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Facial Expression And The Business Cycle

Aromí, José Daniel
Clements, Adam

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Facial Expressions and the Business Cycle: Assessing the Information Content of Communicated Emotions

J. Daniel Aromí
FCE, Universidad de Buenos Aires and FCE, Universidad Católica Argentina

Adam Clements
School of Economics and Finance, Queensland University of Technology

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Abstract

A collection of photographs is used to construct indicators of emotions communicated by facial expressions. The indicators correspond to the US economy for the period 1996-2018. The analyses point to significant associations between the level of economic activity and indices of emotional states. Beyond contemporaneous associations, the indicators are shown to anticipate business cycle dynamics. Indices summarizing emotions linked to policy making and the stock market contain more information than indicators linked to corporations.

1 Introduction

Do facial expressions communicate information regarding current and future economic conditions? Are there differences in the information communicated by emotions displayed by different economic actors? Beyond the ability to anticipate the state of the business cycle, can indicators of emotional states be used to shed light on the mechanisms underlying economic fluctuations?

These questions can now be addressed exploiting enhanced access to images in digital format jointly with machine learning algorithms. In this study, computer vision tools are used to rate pictures in terms of emotions communicated by facial expressions. These appraisals are used to construct indicators of emotional states. Selected pictures correspond to the US economy and are linked to three topics: policy making, the stock market or large corporations. Photographs correspond to those distributed by a news agency and the sample period is 1996-2018. In a second stage, these indicators are evaluated in terms of their association with contemporaneous and subsequent levels of economic activity.

The exercises implemented in this study are motivated by two complementary observations. First, emotional states have strong links with beliefs and decision making. Emotions are correlated with assessments of present and future economic scenarios (Damasio 1994, LeDoux 1989, Lerner et al. 2015). In addition, emotions have an impact on decision making (Benabou & Tirole 2016, Damasio 1994, Elster 1998, Fenton-O'Creevy et al. 2012, Loewenstein 2000, Schwartz 2000, Smith & Dickhaut 2005). Second, subjective states are measured with noise and, at the same time, they play a significant role in macroeconomic dynamics (Pigou 1920, Angeletos & La'O 2013, Beaudry & Portier 2014, Heymann 1998, Evans & Honkapohja 2012, Farmer 2011, Milani 2011). As a result, empirical strategies that allow for more accurate measures of subjective states can result in advances in macroeconomic analysis.

The findings reported in this study suggest that facial expressions constitute a valuable indicator for the analysis of business cycles. A first set of exercises shows that there exist strong contemporaneous associations between the state of the business cycle and communicated emotions. During recessions, the frequency of faces expressing happiness is markedly lower and the frequency of neutral expressions and faces expressing sadness increases. This pattern is observed for the three sets of pictures under analysis, that is, those associated to policy making, the stock market and corporations. In addition, indices summarizing communicated emotions display statistically significant associations with quarterly GDP growth. In the case of the most ample specification of the index, a one standard deviation increment in the index is associated to an increment of 0.56 standard deviations in mean quarterly GDP growth. Significant associations are also found for the indices based on pictures linked to policy making and the stock market but not for the index linked to corporations.

A second set of exercises evaluates the association between the indices of communicated emotions and subsequent states of the business cycle. The indices linked to policy making and the stock market are found to anticipate the state of the business cycle. As in the previous case, this association is not found in the case of the index linked to corporations. The strongest association is found in the case of the index that results from combining the three sets of pictures. In this case, a one standard deviation change in the index anticipates a 0.38 increment in mean GDP growth during the following quarter. Similar associations are found considering cumulative GDP growth up to eight quarters ahead.

As previously indicated, pictures linked to corporations do not communicate as much information about the business cycle as pictures linked to policy making or the stock market. This finding is consistent with endogenous information sets (Mackowiak & Wiederholt 2009). It is plausible to conjecture that, compared to corporate executives, policy makers and stock market participants have higher incentives to acquire macroeconomic information.

This work assesses the information content of emotions communicated by photographs distributed by a news organization. The analysis shows that there is valuable information regarding business cycle dynamics. Beyond this positive result, for a proper interpretation of the findings, it is worth noting that the constructed indicators contain information that is not limited to the emotional state of a target group of economic agents. The indicators also reflect variations in the type of events covered and the selection of pictures by members of the news organization. For example, during expansions the frequency of IPOs increases (Pastor & Veronesi 2005) and, as a result, the index could vary because more pictures cover this type of event. Also, reporters might select pictures to distribute according to their views regarding the extent to which a given image, and its associated emotion, is representative of the event. This is an additional source of variation in the indicator.

In the next section the methodology and data are described. Section 3 provides a preliminary evaluation of the constructed indices. Formal models are estimated in section 4. Conclusions are presented in section 5.

2 Data and methodology

This study constructs indicators of emotions inferred from photographs. These indicators are later evaluated in terms of their association with the business cycle. More specifically, the evaluation of the indices is based on its association with the quarterly seasonally adjusted real GDP growth. This indicator of economic activity is procured from the data portal maintained by Federal Reserve Bank of Saint Louis.[1]

The pictures used for the construction of the indices correspond to previews available from a public platform maintained by a news agency.[2] Importantly, each image displayed in the platform is accompanied by information on date of creation, date of submission and a brief text that describes the content of the picture. This information is exploited to identify the relevant sets of pictures used for different specifications of the indicators.

2.1 Indices of facial expressions

The construction of the indicators of facial expressions can be described as a three step process: selection of photographs, processing of images and aggregation of information inferred from individual faces. The first stage requires specifying a set of economic topics and establishing a strategy to select the relevant images. In the second step, a set of computer vision tools are used to extract faces from pictures and rate them in terms of emotional content. In the final stage, the flow of information provided by these classified images is combined to obtain a quarterly indicator of facial expressions. Below, each step is described in more detail.

2.1.1 Selection of images

The indicators of facial expressions are built targeting different aspects of the US economy. The three topics or areas are: policy making, stock market and corporations. In each of these cases, to identify relevant photographs, the text describing each photograph is evaluated. More specifically, given a specific topic, a list of keywords is constructed

[1] https://fred.stlouisfed.org/.
[2] The platform is AP Images: www.apimages.com.

and photographs with descriptions that include any of these keywords are selected for the computation of the respective index. For example, in the case of policy making "Federal Reserve" and "U.S. Treasury" are among the proposed keywords. If the description of a picture includes any of these terms or any other term in the list of keywords, the picture is selected for the computation of the index associated to policy makers. The list of keywords used in each case is shown in table 1. [3] One additional filter involves the submission date. To avoid forward looking biases, pictures were selected only if the moth of its creation date coincides with the month of the submission date.

Table 1: Keywords by economic topic

Policy Making:	Federal Reserve, US Treasury, U.S. Treasury, Secretary of the Treasury, Treasury Department, Department of the Treasury, Treasury Secretary.
Stock Market:	New York Stock Exchange.
Corporations:	Top 300 companies in the Forbes 2000 list of US corporations. (To avoid false positives, names with less than 5 characters are excluded)

2.1.2 Processing images

A set of computer vision tools are used to measure the emotional content of facial expressions in pictures. These tools are used to implement a series of tasks: face detection, extraction of salient features, training of a classification algorithm and, finally, rating faces in terms of emotional content.[4] All this tasks are implemented using Python. In a first stage, faces are detected in photographs using OpenCV library (Open Source Computer Vision Library: http://opencv.org). Next, salient features, known as "landmarks", are extracted using a facial landmark detector found in library "dlib". In this way, the information of each face is summarized as 68 coordinates that identify locations

[3] Alternative list of keywords have been evaluated with similar results. For example, lists with a larger group of government agencies or a larger set of market venues have been considered. The results are available upon request.

[4] For a brief review of the literature of automatic facial expression recognition see Ko (2018).

of eyebrows, eyes, mouth, nose and jaw.

The classification methodology is given by support vector machines algorithm with linear kernels. The model is trained using a collection faces that have been manually classified in terms of 8 emotional states (anger, contempt, disgust, fear, happiness, neutral pose, sadness and surprise). The algorithm takes the coordinates of the 68 landmarks as inputs and provides scores associated to each emotional state as output. Library "scikit-learn" was used to implement this model. More details on how images were processed is provided in appendix A.

2.1.3 Indicator of facial expressions

The previous steps result in a collection of faces and corresponding creation dates and facial expressions scores. An indicator of facial expression is built summarizing this information at quarterly frequency. The aggregation of information involves three steps. First, quarterly averages of the scores corresponding to the selected pictures is computed. This results in a time series of eight dimensional vectors. Next, the information provided by different emotions is summarized calculating the first principal component. Finally, acknowledging that emotions are perceived with noise, a dynamic factor model is estimated. The estimated non-observable state is estimated using a Kalman filter.

More formally, let $\{r_{ti}\}_{i=1}^{P_t}$ represent the scores linked to the collection of P_t faces detected for quarter t. Then, the average scores for pictures created on that quarter is given by the eight-dimensional vector $\bar{r}_t = \sum_{i=1}^{P_t} r_{ti}/P_t$. Computing the first principal component, a one dimensional vector r_t^* results. This time series is used to estimate the unobservable state using package dlm in platform R.

3 Preliminary analysis of estimated indicators

Four indices are computed according to the procedure described above. Three indicators correspond to different specific aspects of the US economy. In addition, a general indicator is computed combining the photographs that correspond to the previously indicated economic aspects. Table 2 reports, for each version of the indicator, the number of detected faces. In addition, table 2 reports information on average manifestations of emotions. More specifically, following a standard practice in machine learning classification, the scores generated by the algorithm are reported as a probabilities using the softmax function.[5] Independently of the subset of pictures, on average, the highest average probabilities are associated to neutral pose and happiness. Also, compared to pictures linked to policy making, pictures corresponding to the stock market and corporations display a higher probability of happiness and lower probability of neutral pose. Beyond this difference, there are salient similarities in the average probabilities estimated for different sets of images.

Table 2:

Descriptive statistics of images by topic

	Policy Making	Stock Market	Corporations
Number of classified pictures	6866	5723	6825
Mean probability			
Anger	5.1	5.2	4.9
Contempt	1.4	1.5	1.5
Disgust	1.9	2.0	2.2
Fear	1.6	1.8	2.2
Happiness	21.8	27.8	29.6
Neutral	55.4	48.3	48.8
Sadness	4.3	5.4	4.0
Surprise	8.4	7.8	6.6

Notes: Number of photographs are the determined to the presence of the presence of a keyword in the text that describes each photograph. The probability of emotions for each classified face

[5]In other words, the score associated to each emotion is transformed applying the exponential function. Next, this tranformed score is divided by the sum of all similarly transformed scores corresponding the that picture.

is computed applying the softmax function, or normalized exponential function, to the scores computed by the trained classification algorithm.

Table 3 reports information on the contemporaneous association between communicated emotions and the business cycle. During recessions, the probability associated to happiness is lower. On the other hand, the probability associated to neutral, sadness and surprise increases. This is a first indication of an association between communicated emotions and the state of the business cycle. It must be noted that this pattern is observed for the three groups of images. The changes in probabilities is more noticeable in the case of images linked to the stock market.

Table 3:

Average emotions by stage of the business cycle

	Policy Making			Stock Market			Corporations		
	Exp.	Rec.	Dif.	Exp.	Rec.	Dif.	Exp.	Rec.	Dif.
Mean probability									
Anger	5.2	4.7	-0.5	5.2	6.2	1.1	4.9	5.5	0.5
Contempt	1.4	1.5	0.0	1.5	1.6	0.1	1.5	1.5	0.0
Disgust	2.0	1.6	-0.3	2.1	1.7	-0.4	2.3	1.8	0.5
Fear	1.6	1.5	-0.1	1.8	1.8	0.1	2.2	1.7	-0.5
Happiness	22.5	18.8	-3.7	28.6	21.1	-7.6	30.3	24.6	-5.7
Neutral	54.9	57.6	2.7	48.0	50.7	2.7	48.3	52.5	4.2
Sadness	4.2	4.9	0.7	5.2	7.4	2.2	3.8	5.5	1.7
Surprise	8.2	9.4	1.2	7.6	9.5	1.9	6.6	6.9	0.3

Notes: According to NBER's Business Cycle Dating Committee[6] two recessions are covered by the sample period: March 2001-November 2001 and December 2007-June 2009.

[6]https://www.nber.org/cycles.html.

As described in the methodology section, once the images are classified, an index is computed averaging scores observed in each time period, computing the first principal component for average scores and, finally, implementing a Kalman filter. Table 4 shows, for alternative sets of images, the factor loadings for the first principal component. Suggesting that a structural property is being summarized by each first principal components, some common characteristics can be observed. First, happiness always displays the largest loading in absolute value. Facilitating a natural interpretation of the indices, the sign of the loading corresponding to happiness is opposite to the sign of the loadings corresponding to neutral and sadness. In addition, in the case of anger, in three cases the sign of the factor loading coincides with that observed in the cases of neutral expressions and sadness. On the other hand, the factor loading corresponding to fear is consistently equal to the sign of the factor loading corresponding to happiness. Overall, these observations suggest that the first principal component is probably a good summary of the emotional states transmitted by images.

Table 4:

Factor loadings

	Policy Making	Stock Market	Corporations	All
Anger	-0.07	-0.49	0.34	-0.32
Contempt	-0.24	0.10	0.05	-0.04
Disgust	0.24	-0.01	0.15	0.12
Fear	0.16	0.35	0.17	0.19
Happiness	0.72	0.62	0.48	0.72
Neutral	-0.17	-0.18	-0.27	-0.19
Sadness	-0.52	-0.45	-0.61	-0.54
Surprise	-0.16	0.07	-0.39	0.05

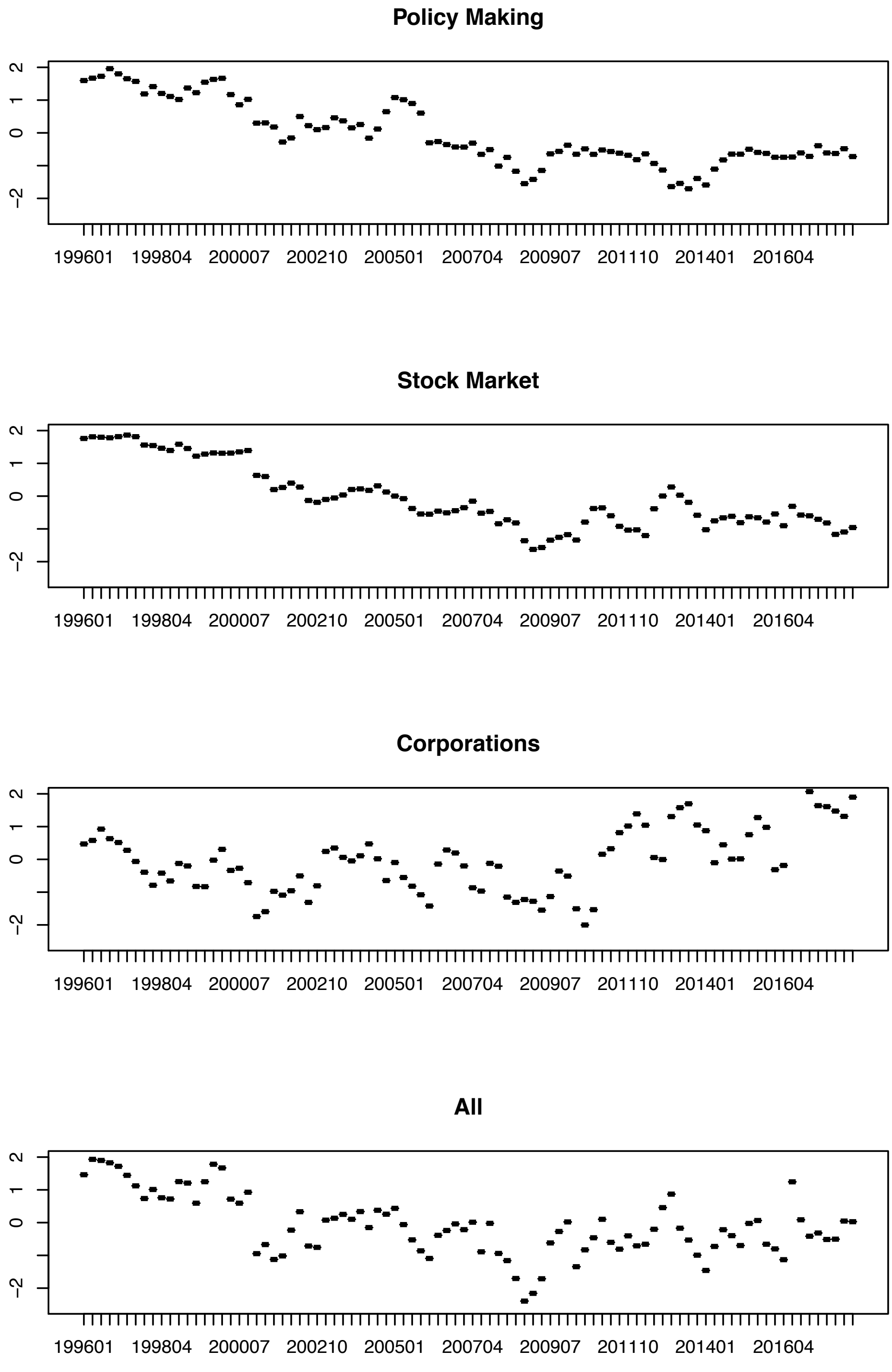

Figure 1: Indices of communicated emotions

Figure 1 shows the trajectory of the computed indices. Some common patterns linking the indices to macroeconomic development can be detected. Coinciding with the insights resulting from the analysis of individual emotions during recessions, the two recessions of the sample period are associated to drops in the value of the indices. In the recession of 2001, the indices decrease from typically very high values observed during the previous years. It is worth noting that these high values during the first years of the sample coincide with the optimism and good economic outcomes observed during that period. During the 2008-2009 crisis, drops are clearly noticeable in the case of the indices linked to policy making and the stock market. In the case of the broad index, coinciding with the most intense stage of the crisis, the lowest value is observed on the fourth quarter of 2008. In the subsequent years, the indices recover from the lows of the 2008-2009 crisis. This preliminary evaluations suggest facial expressions can provide valuable information regarding subjective states and business cycle dynamics. More formal evaluations are presented below.

4 Results

In this section the information provided by the indices based on facial expressions is assessed through simple statistical models. Given a baseline autoregressive model for GDP growth, the association between the business cycle and communicated emotions is evaluated incorporating an index of facial expressions as an explanatory variable. First, the case of contemporaneous associations is considered. Next, the information provided by lagged values of the indices is estimated. The last subsection reports results on robustness exercises and alternative specifications of the empirical model.

4.1 Contemporaneous associations

A simple autoregressive model for GDP growth is extended incorporating the contemporaneous value of an indicator of facial expressions. Formally, the model is given by:

$$g_t = \alpha + \beta_{-1} g_{t-1} + \beta_I I_t + u_t \tag{1}$$

Where g_t is the quarterly growth rate of GDP for quarter t, I_t is an index of facial expressions and u_t is an error term.

Table 5 shows the estimated models. The first column corresponds to the baseline model. The information content of the indices is communicated by the respective estimated coefficients and the variation in the adjusted R^2. All estimated coefficients are positive. With only one exemption, the associations are statistically significant. The strongest link corresponds to the broad index, that is, the index which results from combining the pictures related to policy making, the stock market and corporations. In this case, the estimated coefficient indicates that a one standard deviation increment in the index is associated to an increment of 0.56 standard deviations in GDP growth. Smaller but similar associations are found in the case of indices linked to policy making or the stock market. Notably, in these three cases, once the index of facial expressions is incorporated, the coefficient of the lagged value of GDP growth not significantly different from zero. In the case of the index linked to corporations, after controlling for lagged values of GDP growth, no significant contemporaneous association between the index and GDP growth is found. The adjusted R^2's show very significant gains associated to the incorporation of indices of facial expressions.

These results point to a strong association between the business cycle and communicated emotions. As previously discussed, the evaluated indices are the combined outcome of facial expressions expressed by economic actors (policy makers, traders) and the views of the members of a news agency regarding the images that are worth distributing. In other words, the documented regularities involve both perceived emotions and opinions regarding relevant perceived emotions. This distinction needs to be kept in mind for a proper interpretation of the results.

The estimated models also point to differences in the information content of alternative specification of the index. The weak association in the case of the index linked to corporations can be indicative of different information sets acquired by different economic agents. Policy makers and participants in asset markets might have higher incentives to acquire information regarding macroeconomic scenarios while corporate executives might have stronger incentives to acquire information regarding microeconomic developments.[7]

[7]See Mackowiak & Wiederholt (2009) for a model of rational inattention and information acquisition

Table 5: Simple linear models

	[1]	[2]	[3]	[4]	[5]	[6]
$\hat{\beta}_{-1}$	0.39**	0.18	0.23	0.37*	0.08	-
	[2.3]	[1.3]	[1.3]	[2.5]	[0.7]	
$\hat{\beta}_{Pol.Making}$	-	0.41***	-	-	-	-
		[4.4]				
$\hat{\beta}_{StockMarket}$	-	-	0.35***	-	-	-
			[4.2]			
$\hat{\beta}_{Corporations}$	-	-	-	0.09	-	-
				[1.0]		
$\hat{\beta}_{All}$	-	-	-	-	0.56***	0.61***
					[4.6]	[3.7]
Adj. R^2	0.143	0.254	0.226	0.139	0.350	0.352

Notes: significance levels: "*" 0.10, "**" 0.05 and "***" 0.01. Standard errors are estimated following Newey & West 1987, Newey & West 1994. Parameter estimates are standardized; absolute t-statistics in brackets.

4.2 Associations with subsequent levels of activity

In addition to contemporaneous associations, it is of interest to evaluate whether indices based on communicated emotions are able to capture information regarding future levels of economic activity. In this subsection, this type of associations are measured using a slightly modified version of the simple empirical model used in the previous subsection:

$$g_{[t,t+h]} = \alpha + \beta_0 g_t + \beta_I I_t + u_{[t,t+h]} \tag{2}$$

Where $g_{[t,t+h]}$ is the cumulative growth rate of GDP from quarter t through quarter $t+h$, g_t is the growth rate for quarter t, I_t is an index of facial expressions and $u_{[t,t+h]}$

is an error term. Four windows lengths are considered: $h \in \{1, 2, 4, 8\}$.

Table 6 shows the information regarding the estimated models. In the case of the broad index and indices linked to policy making and the stock market, positive and statistically significant coefficients are observed. As in the previous subsection, the strongest association corresponds to the broad index. For all forecast horizons, the estimated coefficient is significant and close to 0.4. In the case of corporations, the estimated coefficient is larger than in the case of contemporaneous associations but, no significant association is found.

Beyond estimated coefficients, it is worth noting that the incorporation of the index results in substantial increments in adjusted R^2's. For example, in the case of four-quarter-ahead windows, the adjusted R^2 of the baseline model is 0.159. The corresponding metric when the broad index is incorporated increases to 0.234.

Table 6: Estimated forecast models

	h=1	h=2	h=4	h=8
Baseline adj. R^2	0.154	0.196	0.159	0.092
Policy Making				
$\hat{\beta}_{Pol.Making}$	0.297***	0.337***	0.364*	0.390
t-stat.	[3.5]	[2.7]	[1.7]	[1.1]
Adj. R^2	0.203	0.266	0.242	0.191
Stock Market				
$\hat{\beta}_{StockMarket}$	0.202**	0.249*	0.327*	0.443
t-stat.	[2.4]	[2.0]	[1.7]	[1.5]
Adj. R^2	0.168	0.228	0.227	0.228
Corporations				
$\hat{\beta}_{Corporations}$	0.133	0.169	0.148	0.174
t-stat.	[1.4]	[1.3]	[1.1]	[1.2]
Adj. R^2	0.152	0.207	0.161	0.098
All				
$\hat{\beta}_{All}$	0.375***	0.412***	0.388**	0.418**
t-stat.	[3.7]	[2.7]	[2.3]	[2.6]
Adj. R^2	0.223	0.288	0.234	0.188

Notes: significance levels: "*" 0.10, "**" 0.05 and "***" 0.01. Standard errors are estimated following Newey & West 1987, Newey & West 1994. Parameter estimates are standardized; absolute t-statistics in brackets.

4.3 Robustness analysis and alternative specifications

In this subsection, alternative specifications of the empirical models are estimated. These exercises are used to evaluate the robustness of the previously reported results and, at the same time, to obtain more insights regarding the associations between the business cycle and communicated emotions. All the exercises below are computed using the broad version of the index. Two forecasting windows are considered: $h \in \{1, 4\}$

In previous exercises, the proposed models contemplate only the first lag of GDP growth. It can be conjectured that the results could change if more historic information is incorporated. To evaluate this conjecture a model that includes GDP growth over the previous four quarters, $g_{[-4,0]}$, is estimated. Columns 1 and 4 in table 7 show that the results are robust to this type of changes in the dynamic model.

Second, it is of interest to check whether the documented association is observed during a particular time period. With this objective in mind, a flexible model that allows for a change in the slope after 2007 is estimated. More specifically, the model incorporates a new variable equal to the product between the broad index and a dummy variable equal to one after year 2007. Columns 2 and 5 in table 7 show that the estimated slope is higher for the post-2007 period. But the difference is not statistically significant and the estimated slopes for the first half of the sample are similar to the estimated values observed in the original estimations.

Finally, to evaluate non-linearities, a model that allows for different slopes when the index is above or below its average level is considered. With this objective, a new variable is added to the original model. This variable is equal to the product between the broad index and a dummy variable equal to one if the index of facial expressions is below its mean value. The estimated models (columns 3 and 6 in table 7) indicate that the coefficient associated to the non-linear term is not statistically significant. Suggesting a more intense association in the case of negative values, the estimated value is negative in the case of one-quarter-ahead forecasts. In the case of one year ahead forecasts, the sign is positive, suggesting that the association is stronger when the index is above its average value. Overall, the estimations of alternative models suggest that the previously documented patterns are robust to changes in the specifications.

Table 7: Alternative specifications

Window	h=1	h=1	h=1	h=4	h=4	h=4
	[1]	[2]	[3]	[4]	[5]	[6]
$\hat{\beta}_0$	0.13	0.16	0.125	0.17	0.17***	0.18***
	[0.86]	[1.3]	[1.2]	[1.5]	[2.6]	[4.6]
$\hat{\beta}_{[-4,0]}$	0.07	-	-	-0.00	-	
	[0.44]			[0.0]		
$\hat{\beta}_{All}$	0.35***	0.34***	0.26**	0.39**	0.41**	0.45***
	[3,1]	[3.8]	[2.4]	[2.4]	[2.5]	[3.0]
$\hat{\beta}_{All}^{post2007}$	-	0.10	-	-	0.06	-
		[0.3]			[0.2]	
$\hat{\beta}_{neg}$	-	-	0.31	-	-	-0.16
			[0.9]			[0.7]
Adj. R^2	0.216	0.216	0.222	0.230	0.230	0.232

Notes: significance levels: "*" 0.10, "**" 0.05 and "***" 0.01. Standard errors are estimated following Newey & West 1987, Newey & West 1994. Parameter estimates are standardized; absolute t-statistics in brackets.

5 Conclusions

The present study evaluates the information content of facial expressions. With this objective, indicators of facial expressions are constructed. Statistically significant associations with contemporaneous and future business cycle conditions are found. These associations are also economically significant and suggest that facial expressions constitute a valuable form of information regarding subjective states.

These findings can be understood as a lower bound for information content of facial expressions. A more comprehensive collection of pictures together with improved computer vision techniques can be conjectured to result in even more informative indicators. Another direction for future research is related to the selection of pictures. More control over the selection of pictures can allow for a more precise measures of facial expressions manifested by a relevant group of economic actors.

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Appendix A: Further details on image processing

In this appendix more details regarding the tools used and the procedures implemented to generate emotional indicators from photographs:

The face detection algorithm is a Haar-Cascade classifier implemented through OpenCV function "CascadeClassifier". The trained algorithm "haarcascade_frontalface_default" was used to obtain coordinates identifying the location of faces in images.

The pre-trained facial landmarks detection algorithm used in this study is available from library dlib. The function "shape_predictor" together with the trained model "shape_predictor_68_face_landmarks.dat" result in the 68 landmarks used to classify faces.

The collection of labeled faces used to train the classification algorithm is given by the combination of the extended Cohn-Kanade dataset (Cohn et al. 2010) and "muxspace facial expressions database" (https://github.com/muxspace/facial_expressions).Similar results are observed when only the extended Cohn-Kanade dataset is used

The emotion classification algorithm trained for this study is a support vector machine with linear kernel. The algorithm is implemented using Python's "scikit-learn" library. For each emotion a "one versus all" classifier is trained. In this way, the algorithm results in a mapping in which each image is associated to an eight-dimensional vector. The components correspond to emotion scores computed by a specific "one versus all" classifier.