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RESEARCH ARTICLE

OPERATIONALIZING REGULATORY FOCUS IN THE DIGITAL AGE: EVIDENCE FROM AN E-COMMERCE CONTEXT

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Appendix A

Develop a Sentiment Lexicon

We preprocessed the reviews using the Institute of Computing Technology of the Chinese Academy of Sciences' system to decompose them into words and phrases. The sentiment lexicon was developed in two steps. First, we selected words and phrases from the reviews, which were also entries in the Chinese Network Sentiment Dictionary and the NTU Sentiment Dictionary. In this way, we collected 167 positive emotion words and 102 negative emotion words. Second, we coded each positive (negative) emotion word and assigned a sentiment strength with values ranging from 2 (-2) to 5 (-5)[1]. After a 30-word (15 positive emotion words and 15 negative emotion words) trial run and performance check of its capability of ensuring consistent perceptions of the words' sentiment strength, two professional coders examined every word in our lexicon (the training words excluded) and independently assigned them sentiment values. We used Krippendorff's *R* (the ordinal version of Cohen's kappa agreement test) to ensure inter-coder reliability. The reliability coefficients for both the positive and negative emotion words were greater than 0.7 (Archak et al. 2011), suggesting a reasonably high level of consistency across the two coders. After they completed the independent coding, the two coders discussed the discrepancies in order to reach a mutually agreed coding for all words.

Appendix B

The Performance of the Customized SentiStrength Algorithm

In this step, three coders were given verbal instruction and training with 100 product reviews. After verifying that the coders had a consistent perspective on the sentiments in the data, they were asked to code 1,000 online reviews independently based on the degree of positive and negative emotions contained in the reviews. The Krippendorff's R was taken as the inter-coder reliability statistic. Using the numerical difference in the emotion scores as weights, the reliability values were 0.725 for positive and 0.693 for negative sentiment, indicating adequate agreement. We used the majority rule to resolve disagreements among the coders. The customized SentiStrength algorithm was then tested on the same set of 1,000 online reviews that had been classified by the three coders. It is worth noting that our SentiStrength algorithm uses a directory of sentiment words with associated strength measures. During the development of the customized SentiStrength algorithm, we

[1]For details on the design of the SentiStrength algorithm and the coding principle, please refer to Thelwall et al. (2011).

initially obtained sentiment word strengths based on human judgments. In order to optimize the default manual word strengths, we also used a training algorithm (i.e., supervised learning) to fine-tune the sentiment word strengths. The training algorithm started with the baseline human-allocated word strengths for the predefined list and then checked each word strength to see whether an increase or decrease of 1 would improve classification accuracy for the set of 1,000 reviews that had been classified manually (i.e., the training data). The algorithm repeated until all words were checked without making any changes.

Appendix C

Comparison between Customized SentiStrength and SVM

Applied approaches for sentiment analysis can be classified into two categories: machine learning and semantic approach. In our main analysis, we adopted the customized SentiStrength algorithm, which is a semantic approach, to perform sentiment classification of online reviews. In the following, we introduce how the machine learning approach is performed, and present a comparison of the performance of machine learning and semantic approaches.

The machine learning approach aims to train a sentiment classifier using a labeled corpus. A general framework of sentiment analysis based on machine learning consists of four major phases: data preprocessing, text representation, classification, and evaluation. First, Chinese text processing needs an additional segmentation to break up the text into words (Zeng et al. 2011). For this purpose, we adopted the ICTCLAS system developed by the Institute of Computing Technology of the Chinese Academy of Sciences (http://english.ict.cas.cn/) to generate the segmentation of our online product reviews. After calculating the number of function words and the number of punctuation marks in each review, we deleted stop words and punctuation marks from our text.

In the text representation phase, a vector space model was used for text representation. This model helped to address three issues: feature selection, feature dimension reduction, and feature weight calculation. In feature selection, we considered all four types of features referred to by previous scholars (e.g., Abbasi et al. 2008). They are semantic features (e.g., the number of positive/negative sentiment words obtained based on predefined lexicons), stylistic features (e.g., the number of words, the average number of words in sentences), syntactic features (e.g., the number of punctuation marks, the number of function words), and content-specific features (e.g., words [unigrams], word n-grams [n = 2,3]). We obtained 6,094 features from the online product review dataset. Considering the strategy of selecting high-frequency words having a greater impact on sentiment classification (Pang et al. 2002), we used aggressive initial low-frequency feature reduction and removed all content-specific features that occurred less than three times in the data. This process left us with 2,233 features. Finally, in order to build a vector space model for text representation, we used the Boolean method to calculate feature weight because the sentiment types seem to be basically determined when some key features occur (Yao et al. 2011, pp. 315-322).

In the classification phase, we adopted a support vector machine (SVM) as the machine learning algorithm for our robustness check, because this method is considered one of the most effective tools for sentiment classification (Abbasi et al. 2008; Pang et al. 2002). Accordingly, we employed SVMTorch, which deals directly with multi-class classification problems to conduct experiments (http://bengio.abracadoudou.com/SVMTorch.html). Based on the 1,000 manually labeled online reviews, tenfold cross-validation was used to train and test the SVM classifier. To evaluate the performance of the sentiment analysis approach on the basis of machine learning, we used two most widely used criteria, namely, macro-average and accuracy (Ghamrawi and McCallum 2005; Thelwall et al. 2011). Macro-average was utilized to measure the performance of positive and negative classes respectively, while accuracy was used to evaluate the overall performance of sentiment classification. The empirical results indicated that the macro-average of the sentiment analysis approach based on machine learning reached 0.739 and 0.687 for negative and positive class, respectively. Accuracy reached 75.51%.

This comparison of the performance of machine learning and semantic approaches shows that the customized SentiStrength algorithm is more accurate than the SVM. The result is consistent with previous findings, which show that semantic sentiment analysis can obtain impressive accuracy when it is equipped with a high-quality lexicon (Thelwall et al. 2011; Waila et al. 2012). Accordingly, the customized SentiStrength algorithm is a good choice for this work.

Appendix D

Checking the Negativity Bias in Sentiment Strength of Online Reviews

Our comprehensive review of the extant literature shows that negativity bias (Godes and Silva 2012; Li and Hitt 2008; Moe and Schweidel 2012) is an important factor that must be considered in studying online reviews. With regard to negativity bias, both temporal and sequential effects are considered. Li and Hitt (2008) used time as their primary variable and examined negativity bias in the temporal process of review ratings, while Wu and Huberman (2008) looked into the sequential position of the reviews (i.e., how many reviews have already been submitted at time *t*) to uncover the negativity bias. Further, Godes and Silva (2012) integrated these two studies and investigated both the temporal process and sequential effects of online review ratings. Following Godes and Silva, we developed two variables: *Time*, which indicates how much time has elapsed since the first review, and *Sequence*, which indicates the position of the review in the sequence of reviews for a specific product. Figure D1 presents the data aggregated across reviews for each value of *Time* and *Sequence*. The figure shows that sentiment reflected in online reviews is stable and there is no negativity bias.

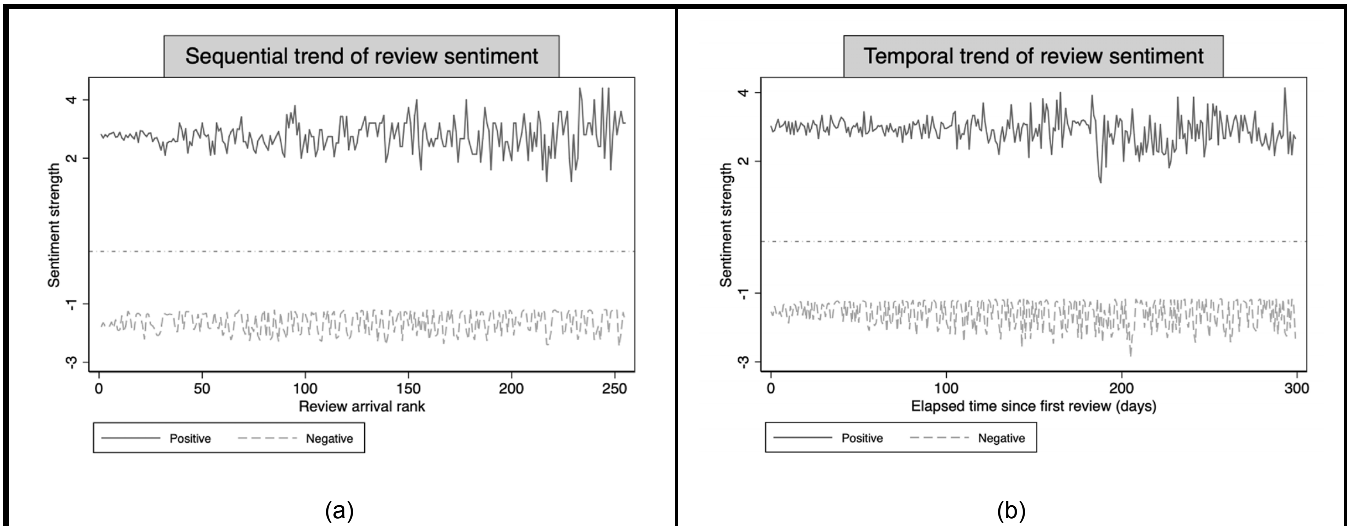

Figure D1. A "Model-Free" View of the Data

We also used a multivariate approach to double check the robustness of the findings. Specifically, we estimated models in which the dependent variable was the sentiment strength (*SenStr*)—positive sentiment strength (*PosSenStr*) and negative sentiment strength (*NegSenStr*)—that was assigned by a reviewer *i* to an item of product *j*. The independent variables of interest are *Time* aiSequencend . We controlled individual-level reviewer heterogeneity by forming a reviewer-level average sentiment strength. The variable *RevAvgSen* (including *PosAvgSen* and *NegAvgSen*) is the average sentiment strength of a customer's reviews on all items. We also controlled customer purchase and review tenure. A consumer's purchase tenure is measured as the difference, in months, between the date of review and the date of his/her first purchase, and a consumer's review tenure refers to the period between first and last review. The variable *Year*2012 indicates whether the review is generated in 2012. Table D1 shows the descriptive statistics of the variables. Given the discrete and ordered nature of our dependent variable, we specified the models using the ordered logit model:

$$
\begin{aligned}
SenStr_{ij} = \kappa I \big(\pi_{\kappa-1} & \\
& < \beta_1 RevAvgSen_1 + \beta_2 Time_{ij} + \beta_3 Sequence_{ij} + \beta_4 Tenure_{ij} \\
& + \beta_5 Year2012_{ij} + \delta_j +_{ij} \le \pi_\kappa \big)
\end{aligned}
$$

where κ denotes the realized value of a sentiment strength of $\kappa \in [1, K]$, being the highest sentiment strength allowed; π_1 through π_κ are cut-off parameters to help identify the intervals; $I(\cdot)$ is the indicator function, which equals one if $\cdot$ is true and zero otherwise; δ_j is the fixed effect of product *j*; and ε_{ij} is the error term. Table D2 shows the estimation results.

Table D1. Descriptive Statistics of Variables for Negativity Bias Analysis

Variables	Mean	SD	Min	Max
Review positive sentiment strength (SSR^{+}_{ijt})	3.725	1.272	1.000	5.000
Review negative sentiment strength (SSR^{-}_{ijt})	-2.129	0.637	-5.000	-1.000
Time (days since first review)	94.661	119.832	1.000	595.000
Sequence (sequential position of reviews)	41.106	91.169	1.000	619.000
Purchase tenure (months since first purchase)	3.212	2.197	0.000	16.000
Review tenure (months since first review)	2.5100	2.066	0.000	16.000
Reviewer positive sentiment strength ($PosAvgSen_i$)	3.699	1.054	1.000	5.000
Reviewer negative sentiment strength ($NegAvgSen_i$)	-2.115	0.461	-5.000	-1.000

The results in Table D2 show that the coefficients of the variables *Time* and *Sequence* are not significant, which indicates that there is no negativity bias in the sentiment of the product reviews in our dataset. This result is consistent with the finding of Vaish et al. (2008), which indicates that individuals' sentiment in online reviews is stable.

Table D2. Empirical Results for Sentiment Bias Analysis

Variable	Positive Sentiment Strength		Negative Sentiment Strength	
	Coefficient	SD	Coefficient	SD
PosAvgSen	2.733E-01***	9.073E-02		
NegAvgSen			4.843E-01***	2.423E-01
Time	-1.922E-04	7.742E-04	1.022E-04	1.525E-04
Sequence	1.346E-04	2.285E-04	-1.966E-03	1.614E-03
Purchase tenure	-1.172-02	9.961E-03	4.014E-03	6.003E-02
Review tenure	3.507E-02	1.399E-02	-6.465E-02	6.368E-02
Year 2012	-3.334E-01***	9.849E-02	-7.476E-01*	4.481E-01
Customer-fixed	Yes		Yes	
Product-fixed	Yes		Yes	
Pseudo-R^2	2.261E-01		3.516E-01	

Notes: ***$p < 0.01$, *$p < 0.1$

Appendix E

The Choice of Threshold Value in the Voting Scheme

We conducted additional analyses in which we improved the threshold of voting scheme gradually. High threshold value might lead to the fact that a majority is not obtained for a customer (i.e., the customer is not classified). We applied the voting scheme in three-ways - one, where customers with no majority are treated as "promotion focused", reported as type of "vote-pro" in the subsequent figure, and two, where such customers are treated as "prevention focused", reported as type of "vote-pre" in the subsequent figure, and three, where such customers are discarded, reported as "vote-dis" in the subsequent figure. We took classification results obtained from field survey as gold standard and calculated classification accuracy by changing the threshold value of voting scheme. The results are reported in Figure E1. As observed from the figure, high threshold value improves classification accuracy for the classified customers but degrade the overall classification performance because of its shrank size of the classified sample.

In order to prevent degradation due to its shrank size of the classified sample, we employed a state-of-the-art supervised machine learning algorithm, SVM, to classify the customers with no-majority votes, using customers' demographics (e.g., age) and their sentiment biases in product reviews (e.g., average positive sentiment-strength bias) as features. The subsample of customers who had obtained class label was used to train the SVM algorithm. The results are reported in Table E1. As observed from the table, the overall classification accuracy for the combined method is slightly higher than 85%. In sum, we found the approach of combining the voting scheme with high threshold and SVM algorithm had better performance. However, this combination approach imposes a round of supervised learning phase, which would unnecessarily increase the complexity of our method. In our field survey section, we show that, despite its simplicity, the original majority voting scheme is effective in producing high quality RF classification.

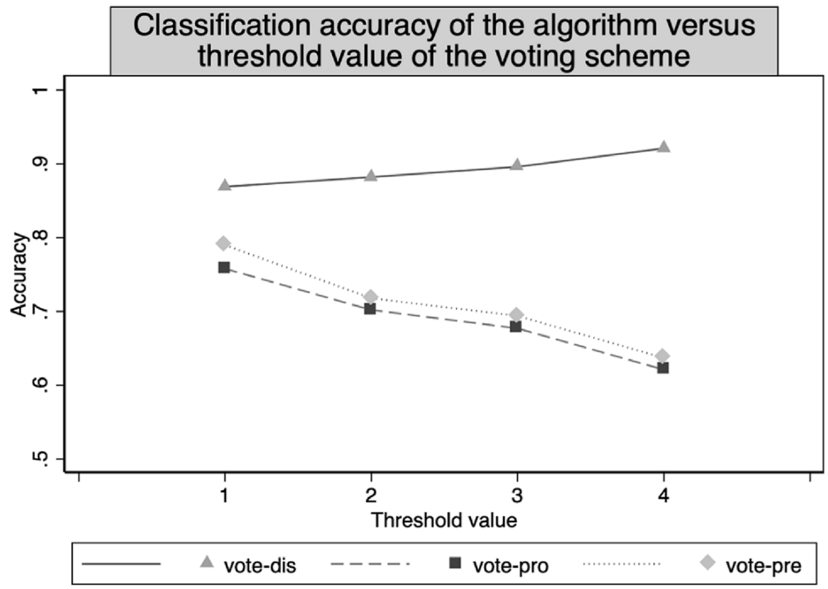

Figure E1. Classification Accuracy Versus Threshold Value

Table E1. The Performance of Combined Method Versus Varying Threshold Value of the Voting Scheme

	Threshold Value of the Voting Scheme			
	1	2	3	4
Classification Accuracy	0.863	0.879	0.887	0.871

Appendix F

Survey Respondents and Selection Bias

Table F1 summarizes the mean value of customer demographics and the average volume of online review activity for non-survey customers and survey respondents. The third column of Table F1 shows the ratio between non-survey customers and survey respondents. We used *t*-test and Mann-Whitney U-test to compare survey respondents with non-survey customers.

The descriptive statistics in Panel A of Table F1 suggest that demographics (i.e., age, gender, income, urban, and south) of survey respondents are similar to that of non-survey customers. Both *t*-test and U-test suggest that there are no demographic differences between survey respondents and non-survey customers. Second, we compare online review activity of survey respondents with online review activity of reviewers outside the survey. The results are reported in Panel B of Table F1. We do not observe a significant difference in the average volume of product reviews between the two groups.

Moreover, we use Figure F1 and Figure F2 to show the box plots and histograms of customer characteristic distributions for the two groups: the survey respondents and the non-survey customers. All of the plots reveal that the distributions for survey respondents and for non-survey customers are similar, which further provide evidences that the 124 respondents to our survey do not suffer from biases to selection.

Table F1. Comparing Customer Characteristics of Non-Survey Customers and Survey Respondents

Variable	Non-Survey Mean	Survey Mean	Ratio	*t*-Test	U-test
Panel A: Customer Demographics					
Female	0.768	0.779	0.986	-0.393	-0.393
Age	32.784	33.000	0.993	-0.764	-0.672
Income	2.141	2.111	1.014	0.347	0.598
Urban	0.196	0.172	1.133	0.816	0.816
South	0.781	0.793	0.985	-0.426	-0.426
Panel B: Customer Review Behavior					
Number of product reviews	6.637	7.120	0.932	-0.874	0.893

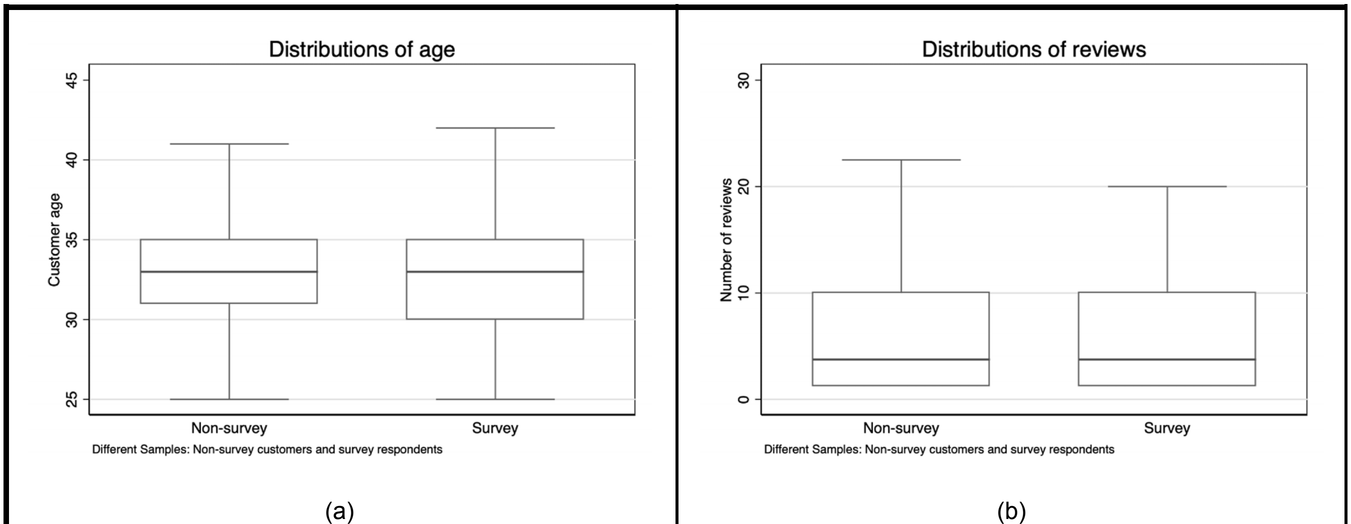

Figure F1. Distribution of Customer Age and Number of Reviews

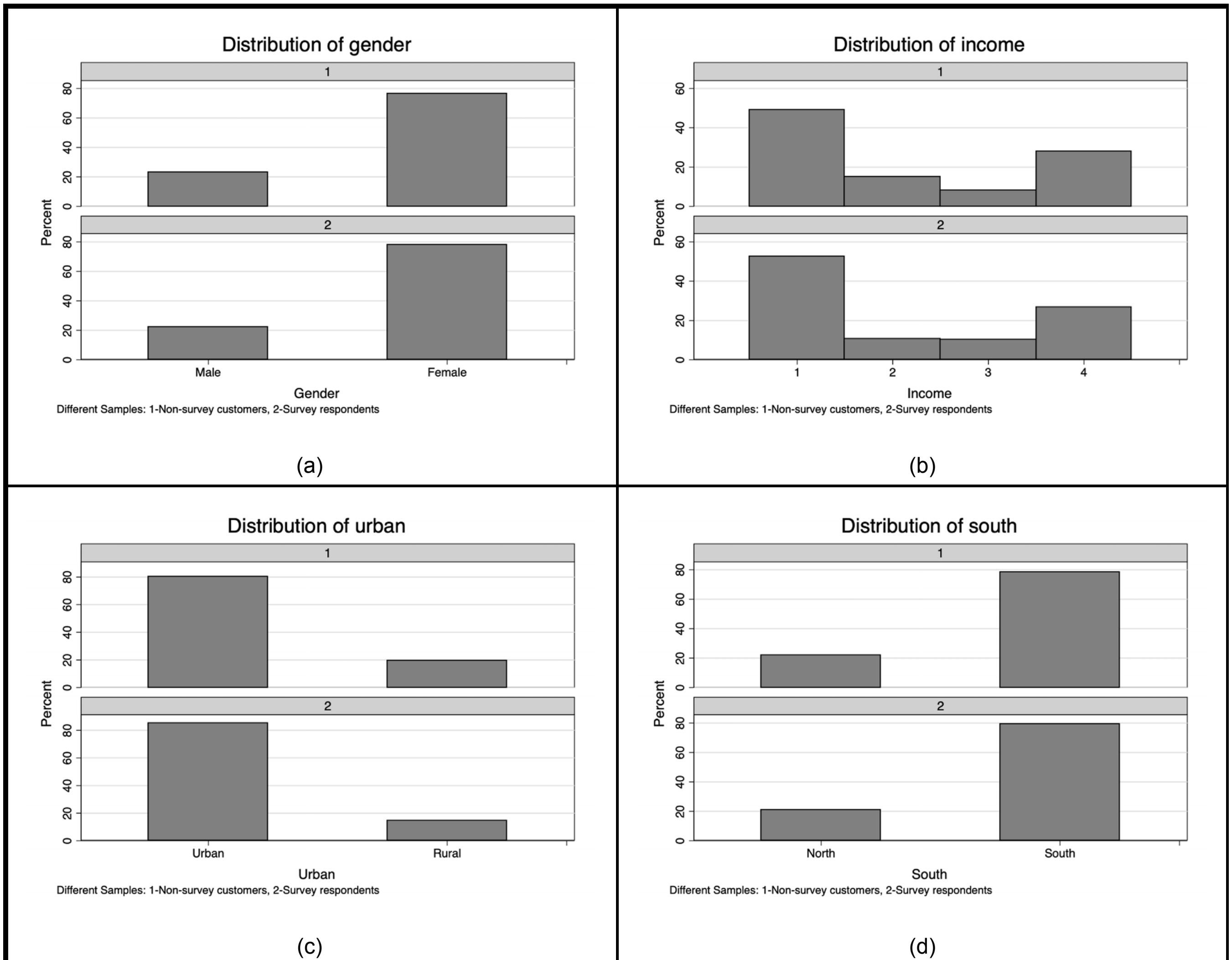

Figure F2. Distribution of Customer Gender, Income, Urban, and South

Appendix G

The Relationship between Survey RF and Sentiment Biases in Reviews

We employ two steps to test the relationship between customers' RF from the survey and their sentiment biases from text mining:

(1) We calculated customers' average positive sentiment bias $\left(Avg\_psb_i = \sum_j \left(SSR_{ij}^{+} - SSP_{ij}^{+} \right) / n \right)$ and average negative sentiment bias $\left(Avg\_nsb_i = \sum_j \left(SSP_j^{-} - SSR_{ij}^{-} \right) / n \right)$, and regressed them on the RF promotion scales as well as the RF prevention scales, respectively, in a linear regression. We found that higher promotion scores are positively related to greater positive-sentiment bias in customers' online reviews ($\beta = 0.40$, $p < 0.01$) and higher prevention scores are positively related to greater negative-sentiment bias in customers' product reviews ($\beta = 0.16$, $p < 0.05$).

(2) We used the procedure proposed by Higgins et al. (1997) to classify the survey respondents into either having a chronic promotion focus or a chronic prevention focus according to the median between their average RF promotion and RF prevention scores. Again, as expected, the chronic promotion-focused group had a higher average positive sentiment bias than the chronic prevention-focused group (mean = 0.15 versus mean = -0.53; $t = -3.3$, $p < 0.01$). Similarly, the chronic prevention-focused group had a higher average negative sentiment bias than the chronic promotion-focused group (mean = 0.13 versus mean = -0.16; $t = 2.85$, $p < 0.01$).

Appendix H

Propensity Score Matching

We conducted a PSM analysis first by modeling the customers' community participation decision. We identified a set of exogenous variables as covariates: (1) gender ($Female_i$); (2) age (Age_i); (3) a zip code-level estimate of the level of household income ($Income_i$); (4) whether a customer disclosed his/her home address when he/she registered ($AddressDisclosed_i$); (5) whether a customer disclosed his/her telephone number when he/she registered ($PhoneDisclosed_i$); (6) whether a customer disclosed his/her MSN number ($MSNDisclosed_i$) when he/she registered; (7) whether a customer lived in an urban area ($Urban_i$); (8) whether a customer lived in the south of the country ($South_i$); (9) review intensity before participation ($ReviewIntensity_i$), which is measured as the ratio of the number of online product reviews posted by a customer in a certain time period to the number of products bought by the customer in the same time period; and (10) RF. We expected a customer's community participation to be related to gender, age, income level, and location (Muniz and O'Guinn 2001), because the focal firm is a clothing retailer that mainly sells stylish apparel. We also expected a user, who has made a decision to take part in the OBC, to be affected by concerns over data privacy (Goh et al. 2013). Further, we expected that a customer's propensity to express his/her opinions on products ($ReviewIntensity_i$) and RF would influence his/her decision to engage in the community. We also examined whether there is a relationship between RF and community participation. The results shown in Table H1 suggest that the community participation behavior of promotion-focused customers differs significantly from that of prevention-focused customers, and that promotion-focused customers are more likely to engage in OBCs than prevention-focused customers.

Table H1. RF and Community Participation

	Prevention (Mean)	Promotion (Mean)	U-test *p*-value	*t*-test *p*-value
Community participation	0.491	0.552	3.097***	3.100***

Note: ***$p < 0.01$

With these exogenous variables, we calculated the probability of a customer participating in the OBC with a logistic model formulation. Table H2 shows the estimated logit model. We then performed matching with the optimal pair-matching algorithm. Each treated customer was matched with the most similar non-treated customer (non-participant). We also tested the balancing property of the propensity score to see if the underlying assumptions of the PSM process held. We checked whether the covariates in the logit model differ between the treatment and control observations. The results are reported in Table H3. As seen in the table, the variables used for the PSM were not significantly different across the two groups of customers' post matching, implying statistical balance. To test whether the common support condition was met, we plotted the propensity score distributions pre- and post-matching of the two groups. Figure H1 describes the kernel density function of the propensity scores of the participation and non-participation groups. It shows that the common support condition is met. As a result of the above procedure, we were able to satisfactorily match treatment customers to a set of control customers, all of whom were included in model estimation next.

Table H2. Results of Estimated Logit Model		
Variable	**Parameter**	**Std. Error**
Female	0.235***	0.085
Age	-0.044***	0.013
Income.2	0.034	0.108
Income.3	-0.261***	0.082
Income.4	-0.238**	0.096
AddressDisclosed	0.534	0.498
PhoneDisclosed	0.567***	0.081
MSNDisclosed	-0.015	0.105
Urban	0.128*	0.075
South	-0.045	0.067
ReviewIntensity	0.045**	0.021
ReguFocus	0.222***	0.080
Constant	0.457	0.664
Pseudo-R^2		0.205

Notes: *p < 0.1, **p < 0.05, ***p < 0.01. The variable *Income* is a category variable, and we use *Income*.2, *Income*.3, and *Income*.4 to indicate the different categories of customer income.

Table H3. Summary of Statistics and Covariate Comparison after Matching				
Variable	**Treatment Group Mean**	**Control Group Men**	**Mean Difference**	***t*-test *p*-value**
Female	0.800	0.805	-0.005	0.708
Age	32.805	32.880	-0.075	0.467
Income.2	0.147	0.140	0.007	0.560
Income.3	0.096	0.099	-0.003	0.754
Income.4	0.236	0.226	0.010	0.508
AddressDisclosed	0.996	0.998	-0.002	0.479
PhoneDisclosed	0.565	0.571	-0.006	0.793
MSNDisclosed	0.216	0.227	-0.011	0.446
Urban	0.184	0.194	-0.010	0.506
South	0.807	0.828	-0.021	0.135
ReviewIntensity	0.310	0.305	0.005	0.755
ReguFocus	0.682	0.667	0.015	0.349

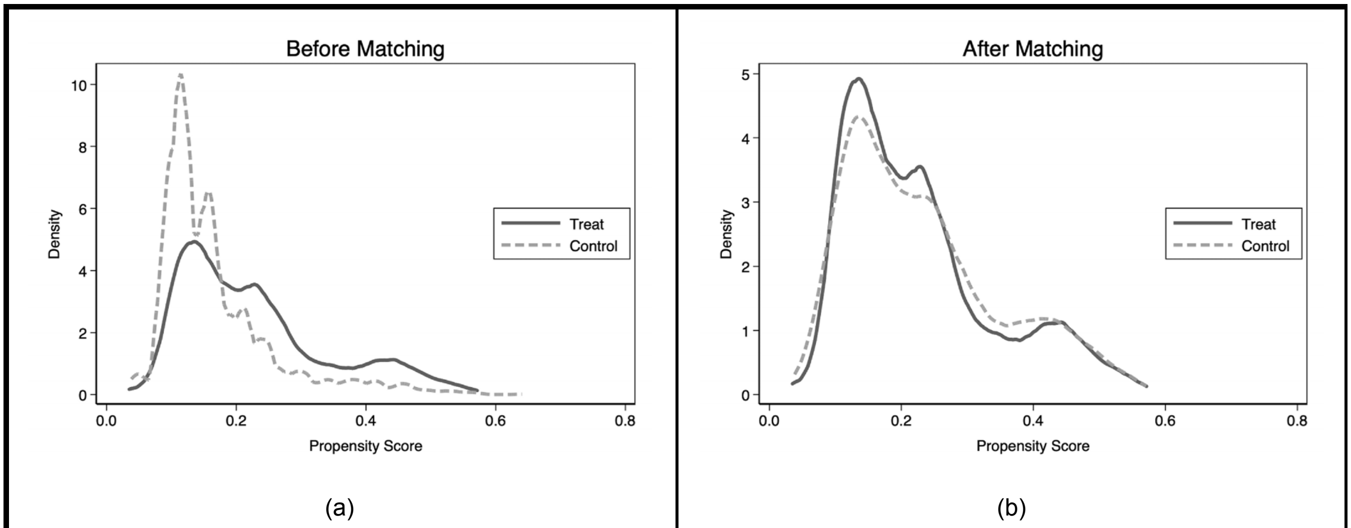

Figure H1. Kernel Density of Participation and Non-Participation Group

Appendix I

Instrumental Variable Specification

In order to theorize the relationships between the instrumental variable (i.e., review intensity) and OBC participation, our review of the literature shows that the main factors that determine people's propensity to post reviews are self-enhancement (Angelis et al. 2012), information acquisition (Berger 2014), social interaction (Hennig-Thurau et al. 2004), and altruism (Dellarocas and Narayan 2006). Meanwhile, similar factors such as social identity (Bagozzi and Dholakia 2006), information motive (Chang et al. 2013), and relational capital (Casaló et al. 2010) are considered to have the most influence on individuals' propensity to engage in a brand community. Accordingly, we could learn that individuals' propensity to either post reviews or engage in a brand community shares the same factors, like social interaction motive, information motive, and self-efficacy motive. Accordingly, evidence is prominent in deducing the correlations between review intensity and OBC participation (relevance assumption).

In addition, scholars have also pointed out that customers' review propensity, as one of their traits, is not related to their purchase frequency. For instance, Hennig-Thurau et al. (2004) demonstrated empirically that customers' propensity to post reviews is not influenced by the frequency of product experience. Moreover, in the study of Arnold et al. (2014), the authors have uncovered that customers often generate a number of reviews even if they did not purchase products. Empirically, we found a strong positive relationship between the variable of OBC participation (*OBCPart*) and review intensity, with an *F*-statistic value of 17.22. Thus, the review intensity variable satisfies the basic requirement for the instrumental variable to be relevant (Bound et al. 1995). Moreover, according to Stock and Yogo (2005), the weak identification test also indicates that the review intensity is not a weak instrument. Next, we tested the exclusion restriction of our instrumental variable. It seems that this instrument meets the exclusion restriction because it is difficult to think of a direct channel by which review intensity can affect purchase frequency. We tested this assumption by regressing purchase frequency on the review intensity variable and other controls. We found that the coefficient of the estimated review intensity variable is non-significant (the coefficient of the estimate is 0.074, $p > 0.1$). This indicates that the review intensity variable satisfies the exogeneity requirement of the instrumental variable in our setup (Angrist and Krueger 1999). To summarize, the review intensity is considered a suitable instrumental variable in our study.

The results of our instrument specification are presented in Table I1. Considering the endogenous variable issue, we reported our results incrementally from Model 7 to Model 8. We also divided the sample data set into two subsamples (one group with customers of promotion focus and the other with customers of prevention focus). We then conducted IV estimation for each subsample. The Model 9 column shows the result of the IV specification for the prevention-focused customers, and the Model 10 column shows the result of the IV specification for the promotion-focused customers. That is, the results from our IV specification are consistent with the results obtained from DID method, indicating that they are robust.

Table I1. Instrumental Variable Specification				
Variables	**Model (7) IV for *OBCPart***	**Model (8) IV for *OBCPart*, Interaction**	**Model (9) IV for *OBCPart*, Prevention Focus**	**Model (10) IV for *OBCPart*, Promotion Focus**
OBCPart	0.542** (0.257)	0.112 (0.191)	-0.333 (1.629)	1.178** (0.506)
OBCPart × *ReguFocus*		0.095** (0.039)		
NeighborPurFreq	0.0165* (0.009)	0.012 (0.011)	0.021 (0.043)	0.034* (0.020)
PromIntensity	0.295*** (0.032)	0.396*** (0.040)	0.263** (0.121)	0.321*** (0.070)
log(*Price*)	-0.097*** (0.017)	-0.076*** (0.019)	-0.138** (0.064)	-0.120*** (0.036)
TranFee	-0.009*** (0.002)	-0.005* (0.002)	-0.012* (0.0073)	-0.005 (0.006)
Intercept	0.438 (0.281)	-0.159 (0.231)	-0.107 (1.635)	0.370 (0.402)
User fixed effects	Yes	Yes	Yes	Yes
Time-specific dummies	Yes	Yes	Yes	Yes

Notes: Standard errors are in parentheses. *$p < .1$, **$p < 0.05$, ***$p < 0.01$.

Appendix J

Inclusion of Additional Variables and Alternative Matching Algorithm

Table J1. Results of Estimated Logit Model with Additional Variables		
Variable	**Parameter**	**Std. Error**
Female	0.234***	0.086
Age	-0.044***	0.013
Income.2	-0.058	0.115
Income.3	-0.289**	0.140
Income.4	-0.212**	0.108
AddressDisclosed	0.329	0.500
PhoneDisclosed	0.423***	0.084
MSNDisclosed	-0.009	0.107
Urban	0.145*	0.083
South	-0.072	0.097
ReviewIntensity	0.051**	0.023
ReguFocus	0.204**	0.082
EamilValidated	0.695***	0.074
EasMidWes.2	0.234**	0.115
EasMidWes.3	0.138	0.162
Constant	0.500	0.669
Pseudo-R^2	0.235	

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. The variable *EasMidWes* is a category variable.

Table J2. Robustness Check of Additional Variables and Alternative Matching Algorithm				
Variables	**Model (11)**	**Model (12) Interaction**	**Model (13) Prevention Focus**	**Model (14) Promotion Focus**
Treated	0.048 (0.045)	0.047 (0.045)	0.183** (0.079)	0.157*** (0.055)
OBCPart	0.041 (0.037)	0.037 (0.037)	0.127* (0.069)	0.013 (0.044)
Treated × *OBCPart*	0.206*** (0.053)	0.081 (0.068)	-0.096 (0.098)	0.329*** (0.063)
Treated × *OBCPart* × *ReguFocus*		0.162*** (0.055)		
NeighborPurFreq	0.069* (0.038)	0.071* (0.038)	0.0569 (0.078)	0.083* (0.044)
PromIntensity	0.396*** (0.040)	0.400*** (0.039)	0.443*** (0.074)	0.379*** (0.047)
ln(*Price*)	-0.075*** (0.019)	-0.075*** (0.019)	-0.075** (0.035)	-0.072*** (0.023)
TranFee	-0.005 (0.003)	-0.004 (0.003)	-0.003 (0.006)	-0.007* (0.004)
Intercept	-0.114 (0.260)	-0.055 (0.261)	-0.302 (0.585)	-0.086 (0.293)
User fixed effects	Yes	Yes	Yes	Yes
Time-specific dummies	Yes	Yes	Yes	Yes
R^2	0.092	0.094	0.134	0.105

Notes: Standard errors in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01

Appendix K

Purchase Expenditure and Subsample Analysis

Table K1. OBC Participation and Customer Purchase Expenditure

Variables	Model (15) No controls	Model (16) Controls	Model (17) Controls, FE, TE	Model (18) Three-Way Difference
Treated	0.105 (0.066)	0.047 (0.045)	0.013 (0.044)	0.012 (0.044)
OBC Part	0.020 (0.052)	0.085** (0.035)	0.022 (0.037)	0.018 (0.038)
Treated × OBCPart	0.255*** (0.079)	0.198*** (0.053)	0.183*** (0.053)	0.097* (0.057)
ReguFocus	0.071* (0.039)	0.029 (0.027)		
Treated × OBCPart × ReguFocus				0.124*** (0.054)
NeighborPurFreq		0.157*** (0.030)	0.059 (0.038)	0.060 (0.038)
PromIntensity		0.375*** (0.038)	0.397*** (0.040)	0.401*** (0.039)
ln(*Price*)		1.029*** (0.018)	1.061*** (0.019)	1.062*** (0.019)
TranFee		-0.004 (0.003)	-0.006* (0.003)	-0.005 (0.003)
Intercept	5.372*** (0.048)	0.323*** (0.104)	-0.064 (0.258)	-0.019 (0.259)
User fixed effects	No	No	Yes	Yes
Time-specific dummies	No	No	Yes	Yes
R^2	0.108	0.539	0.634	0.655

Notes: Standard errors in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table K2. Impacts of OBC Participation on Purchase Expenditure Varying with RF

Variables	Model (19) Subsample: Prevention Focus		Model (20) Subsample: Promotion Focus	
	Coefficient	SD	Coefficient	SD
Treated	0.192***	0.079	0.103*	0.053
OBCPart	0.087	0.069	0.005	0.043
Treatment ×OBCPart	-0.063	0.098	0.278***	0.063
NeighborPurFreq	-0.009	0.075	0.077*	0.044
PromIntensity	0.478***	0.074	0.369***	0.047
ln(*Price*)	1.087***	0.035	1.051***	0.023
TranFee	-0.001	0.006	-0.007*	0.003
Intercept	-0.201	0.582	-0.003	0.291
User fixed effects	Yes		Yes	
Time-specific dummies	Yes		Yes	
R^2	0.605		0.541	

Notes: Standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table K3. Impact of OBC Participation on Customer Purchase Frequency with Subsample			
Variables	**Model (21) Did**	**Model (22) Prevention Focus**	**Model (23) Promotion Focus**
Treated	0.088 (0.205)	0.243 (0.397)	0.210 (0.246)
OBCPart	0.145 (0.157)	0.044 (0.289)	0.240 (0.188)
Treated ×OBCPart	0.057 (0.298)	-0.387 (0.497)	0.515** (0.236)
Treated × OBCPart × ReguFocus	0.313* (0.164)		
NeighborPurFreq	0.437*** (0.137)	-0.119 (0.337)	0.587*** (0.144)
PromIntensity	0.529*** (0.179)	0.852* (0.475)	0.536*** (0.189)
ln(*Price*)	-0.150* (0.084)	-0.344* (0.186)	-0.103 (0.095)
TranFee	-0.001 (0.012)	0.006 (0.025)	-0.001 (0.015)
Intercept	-0.269 (0.486)	-0.966 (1.037)	-0.323 (0.532)
User fixed effects	Yes	Yes	Yes
Time-specific dummies	Yes	Yes	Yes
$R2^2$	0.120	0.174	0.193

Notes: Standard errors in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

Appendix L

Inclusion of Customer Satisfaction

Table L1. Robustness Check of OBC Participation with Delta Purchase				
Variables	Model (24)	Model (25) Interaction	Model (26) Prevention Focus	Model (27) Promotion Focus
Treated	0.023 (0.037)	0.024 (0.037)	0.147** (0.068)	0.125*** (0.045)
OBCPart	0.015 (0.031)	0.017 (0.031)	0.023 (0.059)	0.037 (0.036)
Treated × *OBCPart*	0.118*** (0.044)	0.095* (0.056)	-0.038 (0.084)	0.175*** (0.053)
Treated × *OBCPart* × *ReguFocus*		0.108** (0.046)		
DeltaPurchase	0.994*** (0.268)	0.992*** (0.268)	1.003** (0.507)	0.987*** (0.305)
NeighborPurFreq	0.061* (0.032)	0.061* (0.032)	0.056 (0.066)	0.061* (0.036)
PromIntensity	0.320*** (0.035)	0.322*** (0.033)	0.456*** (0.064)	0.266*** (0.039)
ln(*Price*)	-0.074*** (0.021)	-0.071*** (0.029)	-0.058* (0.030)	-0.032*** (0.019)
TranFee	-0.004 (0.003)	-0.003 (0.003)	-0.003 (0.005)	-0.007** (0.003)
Intercept	-0.105 (0.220)	-0.102 (0.221)	-0.935 (0.501)	-0.103 (0.246)
User fixed effects	Yes	Yes	Yes	Yes
Time-specific dummies	Yes	Yes	Yes	Yes
R^2	0.132	0.135	0.138	0.137

Notes: Standard errors in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Appendix M

Ruling Out Reverse Causality

Table M1. The Impact of Purchase Frequency on OBC Participation				
Panel A: Average Purchase Frequency Before Participation for Treatment and Control Groups				
Variable	**Treatment Group**	**Control Group**	**Difference**	***t*-Test**
	2.282	2.203	0.079	1.286
Panel B: The Impact of Purchase Frequency on Community Participation				
Variable	**First-Step Results**	**Cutoff Point = 0.5**	**Cutoff Point = 0.4**	**Cutoff Point = 0.3**
PriorPurFreq	0.007 (0.009)	0.014 (0.012)	0.012 (0.017)	0.049 (0.051)

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