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An Experimental Analysis of Investor Sentiment*

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Abstract

We use an experiment with a sample of professional investors to study the impact of text and emojis on investment proportion. We find that text - provided as a supplementary information - have a statistically significant on investors' decisions. However, the magnitude of the impact is too small (around 1%) to conclude that investor sentiment has an economically significant impact on investment decisions. We also find that emojis have no impact investment decisions. Overall, our results are consistent with the efficient market hypothesis: in an experimental setting where the payoff and the probability of each decision are known, investment decisions of sophisticated traders are driven mostly by the type of asset, the level of risks and the associated return of each investment and not by investor sentiment.

Keywords: Investor sentiment, Efficient market hypothesis, Natural language, Emojis, Social media, Experimental finance, Behavioral finance.

JEL: C99, G11, G14, G41.

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1 Introduction

Behavioral finance has long studied how noise traders can cause prices to diverge temporarily from fundamental value (Long et al. 1990). Investor sentiment - i.e. beliefs about future cash flows and investment risks that is not justified by the facts at hand - has been identified as one vehicle behind mispricing and divergence from fundamental value. As Baker and Wurgler (2007) state it, “the question is no longer whether investor sentiment affects stock prices, but how to measure investor sentiment and quantify its effects." This paper contributes to this research agenda by studying the impact of languages and emojis using an experiment with a sample of professional investors in a setting in which various aspects of investment decisions are controlled and varied using an experimental setting.

Investor sentiment - computed using sentiment analysis on textual data from newspapers, blog or social media - helps predict future asset prices and volatility (Chen et al. 2014; Renault 2017; Tetlock 2007; Tetlock et al. 2008). However, demonstrating that the relation between investor sentiment and financial market movements is causal is far from being trivial. For example, if we focus on the literature using messages sent on social media to compute investor sentiment (Renault 2020; Sprenger et al. 2014), it remains unclear whereas messages on social media reflect existing information and is thus just a proxy of "soft" information that could not be captured with traditional data, or if messages on social media directly influence other investors behaviors and has a real causal effect.

Studying experimentally investor sentiment thus presents an opportunity to improve our understanding of the price formation process in financial markets and on the role - at the micro-level - of languages on investment decisions. The main scientific interest is to experimentally test the validity of hypotheses often formulated in the literature on market sentiment. In particular, we aim to study the possible causal link between the linguistic corpus used in the work on the measurement of investor sentiment, as one aspect of market sentiment, on investment decisions.

First, our paper contributes to the literature on the impact of languages on investor behavior. Closely related to our paper, Hales et al. (2011) use an experiment and find that vivid language significantly influences the judgment of investors who hold positions "against the market", but do not affect the judgement of investors who hold position in line with other investors (long position in a bullish market, short position in a bearish market). Also running an experiment, Tan et al. (2014) find that language sentiment affect investor behaviour but only when the readability of the text is low. Elliott et al. (2015) find that investors are significantly more willing to invest in a firm when concrete language is used than when abstract language is highlighted. Running our experiment, we find that positive messages - provided as a supplementary information to an investment proposition where the probability and the payoff are known - have a statistically significant marginal impact on the level of investment compared to a baseline condition without messages. However, the magnitude of the effect - around 1% - and the contribution of the variable to the R^2 are both rather small, suggesting that our proxy of investor sentiment only plays a minor role on investment decision.

Second, we contribute on the literature on the impact of images and visualisation on investor behaviour. Elliott et al. (2012) find - on an experiment of 80 MBA students - that investors tend to recommend larger investment in a company when the CEO of a company accept the responsibility of a restatement in an online video than do investors who receive the same information online with a text. In this test paper, we test the hypothesis that investment proposition accompanied by a text including emojis has more impact that investment proposition accompanied simply by a text. Emojis are widely used on social media (more than 20% of the geolocalized tweets used in Kejriwal et al. (2021) contains at least emoji) and each emoji is easily associated with an idea or a sentiment (Kralj Novak et al. 2015). Emojis also improves the accuracy of sentiment analysis algorithm on financial tweets (Mahmoudi et al. 2018; Renault 2020). In our experiment, we don't find that adding emojis to a message changes the investment decision of professional investors. This results holds when we add one emoji or mutliple (three) emojis at the end of messages.

To assess the robustness of our results, we use a specification with user-fixed effects and a specification where we control for gender, age, education, political preferences and beliefs in the efficient market hypothesis. We also analyze if the credibility of the user sending the message (professional or individual) has an impact on the way messages and emojis are perceived by investors in our experiment. Our results holds for all specifications, suggesting the our estimation of the impact of languages and emojis is robust.

The paper is organized as followed. The first Section describes our experimental methodology and related hypotheses. The second Section presents our results. The last Section concludes.

2 Experimental methodology and related hypotheses

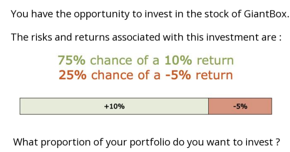
2.1 Experimental design

The experimental study aims at measuring the impact of investor sentiment on investment behavior. Each participant has to decide what proportion of their portfolio they wish to invest in this virtual opportunity. The investment opportunity is described with the use of a lottery which offers either a positive return outcome with a known probability and a negative return outcome with a known probability. The experimental condition includes variations on the asset type, the risk type, the user profile, and the text format.

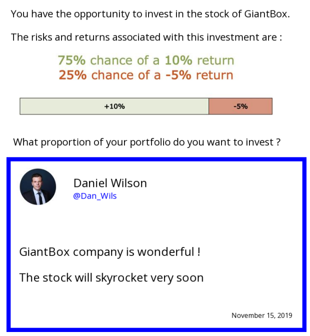
Asset and risk : The investment opportunity is presented in the form of an asset type and there are four different types of assets: stock, corporate bonds, cryptocurrency or initial coin offering (ICO) - which refers to the offering of shares of a company using cryptocurrency. The use of these different assets helps capturing the impact of the main financial vehicles that professionals in finance deal with when making investment decisions. The investment opportunity is presented with three different types of risk: hereafter referred to as Risk profile 1, Risk profile 2, and Risk profile 3. The expected payoffs presented on each investment profile were in line with what is observed in historical returns behavior of the corresponding investment assets. The experimental design purposefully uses combinations of asset classes and return distributions as frames to convey information that is understandable and ecologically relevant to finance professionals. Vignettes without explicit references to existing assets and risks / returns that mimic documented facts about different asset classes may have been too abstract and too detached from reality, potentially leading to inattention and distraction. We define the risks / returns of the different lotteries such as (for example on the risk profile 1) : for the risk, *Risk Bond* $<$ *Risk Stock* $<$ *Risk Crypto* $<$ *Risk ICO* and for the return, *Return Bond* $<$ *Return Stock* $<$ *Return Crypto* $<$ *Return ICO*. While the differences between the risks / returns of bonds and stocks have been documented in the literature - see for example Jordà et al. (2019) - the choice on the risks / returns of cryptocurrencies and ICOs depends on the period considered. For cryptocurrencies, even after the recent market crashes, the return is largely positive over the last 5 - 10 year period (associated with a large volatility) (Trimborn and Härdle 2018). For ICOs, given the large number of scams, we define a very high level of risk (Zetzsche et al. 2017).

User - Text : Inspired by communication on common social media platforms, two user profiles are implemented, a professional profile, namely from an investment firm, and an individual, designated by a fictitious name and a picture. These user profiles are used to implement the three different text conditions. The Text condition consists in adding a short text to accompany the investment proposition, inspired by what is seen on social media, thus in a tweet-like message to study the impact of text alone. As emojis are also common in social media, two other text conditions were implemented, one with one emoji and one with three emojis. Finally, for the visual information, we end up with 4 cases per asset-risk-user combinations: vignettes with no text which are the baselines, vignettes with text and without emoji (each time, with either the professional or the individual user profile), vignettes with text with one emoji (each time, with either the professional or the individual user profile), and vignettes with text with three emojis (each time, with either the professional or the individual user profile). Figure 1 present an example of the baseline and the 3 language cases for a given asset-risk-user combinations.

There are 4 asset types and 3 risk profiles. Thus, there are $4 \times 3 = 12$ vignettes that serve as baselines. The language conditions are implemented with 2 user types and 3 language conditions. Thus, there are $4 \times 3 \times 2 \times 3 = 72$ vignettes that are in the treatment condition. This results in 84 different investment tasks. Table 1 reports the risk profiles and emojis used. A sample of vignettes



((**a**)) Benchmark investment proposition



((**b**)) Investment proposition with a text

((**c**)) Investment proposition with a text + 1 emoji

((**d**)) Investment proposition with a text + 3 emojis

Figure 1: Example of the 4 language conditions ((a), (b), (c) and (d)) for a given asset-risk-user combinations (here: stock - low risk - individual investor)

are presented in the Appendix; in Figure A1 for the Stock asset type, Figure A2 for the Corporate bond asset type, Figure A4 for the Cryptocurrency asset type and Figure A3 for the ICO asset type.

Table 1: Experimental treatments

Asset	Probabilities	Risk Profile	Returns associated	Emoji
Stock	75%-25%	(1)	10% / -5%	📈
		(2)	5% /-5%	💸
		(3)	5% /-10%	💪
Corporate Bond	90% - 10%	(1)	5% / -5%	👍
		(2)	2% /-5%	✅
		(3)	2% /-8%	😀
ICO	10%-90%	(1)	1000% / -50%	🚀
		(2)	500% /-50%	🔥
		(3)	500% /-100%	🤑
Cryptocurrency	50%-50%	(1)	30% / -10%	📉
		(2)	20% /-10%	💩
		(3)	20% /-20%	💀

2.2 Experimental implementation

First, before performing the main experimental task, demographic information about the participants (including age, gender, profession, political preferences, etc.) was collected. Second, participants made their decisions in the experimental task. Finally, after completing the experimental task, participants' attitudes towards the efficient market hypothesis was measured. Indeed, according to the efficient market hypothesis (Fama 1970), all information available concerning a financial asset is materialized in its price by rational market agents. As new information emerges, it is immediately reflected in the price of the corresponding asset. It can consequently be stated that the price of an asset is a reflection of the information available about it. If that is the case, information from social media is useless.

The participants were asked to answer five questions that aimed at documenting their level of agreement with the efficient market hypothesis. Participants had to rate - from "strongly agree" to "strongly disagree" - the 5 following propositions : (1) Public information is priced into securities ; (2) Information from social media is priced into securities; (3) Technical analysis can provide an advantage for an investor; (4) Fundamental analysis can provide an advantage for an investor; (5) It is possible to beat the market. These questions aimed at documenting the potential effects of attitudes towards the efficient market hypothesis in that it may impact their perception of text and emojis in the vignettes.

220 financial professionals were recruited for the experiment using Qualtrics Research, a survey research firm (https://www.qualtrics.com/). Qualtrics Research allows access to targeted professional populations as well as representative samples in the United States. The professions of the participants were as follows: financial analysts make up for 63.80% of that sample, professional investors 16.29%, portfolio managers 11.76%, traders 7.24% and venture capitalists 0.90%. Qualtrics operates with proprietary panels and the research participants are required to fill out a targeting questionnaire when they join panels. They are required to reveal their job position which then allows Qualtrics to direct them to appropriate studies. The experiment generated 18,467 observations (i.e. 84 x 220 = 18,480 - 13 missing observations due to a few participants not responding in 13 instances in total).

In the experiment, each participant was rewarded at the end of the experiment conditional on full participation with a flat fee. We decided to use an experimental design as we feared that using incentivized choices with finance professionals may have distorted their perception as stakes in the experiment are, by definition, infinitely smaller than what finance professionals face in real markets.s. Furthermore, a large literature shows that patterns of behavior are similar across incentivization methodologies, notably with professionals (Abdellaoui et al. 2013; Bardsley et al. 2010; Beattie and Loomes 1997; Camerer and Hogarth 1999; Fréchette 2015; Hackethal et al. 2020). Finally, although our participants were paid, one can hypothesize that their willingness to participate in the study suggests that they were interested in performing the task. However, we fully acknowledge that there is certainly no easy solution to incentivize finance professionals.

2.3 Related hypotheses

The experimental methodology allows us to posit the following hypotheses:

- **H1** The proportion invested in a given asset-risk combination is higher when the proposition is accompanied with a text.
- **H2** The proportion invested in a given asset-risk combination is higher when emojis are displayed than when they are not.
- **H3** The proportion invested in a given asset-risk-user combination is higher when the message is sent by a professional investors than when it is send by an individual investors.

3 Results

3.1 Distributions and means of investment proportions

Figure 2 reports the distributions of investment proportions by treatment. The distributions by treatment show that the presence of text, regardless of whether or not it is combined with emojis, leads to an increase in investment decisions, concentrated mainly in the 65%-95% interval.

Table 2 reports the means of investment proportions by treatment conditions and by investment assets. The results show that investment are highest in the corporate bonds investment asset (in the region of 57 to 59), followed by the stock market investment asset (in the region of 57), the cryptocurrency investment asset (in the region of 52 to 54) and finally the ICO investment asset (in the region of 50 to 51). Table 3 shows that the differences in means across investment assets are statistically significant while the differences across language conditions (no text / text / text + 1 emoji / text + 3 emojis) is not statistically significant. This preliminary result does not take into account all the variables of our experiment (level of risk, type of users) and does not allow to control for user-fixed effects. We therefore use a multivariate regression method in the following section to better capture the effect of language conditions on investment decisions.

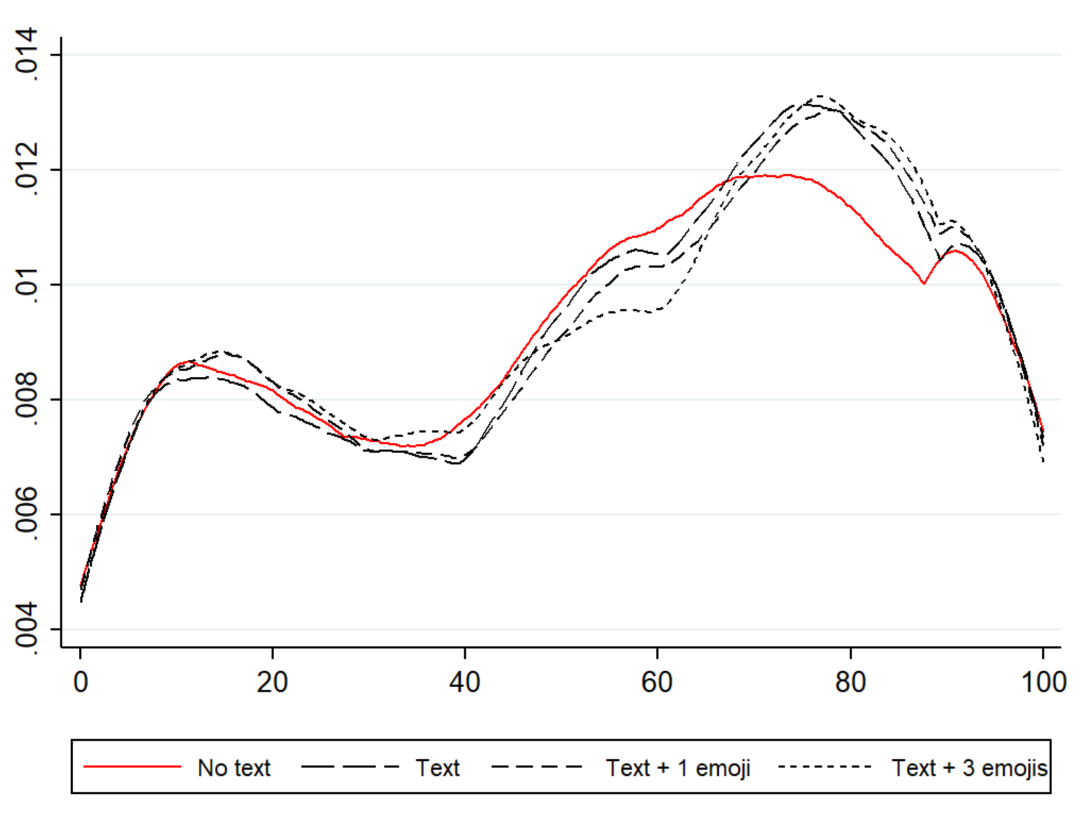


Figure 2: Distributions of investment proportions by treatment

Table 2: Investment decision by asset and by language information (text and emoji(s))

Language	Stock	Corporate bonds	Cryptocurrency	ICO
No text	57,54	57,80	53,25	50,57
Text	57,57	59,07	54,20	51,76
Text + 1 emoji	57,38	59,41	52,91	51,04
Text + 3 emojis	57,88	58,90	52,91	51,10

Table 3: Statistical analysis of the impact of assets on investment decisions

Comparisons	*p*-value	Direction of the effect
Stock vs Corporate bonds	0.0033	Stock $<$Corporates bonds
Stock vs Cryptocurrency	0.0000	Stock $>$Cryptocurrency
Stock vs ICO	0.0000	Stock $>$ ICO
Corporate bonds vs Cryptocurrency	0.0000	Corporate bonds $>$ Cryptocurrency
Corporate bonds vs ICO	0.0000	Corporate bonds $>$ ICO
Cryptocurrency vs ICO	0.0056	Cryptocurrency $>$ ICO
No text vs Text	0.1964	No effect
No text vs Text + 1 emoji	0.4829	No effect
No text vs Text + 3 emojis	0.4992	No effect
Text vs Text + 1 emoji	0.4922	No effect
Text vs Text + 3 emojis	0.4696	No effect
Text + 1 emoji vs Text + 3 emojis	0.9743	No effect

3.2 Regression analysis

Two main analyses are conducted. First, a simple and overarching model which focuses on the impact of the main treatment variables i.e. investment assets, risk profiles and language conditions is reported. Second, a more detailed analysis further documents the robustness of the results by subdividing the language conditions in the two implementations that were used i.e. the language conditions accompanied with a individual user and the language conditions accompanied with a professional user. We further test the validity of the results by adding control variables and interactions to our model. In addition to regressions clustered at the individual (participant) level, individual fixed-effect are used to provide an additional control for the effects of individual characteristics which may not be observable with the self-reported control variables that were collected at the time of the experiment. In all regressions, the benchmark asset-risk-text is stock, the risk profile 1 and the baseline vignette with no text.

3.2.1 Main treatments variables

Table 4 reports the results of the first above-mentioned analysis. The first result column reports the analysis with individual participant clusters.[1] The second result column reports the analysis with individual participant clusters and individual participant fixed effects.

The results show that the corporate bonds asset are systematically associated with an increase in investment proportions compared to the benchmark. Cryptocurrency and ICO assets are associated with a decrease. These results are consistent both in consistency and in magnitude with the means reported in Table 2. The regressions reports that Risk profile 2 and 3 are associated with a systematic decrease in investment proportions, which is to be expected given that these correspond to less profitable and riskier investment propositions compared to the benchmark. Note that the more significant drops in invested proportions that are associated with the Risk profile 3 are consistent with the fact that the Risk profile 3 present a higher loss in the negative return outcome. In that respect, participants behave in a fashion that is consistent with both loss aversion and economic rationality.

The results on the impact of text and emojis are also very consistent across the different regression specifications. Consistent with **H1**, the proportion invested in a given asset-risk combination is higher - at the 5% level - when the proposition is accompanied with a text. Investment proposition accompanied with a text generate an increase of the proportion investment of around 0.9%, consistent with the differences between the line "No text" and "Text" in Table 2. However, the results do not validate **H2**, as the proportion invested in a given asset-risk combination is not higher when emojis are displayed than when they are not. The number of emojis (one or three) has no impact on the proportion invested which is not surprising following the distribution of investment proportion by treatment that we observe in Figure 2.

As explained in the experimental methodology section, vignettes used a combination of asset frames and risk profiles to convey information to participant ecologically relevant information. The use of a single factor by asset risk in the main regressions is made possible by the fact that

[1]We use clustered standard errors to account for heteroskedasticity across participants.

Table 4: Baseline regression

Corporate bonds	1.331***	1.326***
	(0.415)	(0.418)
Cryptocurrency	-4.309***	-4.280***
	(0.719)	(0.721)
ICO	-6.457***	-6.457***
	(1.031)	(1.037)
Risk profile 2	-0.706***	-0.710***
	(0.260)	(0.262)
Risk profile 3	-1.289***	-1.268***
	(0.310)	(0.310)
Text	0.893**	0.888**
	(0.379)	(0.382)
Text + One emoji	0.413	0.439
	(0.373)	(0.374)
Text + Three emojis	0.407	0.405
	(0.362)	(0.364)
Constant	57.71***	75.10***
	(1.646)	(0.516)
Observations	18,467	18,467
R-squared	0.012	0.712
Individual clusters	Yes	Yes
Individual fixed effects	No	Yes

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

the different risk profiles impact decisions as expected. This suggests that participants treated equivalently the different risk profiles across assets. The robustness checks - as asset classes have different risk-return profiles - are available in the Appendix. Table A1 report models where we interact each asset class with each risk profile and where we use the Sharpe ratio of each lottery as a control variable. Overall, the significance and the coefficient of the variables related to the messages (Text ; Text + One emoji ; Text + Three emojis) are insensitive to the inclusion of those control variables.

To control for the valence of text and emojis, as they are positive for stocks, bonds and ICOs but negative for cryptocurrency, we split the sample in two, running the previous regressions once excluding cryptocurrency and once considering only cryptocurrency. The results are presented in Table A2 and Table A3 show that, although not significant when considering the "cryptocurrency" sample alone, the variable "Text" is robust and remains significant and the related coefficient are stable when excluding cryptocurrency from the whole sample.

3.2.2 Subdivision of the language conditions and additional control variables

Table 5 reports the results of the second above-mentioned analysis. The first result column reports the analysis with individual clusters and no control variables. The second result column reports the analysis with individual participant clusters and individual participant fixed effects and no control variables. The third result column reports the analysis with individual clusters and demographic variables as control variables. The fourth result column reports the analysis with individual clusters and demographic variables and the answers to the questions related to the efficient market hypothesis as control variables.

The results is consistent with **H3** in that the proportion invested in a given asset-risk-user combination is higher when the message is sent by a professional investors than when it is send by an individual investors. The magnitude of the difference is, however, very small (around 0.3%) and not statistically significant (*p*-value = 0.7944 using as a Mann-Whitney ranksum test comparing the difference in means across the two types of user). As before, there is no statistically significant impact of emojis on proportions invested. This shows that there is no heterogeneous effects of emojis by user condition.

Demographic control variables document that education (holding a Master, JD and equivalent degrees and up) and political preference (being sympathetic to the Republican political agenda, compared to being sympathetic to the Democrats and the Independents) are associated with higher proportions invested. Gender and age have no effect. Finally, the questions related to the efficient market hypothesis allow to document that participants who self-report agreeing with the efficient market hypothesis (for Question 1, 2 and 4) have a tendency to increase the proportion they invest. Question 3 yields no significant result and Question 5 yields the opposite result, which may be due to the fact that those who report agreeing with the efficient market hypothesis tend to score high on this last question ("It is possible to beat the market"). Overall, the magnitude of the effect of these questions is larger than the effects of text, which suggest that innate characteristics of participants with respect to their attitudes towards the efficient market hypothesis have a much bigger effect that information related to investor sentiment as presented in the case of our experiment.

We further test the hypothesis that people who believe in EMH are less likely to be influenced by the text by interacting the answer to the five EMH questions to our "Text" variables. For each financial question, we create a dummy variable equal to 1 if the answer of the individual to this question is above the mean of the answers. For example, for the financial question 1 "Public information is priced into securities ?" the dummy is equal to 1 for all the individuals who answer "agree" or "strongly agree" and 0 otherwise. Results of the regressions are reported on Appendix in Table A4. All the interactions between EMH beliefs and our main treatment variable (Text) are not significant : participants with a strong belief in EMH tend to invest more (on average) but their level of investment is not impacted (marginally) by the presence of Text.

Table 5: Regression with subdivision of the language conditions and additional control variables

Corporate bonds	1.331***	1.326***	1.331***	1.331***
	(0.415)	(0.418)	(0.415)	(0.415)
Cryptocurrency	-4.309***	-4.280***	-4.299***	-4.298***
	(0.719)	(0.721)	(0.719)	(0.720)
ICO	-6.457***	-6.457***	-6.457***	-6.457***
	(1.031)	(1.037)	(1.031)	(1.031)
Risk profile 2	-0.706***	-0.711***	-0.706***	-0.706***
	(0.260)	(0.262)	(0.260)	(0.260)
Risk profile 3	-1.289***	-1.268***	-1.282***	-1.281***
	(0.310)	(0.310)	(0.310)	(0.310)
Individual + Text	0.775*	0.765*	0.775*	0.775*
	(0.412)	(0.415)	(0.412)	(0.412)
Individual + Text + 1 emoji	0.329	0.329	0.329	0.329
	(0.396)	(0.399)	(0.396)	(0.396)
Individual + Text + 3 emojis	0.239	0.247	0.242	0.243
	(0.399)	(0.401)	(0.399)	(0.399)
Professional + Text	1.011**	1.011**	1.011**	1.011**
	(0.449)	(0.451)	(0.449)	(0.449)
Professional + Text + 1 emoji	0.497	0.550	0.506	0.516
	(0.429)	(0.429)	(0.428)	(0.428)
Professional + Text + 3 emojis	0.575	0.564	0.580	0.572
	(0.426)	(0.429)	(0.426)	(0.426)
Gender (Men = 1)			-2.181	-2.977
			(3.312)	(3.150)
Year of birth			0.111	-0.0476
			(0.158)	(0.139)
Master degree and up			10.00***	5.931**
			(3.307)	(2.992)
Political preference (Republican = 1)			11.73***	5.948*
			(3.385)	(3.030)
Financial question 1				4.533***
				(1.652)
Financial question 2				4.214***
				(1.278)
Financial question 3				2.241
				(1.457)
Financial question 4				3.411**
				(1.483)
Financial question 5				-3.759***
				(1.250)
Constant	57.71***	75.10***	-169.3	110.4
	(1.646)	(0.516)	(314.2)	(275.3)
Observations	18,467	18,467	18,467	18,467
R-squared	0.012	0.712	0.076	0.209
Individual clusters	Yes	Yes	Yes	Yes
Individual participant fixed effects	No	Yes	No	No

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

4 Conclusion

Our experimental study contributes to answering three important questions in the field of behavioral finance research: (1) how investors are influenced by exposure to textual content, (2) how they react when this textual content is accompanied by an emoji, and (3) is their reaction the same if this content and these emojis are sent by an individual user or by a professional.

Overall, our results confirm that professional (sophisticated) investors are marginally influenced by text associated with an investment proposal. We find a statistically significant effect of exposure to text but the magnitude of the effect is small (about 1%) and much smaller than the effect of assets and of risk levels. This result is consistent with what can be expected by the sophisticated population studied in our experiment: when the payoff and the probability of each decision are known, investment decisions of financial professionals are driven mostly by the type of asset, the level of risks and the associated return of each investment and not by investor sentiment.

While we focus on professional investors in our experiment, we believe that it would be interesting to analyze the impact of text and emojis on investment decisions in non-professional populations. Indeed, if investor sentiment has a larger impact on non-professional investors who are the noise traders in the market, then our study should be replicated with diverse populations to further test the validity of our results. Overall, our experimental analysis on financial professionals suggest that this population acts rationally, consistent with the efficient market hypothesis.

References

Abdellaoui, M., Bleichrodt, H., and Kammoun, H. (2013). Do financial professionals behave according to prospect theory? An experimental study. *Theory and Decision*, 74(3):411–429.

Baker, M. and Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2):129–152.

Bardsley, N., Cubitt, R., Loomes, G., Moffatt, P., Starmer, C., and Sugden, R. (2010). *Experimental Economics - Rethinking the Rules*. Princeton University Press, Princeton.

Beattie, J. and Loomes, G. (1997). The Impact of Incentives upon Risky Choice Experiments. *Journal of Risk and Uncertainty*, 14(2):155–168.

Camerer, C. F. and Hogarth, R. (1999). The effects of financial incentives in experiments: A review and capital-labor-production framework. *Journal of Risk and Uncertainty*, 19(1-3):7–42.

Chen, H., De, P., Hu, Y. J., and Hwang, B.-H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *The Review of Financial Studies*, 27(5):1367–1403.

Elliott, W. B., Hodge, F. D., and Sedor, L. M. (2012). Using online video to announce a restatement: Influences on investment decisions and the mediating role of trust. *The Accounting Review*, 87(2):513–535.

Elliott, W. B., Rennekamp, K. M., and White, B. J. (2015). Does concrete language in disclosures increase willingness to invest? *Review of Accounting Studies*, 20(2):839–865.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2):383–417.

Fréchette, G. (2015). Laboratory experiments: Professionals versus students. In Fréchette, G. and Schotter, A., editors, *Handbook of Experimental Economic Methodology*. Oxford University Press.

Hackethal, A., Kirchler, M., Laudenbach, C., Razen, M., and Weber, A. (2020). On the role of monetary incentives in risk preference elicitation experiments. Working Papers 2020-29, Faculty of Economics and Statistics, University of Innsbruck.

Hales, J., Kuang, X., and Venkataraman, S. (2011). Who believes the hype? an experimental examination of how language affects investor judgments. *Journal of Accounting Research*, 49(1):223–255.

Jordà, Ò., Knoll, K., Kuvshinov, D., Schularick, M., and Taylor, A. M. (2019). The rate of return on everything, 1870–2015. *The Quarterly Journal of Economics*, 134(3):1225–1298.

Kejriwal, M., Wang, Q., Li, H., and Wang, L. (2021). An empirical study of emoji usage on twitter in linguistic and national contexts. *Online Social Networks and Media*, 24:100149.

Kralj Novak, P., Smailović, J., Sluban, B., and Mozetič, I. (2015). Sentiment of emojis. *PloS one*, 10(12):e0144296.

Long, J. B. D., Shleifer, A., Summers, L. H., and Waldmann, R. J. (1990). Noise trader risk in financial markets.

Journal of Political Economy, 98(4):703–738.

Mahmoudi, N., Docherty, P., and Moscato, P. (2018). Deep neural networks understand investors better. *Decision Support Systems*, 112:23–34.

Renault, T. (2017). Intraday online investor sentiment and return patterns in the us stock market. *Journal of Banking & Finance*, 84:25–40.

Renault, T. (2020). Sentiment analysis and machine learning in finance: a comparison of methods and models on one million messages. *Digital Finance*, 2(1):1–13.

Sprenger, T. O., Sandner, P. G., Tumasjan, A., and Welpe, I. M. (2014). News or noise? using twitter to identify and understand company-specific news flow. *Journal of Business Finance & Accounting*, 41(7-8):791–830.

Tan, H.-t., Ying Wang, E., and Zhou, B. (2014). When the use of positive language backfires: The joint effect of tone, readability, and investor sophistication on earnings judgments. *Journal of Accounting Research*, 52(1):273–302.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of finance*, 62(3):1139–1168.

Tetlock, P. C., Saar-Tsechansky, M., and Macskassy, S. (2008). More than words: Quantifying language to measure firms' fundamentals. *The journal of finance*, 63(3):1437–1467.

Trimborn, S. and Härdle, W. K. (2018). Crix an index for cryptocurrencies. *Journal of Empirical Finance*, 49:107–122.

Zetzsche, D. A., Buckley, R. P., Arner, D. W., and Föhr, L. (2017). The ico gold rush: It's a scam, it's a bubble, it's a super challenge for regulators. *University of Luxembourg Law Working Paper*, (11):17–83.

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Appendix

Figure A1: Vignettes related to stocks - Risk Profile 1 [Cases 1 to 7]

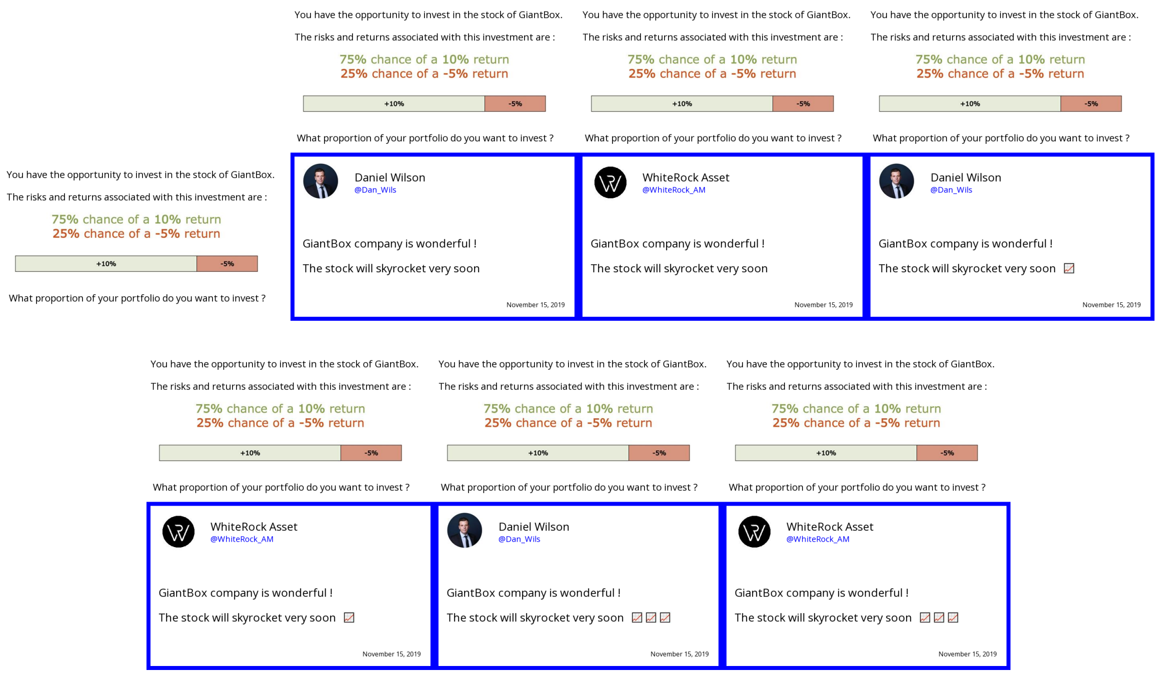

Figure A2: Vignettes related to bonds - Risk Profile 1 [Cases 22 to 28]

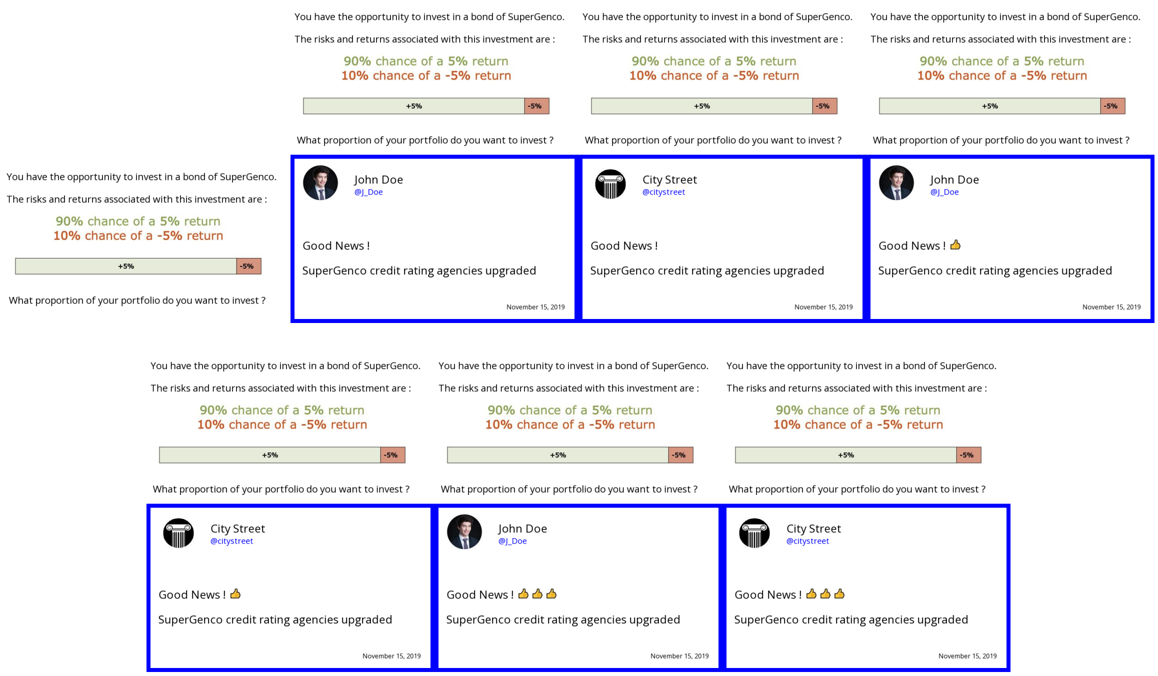

Figure A3: Vignettes related to ICO - Risk Profile 1 [Cases 43 to 49]

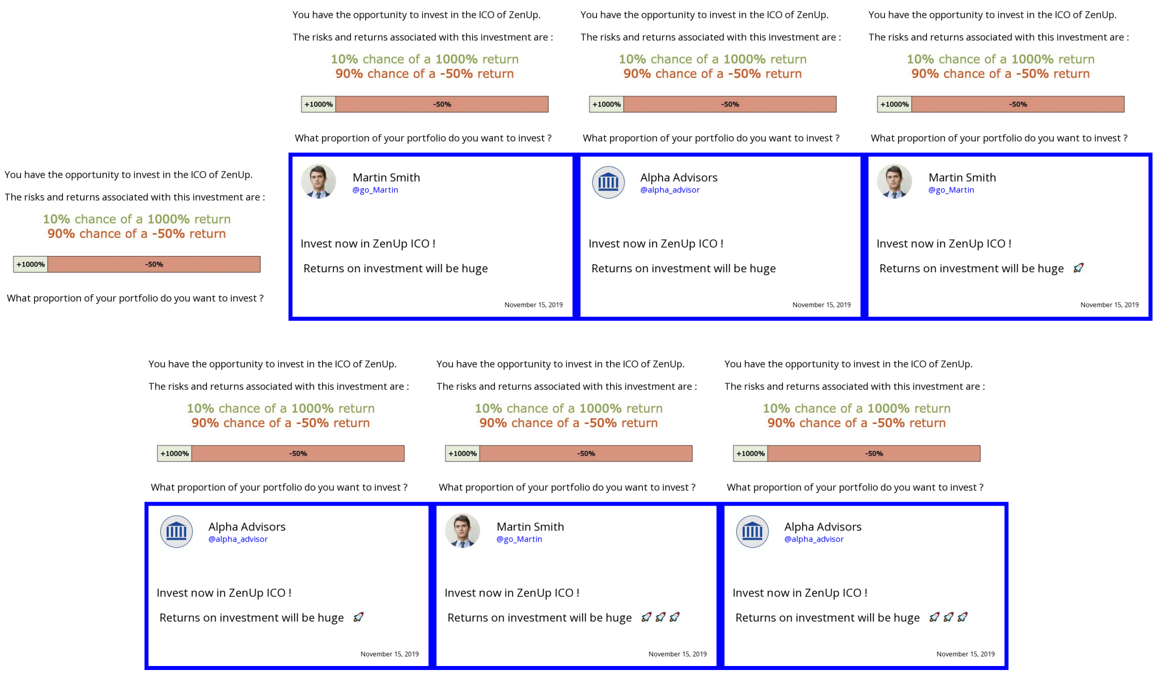

Figure A4: Vignettes related to cryptocurrency - Risk Profile 1 [Cases 64 to 70]

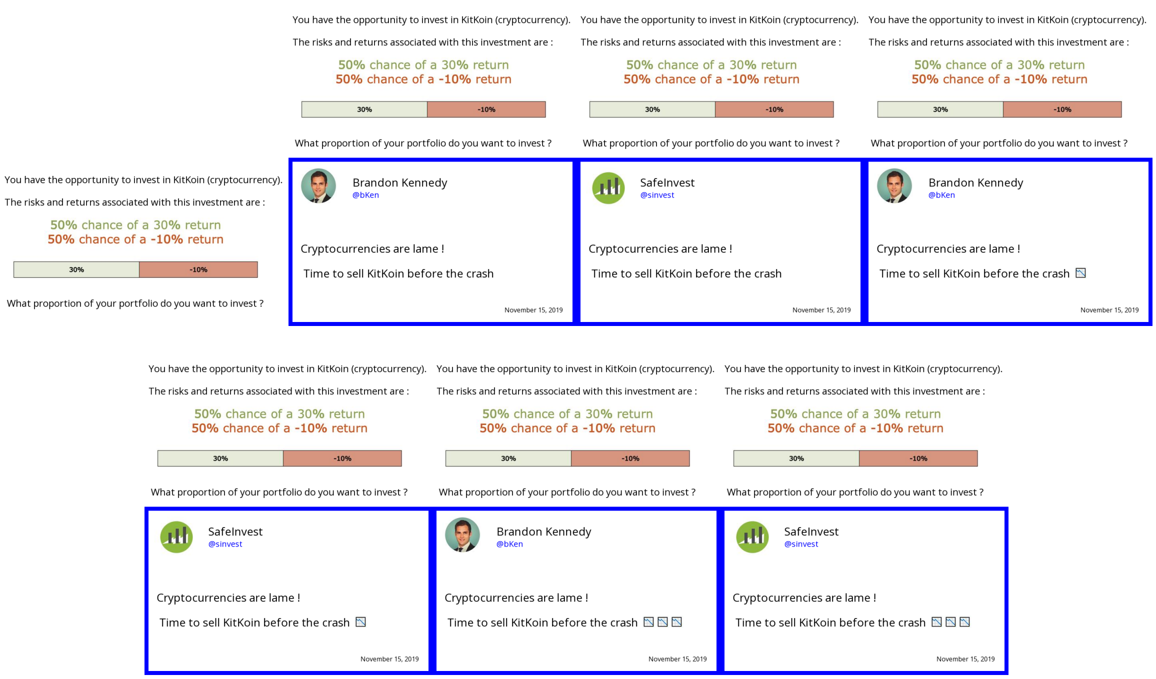

Table A1: Regressions with asset-risk profile combinations

Stock with risk profile 2	2.227***	2.227***	2.227***	2.227***
	(0.555)	(0.555)	(0.555)	(0.558)
Stock with risk profile 3	2.872***	2.872***	2.872***	2.872***
	(0.666)	(0.666)	(0.666)	(0.670)
Corporate bonds with risk profile 2	0.223	0.223	0.222	0.206
	(0.536)	(0.536)	(0.536)	(0.540)
Corporate bonds with risk profile 3	3.117***	3.117***	3.117***	3.117***
	(0.821)	(0.821)	(0.822)	(0.826)
Cryptocurrency with risk profile 2	-0.569	-0.569	-0.569	-0.569
	(0.573)	(0.573)	(0.573)	(0.577)
Cryptocurrency with risk profile 3	-0.625	-0.594	-0.592	-0.539
	(0.575)	(0.571)	(0.573)	(0.563)
ICO with risk profile 2	-1.838***	-1.838***	-1.838***	-1.838***
	(0.585)	(0.585)	(0.585)	(0.589)
ICO with risk profile 3	-2.328***	-2.328***	-2.328***	-2.328***
	(0.644)	(0.644)	(0.644)	(0.648)
Text	0.893**	0.893**	0.893**	0.888**
	(0.379)	(0.379)	(0.379)	(0.382)
Text + 1 emoji	0.413	0.417	0.422	0.439
	(0.373)	(0.373)	(0.373)	(0.374)
Text + 3 emojis	0.407	0.411	0.407	0.405
	(0.362)	(0.362)	(0.362)	(0.364)
Sharpe ratio	0.171***	0.171***	0.171***	0.171***
	(0.0234)	(0.0234)	(0.0234)	(0.0235)
Gender (Men = 1)		-2.181	-2.978	
		(3.312)	(3.150)	
Year of birth		0.111	-0.0476	
		(0.158)	(0.139)	
Master degree and up		10.00***	5.931**	
		(3.307)	(2.992)	
GOP		11.73***	5.948*	
		(3.385)	(3.030)	
Financial question 1			4.533***	
			(1.652)	
Financial question 2			4.214***	
			(1.278)	
Financial question 3			2.241	
			(1.457)	
Financial question 4			3.411**	
			(1.483)	
Financial question 5			-3.759***	
			(1.251)	
Constant	52.71***	-174.3	105.4	70.10***
	(1.789)	(314.2)	(275.3)	(0.488)
Observations	18,467	18,467	18,467	18,467
R-squared	0.011	0.075	0.208	0.711
Individual participant clusters	Yes	Yes	Yes	Yes
Individual participant fixed effects	No	Yes	No	No

Robust standard errors in parentheses, *** p<0.01, ** *p*<0.05, * p<0.1

Table A2: Regressions without Cryptocurrency asset

Corporate bonds	1.331***	1.331***	1.331***	1.325***
	(0.415)	(0.415)	(0.415)	(0.418)
ICO	-6.457***	-6.457***	-6.457***	-6.457***
	(1.031)	(1.031)	(1.031)	(1.039)
Risk profile 2	-0.578*	-0.578*	-0.578*	-0.584*
	(0.297)	(0.297)	(0.297)	(0.300)
Risk profile 3	-1.210***	-1.210***	-1.210***	-1.210***
	(0.343)	(0.343)	(0.343)	(0.346)
Text	0.855*	0.855*	0.854*	0.848*
	(0.452)	(0.452)	(0.452)	(0.456)
Text + one emoji	0.648	0.648	0.648	0.648
	(0.484)	(0.484)	(0.484)	(0.488)
Text + three emojis	0.635	0.635	0.635	0.635
	(0.481)	(0.481)	(0.481)	(0.485)
Gender (Men = 1)		-2.199	-3.007	
		(3.311)	(3.165)	
Year of birth		0.108	-0.0447	
		(0.159)	(0.142)	
Master degree and up		9.549***	5.511*	
		(3.317)	(3.017)	
GOP		11.70***	6.000*	
		(3.418)	(3.092)	
Financial question 1			4.143**	
			(1.692)	
Financial question 2			4.229***	
			(1.307)	
Financial question 3			1.817	
			(1.483)	
Financial question 4			3.291**	
			(1.471)	
Financial question 5			-3.721***	
			(1.259)	
Constant	57.52***	-163.5	107.0	73.67***
	(1.648)	(315.6)	(282.1)	(0.553)
Observations	13,856	13,856	13,856	13,856
R-squared	0.013	0.074	0.199	0.706
Individual participant clusters	Yes	Yes	Yes	Yes
Individual participant fixed effects	No	Yes	No	No

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A3: Regressions with Cryptocurrency asset only

Risk profile 2	-1.092**	-1.092**	-1.092**	-1.092*
	(0.553)	(0.553)	(0.553)	(0.566)
Risk profile 3	-1.530***	-1.499***	-1.495***	-1.484***
	(0.534)	(0.533)	(0.534)	(0.548)
Text	1.008	1.008	1.008	1.008
	(0.678)	(0.678)	(0.679)	(0.695)
Text + one emoji	-0.295	-0.276	-0.258	-0.211
	(0.648)	(0.647)	(0.648)	(0.666)
Text + three emojis	-0.278	-0.261	-0.274	-0.309
	(0.692)	(0.691)	(0.691)	(0.709)
Gender (male =1)		-2.126	-2.891	
		(3.446)	(3.233)	
Year of birth		0.120	-0.0566	
		(0.165)	(0.139)	
Master degree and up		11.36***	7.192**	
		(3.402)	(3.058)	
GOP		11.82***	5.792*	
		(3.443)	(3.027)	
Financial question 1			5.703***	
			(1.602)	
Financial question 2			4.169***	
			(1.271)	
Financial question 3			3.516**	
			(1.482)	
Financial question 4			3.773**	
			(1.556)	
Financial question 5			-3.874***	
			(1.268)	
Constant	53.97***	-191.0	116.9	75.15***
	(1.800)	(328.3)	(275.3)	(0.603)
Observations	4,611	4,611	4,611	4,611
R-squared	0.001	0.079	0.241	0.790
Individual participant clusters	Yes	Yes	Yes	Yes
Individual participant fixed effects	No	Yes	No	No

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4: Regressions with Financial questions and control variables

Corporate bonds	1.330***	1.331***	1.332***	1.332***	1.332***
	(0.415)	(0.415)	(0.415)	(0.415)	(0.415)
Cryptocurrency	-4.294***	-4.296***	-4.298***	-4.298***	-4.300***
	(0.719)	(0.718)	(0.718)	(0.719)	(0.720)
ICO	-6.457***	-6.457***	-6.457***	-6.457***	-6.457***
	(1.031)	(1.031)	(1.031)	(1.031)	(1.031)
Risk profile 2	-0.707***	-0.706***	-0.706***	-0.706***	-0.706***
	(0.260)	(0.260)	(0.260)	(0.260)	(0.260)
Risk profile 3	-1.278***	-1.280***	-1.281***	-1.281***	-1.282***
	(0.310)	(0.310)	(0.310)	(0.310)	(0.310)
Text	1.072**	0.861*	1.105***	0.848**	0.614
	(0.536)	(0.484)	(0.385)	(0.388)	(0.437)
Text + one emoji	0.420	0.422	0.419	0.419	0.421
	(0.373)	(0.372)	(0.373)	(0.373)	(0.373)
Text + three emojis	0.412	0.409	0.411	0.411	0.407
	(0.362)	(0.362)	(0.362)	(0.362)	(0.362)
Gender	-3.251	-2.184	-1.987	-1.931	-3.432
	(3.218)	(3.194)	(3.288)	(3.275)	(3.191)
Birth	0.0486	0.0883	0.116	0.114	0.104
	(0.153)	(0.156)	(0.163)	(0.161)	(0.163)
Master degree and up	9.302***	6.612**	9.449***	9.762***	8.460***
	(3.199)	(3.223)	(3.293)	(3.284)	(3.192)
GOP	8.698***	9.009***	11.42***	11.75***	11.09***
	(3.313)	(3.205)	(3.346)	(3.352)	(3.161)
Financial question 1 High	13.28***				
	(3.241)				
Text * Financial question 1 High	-0.302				
	(0.547)				
Financial question 2 High		14.30***			
		(3.218)			
Text * Financial question 2 High		0.0655			
		(0.506)			
Financial question 3 High			-5.813*		
			(3.284)		
Text * Financial question 3 High			-0.610		
			(0.566)		
Financial question 4 High				-4.275	
				(3.347)	
Text * Financial question 4 High				0.138	
				(0.568)	
Financial question 5 High					-15.22***
					(3.161)
Text * Financial question 5 High					0.501
					(0.503)
Constant	-51.51	-128.9	-176.9	-174.9	-144.5
	(304.0)	(309.9)	(322.7)	(319.6)	(324.5)
Observations	18,467	18,467	18,467	18,467	18,467
R-squared	0.120	0.129	0.085	0.081	0.138

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$