.302
		(0.40)	(0.34)	(1.36)
R&D		0.023	0.031	0.145
		(0.09)	(0.11)	(0.26)
Gross profitability		−0.112	−0.115	−0.035
		(1.34)	(1.37)	(0.42)
F-score		0.000	0.000	−0.000
		(0.10)	(0.11)	(0.05)
Log(Dollar volume)			0.005	0.009
			(1.28)	(0.92)
Log(CV of dollar volume)			0.005	0.018
			(0.66)	(1.84)*
Log(Market cap)	0.005	0.005	0.002	0.002
	(0.77)	(0.84)	(0.23)	(0.19)
Book-to-market	0.002	0.001	0.001	0.003
	(0.26)	(0.14)	(0.17)	(0.14)
Stock return $_{m-12,m-1}$	0.000	0.000	0.000	−0.006
	(0.05)	(0.22)	(0.03)	(0.64)
Book leverage	−0.022	−0.016	−0.017	0.008
	(0.85)	(0.57)	(0.62)	(0.18)
Asset tangibility	−0.020	−0.013	−0.007	−0.096
	(0.22)	(0.14)	(0.07)	(0.69)
Log(1+# of analysts)	−0.011	−0.011	−0.013	−0.021
	(1.45)	(1.45)	(1.51)	(1.43)
Institutional ownership	0.016	0.014	0.007	0.025
	(1.04)	(0.93)	(0.41)	(0.91)
Net buying by HFs				0.000
				(0.16)
Analyst revision				−0.177
				(1.02)
Number of observations	19,603	19,554	19,554	9,900
Adjusted R-squared	0.07	0.07	0.07	0.07

4.Empirical results

Abnormal customer ratings and stock return predictability

Calendar-time portfolio tests

For each month from July 2004 through December 2015, I sort sample stocks into tercile portfolios based on abnormal customer ratings. I then track the performance of the three portfolios over the following month. I employ two weighting schemes across firms, weighting by the number of reviews and equal weighting.

I use the Fama-French- Carhart four-factor model to adjust returns. I compute a four-factor alpha by regressing monthly portfolio excess returns on the monthly returns from the risk factors.

		Market	SMB	HML	UMD
Panel A: Review weighting					
T1 (low abnormal rating)	−0.198%	1.124	0.482	0.132	−0.308
	(0.74)	(15.69)***	(3.83)***	(1.11)	(4.91)***
T2	−0.014%	1.245	0.246	0.022	−0.188
	(0.06)	(19.90)***	(2.24)**	(0.21)	(3.43)***
T3 (high abnormal rating)	0.532%	1.051	0.179	0.165	−0.134
	(1.98)**	(14.50)***	(1.41)	(1.37)	(2.11)**
Long/Short (high - low)	0.730%	−0.073	−0.303	−0.033	0.174
	(2.17)**	(0.81)	(1.90)*	(0.22)	(2.19)**
Panel B: Equal weighting					
T1 (low abnormal rating)	−0.024%	1.006	0.513	0.003	−0.239
	(0.15)	(22.19)***	(6.44)***	(0.04)	(6.01)***
T2	0.264%	1.081	0.385	0.152	−0.090
	(1.52)	(23.09)***	(4.68)***	(1.96)*	(2.19)**
T3 (high abnormal rating)	0.533%	0.956	0.636	−0.115	−0.361
	(2.52)**	(16.74)***	(6.34)***	(1.21)	(7.20)***
Long/short (high - low)	0.557%	−0.050	0.123	−0.118	−0.121
	(2.66)***	(0.88)	(1.24)	(1.26)	(2.45)**

the sources of the predictability of future stock returns based on abnormal customer ratings

1. the return predictability of consumer opinions should be stronger for stocks with more binding limits to arbitrage. I use idiosyncratic stock return volatility as a measure for arbitrage costs.

	Review weighting	Equal weighting
Panel A: By idiosyncratic volatility		
High idiosyncratic volatility	1.366%	1.030%
	(2.12)**	(2.50)**
Low idiosyncratic volatility	−0.015%	0.131%
	(0.05)	(0.63)
Long/short (high - low)	1.380%	0.899%
	(1.81)*	(1.86)*

2.limits to investor attention and information processing capacities may delay the incorporation of customer information into the stock price. I use analyst coverage and firm size as proxies for investor attention

	Review weighting	Equal weighting
Panel B: By analyst coverage		
Low analyst coverage	1.480%	0.734%
	(2.38)**	(2.11)**
High analyst coverage	0.190%	0.393%
	(0.53)	(1.57)
Long/short (low - high)	1.291%	0.341%
	(1.73)*	(0.78)
Panel C: By market capitalization		
Small firms	1.162%	1.181%
	(2.42)**	(2.75)***
Large firms	0.597%	0.412%
	(2.11)**	(1.72)*
Long/short (small - large)	0.565%	0.768%
	(0.97)	(1.52)

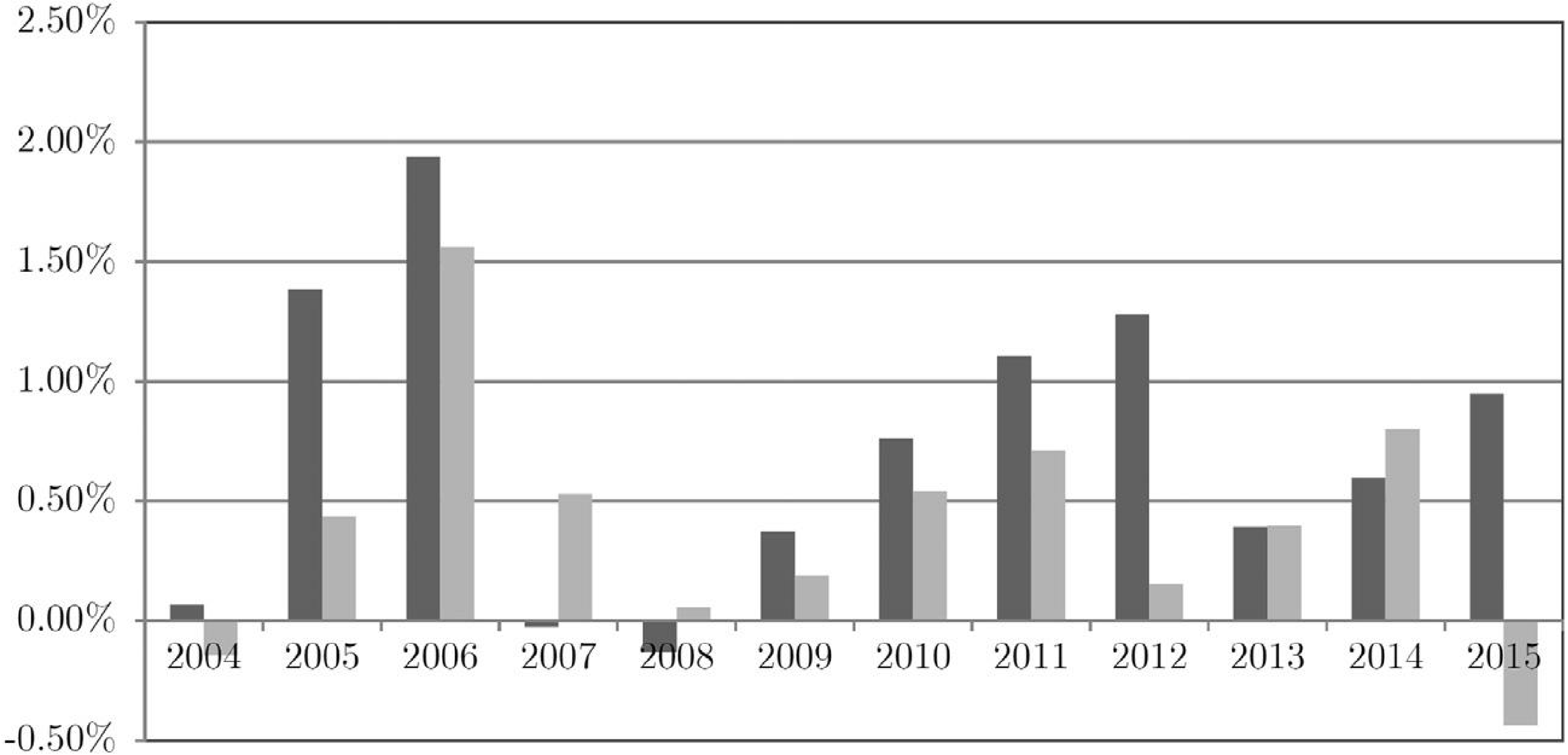
Robustness checks

	Review weighting	Equal weighting
Panel A: Alternative risk adjustments		
Using the Fama and French three-factor model	0.787% (2.31)**	0.517% (2.43)**
Using the Fama and French five-factor model	0.789% (2.24)**	0.513% (2.32)**
Using a liquidity-augmented Fama–French–Carhart model	0.771% (2.26)**	0.602% (2.85)***
Using industry-adjusted abnormal returns	0.678% (1.98)*	0.476% (2.32)**
Panel B: Alternative measures for abnormal ratings		
Prior six months as benchmark	0.592% (2.01)**	0.573% (2.03)**

The increase in the popularity of customer reviews can have two effects on the stock return predictability of consumer opinions over time.

First, aggregating over a larger number of consumer reviews can reduce noise and provide more precise information about the products.

Second, as consumer reviews become more informative, more arbitrageurs may trade on the information embedded in the reviews. As a result, the information may be incorporated into stock prices more rapidly, giving rise to weaker return predictability of consumer opinions in more recent years.


2.50%
2.00%
1.50%
1.00%
0.50%
0.00%
-0.50%
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015

Long-run stock returns

Holding period	Review weighting	Equal weighting
Months [2, 4]	0.122%	0.143%
	(0.56)	(0.97)
Months [2, 7]	0.132%	0.084%
	(0.74)	(0.75)
Months [2, 10]	0.093%	0.095%
	(0.61)	(0.91)
Months [2, 13]	0.009%	0.110%
	(0.07)	(1.18)

Fama–MacBeth regressions

I conduct Fama–MacBeth regressions to test the return predictability of abnormal customer ratings by explicitly controlling for accounting variables measured contemporaneously to customer ratings and other known predictors in the cross section of stock returns.

$$Excess\,\mathrm{Re}\,t_{i,t+1} = \alpha + \beta_1 AbnRating_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t}$$

	Dependent variable: One-month-ahead excess stock returns (percent)					
	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal customer ratings	1.718	1.681	1.525	1.426	1.580	1.323
	(2.44)**	(2.34)**	(2.27)**	(2.23)**	(2.18)**	(2.08)**
Gross profitability			4.125	3.360		3.295
			(2.22)**	(1.65)		(1.57)
F-score			0.396	0.412		0.391
			(5.02)***	(4.65)***		(4.26)***
Advertising				1.122		0.456
				(0.31)		(0.13)
R&D				−3.672		−3.882
				(0.37)		(0.43)
Log(Dollar volume)					−0.204	−0.175
					(2.06)**	(1.70)*
Log(CV of dollar volume)					−0.868	−0.747
					(2.76)***	(2.40)**
Log(Market cap)		−0.056	−0.087	−0.115	0.054	−0.017
		(0.49)	(0.78)	(1.01)	(0.44)	(0.13)
Book-to-market		0.342	0.829	0.644	0.309	0.561
		(0.69)	(1.53)	(1.08)	(0.61)	(0.88)
Stock return $_{m-12,m-1}$		0.035	−0.331	−0.297	0.303	−0.061
		(0.05)	(0.47)	(0.40)	(0.42)	(0.08)
Number of observations	20,562	20,562	20,562	20,562	20,562	20,562
Average R-squared	0.01	0.07	0.10	0.13	0.11	0.17

Abnormal customer ratings and cash flow surprises

Because revenues and earnings are released at a quarterly frequency, I compute the abnormal customer rating at a quarterly frequency as the average customer rating during a quarter minus that during the prior four quarters.

$$SURPRISE_{i,q} = \alpha + \tau_q + \beta_1 AbnRating_{i,q} + \beta_2 SURPRISE_{i,q-1} + \gamma X_{i,q-1} + \varepsilon_{i,q}$$

	Dependent variable: Revenue surprise (SURGE)				
	(1)	(2)	(3)	(4)	(5)
Abnormal customer ratings	0.443	0.440	0.340	0.359	0.360
	(2.16)**	(2.26)**	(2.17)**	(2.16)**	(2.25)**
Lagged dependent variable			1.248		
			(26.63)***		
Log(Market cap)		−0.020	−0.026		0.174
		(0.50)	(1.14)		(1.45)
Book-to-market		−0.100	−0.027		−0.072
		(1.23)	(0.50)		(0.75)
Advertising		−1.873	0.115		−0.133
		(2.59)**	(0.29)		(0.07)
R&D		0.479	1.273		−3.817
		(0.17)	(0.75)		(1.47)
Gross profitability		0.067	−0.012		0.016
		(3.70)***	(0.80)		(0.98)
F-score		0.875	−0.569		2.507
		(1.36)	(1.47)		(3.11)***
Log(Dollar volume)		0.084	0.029		0.061
		(3.00)***	(1.66)*		(1.00)
Log(CV of dollar volume)		−0.125	−0.076		−0.133
		(1.39)	(1.22)		(1.51)
Stock return $_{t-30,t-3}$		0.528	0.121		0.404
		(5.27)***	(1.92)*		(4.12)***
Stock return$_{t-365,t-31}$		0.924	0.677		0.942
		(4.02)***	(3.89)***		(5.29)***
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	Yes	Yes
Number of observations	7,283	7,283	7,283	7,283	7,283
Adjusted R-squared	0.07	0.12	0.41	0.29	0.31

	Dependent variable: Earnings surprise (SUE)				
	(1)	(2)	(3)	(4)	(5)
Abnormal customer ratings	0.077	0.080	0.076	0.074	0.073
	(2.33)**	(2.40)**	(2.26)**	(2.07)**	(1.92)*
Lagged dependent variable			0.096		
			(2.64)***		
Forecast dispersion		−3.087	−3.387		−2.963
		(0.90)	(1.15)		(1.26)
Log(Market cap)		−0.033	−0.031		−0.078
		(1.88)*	(1.77)*		(1.47)
Book-to-market		0.053	0.039		−0.178
		(0.56)	(0.44)		(1.23)
Advertising		−0.163	−0.112		1.370
		(0.54)	(0.40)		(2.28)**
R&D		2.558	2.284		0.341
		(2.83)***	(2.81)***		(0.16)
Gross profitability		0.009	0.006		0.002
		(1.35)	(0.90)		(0.34)
F-score		0.057	−0.036		0.336
		(0.25)	(0.16)		(0.80)
Log(Dollar volume)		0.044	0.041		0.027
		(2.30)**	(2.11)**		(0.88)
Log(CV of dollar volume)		0.013	0.011		0.034
		(0.48)	(0.45)		(1.08)
Stock return $_{t-30,t-3}$		0.193	0.161		0.150
		(3.99)***	(3.61)***		(2.57)**
Stock return$_{t-365,t-31}$		0.660	0.647		0.632
		(3.34)***	(3.32)***		(3.33)***
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	Yes	Yes
Number of observations	5,503	5,503	5,503	5,503	5,503
Adjusted R-squared	0.02	0.04	0.06	0.11	0.13

Abnormal customer ratings and trading by sophisticated investors

To examine whether abnormal customer ratings predict hedge fund trades, I run Fama–MacBeth regressions of net purchases by hedge funds and those by non–hedge funds in quarter q

$$NetBuy_{i,q} = \alpha + \beta_1 AbnRating_{i,q-1} + \beta_2 \mathrm{Re}\,t_{i,q} + \beta_3 \mathrm{Re}\,t_{i,q-1} + \beta_3 \mathrm{Re}\,t_{i,[q-5,q-2]} + \gamma X_{i,q-1} + \varepsilon_{i,q}$$

Because some hedge fund managers have better information processing abilities than others,I hypothesize that hedge funds with more trading in stocks that have consumer reviews are likely to be better informed. I term these hedge funds “specialized hedge funds”.

I partition hedge funds into two groups based on the median of the trading weight in stocks with Amazon.com reviews, i.e., trading volume in stocks with Amazon.com reviews as a fraction of total trading volume over the last four quarters.

I infer trading volume from disclosed quarterly holdings by assuming that hedge funds do not trade intra-quarterly between two consecutive quarterly reports and the changes in holdings during a quarter occur at the end of the quarter.

	Net buying by HFs (1)	Net buying by non-HFs (2)	Net buying by specialized HFs (3)	Net buying by less specialized HFs (4)
Abnormal customer ratings	0.227	−0.047	0.183	0.058
	(2.39)**	(0.29)	(2.74)***	(1.07)
Log(Market cap)	−0.017	−0.093	0.036	−0.040
	(0.41)	(1.09)	(0.88)	(3.09)***
Book-to-market	0.151	−0.412	0.114	−0.008
	(1.66)	(2.46)**	(2.24)**	(0.13)
Advertising	−0.338	−1.850	0.035	−0.332
	(0.55)	(1.47)	(0.08)	(0.85)
R&D	−1.469	−13.454	1.712	−1.296
	(0.58)	(2.16)**	(0.96)	(0.91)
Gross profitability	0.086	−0.045	−0.241	0.042
	(0.15)	(0.04)	(0.51)	(0.15)
F-score	−0.005	0.021	−0.012	0.000
	(0.30)	(0.51)	(1.25)	(0.04)
Log(Dollar volume)	0.007	0.058	−0.040	0.032
	(0.19)	(0.88)	(1.06)	(2.83)***
Log(CV of dollar volume)	−0.009	−0.035	0.031	−0.053
	(0.10)	(0.23)	(0.58)	(1.42)
Stock return$_q$	0.141	2.687	−0.135	0.254
	(0.52)	(4.65)***	(0.49)	(1.26)
Stock return$_{q-1}$	0.029	−0.023	−0.183	0.011
	(0.10)	(0.03)	(0.64)	(0.05)
Stock return $_{[q-5,q-2]}$	0.010	0.108	0.049	−0.042
	(0.09)	(0.49)	(0.58)	(0.81)
Number of observations	7,886	7,886	7,886	7,886
Average R-squared	0.13	0.12	0.12	0.12

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5. Conclusion

- I examine the investment value of consumer opinions. Using a large data set of customer product reviews on Amazon.com, I find that abnormal customer ratings positively predict subsequent stock returns.

- The results appear to be concentrated among stocks with high idiosyncratic volatilities, stocks with low analyst coverage, and small-cap stocks, which likely face high arbitrage costs and more binding limits to investor attention.

- Fama–MacBeth regressions show that the return predictability of customer ratings continues to hold after controlling for firm characteristics such as gross profitability, advertising, and trading volume. I find that abnormal customer ratings positively predict revenue and earnings surprises and the return predictability does not reverse in the long run.

- Last, abnormal customer ratings are a significant predictor of net purchases by hedge fund managers, suggesting that sophisticated investors exploit the information contained in consumer opinions.

- Taken together, these findings provide evidence that the aggregated opinions of consumer crowds contain valuable information about cash flows and stock pricing.

- The results in this paper highlight the role of consumers as information producers in financial markets. Compared with traditional information intermediaries such as equity analysts, consumer crowds can provide more timely information on a company’s products and cash flows.

- Given the collective wisdom of consumers, future research should investigate how firms and other stakeholders such as creditors and suppliers can make use of the information conveyed by consumer opinions.

THANKS!