A Picture is Worth a Thousand Words: Measuring Investor Sentiment by Combining Machine Learning and Photos from News*

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content

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1.Introduction

Background

- Numerous studies document how investor sentiment helps us understand and predict the market risk premium over time and stock returns cross-sectionally。
- Machine learning has seen wide use among academics in finance， recent developments in machine learning introduce techniques that make the task of analyzing large amounts of photos possible。

1.Introduction

Research contents

- How PhotoPes is related to the value- and equal-weighted CRSP index returns.
- Whether PhotoPes and investor pessimism embedded in text (TextPes) are significantly correlated?
- Which type of information is more effectively or only transmitted by photos in the context of news and financial markets.
- we further validate PhotoPes as a proxy for investor sentiment by showing it has larger effect on stocks whose valuations are difficult to arbitrage.
- we provide additional insights to help us better understand the channel through which PhotoPes relates to market returns.
- we perform a battery of robustness tests.

1.Introduction

Contributions

- we demonstrate the importance of visual content in helping explain and predict the market risk premium and investors' behavior.
- we demonstrate how to overcome key hurdles of studying the importance of visual content in financial markets by employing machine learning techniques for photo classification
- we show that pessimism embedded in news photos complements and, in some cases, subsumes pessimism embedded in news text.

1.Introduction

Related researches

- researchers have used news (Tetlock, 2007), Google Search data (Da, Engelberg, and Gao, 2015), Twitter data (Chen, De, Hu, and Hwang, 2014), company financial reports (Loughran and McDonald, 2011; Jiang Lee, Martin, and Zhou, 2019), weather (Hirshleifer and Shumway, 2003), and sporting events (Edmans et al., 2007) to proxy for investor sentiment.
- Several studies document how a mere photo is able to predict important outcomes such as political elections, personal loan decisions, firm market value, and CEO compensation (Todorov, Mandisodza, Goren, and Hall, 2005; Duarte, Siegel, and Young, 2012; Halford and Hsu, 2014; Graham, Harvey, and Puri, 2016).

1.Introduction

FRAMEWORK

how we get and filter the data and construct the variables

The impact of PhotoPes on market returns

Applications of PhotoPes

What affect the impact of PhotoPes on market return

Mechanisms of PhotoPes

Robustness

Conclusion

2.Data

Data source : photos from the Getty Images’ Editorial News Section between January 1926 and June 2018.

Training set source: DeepSent dataset

Clean labels : photos where all five MTurk survey participants agree on the sentiment label.

Noisy labels : at least four out of five MTurk survey participants agree on the label.

2.Data

- Photo classification : Convolutional Neural Networks (CNNs) ,a popular machine learning technique for classifying photos, to construct an investor sentiment index from a large sample of photos in the press.
- Model: learning rate of 0.01 and 5,000 learning steps, train batch size 100. reserve 10% of the training photos for the validation sample, and 10% for the test sample.

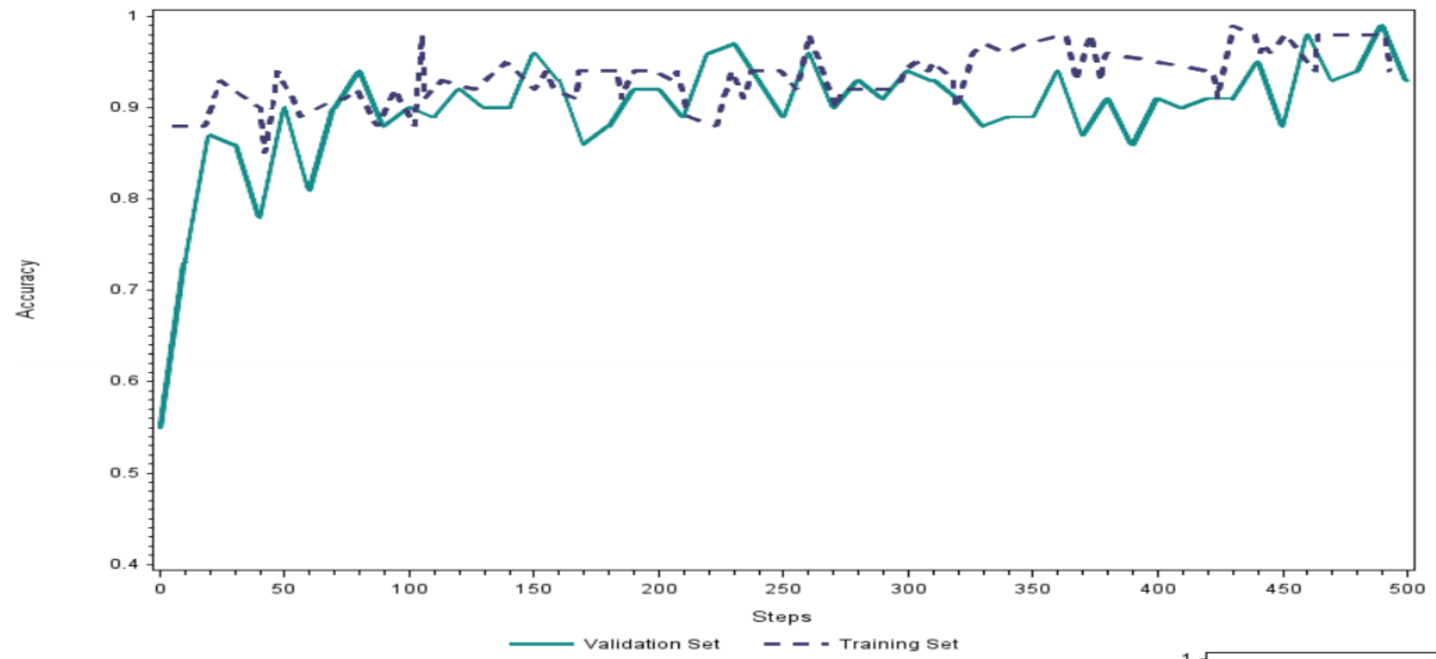


Figure 1:Model Accuracy with clean labels

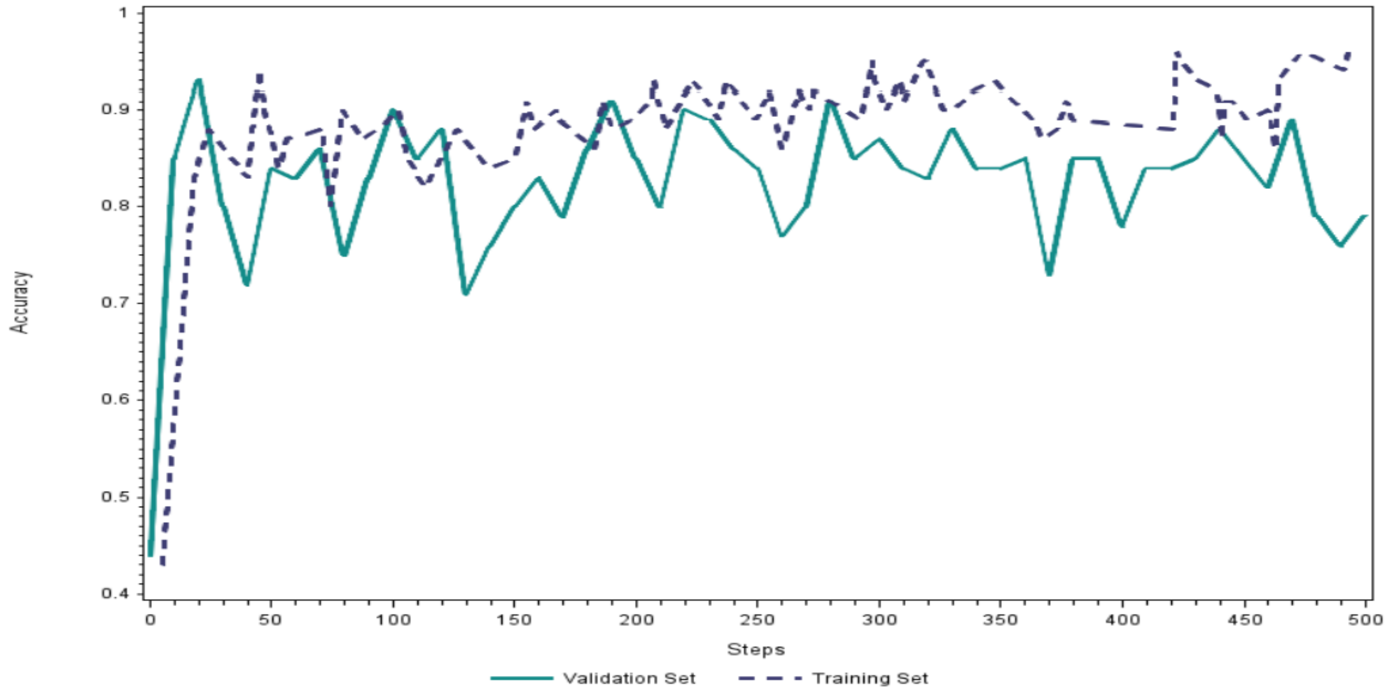


Figure 1:Model Accuracy with noisy labels

We achieve 81.7% test accuracy for the noisy label model, and 87.1% accuracy for the clean label model.

Select 100 photos using stratified sampling from our Getty Images sample and classify each photo in MTurk by five individuals. pass these photos through the model

		Actual	
		Positive	Negative
Prediction	Positive	60	6
	Negative	17	17

This table shows that our model trained with the DeepSent training set performs well at classifying photo from Getty Images.

2.Data

Photo filter

- Each day, we sort photos by popularity, and download the 20 most popular photos, and collect information on the popularity ranking of the photo, date the photo is taken, photo identification number, and description of the photo and associated event.
- A given day has at least 15 total photos available,
- The photo description contains at least one negative or positive word according to the Loughran and McDonald (2011) dictionaries

	# of photos after each screening process		
	Top 10	Top 15	Top 20
Original number of photos	310,433	453,869	586,832
Photos on trading day	214,276	314,242	406,837
At least 15 photos in a day	194,570	291,775	384,370
At least one word from LM dictionary	74,044	169,886	220,136

2.Data

$$PhotoPes_t = \frac{\sum_i \left(Neg_{it} \times \frac{1}{Popularity\ Rank_{it}}\right)}{\sum_i \frac{1}{Popularity\ Rank_{it}}},$$

$$TextPes_t = \frac{\sum_i \left(\frac{N_{it} - P_{it}}{n_{it}} \times \frac{1}{Popularity\ Rank_{it}}\right)}{\sum_i \frac{1}{Popularity\ Rank_{it}}},$$

Variable	N	Mean	Median	P25	P75	Std dev
NYTPes	17,000	0.009	0.009	0.003	0.015	0.009
PhotoPes	19,243	0.115	0.057	0.000	0.171	0.146
PhotoPes'	19,243	0.309	0.250	0.000	0.500	0.300
TextPes	19,243	0.011	0.009	0.001	0.020	0.017
TextPes'	19,243	0.028	0.031	0.008	0.050	0.034

	PhotoPes	*TextPes*	*NYTPes*
TextPes	0.199*** (<0.001)		
NYTPes	0.033 (0.305)	0.155*** (<0.001)	
MCSI	-0.088* (0.053)	0.114** (0.012)	0.222*** (<0.001)

3.Results: The impact of *PhotoPes* on market returns

Panel A: Sample Statistics for value-weighted CRSP index returns					
N	Mean	P50	P25	P75	Std Dev
23230	0.036	0.071	-0.394	0.502	1.063

Panel B: Time-Series Regression for value-weighted CRSP index returns					
	γ	t-stat		β	t-stat
R_{t-1}	0.043**	2.558	Tue	0.001***	5.830
R_{t-2}	-0.012	-0.717	Wed	0.002***	8.037
R_{t-3}	0.013	0.885	Thu	0.001***	5.832
R_{t-4}	-0.010	-0.691	Fri	0.002***	6.943
R_{t-5}	-0.004	-0.276	Sat	0.009***	36.112

Panel C: Sample Statistics for equal-weighted CRSP index returns					
N	Mean	P50	P25	P75	Std Dev
23230	0.071	0.123	-0.298	0.492	1.044

Panel D: Time-Series Regression equal-weighted CRSP index returns					
	γ	t-stat		β	t-stat
R_{t-1}	0.151***	6.889	Tue	0.002***	6.979
R_{t-2}	0.030	1.603	Wed	0.003***	11.744
R_{t-3}	0.041**	2.497	Thu	0.002***	10.492
R_{t-4}	0.016	1.041	Fri	0.003***	13.402
R_{t-5}	0.019	1.194	Sat	0.009***	35.052

$$R_t = \gamma L_s(R_t) + \beta X_t + \varepsilon_t,$$

Both the VWRETD and EWRETD show significant autocorrelation in the returns

3.Results: The impact of *PhotoPes* on market returns

$$R_t = \beta_1 PhotoPes_t + \beta_2 L_s(PhotoPes_t) + \beta_3 L_s(R_t) + \beta_4 L_s(R_t^2) + \beta_5 X_t + \varepsilon_t,$$

	Top 10				Top 15				Top 20			
	(1)		(2)		(3)		(4)		(5)		(6)	
	$VWRETD_t$		$EWRETD_t$		$VWRETD_t$		$EWRETD_t$		$VWRETD_t$		$EWRETD_t$	
Variables	β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$PhotoPes_t$	-0.019**	-2.163	-0.019**	-2.248	-0.019**	-2.249	-0.020**	-2.333	-0.016*	-1.890	-0.017**	-2.023
$PhotoPes_{t-1}$	0.010	1.185	0.017*	1.956	0.014*	1.693	0.017**	2.110	0.016**	1.971	0.021**	2.468
$PhotoPes_{t-2}$	-0.002	-0.214	-0.002	-0.259	-0.005	-0.563	-0.002	-0.286	-0.006	-0.701	-0.004	-0.444
$PhotoPes_{t-3}$	0.017**	2.067	0.015*	1.826	0.008	1.057	0.007	0.874	0.006	0.790	0.004	0.559
$PhotoPes_{t-4}$	-0.012	-1.393	-0.013	-1.514	-0.008	-0.934	-0.008	-1.007	-0.008	-0.910	-0.008	-0.986
$PhotoPes_{t-5}$	-0.010	-1.188	-0.002	-0.219	-0.011	-1.339	-0.003	-0.359	-0.011	-1.387	-0.004	-0.448
$\beta_1+\beta_2$	-0.016		-0.004		-0.021		-0.009		-0.019		-0.008	
$\chi^2(1)[\beta_1+\beta_2=0]$	0.812		0.087		1.499		0.323		1.233		0.192	
p-value	0.368		0.769		0.221		0.570		0.267		0.661	
Adj R-sq	0.015		0.050		0.012		0.048		0.011		0.047	
N	16,430		16,430		18,513		18,513		19,213		19,213	

We cannot reject the hypothesis that the reversal in lags 1 through 5 exactly offsets the initial decline in returns, our main results are consistent with a behavioral story and do not support the new information or the stale information story.

3.Results: *PhotoPes* and sentiment embedded in text

$$R_t = \beta_1 PhotoPes_t + \beta_2 Text_t + \beta_3 L_s(PhotoPes_t) + \beta_4 L_s(Text_t) + \beta_5 L_s(R_t) + \beta_5 L_s(R_t^2) + \beta_6 X_t + \varepsilon_t,$$

	(1)		(2)		(3)		(4)		(5)		(6)	
	$VWRETD_t$		$EWRETD_t$		$VWRETD_t$		$EWRETD_t$		$VWRETD_t$		$EWRETD_t$	
Variables	β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$PhotoPes_t$	-0.017*	-1.876	-0.018**	-2.021	-0.017*	-1.869	-0.018*	-1.858	-0.017*	-1.874	-0.018*	-1.866
$TextPes_t$	-0.012	-1.496	-0.009	-1.233								
$NYTPes_t$					-0.045***	-4.350	-0.053***	-4.986	-0.046***	-4.466	-0.054***	-5.080
Interaction									-0.025**	-2.393	-0.027***	-2.660
$PhotoPes_{t-1}$	0.011	1.253	0.017*	1.922	0.018*	1.942	0.026***	2.679	0.018*	1.913	0.025***	2.649
$PhotoPes_{t-2}$	0.000	0.026	0.000	-0.017	-0.006	-0.605	-0.006	-0.641	-0.006	-0.619	-0.006	-0.657
$PhotoPes_{t-3}$	0.018**	2.115	0.016*	1.918	0.025***	2.792	0.022**	2.479	0.025***	2.819	0.022**	2.511
$PhotoPes_{t-4}$	-0.010	-1.128	-0.011	-1.297	-0.014	-1.556	-0.014	-1.473	-0.014	-1.551	-0.014	-1.467
$PhotoPes_{t-5}$	-0.010	-1.186	-0.002	-0.210	-0.008	-0.887	0.000	0.021	-0.008	-0.917	0.000	-0.012
$TextPes_{t-1}$	-0.004	-0.445	0.000	0.057								
$TextPes_{t-2}$	-0.012	-1.405	-0.011	-1.485								
$TextPes_{t-3}$	-0.001	-0.188	-0.004	-0.538								
$TextPes_{t-4}$	-0.014*	-1.717	-0.011	-1.436								
$TextPes_{t-5}$	0.000	-0.023	0.000	-0.043								
$NYTPes_{t-1}$					0.011	1.065	0.018*	1.836	0.011	1.086	0.018*	1.845
$NYTPes_{t-2}$					0.009	0.943	0.005	0.454	0.009	0.892	0.004	0.399
$NYTPes_{t-3}$					0.008	0.844	0.008	0.871	0.009	0.857	0.008	0.887
$NYTPes_{t-4}$					-0.010	-1.025	-0.003	-0.381	-0.010	-1.035	-0.004	-0.390
$NYTPes_{t-5}$					-0.005	-0.512	-0.006	-0.665	-0.005	-0.525	-0.006	-0.679
$\chi^2(1)[\beta_1+\beta_2=0]$	0.107		0.423		3.930**		6.452**		4.409**		7.114	
p-value	0.744		0.515		0.047		0.011		0.036		0.008	
$\chi^2(1)[\beta_3+\beta_4=0]$	2.623		3.666*		0.000		0.072		0.000		0.073	
p-value	0.105		0.056		0.984		0.788		0.984		0.786	
Adj R-sq	0.015		0.050		0.026		0.072		0.027		0.072	
N	16,430		16,430		13,848		13,848		13,848		13,848	

Variables	(7) VWRETD$_t$ β	(7) VWRETD$_t$ t-stat	(8) EWRETD$_t$ β	(8) EWRETD$_t$ t-stat	(9) VWRETD$_t$ β	(9) VWRETD$_t$ t-stat	(10) EWRETD$_t$ β	(10) EWRETD$_t$ t-stat
$PhotoPes_t$	-0.019**	-2.169	-0.019**	-2.251	-0.019**	-2.153	-0.019**	-2.271
$TextPesH_t$	-0.011	-1.271	-0.015	-1.605				
$TextPesML_t$					-0.006	-0.775	0.001	0.069
$PhotoPes_{t-1}$	0.010	1.175	0.017*	1.940	0.010	1.149	0.017*	1.931
$PhotoPes_{t-2}$	-0.002	-0.233	-0.002	-0.275	-0.002	-0.211	-0.002	-0.286
$PhotoPes_{t-3}$	0.017**	2.076	0.015*	1.849	0.017**	2.060	0.015*	1.813
$PhotoPes_{t-4}$	-0.012	-1.401	-0.013	-1.521	-0.012	-1.408	-0.014	-1.538
$PhotoPes_{t-5}$	-0.010	-1.190	-0.002	-0.227	-0.010	-1.186	-0.002	-0.234
$TextPesH_{t-1}$	0.001	0.090	0.006	0.651				
$TextPesH_{t-2}$	-0.006	-0.789	0.001	0.123				
$TextPesH_{t-3}$	0.000	-0.021	-0.001	-0.116				
$TextPesH_{t-4}$	-0.008	-0.997	-0.007	-0.820				
$TextPesH_{t-5}$	0.004	0.518	0.000	0.004				
$TextPesML_{t-1}$					0.002	0.306	0.000	0.002
$TextPesML_{t-2}$					-0.003	-0.423	0.005	0.730
$TextPesML_{t-3}$					0.010	1.221	0.009	1.147
$TextPesML_{t-4}$					0.008	1.019	0.006	0.880
$TextPesML_{t-5}$					-0.005	-0.575	-0.004	-0.528
$\chi^2(1)[\beta_1+\beta_2=0]$	6.452**		0.161		1.128		2.979*	
p-value	0.011		0.688		0.288		0.084	
$\chi^2(1)[\beta_3+\beta_4=0]$	0.072		0.365		0.177		0.011	
p-value	0.788		0.546		0.674		0.916	
Adj R-sq	0.014		0.050		0.014		0.050	
N	16,430		16,430		16,430		16,430	

3.Results: Which information is more effectively transmitted by photos

$$R_t = (T_t)[\beta_1 PhotoPes_t + \beta_2 L_s(PhotoPes_t) + \beta_3 NYTPes_t + \beta_4 L_s(NYTPes_t) + \beta_5 Interaction_t + \beta_6 L_s(R_t) + \beta_7 L_s(R_t^2)] + (1 - T_t)[\gamma_1 PhotoPes_t + \gamma_2 L_s(PhotoPes_t) + \gamma_3 NYTPes_t + \gamma_4 L_s(NYTPes_t) + \gamma_5 Interaction_t + \gamma_6 L_s(R_t) + \gamma_7 L_s(R_t^2)] + \beta_8 X_t + \varepsilon_t,$$

	$VWRETD_t$				$EWRETD_t$			
	(1)				(2)			
	T_t= Traumatic period				T_t= Traumatic period			
Variables	β	t-stat	γ	t-stat	β	t-stat	γ	t-stat
$PhotoPes_t$	-0.255**	-2.398	-0.017*	-1.823	-0.153**	-2.123	-0.017*	-1.833
$NYTPes_t$	-0.083	-0.716	-0.045***	-4.370	-0.076	-0.897	-0.054***	-5.008
Interaction	0.109	0.819	-0.026**	-2.404	0.013	0.197	-0.028***	-2.663
$PhotoPes_{t-1}$	-0.244**	-2.135	0.018**	1.988	-0.101	-1.171	0.026***	2.698
$PhotoPes_{t-2}$	0.085	0.542	-0.006	-0.637	-0.057	-0.432	-0.006	-0.639
$PhotoPes_{t-3}$	-0.107	-0.591	0.025***	2.771	0.005	0.057	0.022**	2.455
$PhotoPes_{t-4}$	-0.146	-1.185	-0.014	-1.552	-0.060	-0.619	-0.014	-1.468
$PhotoPes_{t-5}$	-0.079	-0.640	-0.009	-0.939	0.036	0.359	0.000	-0.036
$NYTPes_{t-1}$	-0.006	-0.042	0.011	1.065	0.056	0.615	0.018*	1.830
$NYTPes_{t-2}$	0.186	1.063	0.008	0.841	0.050	0.350	0.004	0.361
$NYTPes_{t-3}$	0.061	0.586	0.009	0.852	0.034	0.373	0.008	0.901
$NYTPes_{t-4}$	-0.038	-0.316	-0.010	-1.054	-0.017	-0.192	-0.004	-0.405
$NYTPes_{t-5}$	-0.143	-1.026	-0.004	-0.488	-0.097	-1.018	-0.006	-0.657

3.Results: Which information is more effectively transmitted by photos

$\beta_1+\beta_2+\beta_3+\beta_4$ or $\gamma_1+\gamma_2+\gamma_3+\gamma_4$	-0.660	-0.060	-0.367	-0.091
$\chi^2(1)[\beta_1+\beta_2+\beta_3+\beta_4$ or $\gamma_1+\gamma_2+\gamma_3+\gamma_4=0]$	5.284	1.484	1.527	0.720
p-value	0.022	0.223	0.217	0.396
$\beta_1+\beta_2+\beta_3+\beta_4+\gamma_1+\gamma_2+\gamma_3+\gamma_4$	-0.720		-0.458	
$\chi^2(1)[\beta_1+\beta_2+\beta_3+\beta_4+\gamma_1+\gamma_2+\gamma_3+\gamma_4=0]$	5.727		1.710	
p-value	0.017		0.191	
Adj R-sq	0.026		0.071	
N	13,847		13,847	

3.Results: photos in the top 5% in the popularity rank distribution in a given month

$$R_i = \beta_1 PhotoPes_t + \beta_2 NYTPes_t + \beta_3 L_s(R_t) + \beta_4 L_s(R_t^2) + \beta_5 X_t + \varepsilon_t,$$

Top 5% Most Popular Photos Dataset								
	$VWRETD_t$		$VWRETD_{\{t+1,t+18\}}$		$VWRETD_{\{t+19,t+20\}}$		$VWRETD_{\{t,t+20\}}$	
	(1)		(2)		(3)		(4)	
Variables	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$PhotoPes_t$	-0.027***	-2.625	-0.055	-1.065	0.027*	1.741	-0.029	-0.534
Adj R-sq	0.006		0.013		0.002		0.013	
N	10,577		10,577		10,558		10,577	
	$EWRETD_t$		$EWRETD_{\{t+1,t+18\}}$		$EWRETD_{\{t+19,t+20\}}$		$EWRETD_{\{t,t+20\}}$	
	(5)		(6)		(7)		(8)	
Variables	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$PhotoPes_t$	-0.020**	-2.086	0.038	0.582	0.041**	2.427	0.079	1.149
Adj R-sq	0.050		0.040		0.007		0.035	
N	10,577		10,577		10,558		10,577	
	$VWRETD_t$		$VWRETD_{\{t+1,t+18\}}$		$VWRETD_{\{t+19,t+20\}}$		$VWRETD_{\{t,t+20\}}$	
	(9)		(10)		(11)		(12)	
Variables	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$PhotoPes_t$	-0.034***	-3.218	-0.073	-1.324	0.031*	1.911	-0.043	-0.745
$NYTPes_t$	-0.023*	-1.863	0.056	1.001	0.028	1.466	0.084	1.434
Interaction	-0.002	-0.214	0.000	-0.007	0.000	-0.017	-0.001	-0.013
Adj R-sq	0.012		0.007		0.002		0.006	
N	7,472		7,472		7,472		7,472	
	$EWRETD_t$		$EWRETD_{\{t+1,t+18\}}$		$EWRETD_{\{t+19,t+20\}}$		$EWRETD_{\{t,t+20\}}$	
	(13)		(14)		(15)		(16)	
Variables	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$PhotoPes_t$	-0.025***	-2.584	0.020	0.283	0.046**	2.564	0.065	0.891
$NYTPes_t$	-0.018	-1.618	0.141**	2.023	0.047***	2.651	0.187**	2.541
Interaction	-0.002	-0.178	0.054	0.755	0.008	0.331	0.062	0.816
Adj R-sq	0.100		0.061		0.020		0.053	
N	7,472		7,472		7,472		7,472	

where i = t, (t+1,t+18), (t+19,t+20), and (t,t+20).

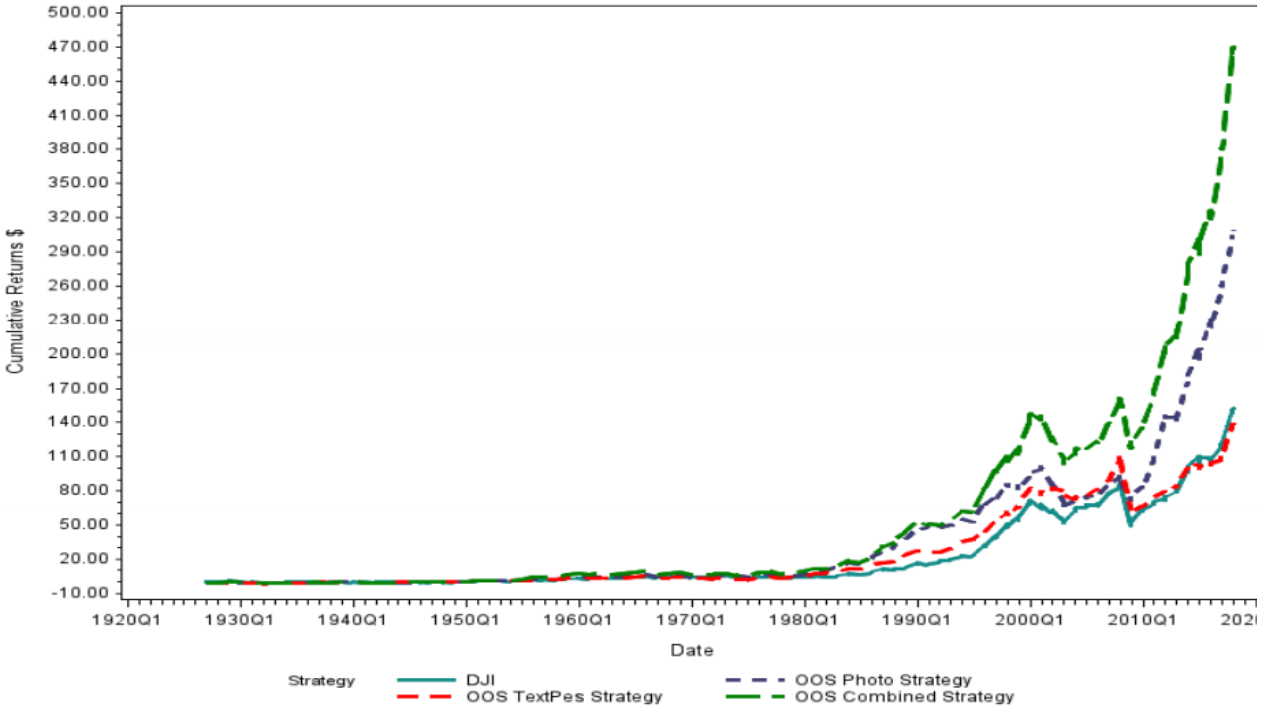
3.Results: Applications

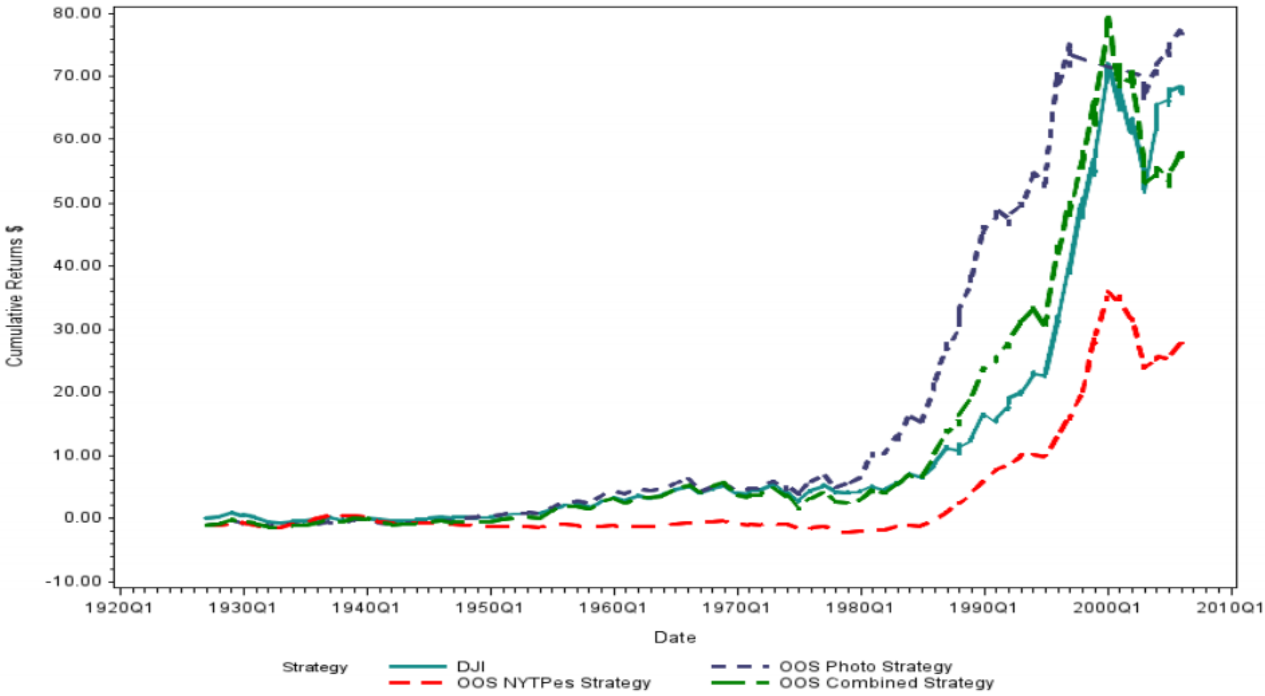
Three real-world trading strategies: we use residuals from regressing PhotoPes or TextPes on lagged returns and day-of-the-week dummies, denoted PhotoPes$\perp$ or TextPes$\perp$.

- The first strategy is based on news pessimism embedded in photos— following days in which PhotoPes$\perp$ is above its 251-day rolling historical mean, we invest in the DOW at market close of day t and sell on market close one day later (t+1).
- The second strategy is based on pessimism embedded in text— following days in which TextPes$\perp$ is above its 251-day rolling historical mean, we invest in the DOW at market close of day t and sell on market close one day later (t+1).
- The second strategy is based on pessimism embedded in text— following days in which TextPes$\perp$ is above its 251-day rolling historical mean, we invest in the DOW at market close of day t and sell on market close one day later (t+1), at market close of day t and sell on market close one day later (t+1).

If the above conditions are not met, we buy T-bills and sell one day later, We incorporate into our strategy returns calculations a 1 basis point per day for trading costs

3.Results: Applications





3.Results: how limits to arbitrage affect the relation between *PhotoPes* and market returns

$$R_t = \beta_1 PhotoPes_t + \beta_2 L_s(PhotoPes_t) + \beta_3 L_s(R_t) + \beta_4 L_s(R_t^2) + \beta_5 X_t + \varepsilon_t,$$

	Sigma$_t$											
	(1)		(2)		(3)		(4)		(5)		(6)	
	High		4		3		2		Low		H-L	
Variables	β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat
PhotoPes$_t$	-0.033***	-2.902	-0.024**	-2.241	-0.019*	-1.937	-0.014*	-1.776	-0.009*	-1.682	-0.024***	-3.103
PhotoPes$_{t-1}$	0.026**	2.293	0.019*	1.794	0.016*	1.665	0.012	1.617	0.009*	1.906	0.018**	2.190
PhotoPes$_{t-2}$	-0.005	-0.398	-0.002	-0.222	-0.001	-0.128	-0.001	-0.157	-0.001	-0.194	-0.003	-0.325
PhotoPes$_{t-3}$	0.015	1.404	0.015	1.484	0.018**	2.002	0.015**	2.039	0.010**	2.164	0.007	0.829
PhotoPes$_{t-4}$	-0.014	-1.239	-0.017	-1.500	-0.015	-1.532	-0.012	-1.450	-0.009*	-1.888	-0.004	-0.448
PhotoPes$_{t-5}$	0.005	0.457	-0.003	-0.301	-0.005	-0.502	-0.005	-0.631	-0.003	-0.654	0.010	1.188
$\beta_1+\beta_2$	-0.006		-0.012		-0.006		-0.005		-0.003		0.004	
$\chi^2(1)[\beta_1+\beta_2=0]$	0.071		0.303		0.073		0.067		0.093		0.037	
p-value	0.790		0.582		0.788		0.795		0.760		0.848	
Adj R-sq	0.085		0.044		0.032		0.031		0.054		0.100	
N	16,429		16,429		16,429		16,429		16,429		16,429	

3.Results: how the relation between pessimism embedded in photos varies depending on uncertainty

$$R_t = (N_t)[\beta_1 PhotoPes_t + \beta_2 L_s(PhotoPes_t) + \beta_3 L_s(R_t) + \beta_4 L_s(R_t^2)] + (1 -$$

$$N_t)[\gamma_1 PhotoPes_t + \gamma_2 L_s(PhotoPes_t) + \gamma_3 L_s(R_t) + \gamma_4 L_s(R_t^2)] + \beta_5 X_t + \varepsilon_t,$$

- NVIX is a news implied volatility index constructed from textual analysis of front-page news articles in the Wall Street Journal. It is developed by Maneala and Moreira (2017) to capture aggregate uncertainty.
- Nt is a dummy variable that takes a value of one if date t is in a month that has above median NVIX value

	$VWRETD_t$				$EWRETD_t$			
	(1)				(2)			
	High NVIX		Low NVIX		High NVIX		Low NVIX	
Variables	β	t-stat	γ	t-stat	β	t-stat	γ	t-stat
$PhotoPes_t$	-0.035**	-2.290	0.001	0.088	-0.033**	-2.096	-0.003	-0.468
$PhotoPes_{t-1}$	0.020	1.301	0.000	-0.057	0.028*	1.778	0.007	1.034
$PhotoPes_{t-2}$	0.006	0.401	-0.009	-1.015	0.006	0.401	-0.009	-1.270
$PhotoPes_{t-3}$	0.027*	1.819	0.013	1.529	0.023	1.517	0.011	1.481
$PhotoPes_{t-4}$	-0.019	-1.166	-0.004	-0.522	-0.024	-1.441	-0.001	-0.087
$PhotoPes_{t-5}$	-0.015	-1.004	-0.007	-0.853	0.001	0.089	-0.007	-0.908
$\beta_1+\beta_2$ or $\gamma_1+\gamma_2$	-0.016		-0.006		0.001		-0.002	
$\chi^2(1)[\beta_1+\beta_2$ or $\gamma_1+\gamma_2=0]$	0.282		0.141		0.004		0.017	
p-value	0.595		0.707		0.951		0.897	
$\beta_1+\beta_2+\gamma_1+\gamma_2$	-0.022				-0.001			
$\chi^2(1)[\beta_1+\beta_2+\gamma_1+\gamma_2=0]$	0.422				0.000			
p-value	0.516				0.993			
Adj R-sq	0.018				0.056			
N	15,923				15,923			

3.Results: which type of news is behind the underlying predictability power of PhotoPes

Data:4,939 photos from “Business” section, “Business this week”, and “Finance and economics” section of *The Economist*

$$R_i = \beta_1 PhotoPes_t + \beta_2 PhotoPes_{t-5} + \beta_3 L_s(R_t) + \beta_4 L_s(R_t^2) + \beta_5 X_t + \varepsilon_t,$$

where Ri denotes daily log-returns on VWRETD or EWRETD on day i (i = t, t+1, and (t,t+1))

3.Results: which type of news is behind the underlying predictability power of PhotoPes

	The Economist Data					
	(1)		(2)		(3)	
Variables	$VWRETD_t$		$VWRETD_{t+1}$		$VWRETD_{\{t,t+1\}}$	
	β	t-stat	β	t-stat	β	t-stat
$PhotoPes_t$	-0.127**	-2.178	0.106**	2.552	-0.013	-0.184
$PhotoPes_{t-5}$	0.113*	1.800	0.025	0.559	0.140*	1.839
Adj R-sq	0.010		0.048		0.011	
N	586		586		586	
	(4)		(5)		(6)	
Variables	$EWRETD_t$		$EWRETD_{t+1}$		$EWRETD_{\{t,t+1\}}$	
	β	t-stat	β	t-stat	β	t-stat
$PhotoPes_t$	-0.111**	-2.203	0.115***	3.043	0.003	0.048
$PhotoPes_{t-5}$	0.080*	1.686	0.016	0.420	0.103	1.641
Adj R-sq	0.051		0.066		0.055	
N	586		586		586	

3.Results: weather positive sentiment has a bigger effect on market returns compared to negative sentiment

$$R_t = \beta_1 PhotoPes_{rank5_t} + \beta_2 PhotoPes_{rank4_t} + \beta_3 PhotoPes_{rank3_t} + \beta_4 PhotoPes_{rank2_t} +$$

$$\beta_5 PhotoPes_{rank1_t} + \beta_6 L_s(R_t) + \beta_7 L_s(R_t^2) + \beta_8 X_t + \varepsilon_t,$$

	$VWRETD_t$		$EWRETD_t$	
	(1)		(2)	
Variables	β	t-stat	β	t-stat
$PhotoPes_{rank5}$	0.006	0.399	-0.002	-0.105
$PhotoPes_{rank4}$	0.107	1.316	0.062	0.766
$PhotoPes_{rank3}$	-0.143**	-2.137	-0.109*	-1.660
$PhotoPes_{rank2}$	-0.113*	-1.695	-0.089	-1.372
$PhotoPes_{rank1}$	-0.087***	-2.963	-0.067**	-2.371
$\beta_1+\beta_2+\beta_3+\beta_4+\beta_5$	-0.230		-0.205	
$\chi^2(1)[\beta_1+\beta_2+\beta_3+\beta_4+\beta_5=0]$	3.784*		3.088*	
p-value	0.052		0.079	
Adj R-sq	0.014		0.050	
N	16,430		16,430	

3.Results: The impact of PhotoPes on trading volume

- whether PhotoPes is a proxy for trading costs or investors' beliefs
- if PhotoPes is viewed as a proxy for trading costs (i.e., liquidity shock), then one would expect a spike in PhotoPes should lead to a decrease in trading volume

$$V_t = \beta L_s(V_t) + \gamma X_t + \varepsilon_t,$$

- Vt denotes the log of aggregate daily NYSE trading volume
- εt, normalize it to have unit variance and mean of zero, and use it as the key dependent variable in the regressions b$(\bar{V}_t)$w

$$\bar{V}_t = \beta_1 PhotoPes_t^{high} + \beta_2 PhotoPes_t^{low} + \beta_3 L_s\left(PhotoPes_t^{high}\right) + \beta_4 L_s\left(PhotoPes_t^{low}\right) +$$

$$\beta_5 L_s(R_t) + \beta_6 L_s(R_t^2) + \varepsilon_t,$$

3.Results: The impact of PhotoPes on trading volume

Variables	NYSE Volume β	NYSE Volume t-stat
$PhotoPes_t^{high}$	0.018	1.186
$PhotoPes_t^{low}$	0.001	0.024
$PhotoPes_{t-1}^{high}$	0.032**	2.055
$PhotoPes_{t-1}^{low}$	0.032**	2.055
$PhotoPes_{t-2}^{high}$	0.014	0.933
$PhotoPes_{t-2}^{low}$	0.000	0.007
$PhotoPes_{t-3}^{high}$	0.004	0.305
$PhotoPes_{t-3}^{low}$	0.008	0.305
$PhotoPes_{t-4}^{high}$	0.037**	2.058
$PhotoPes_{t-4}^{low}$	-0.008	-0.260
$PhotoPes_{t-5}^{high}$	0.028*	1.830
$PhotoPes_{t-5}^{low}$	-0.032	-1.104
	$X^2(1)$	p-value
$\beta_1=\beta_2$	0.188	0.6642
$\beta_3=\beta_4$	4.558**	0.0328
Adj R-sq	0.003	
N	14,488	

3.Results: Does PhotoPes proxy for investor sentiment or directly affects it

$$Media_t = \beta_1 L_s(R_t) + \beta_2 L_s(Media_t) + \beta_3 L_s(R_t^2) + \beta_4 X_t + \varepsilon_t,$$

Mediat is PhotoPes, TextPes, NYTPes, Influential, or Economist.

	(1)		(2)		(3)		(4)		(5)	
	$PhotoPes_t$		$TextPes_t$		$NYTPes_t$		$Influential_t$		$Economist_t$	
Variables	β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat
R_{t-1}	-0.001	-0.166	-0.002	-0.277	-0.354***	-30.736	-0.015	-1.425	0.008	0.144
R_{t-2}	-0.002	-0.295	-0.005	-0.617	-0.050***	-5.564	0.010	1.095	-0.054	-0.946
R_{t-3}	-0.003	-0.346	0.001	0.158	0.008	0.948	-0.006	-0.643	-0.061	-1.218
R_{t-4}	-0.013*	-1.713	-0.006	-0.820	-0.001	-0.059	-0.012	-1.087	-0.003	-0.076
R_{t-5}	0.003	0.325	0.007	0.978	0.020**	2.389	0.002	0.169	0.051	0.990
Adj R-sq	0.020		0.020		0.215		0.000		-0.003	
N	16,430		16,430		16,985		10,577		395	

3.Results: Robustness

$$R_t = \beta_1 PhotoPes_t + \beta_2 L_s(PhotoPes_t) + \beta_3 L_s(R_t) + \beta_4 L_s(R_t^2) + \beta_5 X_t + \varepsilon_t,$$

Variable construction

	Cutoff = {0.55, 0.45}		Cutoff = {0.60, 0.40}		Cutoff = {0.65, 0.35}	
	(1)		(2)		(3)	
	$EWRETD_t$		$EWRETD_t$		$EWRETD_t$	
Variables	β	t-stat	β	t-stat	β	t-stat
$PhotoPes_t$	-0.019**	-2.176	-0.015*	-1.774	-0.014*	-1.662
$PhotoPes_{t-1}$	0.020**	2.395	0.021**	2.513	0.017*	1.946
$PhotoPes_{t-2}$	-0.006	-0.715	-0.007	-0.833	-0.008	-0.914
$PhotoPes_{t-3}$	0.006	0.774	0.004	0.551	0.006	0.747
$PhotoPes_{t-4}$	-0.008	-1.007	-0.011	-1.313	-0.011	-1.295
$PhotoPes_{t-5}$	-0.002	-0.290	-0.003	-0.348	-0.001	-0.174
$\beta_1+\beta_2$	-0.009		-0.011		-0.011	
$\chi^2(1)[\beta_1+\beta_2=0]$	0.320		0.402		0.502	
p-value	0.571		0.526		0.479	
Adj R-sq	0.047		0.047		0.047	
N	18,384		18,208		18,016	
	No Winsorization		No Weighting		Predicted likelihood	
	(4)		(5)		(6)	
	$EWRETD_t$		$EWRETD_t$		$EWRETD_t$	
Variables	β	t-stat	β	t-stat	β	t-stat
$PhotoPes_t$	-0.021**	-2.293	-0.016**	-2.025	-0.019**	-2.178
$PhotoPes_{t-1}$	0.018**	2.056	0.006	0.765	0.020**	2.286
$PhotoPes_{t-2}$	-0.002	-0.244	0.002	0.232	-0.007	-0.831
$PhotoPes_{t-3}$	0.015*	1.881	0.021**	2.507	0.015*	1.834
$PhotoPes_{t-4}$	-0.014	-1.558	-0.013	-1.534	-0.013	-1.458
$PhotoPes_{t-5}$	-0.002	-0.186	-0.001	-0.158	-0.002	-0.220
$\beta_1+\beta_2$	-0.021		-0.022		-0.021	
$\chi^2(1)[\beta_1+\beta_2=0]$	0.089		0.004		0.096	
p-value	0.765		0.951		0.757	
Adj R-sq	0.050		0.050		0.050	
N	16,430		16,430		16,430	

3.Results: Robustness

$$R_t = \beta_1 PhotoPes_t + \beta_2 L_s(PhotoPes_t) + \beta_3 L_s(R_t) + \beta_4 L_s(R_t^2) + \beta_5 X_t + \varepsilon_t,$$

Sample period and machine learning

	Noisy Labels		Start in 1945		Open-Close Returns		Orthogonalized *PhotoPes*	
	(1)		(2)		(3)		(4)	
	$EWRETD_t$		$EWRETD_t$		DOW_t		$EWRETD_t$	
Variables	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$PhotoPes_t$	-0.020**	-2.363	-0.015**	-2.052	-0.015*	-1.819	-0.018**	-2.008
$PhotoPes_{t-1}$	0.019**	2.181	0.006	0.880	0.005	0.661	0.014	1.575
$PhotoPes_{t-2}$	0.001	0.160	-0.001	-0.158	0.002	0.186	0.000	-0.041
$PhotoPes_{t-3}$	0.008	0.988	0.014*	1.864	0.017**	2.185	0.013	1.431
$PhotoPes_{t-4}$	-0.012	-1.415	-0.009	-1.209	-0.011	-1.293	-0.012	-1.256
$PhotoPes_{t-5}$	-0.008	-0.909	-0.009	-1.133	-0.012	-1.505	-0.001	-0.126
$\beta_1+\beta_2$	-0.012		-0.014		-0.014		-0.004	
$\chi^2(1)[\beta_1+\beta_2=0]$	0.479		0.841		0.683		0.059	
p-value	0.489		0.359		0.409		0.808	
Adj R-sq	0.050		0.064		0.009		0.047	
N	16,430		14,201		16,358		14,159	

4. Conclusion

contributions to the literature.

- Pessimism embedded in news photos contains useful information consistent with an investor sentiment proxy.
- Pessimism embedded in news photos complements and, in some cases, subsumes pessimism embedded in news text.
- The benefit of using cutting-edge photo classification techniques to study how the information in a large sample of news photos is relevant in context of financial markets

Future researchers

- Advance the machine learning technique for photos classification to help bridge the gap with text classification models to better capture sentiment and other important content embedded in news photos.