Pontificia Universidad Católica Argentina
"Santa María de los Buenos Aires"

FACIAL EXPRESSIONS AND THE BUSINESS CYCLE: ASSESSING THE INFORMATION CONTENT OF COMMUNICATED EMOTIONS

Por Daniel Aromí y Adam Clements

Facultad de Ciencias Económicas

Departamento de Investigación "Francisco Valsecchi"

Documento de Trabajo en Economía N°64

Diciembre de 2020

FACIAL EXPRESSIONS AND THE BUSINESS CYCLE: ASSESSING THE INFORMATION CONTENT OF COMMUNICATED EMOTIONS

J. Daniel Aromí

Adam Clements

Abstract

This paper is the first to consider the link between information conveyed by the facial expressions of a range of economic actors and economic activity. A collection of photographs is used to construct indicators of emotions communicated by the facial expressions. The indicators correspond to the US economy for the period 1996-2018. Significant links between the level of economic activity and indices of emotional states are observed. 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.

Keywords: Business cycles, forecasts, facial expressions

JEL: E7, E3.

Moreau de Justo 1400, Edificio Santo Tomás Moro, 4to. Piso
Puerto Madero – Ciudad de Buenos Aires

I. Introduction

There is a well established literature that considers the information contained in text communicated through mass media outlets, social networks or even macroeconomic announcements (Tetlock 2007, Bollen et al. 2011, Baker et al. 2016, Smales and Apergis 2017). Moving beyond textual analysis, this paper considers if the facial expressions captured by the press communicate information regarding current and future economic conditions. In considering this issue, the information communicated by the emotions displayed by different economic actors will be examined. This issue can now be addressed exploiting enhanced access to images in digital format and advances in machine learning algorithms. In this study, computer vision tools are used to rate photographs taken by the media in terms of emotions communicated by facial expressions, with these ratings used to construct indicators of emotional states. Selected pictures are of individuals related to the US economy and are linked to three topics: policy making, the stock market and large corporations. These pictures correspond to different economically relevant events, such as press conferences, congressional reports, trading floor activity, IPOs and corporate announcements. Photographs correspond to those distributed by a news agency over the sample period 1996-2018. In the second stage, these indicators are evaluated in terms of their association with contemporaneous and subsequent levels of economic activity.

Previous research has suggested that facial expressions convey information along different dimensions, seminal work on emotions (Tomkins 1962{1963), social judgements in different contexts such as leadership and voting outcomes (Little, Burriss, Jones, and Roberts 2007, Re et. al. 2013), decision-making in competitive games (Rojas, Masip, Todorov and Vitria 2011) and trustworthiness (Todorov and Oosterhof 2011) among many others. An association between trustworthiness of facial expressions and economic activity has been revealed by Safra, Chevallier, Grezes and Baumard (2020). This work builds upon the link between facial expressions and emotions, as 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 and Tirole 2016, Damasio 1994, Elster 1998, Fenton-O'Creevy et al. 2012, Loewenstein 2000, Schwartz 2000, Smith and Dickhaut 2005). While subjective beliefs regarding the state of the economy are measured with noise, at the same time, they play a significant role in macroeconomic dynamics (Pigou 1920, Angeletos and La'O 2013, Beaudry and Portier 2014, Heymann 1998, Evans and Honkapohja 2012, Farmer 2011, Milani 2011). Therefore, empirical strategies that allow for more accurate measures of subjective states, determined here from the facial expressions of economic actors, can result in advances in macroeconomic analysis.

The findings reported here, suggest that facial expressions contain valuable information relating to business cycle conditions. In other words, those in the public eye should be careful, not only about the spoken or written words they use, but also the facial expressions they convey. First, a contemporaneous association between the state of the business cycle and communicated emotions is identified. 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 in all three sets of pictures, those associated with policy making, the stock market and corporations. The indices of emotion are significantly related to quarterly GDP growth. In the case of the broadest specification of the index, a one standard deviation increment in the index is associated with 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. This finding is consistent with endogenous information sets (Mackowiak and 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.

Further analysis examines 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 be related to the future state of the business cycle. As in the earlier analysis, the index linked to corporations is not important. The strongest association is found in the case of the index that combines the three sets of pictures. In this case, a one standard deviation change in the index leads to 0.38 standard deviations increment in mean GDP growth during the following quarter. Similar associations are found considering cumulative GDP growth up to eight quarters ahead. Impulse response functions are computed to provide a complementary description of the dynamic associations. These estimations point to a persistent effect of shocks to indicators of emotions on future economic activity.

Section 2 presents the methodology and underlying data sources. Section 3 provides a preliminary evaluation of the constructed indices. Formal models are estimated in Section 4. Conclusions are presented in Section 5.

II. Data and methodology

This study constructs indicators of emotions from the facial expressions inferred from media photographs of a range of economic actors. 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.

II.I 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 ow 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.

II.I.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, for each topic, a list of keywords is constructed 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 with 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 creation date's month coincides with the submission date's month.

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

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)

II.I.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 of these tasks are implemented using functions from Python libraries. In the 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 the library "dlib". In this way, the information of each face is summarized as 68 coordinates that identify locations of eyebrows, eyes, mouth, nose and jaw.

The classification methodology is based on a support vector machine algorithm with linear kernels. The model is trained using a collection of 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 linked 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.

II.I.3 Indicators of facial expressions

The previous steps result in a collection of faces, with corresponding creation dates and facial expression scores. An indicator of facial expression is built summarizing this information at a quarterly frequency. Initially, quarterly indicators corresponding to each facial expression are computed using the average value of the score for the corresponding pictures. Then, the information corresponding to these 8 indicators is summarized using two alternative dimensionality reduction techniques. The first alternative involves using principal component analysis (PCA). In addition to this widely used technique, we consider sparse principal component analysis (Zou et al. 2006). This method restricts the complexity of the model and, in this way, it

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

might be able to reduce the variance of the estimated indicator.5 In the final step, acknowledging that quarterly observations constitute a noisy indicator of an unobservable state, the Kalman filter is used to generate a filtered indicator.

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

III. Preliminary analysis of estimated indicators

Four indices are computed according to the procedure described above. Three indicators correspond to the three specific economic topics discussed above. In addition, a general indicator is computed combining the photographs corresponding to the three topics. For each version of the indicator, Table 2 reports both the number of photographs linked with each topic and the rate of occurrence of each emotion linked to each topic. More specifically, following standard practice in machine learning classification, the scores generated by the algorithm are reported as probabilities or fractions using the softmax function.6 Irrespective of the subset of pictures, on average, the highest average probabilities are associated with neutral and happiness emotions. 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 a neutral expression. Beyond these differences, there are noticeable similarities in the average probabilities estimated for the different sets of images.

[5] To compute sparse PCA, each series was standardized. The penalty parameter was selected through cross validation and partitions of the sample into 5 subsets of consecutive observations. R package PMA was used for the estimation.
[6] In other words, the score associated with each emotion is transformed applying the exponential function. Next, this transformed score is divided by the sum of all similarly transformed scores corresponding to that picture.

Table 2: Descriptive statistics of images by topic. The probability of emotions for each classified face is computed applying the softmax function, or normalized exponential function, to the scores computed by the trained classification algorithm.

	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

Table 3 reports the contemporaneous association between communicated emotions and the business cycle. During recessions, the probability associated with happiness is lower, and the probability linked to neutral, sadness and surprise increases.7 This is the 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 are more noticeable in the case of images linked to the stock market.

Figure 1 displays additional information on the distribution of scores for selected facial expressions. In the case of happiness, differences in scores across different stages of the business cycle are particularly noticeable for pictures linked to the stock market and corporations. In the case of neutral expressions, the difference is particularly noticeable in the case of pictures linked to policy making.

[7] Notes: According to NBER's Business Cycle Dating Committee, https://www.nber.org/cycles.html, two recessions are covered by the sample period: March 2001-November 2001 and December2007-June 2009.

Moreau de Justo 1400, Edificio Santo Tomás Moro, 4to. Piso
Puerto Madero – Ciudad de Buenos Aires

Table 3: Average emotions (in the form of mean probability) by stage of the business cycle. Difference (Dif.) between expansion (Exp.) and Recession (Rec.).

	Policy Making			Stock Market			Corporations		
	Exp.	Rec.	Dif.	Exp.	Rec.	Dif.	Exp.	Rec.	Dif.
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	42.9	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

As described in Section 2, once the images are classified, an index is computed averaging scores observed in each time period, computing the first principal component for average scores. Table 4 shows, for alternative sets of images and different dimensionality reduction techniques, the factor loadings corresponding to each first principal component. The results for PCA (panel A) suggest that a structural property is being summarized by each first principal component as multiple common features can be observed. First, happiness always displays the largest loading in absolute terms. 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, with a single exception, the sign of the factor loading corresponding to anger coincides with that observed for neutral expressions and sadness. Surprisingly, the sign of the factor loading corresponding to fear is consistently equal to the sign of the factor loading corresponding to happiness. This is the only finding that is at odds with the expected associations.

The factor loadings for sparse PCA (panel B) suggest that there are gains associated to simple aggregation strategies. In all cases, the cross validation exercises selected a large penalization parameter. As a result, first principal components under sparse PCA, are equal to the value of a single facial expression indicator. For two collections of picture, policy making and all, the selected facial expression is “happiness". In the remaining two subsets the selected facial expression is “neutral".

Figure 1: Facial expressions during expansions and recessions

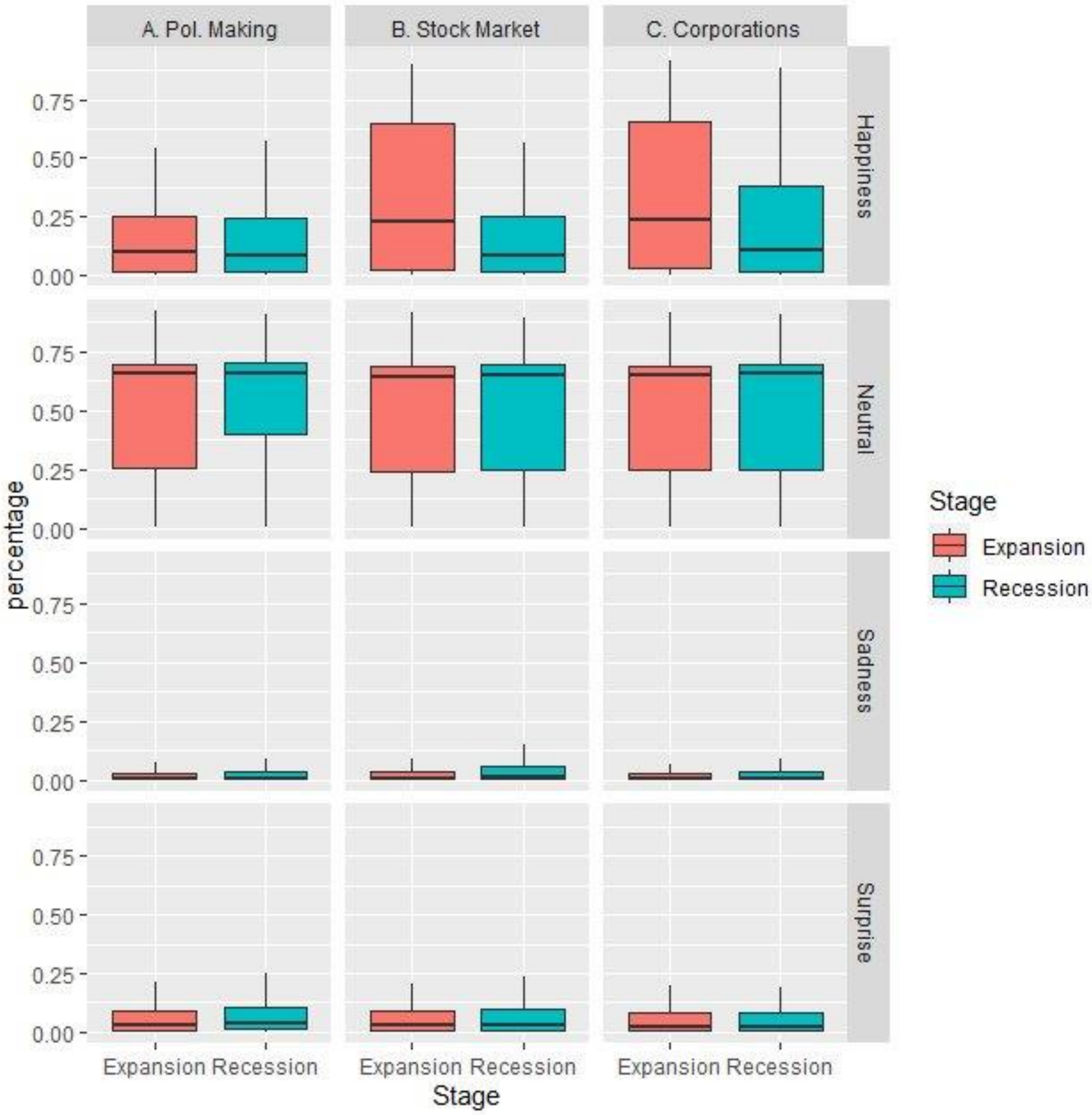
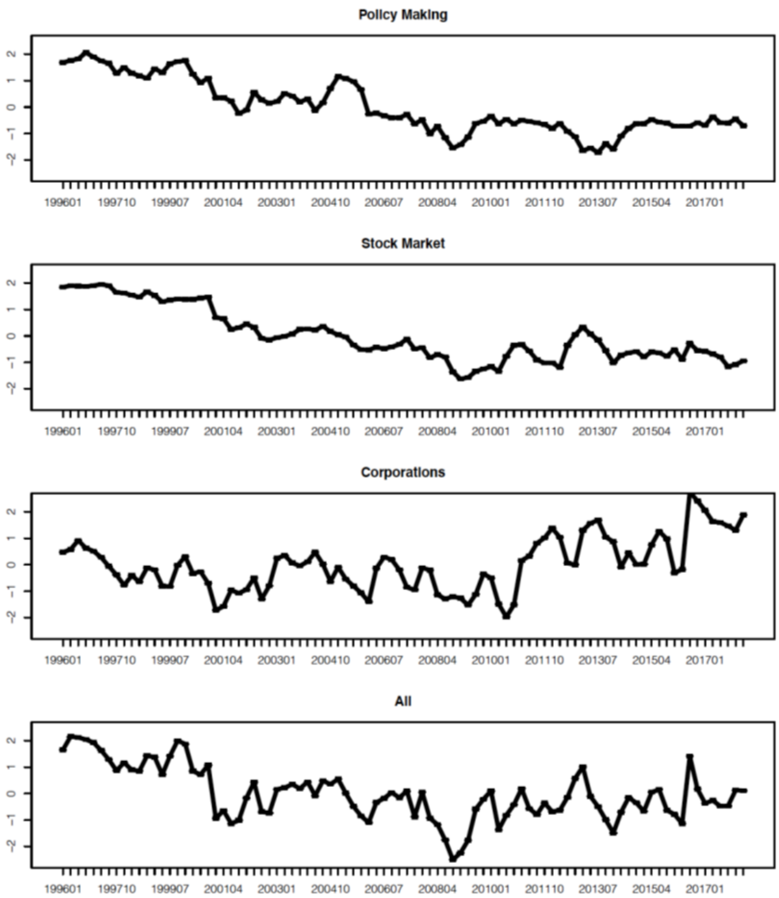


Figure 2 shows the trajectory of the indices computed using PCA. Some common patterns linking the indices to macroeconomic development can be detected. Coinciding with the insights resulting from the analysis of individual emotions during recessions, the two recessions of the sample period are associated with drops in the value of the indices. In the recession of 2001, with only one exception, the indices decrease from 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 buoyant economic conditions observed during that period (Blinder 2000). 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 in the fourth quarter of 2008. In the subsequent years, the indices recover from the lows of the 2008-2009 crisis. This preliminary analysis suggests facial expressions may provide valuable information regarding subjective states and business cycle dynamics. A more formal analysis of the informational content of the indices is presented below.

Table 4: Factor loadings for each index on the the emotions.

	Policy	Stock	Corps.	All
A. PCA				
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
B. Sparse PCA				
Anger	0	0	0	0
Contempt	0	0	0	0
Disgust	0	0	0	0
Fear	0	0	0	0
Happiness	1	0	0	1
Neutral	0	1	1	0
Sadness	0	0	0	0
Surprise	0	0	0	0

Figure 2: Indices of communicated emotions



IV. Results

In this Section, the links between the indices of emotion and economic activity are examined in more detail. The information content of the indices is first examined through an autoregressive model for GDP growth that is extended using the indices as explanatory variables. First, the case of contemporaneous associations is considered. Next, the information provided by lagged values of the indices is estimated. This is followed by a number of robustness exercises and alternative specifications of the empirical model. Finally, the full dynamic interactions between the indices and growth are considered.

IV.I 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 estimation results for a range of models based on Equation 1. The first column corresponds to the baseline model with no emotion indices. The information content of the indices is highlighted by the respective estimated coefficients from the remaining models along with the variation in the adjusted R^2. All estimated coefficients associated with the indices are positive, and with only one exception they are statistically significant. This results holds across indices based on both PCA and sparse PCA. 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 increase in the index is associated with an increase of 0.56 standard deviations in GDP growth. Smaller but similar associations are found in the case of indices linked to policy making and 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 is 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^2s show very significant gains linked to the incorporation of indices of facial expressions.

These results point to a strong association between the business cycle and communicated emotions. It is worth noting that the evaluated indices are the combined outcome of facial expressions expressed by economic actors (policy makers, traders), and the views of the members of the photographers and editors of the news agency in terms of the images they view as 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 specifications of the index. The weak association in the case of the index linked to corporations, may reflect the 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.[8]

IV.II Associations with future activity

In addition to contemporaneous associations, it is of interest to evaluate whether the indices of emotions capture information regarding future levels of economic activity. This is achieved using a slightly modified version of the model in Equation 1:

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

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 forecast horizons are considered: $h \in \{1, 2, 4, 8\}$.

Table 6 shows the estimation results based on Equation 2. In the case of the broad index and indices linked to policy making and the stock market, positive and statistically significant coefficients are observed with the exception of the case for h = 8. As with the previous results, 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, in all cases, the inclusion of an index results in a substantial increase in adjusted R^2. For example, in the case of four-quarter-ahead horizon, the adjusted R^2 of the baseline model is 0.159. The corresponding metric when the broad index is incorporated increases to 0.234.

These results show that there is valuable information regarding business cycle dynamics. Beyond this 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

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

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 increase (Pastor and 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.

IV.III Out-of-sample forecasting

We implement an out of sample forecasting exercise to provide further insights into the information content of the facial expression indices. The sample is divided into two subsets. The in-sample period is 1996-2006 and the out-of-sample period corresponds to 2007-2018. Following the full-sample analysis described above, autoregressive models are estimated to generate baseline forecasts. These forecasts are then compared to forecasts generated by models that extend the autoregressive model incorporating an indicator of facial expressions. Three exercises are considered: nowcasts, quarter ahead forecasts and one year ahead forecasts.[9]

It must be noted that the sample is relatively short for this type of demanding forecasting exercise. As a result, the results described below can be considered to be informative but should not be interpreted as a definitive test of the information content of the indices. Table 7 shows that forecasts that use facial expression indices are associated with lower MSEs than those corresponding to the baseline autoregressive models. In addition, consistent with the results shown above, sparse PCA is associated to more accurate forecasts than traditional PCA. On the other hand, with the exemption of nowcasts, these differences fail are consistently significant even though the reductions in MSE (in the form of the ratios) are large in magnitude. While MSE is easily interpreted, and understood as a loss function, Patton and Sheppard (2009) provide simulation based evidence showing MSE provides only low power in statistical test comparing forecast performance. This observation, coupled with the small sample sizes here, account for the difficulty in identifying statistically significant differences in forecast accuracy for the models containing the the emotion indices.

IV.IV Robustness analysis and alternative specifications

In this subsection, a number of alternative specifications of the empirical model are estimated to evaluate the robustness of the previously reported results. At the same time, these exercises lead to additional insights regarding the link between the business cycle and communicated emotions.

[9] In the case of nowcasts, the index of facial expression for quarter t is added as a regressor to an autoregressive model in which the level of activity on quarter t is a function of its one quarter lagged value.

All the exercises below are based on the broad version of the index, with two forecasting windows considered: $h \in \{1, 4\}$

In the earlier analysis, the proposed models consider only the first lag of GDP growth. It can be conjectured that the results could change if an alternative dynamic specification is considered. 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 8 show that the results are robust to this type of changes in the model. The estimated coefficients of index of communicated emotions are similar and remain significant.

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. The split point is selected in a way that the sample is divided in two subsets of similar size. Also, it is important to note that the 2008-2009 Global Financial Crisis is contained in the second sub-period. Under this specification, the model includes 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 8 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 results. In particular, these results suggest that the reported regularities are not driven by the large disturbance associated with the 2008-2009 Global Financial Crisis.

Finally, to consider possible non-linearities, a model that allows for different slopes when the index is above or below its average level is considered. With this objective in mind, a new variable is added to the original model that is equal to the product of the broad index and a dummy variable equal to one if the index of facial expressions is below its mean value. The estimation results (columns 3 and 6 in Table 8) show that the coefficient associated with the non-linear term is not statistically significant. Overall, the estimation results from the alternative models suggest that the previously documented patterns are robust to changes in the specifications, which changes in economic and market conditions.

IV.V Dynamic links between emotions and growth

To examine the full dynamic effect between emotions and GDP, the following Vector AutoRegressive (VAR) structure is used:

$$\boldsymbol{Y}_t = \beta_0 + \beta_1 \boldsymbol{Y}_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim iid(\mathbf{0}, \boldsymbol{\Sigma}), \tag{3}$$

where:

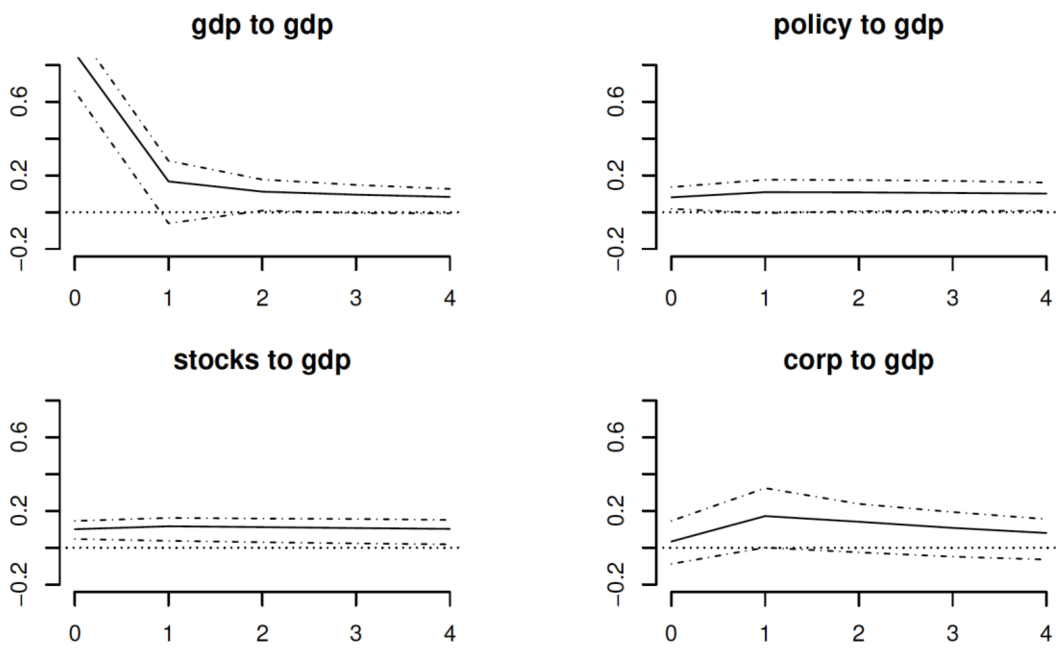
$$\boldsymbol{Y}_t = \begin{pmatrix} gdp_t \\ policy_t \\ stock_t \\ corps_t \end{pmatrix} \tag{4}$$

A VAR(1) structure is chosen on the basis of AIC and BIC.

Based on the VAR(1) model, Table 9 presents a number of Granger causality results to obtain a deeper understanding of the interactions between emotions and activity. The first set of results relate to whether economic growth Granger causes all three emotion indices, and vice-versa. Causality from growth to emotions, is only significant at 10%, while a very significant causal effect is identified from *policy* to *gdp* and the other indices. In the final two panels, causality results are reported for *gdp* and *policy*, and *gdp* and all (the combined index). These are based on smaller two-dimensional versions of $\boldsymbol{Y}_t$ These two sets of results show that there is a consistent pattern in terms of causality from the emotion indices to *gdp*. Overall, these results show that economic activity does not have strong and consistent effects on future emotions, but emotions do have a consistent causal effect on future economic activity. These effects are now examined in more detail below in the context of impulse response functions.

Figure 3 shows generalized impulse response functions (GIRFs) are based on the VAR defined by $\boldsymbol{Y}_t$ in equation 4. Given the causality results, the effect on shocks on future *gdp* is the focus here. A shock to *gdp* has a positive impact on the future values of *gdp* though the effect is not quite significantly positive until two quarters into the future. Shocks to both *policy* and *stocks* have a smaller but long lasting significant positive impact on the evolution of *gdp*. In contrast, shocks to *corp* do not have a significant impact on future *gdp*, a result consistent with the earlier regression results. Overall, these results indicate that emotions communicated by policy makers and stock market participants have an important dynamic impact on economic growth.

Figure 3: Generalised IRFs for shocks to all four elements in $\boldsymbol{Y}_t$ on gdp_t



V. Conclusions

This study examined the information content of the facial expressions of various economic actors. With this objective, indicators of facial expressions were constructed. Statistically significant associations, both with contemporaneous and future business cycle conditions were found. These results, show that the emotions conveyed by individuals in the public spotlight convey important information regarding business conditions. An implication of these results, is that beyond their spoken words, such individuals should be careful regarding the emotions they convey as they contain information.

These findings can be understood as a lower bound on the informational 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 more precise measures of channels that explain the regularities reported in the current study.

VI. References

Baker, S. R., Bloom, N., Davis, S. J., 2016. Measuring economic policy uncertainty. The quarterly journal of economics, 131(4), 1593-1636.

Beaudry, P., Portier, F., 2014. News-driven business cycles: Insights and challenges. Journal of Economic Literature, 52(4), 993-1074.

Bénabou, R., Tirole, J., 2016. Mindful economics: The production, consumption, and value of beliefs. Journal of Economic Perspectives, 30(3), 141-64.

Blinder, A., 2000. The Internet and the New Economy. Brookings Policy Brief, No. 60.

Bollen, J., Mao, H., Zeng, X, 2011. Twitter mood predicts the stock market. Journal of Computational Science, 2(1), 1-8.

Damasio, A., 1994. Descartes' error: Emotion, reason and the human brain, New York: Putnam.

Elster, J., 1998. Emotions and economic theory. Journal of Economic Literature, 36(1), 47-74.

Evans, G. W., Honkapohja, S., 2012. Learning and expectations in macroeconomics. Princeton University Press.

Farmer, R. E., 2011. Confidence, crashes and animal spirits. The Economic Journal, 122(559), 155-172.

Faust, J., Gilchrist, S., Wright, J. H., & Zakrajssek, E. (2013). Credit spreads as predictors of real-time economic activity: a Bayesian model-averaging approach. Review of Economics and Statistics, 95(5), 1501-1519.

Fenton-O'Creevy, M., Lins, J. T., Vohra, S., Richards, D. W., Davies, G., Schaaff, K., 2012. Emotion regulation and trader expertise: Heart rate variability on the trading floor. Journal of Neuroscience, Psychology, and Economics, 5(4), 227.

Heymann, D., Sanguinetti, P., 1998. Business cycles from misperceived trends. ECONOMIC NOTES-SIENA, 205-232.

Ko, B., 2018. A brief review of facial emotion recognition based on visual information. Sensors, 18(2), 401. LeDoux, J. E., 1989. Cognitive-emotional interactions in the brain. Cognition and Emotion, 3(4), 267-289.

Lerner, J. S., Li, Y., Valdesolo, P., Kassam, K. S., 2015. Emotion and decision making. Annual review of psychology, 66, 799-823.

Little, A.C. and Burriss, R.P. and Jones, B.C. and Roberts, S.C., 2007. Facial appearance affects voting decisions. Evolution and Human Behavior, 28(1), 18-27.

Loewenstein, G., 2000. Emotions in economic theory and economic behavior. American Economic Review, 90(2), 426-432.

Lucey, P., Cohn, J. F., Kanade, T., Saragih, J., Ambadar, Z., Matthews, I. (2010, June). The extended Cohn-Kanade dataset (ck+): A complete dataset for action unit and emotion-specified expression. In 2010 IEEE Computer Society Conference on Computer Vision and Pattern

Recognition-Workshops (pp. 94-101). IEEE.

Mackowiak, B., Wiederholt, M., 2009. Optimal sticky prices under rational inattention. American Economic Review, 99(3), 769-803.

Milani, F., 2011. Expectation shocks and learning as drivers of the business cycle. The Economic Journal, 121(552), 379-401.

Newey W. K., West K. D. 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica, 55, 703-708.

Newey, W. K., West, K. D. 1994. Automatic lag selection in covariance matrix estimation. The Review of Economic Studies, 61(4), 631-653.

Pástor, L., Veronesi, P., 2005. Rational IPO waves. The Journal of Finance, 60(4), 1713-1757.

Patton, A. J., Sheppard, K. 2009. Evaluating volatility and correlation forecasts. In Handbook of Financial Time Series, eds. Andersen, T. G. and Davis, R. A. and Kreiss, J. P. and Mikosch, T. Springer-VErlag, Berlin.

Pigou, A. C., 1920. The Economics of Welfare. London, Macmillan and Co.

Re, D.E. and Hunter, D.W. and Coetzee, V. and Tiddeman, B.P. and Xiao, D. and DeBruine, L.M. and Jones, B.C. and Perrett, D.I., 2013. Looking Like a Leader{Facial Shape Predicts Perceived Height and Leadership Ability. PLoS ONE, 12(8), 1-10.

Rojas, Q.M. and Masip, D. and Todorov, A. and Vitria, J. Automatic Prediction of Facial Trait Judgments: Appearance vs. Structural Models., PLos ONE, 6, 373-380.

Safra, L. Chevallier, C., Grezes, J., Baumard, N. 2020. Tracking historical changes in trustworthiness using machine learning analyses of facila cues in paintings, Nature Communications, https://doi.org/10.1038/s41467-020-18566-7.

Schwarz, N., 2000. Emotion, cognition, and decision making. Cognition and Emotion, 14(4), 433-440.

Smales, L.A., Apergis, N., 2017. Understanding the impact of monetary policy announcements: The importance of language and surprises, Journal of Banking and Finance, 80, 33-50.

Smith, K., Dickhaut, J., 2005. Economics and emotion: Institutions matter. Games and Economic Behavior, 52(2), 316-335.

Tetlock, P., 2007. Giving Content to Investor Sentiment: The Role of Media in the Stock Market. Journal of Finance, 62, 1139-1168.

Todorov, A. and Oosterhof, N.N., 2011. Modeling social perception of faces. Social Sciences, 104(3), 535-559.

Tomkins, S. S, 1962{1963. Affect, imagery, consciousness (Vols. 1 and 2), New York: Springer.

Zou, H., Hastie, T., & Tibshirani, R. (2006). Sparse principal component analysis. Journal of computational and graphical statistics, 15(2), 265-286.

VII. **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.

Table 5: Estimation results for Equation 1

	[1]	[2]	[3]	[4]	[5]	[6]
A. PCA						
$\hat{\beta}_{-1}$	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
B. Sparse PCA						
$\hat{\beta}_{-1}$	0.39**	0.21	0.23	0.31*	0.05	-
	[2.3]	[1.1]	[1.3]	[2.1]	[0.4]	
$\hat{\beta}_{Pol.Making}$	-	0.38***	-	-	-	-
		[4.3]				
$\hat{\beta}_{StockMarket}$	-	-	0.200***	-	-	-
			[2.8]			
$\hat{\beta}_{Corporations}$	-	-	-	0.212***	-	-
				[2.7]		
$\hat{\beta}_{All}$	-	-	-	-	0.63***	0.66***
					[4.8]	[4.1]
Adj. R^2	0.143	0.242	0.176	0.172	0.383	0.389

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.

Table 6: Estimation results for Equation 2

		h=1	h=2	h=4	h=8
Baseline adj. R^2		0.154	0.196	0.159	0.092
A. PCA					
Policy Making	$\widehat{\beta}_{Pol.Making}$	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	$\widehat{\beta}_{StockMarket}$	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	$\widehat{\beta}_{Corporations}$	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	$\widehat{\beta}_{All}$	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
B. Sparse PCA					
Policy Making	$\widehat{\beta}_{Pol.Making}$	0.291***	0.313***	0.319*	0.333
	t-stat	[3.3]	[2.66]	[1.8]	[1.4]
	Adj. R^2	0.199	0.253	0.226	0.212
Stock Market	$\widehat{\beta}_{StockMarket}$	0.172**	0.225	0.261	0.346
	t-stat	[2.4]	[1.6]	[1.3]	[1.0]
	Adj. R^2	0.168	0.222	0.202	0.177
Corporations	$\widehat{\beta}_{Corporations}$	0.293***	0.319**	0.372*	0.536***
	t-stat	[3.3]	[2.5]	[1.9]	[5.8]
	Adj. R^2	0.210	0.268	0.266	0.336
All	$\widehat{\beta}_{All}$	0.454***	0.501***	0.480**	0.488**
	t-stat	[4.0]	[3.0]	[1.9]	[2.2]
	Adj. R^2	0.248	0.316	0.271	0.210

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.

Table 7: Out of sample forecast results

	Nowcast	One quarter ahead	One year ahead
Baseline			
MSE (A)	0.0069	0.0069	0.0206
PCA			
MSE (B)	0.0058	0.0065	0.0196
Ratio (B/A)	0.839	0.935	0.951
p-value	0.02	0.18	0.23
Sparse PCA			
MSE (C)	0.0056	0.0060	0.0185
Ratio (C/A)	0.800	0.869	0.894
p-value	0.01	0.06	0.13

Significance levels: “*" 0.10, “**" 0.05 and “***" 0.01. p-values are computed using bootstrap following Faust et al. (2013).

Table 8: Estimation results for the alternative specifications

Window	h=1 [1]	h=1 [2]	h=1 [3]	h=4 [4]	h=4 [5]	h=4 [6]
$\hat{\boldsymbol{\beta}}_{\mathbf{0}}$	0.13	0.16	0.125	0.17	0.17***	0.18***
	[0.86]	[1.3]	[1.2]	[1.5]	[2.6]	[4.6]
$\hat{\boldsymbol{\beta}}_{[-4,0]}$	0.07	-	-	-0.00	-	-
	[0.44]			[0.0]		
$\hat{\boldsymbol{\beta}}_{All}$	0.35***	0.34***	0.26**	0.39**	0.41**	0.45***
	[3.1]	[3.8]	[2.4]	[2.4]	[2.5]	[3.0]
$\hat{\boldsymbol{\beta}}_{All}^{post2007}$	-	0.10	-	-	0.06	-
		[0.3]			[0.2]	
$\hat{\boldsymbol{\beta}}_{neg}$	-	-	0.31	-	-	-0.16
			[0.9]			[0.7]
Adj. R^2	0.216	0.216	0.222	0.230	0.230	0.232

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.

Table 9: Granger causality results. p-values are reported.

H0: gdp does not Granger-cause policy, stock, corps	0.0721
H0: Policy does not Granger-cause gdp, stock, corps	0.0053
H0: gdp does not Granger-cause Policy	0.2703
H0: Policy does not Granger-cause gdp	0.0029
H0: gdp does not Granger-cause Policy	0.0956
H0: Policy does not Granger-cause gdp	0.0018