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The Consumer confidence index and short-term private consumption forecasting in Peru

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The Consumer confidence index and short-term private consumption forecasting in Peru[1]

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Abstract

The Consumer Confidence Index of APOYO Consultoría (INDICCA) is computed based on the responses to ten questions of a monthly survey in the city of Lima which aim to reflect the consumers' spending intentions. We evaluate some sub-components of INDICCA in terms of their predictive and explanatory power of private consumption. In this process, we also evaluate the disaggregation on socioeconomic levels of this index, and a synthetic indicator of confidence based on dynamic factor models suggested by Jonsson and Lindén (2009) as an alternative way to combine the information contained in the sub-components of this index. We find that the explanatory and predictive power of private consumption models in Peru is enhanced when consumer confidence indices are included. However, this improvement is only marginal when other control variables such as employment or inflation are added. In particular, the optimal consumer confidence indicator is the synthetic indicator constructed with the dynamic factor model procedure. The results presented in this paper, although valid for some sub-components, are still inconclusive for the overall INDICCA.

JEL Classification : E21, E27, C22.
Keywords : consumer confidence, consumer tendency surveys, private consumption, forecasting.

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1. Introduction.

Ipsos APOYO Opinión y Mercado, a Peruvian market research company, conducts a monthly survey in order to assess the attitudes and expectations of consumers in Metropolitan Lima. To synthesize the information gathered in those surveys, the business consulting firm Apoyo Consultoría calculates the Consumer Confidence Index of Apoyo Consultoría (INDICCA: *Índice de Confianza del Consumidor de Apoyo Consultoría*), which aims to measure the willingness of consumers to spend. This index is defined as the weighted average of responses of surveyed people on their current and expected appraisal on five areas: (i) consumer prices, (ii) job availability, (iii) the household's economic situation, (iv) the intention to make home improvements and (v) the country's economic situation (ten questions in total).

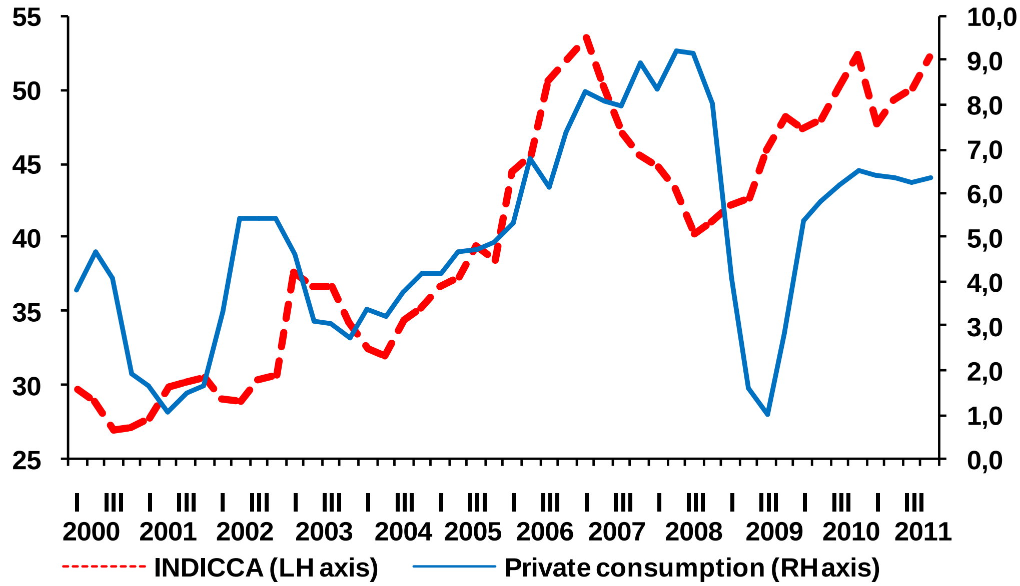
INDICCA is published in a report a few days after the end of every month. This short publication delay makes it a potentially powerful variable to anticipate aggregate private consumption in Peru, which is published with a two-month delay for the latest quarter. For these reasons, this index is closely followed by government agencies such as the Minister of Finance and the Peruvian Central Bank, as well as private sector firms. This index offers an alternative to the business expectation survey and the macroeconomic expectations survey, both of which are conducted by the Peruvian Central Bank. Carrera (2012) and Mendoza and Morales (2012) work on those surveys and complement this paper.

Despite its broad reach, the relationship between INDICCA and private consumption in Peru has not been yet assessed in applied work. Furthermore, although it is calculated in a similar way than other well-known consumer confidence indexes around the world (for example, the University of Michigan's consumer sentiment index); INDICCA has a relatively short existence, since it was first applied in March 2003. This short span makes it unsuitable for econometric evaluation, especially if we are interested in assessing its explanatory and predictive power with respect to private consumption. Nonetheless, out of the 10 questions comprising the construction of the INDICCA, the questions regarding the household´s economic situation (questions number i and ii) have been asked since 1Q1994. This feature makes it more than suitable for econometric work that seeks to evaluate its explanatory and forecasting power of private consumption.

Although its long span is good news for the econometric reasons described above, a simple visual inspection shows that question (ii)[1] and private consumption growth in Peru are not highly correlated as seen in Figure 1. Similar conclusions have been obtained by Ludvingson (2004), Croushore (2006) and Madsen and McAleer (2000) when analyzing the relationship between consumer confidence indices and private consumption in the United States, if control variables such as income and wealth are taken into consideration. However, the search of a consumer confidence index which is more related to private consumption cannot be limited to the aggregate index as suggested by Jonsson and Lindén (2009). A sub-component or a special combination of them might yield better results.

[1] We only use this question since it is referred to the future economic situation (what households expect for the next twelve months) so we believe it is the best to forecast future consumption.

Figure 1: INDICCA (Question ii) and private consumption growth



Therefore, this study aims to find the best coincident or leading consumer confidence indicator to explain and forecast private consumption in Peru, exploiting the information contained in question (ii) and its sub-components. Furthermore, we will construct a synthetic indicator of confidence based on dynamic factor models as an alternative way to combine the information contained in the sub-components of question (ii), as suggested by Jonsson and Lindén (2009). In addition, an important contribution of this paper is that we not only evaluate the explanatory and predictive power of consumer confidence indexes in levels, but also their volatility among consumers. This transformation (the use of the volatility of the index among consumers) aims to explore the impact of consumer confidence volatility on private consumption growth as a way to capture the precautionary savings motive developed by Leland (1968). After all, if consumer confidence indexes are more volatile –that is, if there is more uncertainty-, consumers should tend to consume less (save more). Finally, once we obtain the different consumer confidence indexes based on combinations of the sub-components of INDICCA, we then assess their short-term predictive usefulness for private consumption in a real-time exercise. Hence, we are able to determine the usefulness of consumer confidence indices for everyday macroeconomic analysis as conducted by policy-makers and private firms.

We find that the inclusion of consumer confidence indices improves the explanatory and predictive power of models of private consumption in Peru, but only marginally when other control variables such as employment or inflation are added. In particular, the optimal consumer confidence indicator is the synthetic indicator constructed with the dynamic factor model procedure. Additionally, the volatility of consumer confidence turns out to be non-significant. Finally, as time passes, we will be able to evaluate the overall INDICCA in order to exploit the explanatory and predictive power of its different subcomponents and its combinations for private consumption in Peru. So the results presented in this paper, although valid for question (ii) in the INDICCA survey, are still inconclusive for the overall index.

The structure of this paper is as follows. Section 2 deals with the theoretical and empirical literature related to the relationship between consumer confidence and private consumption. Section 3 describes in detail the consumer confidence index of APOYO Consultoría (INDICCA). Section 4 presents the econometric methodology and the main results. Finally, section 5 provides the main conclusions.

2. What does the theoretical and empirical literature say about the relationship between consumer confidence and private consumption?

2.1 Economic theory and the consumer confidence index.[2]

The role of consumer confidence in private consumption theory is not obvious. Despite their age, the most well-known theories which aim at explaining private consumption behavior are the life cycle[3] (LC) and the permanent income[4] hypotheses (PIH). These theories predict that consumption depends on permanent income, which can be understood as the present value of all income that an individual expects to earn in his lifetime. In addition, these theories imply that private consumption is not related to current income, and if individuals are rational, their consumption behavior will follow a random walk (Hall, 1978). Therefore, there is no role for consumer confidence as a determinant of private consumption according to these authors.

However, numerous studies have found that private consumption is related to current income, which rejects the LC-PIH in its purest form. In order to overcome this flaw, many authors proposed theoretical refinements in order to adapt the LC-PIH to the empirical evidence. One such adaptation was proposed by Campbell and Mankiw (1989), who developed a model in which some consumers behave exactly like LC-PIH establishes and others let their spending equal their current income. Although this theoretical adaptation improves the LC-PIH in terms of empirical results, it does not leave room for consumer's confidence to become a determinant of private consumption movements.

Another line of theoretical research relates to the incorporation of uncertainty in order to explain the evolution of consumption (Leland, 1968). This approach states that the more uncertainty consumers have about their income, the more they will be prone to be "myopic", so they will not follow a behavior consistent with the LC-PIH. Thus, a sharp fall of current income could increase uncertainty and, thus, their need to save by reducing consumption. Although not explicitly assumed, consumer confidence can be useful as a determinant of consumption as long as it reflects the uncertainty of consumers about their future income flow.

However, Katona (1968) criticizes the previous models and affirms that private consumption is determined by the possibility of obtaining goods depending on the wealth and disposable income of individuals, as well as their willingness to spend. The latter, according to Katona, is a product of complex psychological relations and cannot be explained conveniently in a hard measurement like income or wealth. According to this line of reasoning, consumer confidence is not only a reflection of real variables like income or

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[2] Based on Jonsson and Lindén (2009).
[3] Modigliani (1954).
[4] Friedman (1957).

wealth, but also captures a unique psychological element which could be used as an additional explanation of shifts in private consumption.

Katona's theory can also be understood under the neoclassical economic theory of consumption. The latter can be summarized in a standard Euler equation as the one described below:

$$u'(c_t) = \beta E_t u'(c_{t+1})(1 + r_{t+1}) \quad (1)$$

where: $u'(c_t)$ is the marginal utility of consumption in period t, $E_t u'(c_{t+1})$ is expected value with information at period t of the marginal utility of consumption in period $t+1$, β is the discount factor which reflects impatience of consumers (lower value implies higher impatience).

What equation (1) shows is that consumption depends on consumers' expectations with all the relevant information at period t. These expectations may be synthesized in consumer surveys about future consumption plans. The objective of consumer confidence indexes as the one constructed by Katona and INDICCA is to capture some aspects of these future consumption plans (willingness to spend). Since consumption depends on what consumers expect, asking them about their expectations should be useful in explaining and forecasting private consumption.

2.2 What does the empirical literature say about the relationship between consumer confidence and private consumption?

Starting with Katona (1968)'s seminal work, many studies were conducted in order to evaluate the explanatory and predictive power of consumer confidence indices for private consumption, especially in advanced economies. Despite the large empirical body of applied literature, there is not a uniform conclusion on the role of consumer confidence in private consumption forecasting.

On one side, some studies have found a significant but small relationship between consumer confidence (or a subcomponent of it) and private consumption. In this line, we can mention Bram and Ludvigson (1998) and Eppright et al. (1998) who conclude that consumer confidence has a certain predictive power of household consumption for the US economy. For the UK, Easaw et al. (2005) found that consumer confidence is useful to predict the consumption of durable goods, even when control variables such as income are incorporated. However, its predictive power is null regarding consumption of non-durable goods, where the significance of the consumer confidence variable disappears when control variables are included. Other studies that find a significant relationship between consumer confidence and household consumption are Batchelor and Dua (1998), Garner (2002), Klein and Ladiray (2002), Al-Eyd et al. (2008) and Jonsson and Lindén (2009) who deploy times series analysis and leading indices.

However, there is also an important body of empirical literature that finds no significant relationship between consumer confidence and household consumption. For instance, Carroll et al. (1994) found that consumer confidence has a marginal explanatory power with respect to American private consumption when control variables such as wealth and incomes are incorporated. Ludvingson (2004) confirms that the incremental predictive power of the index of consumer sentiment and the index of consumer confidence with respect to private consumption in the US is small when control variables are added. For the case of Great Britain, the conclusions about the relationship between consumer confidence and private consumption are similar to those found in the applied literature for the US. Madsen and McAleer (2000) found that consumer confidence was not very useful to predict the evolution of private consumption. Finally, Croushore (2006), using a real-time database, finds that consumer confidence does not improve the short-term forecasts of private consumption when they are controlled by the lag of private consumption and share prices.

The possible explanation of this apparent contradiction is that studies that do not find a relationship between consumer confidence and household spending are usually based in the aggregate confidence index. As we will see for the Peruvian case, aggregation can reduce the predictive power of consumer confidence since some sub-component (or a combination of them) can perform potentially better, as suggested by Jonsson and Lindén (2009). Another possible explanation is that studies that do not find a relationship between consumer confidence and household are based on long-term analyses in which, by definition, consumer confidence should not have an impact on household consumption since it converges to its mean. As a result, both of these aspects will be taken into account in our empirical analysis. Finally, it is worth mentioning that we have not found any empirical studies analyzing the relationship of consumer confidence and private consumption in Peru.

3. The Consumer Confidence Index of Apoyo Consultoría (INDICCA).

Since 2003, the market research firm Ipsos APOYO conducts a survey of approximately 800 people in Metropolitan Lima in order to gauge their confidence about present and future economic conditions. In order to synthesize the information collected in those surveys, the business consulting firm APOYO Consultoría calculates INDICCA, an indicator that is published in a monthly report a few days after the end of each month. Since it seeks to represent a thermometer of consumer's confidence about present and future economic conditions, INDICCA is followed by public institutions such as The Ministry of Finance, the Central Reserve Bank of Peru, and private firms in general.

INDICCA is formed by the weighted sum of responses to the survey questions regarding the current and future perceptions of consumers about 5 topics in particular: (i) The household economic situation (EFA), (ii) The economic situation of the country (EPA), (iii) The conditions to make home improvements (HOG), (iv) The level of prices in the economy (PREC) and (v) the conditions to find a job (TRAB). The precise wording of the questions that are asked about these topics, their possible answers and their assigned scores are:

1. How is your current economic situation with respect to the last 12 months?
2. How do you think your household's situation will be in 12 months?
3. How do you think the economic situation of the country will be with respect to the last 12 months?
4. How do you think the economic situation of the country will be in 12 months?
5. How do you qualify the current moment to make home improvements or buy appliances with respect to 12 months ago?
6. How do you think your situation to make home improvements or buy appliances will be in 12 months?
7. How do you think the possibility of finding job is with respect to the last 12 months?

8. How do you think the possibility of finding job will be in twelve months?
9. With respect to the last 12 months, do you think that prices today are…?
10. With respect to current prices, do you think that prices will be… in 12 months?

Table 1: Consumer Confidence Index's Questions

		Much worse	Slightly worse	Similar	Slightly better	Much better	No comments
Q.1	Present household´s economic situation	1	2	3	4	5	99
Q.2	Future household´s economic situation	1	2	3	4	5	99
Q.3	Present country´s economic situation	1	2	3	4	5	99
Q.4	Future country´s economic situation	1	2	3	4	5	99
Q.5	Present conditions to improve housing and purchase housing appliances	1	2	3	4	5	99
Q.6	Present conditions to improve housing and purchase housing appliances	1	2	3	4	5	99
Q.7	Present labor conditions	1	2	3	4	5	99
Q.8	Future labor conditions	1	2	3	4	5	99

		Very high	High	Similar	Low	Very low	No comments
Q.9	Present prices	1	2	3	4	5	99
Q.10	Future prices	1	2	3	4	5	99

Based on the responses given by each interviewee to the 10 questions of the poll, we can obtain the total score for each individual according to the following formula that includes the score obtained in each topic:

$$\text{Present INDICCA}_i = (1{,}5\,\text{EFA} + 1{,}5\,\text{EPA} + \text{HOG} + \text{TRAB} + \text{PREC}) \quad (2)$$

$$\text{Future INDICCA}_i = (1{,}5\,\text{EFA}' + 1{,}5\,\text{EPA}' + \text{HOG}' + \text{TRAB}' + \text{PREC}') \quad (3)$$

$$\text{INDICCA}_i = \frac{\text{Present INDICCA}_i + \text{Future INDICCA}_i}{2}, \quad (4)$$

where i represents each individual and: EFA = present household economic situation, EPA = present economic situation of the country, HOG = present conditions to make home improvements, PREC = present level of prices in the economy, TRAB = present conditions to find a job, EFA' = future household economic situation, EPA' = future economic situation of the country, HOG' = future conditions to make home improvements., PREC' = future level of prices in the economy, TRAB' = future conditions to find a job.

Thus we obtain an individual score that takes values between 6 and 30 points. Then, the scores obtained are interpolated for each individual in a scale between 0 and 100. For example, if the interviewee obtains 15 points, his final score is 37,5 points. Finally, using the score previously obtained for each interviewee, a weighted average for the total of interviewees is calculated generating the indicator of confidence for the evaluated sample.

$$\text{INDICCA} = \frac{\sum_{i=1}^{800} \text{INDICCA}_i * \text{weight}_i}{\sum_{i=1}^{800} \text{weight}_i}, \quad (5)$$

where *weight* represents the relative importance of each i consumer in the survey. The survey is not conducted as a panel (different consumers are surveyed each month) but the weights are relatively stable throughout time. The weights are constructed by Ipsos APOYO based on the socioeconomic structure of the population in Metropolitan Lima.

INDICCA takes values between 0 and 100 where a level of 100 reflects complete consumer optimism or the largest disposition of consumers to spend; a level of 50 means that consumers are neither optimistic nor pessimistic; and a level of 0 means absolute pessimism or the minimum disposition of consumers to spend. It is worth noting that the methodology described is similar to the one used for the construction of indicators of consumer confidence in the US and Europe, so INDICCA results are internationally comparable.

With this level of disaggregation of information, it is possible to build a current INDICCA based on subcomponents related to the current outlook about the 5 topics already mentioned. On the same token, it is possible to construct a future INDICCA with the respective 5 subcomponents. Also, since descriptive information is collected from the interviewee, it is possible to build various combinations of indices either by socio-economic level, sex, and even age. However, we must take into account problems of representativeness in the population inference of the survey. Therefore, we will analyze the information only by socio-economic levels.

As mentioned in the introduction, the information about INDICCA is available since March 2003 which represents a relatively short estimation span. However, Ipsos APOYO has asked questions about household´s economic situation since 1Q1994 (questions (i) and (ii)). Therefore, we take advantage of this longer time span and use the information contained in question (ii) about future households' economic situation. We only use this question since it is referred to the future economic situation (what households expect for the next twelve months) so we believe it is the best to forecast future consumption. In particular, we construct an indicator of net future household´s confidence as the difference between the percentage of people that expect that his future household´s economic situation will improve in the next twelve months from now, and the percentage that expects it to worsen. We call this indicator INDICCA for simplicity in the remainder of this document. Furthermore, we construct indicators of net future household´s confidence for the five different socioeconomic levels (SEL) surveyed.

4. Methodology.

To find the best coincident or leading consumer confidence indicator to explain and real-time forecast private consumption in Peru, we develop a three-stage methodology. In the first stage, we construct the database of confidence indicators, based on the information in question (ii) and its subcomponents. Furthermore, we create a synthetic indicator based on dynamic factor models. In the second stage we perform some preliminary analysis of the relation among consumer confidence indicators and private consumption. For this we perform Granger causality analysis and dynamic cross-correlations. Finally, in the third stage, we estimate and evaluate different models for private consumption, including models with confidence indicators. Then we assess whether the addition of consumer confidence improves the real-time forecast power of simple models, especially in a period of stress or crisis like the international crisis of 2008-2009.

4.1 Construction of the database.

The objective of this stage is to construct a database based on the information of question (ii) about the household appraisal of its own economic situation. As mentioned in section 3, we construct an indicator of net future household confidence as the difference between the percentage of people who expect that their future household´s economic situation will improve in the next twelve months from now and the percentage of those who expect it to worsen. We call this indicator INDICCA from now on. Furthermore, we construct indicators of net future household´s confidence for the five different socio-economic levels (SEL) surveyed.

INDICCA (question ii) is constructed as a weighted average of the net future household confidence of each SEL. The weights reflect the importance of each SEL in the socio-economic structure of Metropolitan Lima (SEL D and E are the most important). However, this aggregation method may not be the best to forecast private consumption. Therefore, we propose an alternative aggregation method based on dynamic factor models as suggested by Jonsson and Lindén (2009) in order to create a synthetic indicator of consumer confidence (DFM from now on). We use the dynamic factor model developed by Sargent and Sims (1977) and Engle and Watson (1981). This kind of model allows us to reduce the dimensionality of a series of variables since it can characterize the co-movements among macroeconomic variables. The model is based in the fact that a series can be decomposed in two orthogonal components: a commonly shared component and an idiosyncratic component as follows:

$$Y_t = \beta F_t + U_t \tag{6}$$

$$F_t = AF_{t-1} + V_t \tag{7}$$

In equation (6), Y_t is a vector of endogenous and observable variables; F_t is the non-observable common factor (the synthetic indicator we aim to obtain); and U_t represents the specific or idiosyncratic shock of each variable. In equation (7) we present the structure of the factor, where A is a matrix and V_t is a residual vector.

The first step to estimate the model is to choose the number of factors to estimate. For this, we use the number of factors chosen by a simple principal component analysis which evaluates the additional information conveyed by each additional factor. Under this analysis, we chose only one factor to estimate.

Then, the model is estimated in a state-space representation using Cuasi Maximun likelihood (CML) and Kalman filter techniques. These techniques are superior to simple Maximum Likelihood (ML), since they are flexible enough to incorporate a family of distributions and not only one distribution as ML[5] does.

[5] The results of theses procedures can be provided by the authors upon request.

4.2 Preliminary analysis of the relation among consumer confidence and private consumption

We have evaluated the stationarity of all series included in this analysis and in the estimated models. This evaluation was conducted through the use of conventional unit root tests and unit root tests with structural breaks. As a result, we have found that all the transformations of the series included in the estimation are stationary. For further details about the unit root tests applied and the results of the tests refer to the Annex of this paper.

Before proceeding with the description of the methodology, we must take into account the difference in frequency between private consumption and the consumer confidence. There are two options: to convert the monthly series of expectations into quarters or to convert the quarterly series of private consumption into months. Following Johnson and Lindén (2009), the former option was preferred using quarterly averages, since this method requires fewer assumptions and allows us to smooth the short-term shocks arising on a monthly basis.

In order to conduct a preliminary assessment of the relation between consumer confidence and private consumption, we perform Granger causality analysis. This analysis was conducted over the whole available sample (2001-2011). The results are presented in Table 1, which contains p-values for F-statistic of redundancy tests. In the column labeled “y not → x” we present the probabilities that the annual change of private consumption is not a cause of consumer tendency survey variables. In the column labeled “x not → y” we show the probability that a consumer tendency survey variable is not a cause – in Granger`s sense - of the annual change of real private consumption.

Table 2: Granger Causality test between consumer confindence indicators (x) and private consumption growth (y), 1Q2001-4Q2011[6]

	x not → y	y not → x	Period of max correlation with private investment growth	Maximum correlation
INDICCA SEL A	0.173	0.988	0	0.341
INDICCA SEL B	0.021	0.343	0	0.429
INDICCA SEL C	0.674	0.458	0	0.391
INDICCA SEL D	0.856	0.035	2	0.500
INDICCA SEL E	0.948	0.458	0	0.175
TOTAL INDICCA	0.216	0.414	-1	0.585
INDICCA DFM	0.017	0.175	-1	0.621

[6] In Table 2, we report the results of the Granger causality test including two lags. Since these results tend to be affected by the number of lags included, we conducted the test including up to 8 lags and found the same results.

We find that only INDICCA SEL B and INDICCA DFM Granger cause annual changes in real private consumption. This result leads us to think that these variables may be potential candidates for forecasting models of real private consumption. Then we perform a simple dynamic cross-correlation exercise to assess the maximum correlation level between the consumer confidence variables and real private consumption growth, as well the lag/lead period where this maximum correlation occurred. We found that the maximum correlation for INDICCA SEL B and INDICCA DFM was registered in periods t and $t-1$, respectively. Moreover, we found that the maximum correlations of the two variables mentioned above are high (greater than 0.4), and in particular, INDICCA DFM has the highest correlation. This may imply that this variable may be the optimal consumer confidence index in terms of explanatory and predictive power of real private consumption growth.

4.3 Model estimation and real-time forecasting assessment.

At this stage, we estimate by ordinary least squares a number of purely autoregressive models, as well as models with control variables for the annual growth rate of private consumption. We select the models with the best goodness-of-fit indicators and with adequate behavior of the residuals. Then, we assess whether the addition of expectations improves the real-time forecast of private consumption growth, especially in a period of stress or crisis. For this, we use statistics and tests to assess superior predictive ability such as U-Theil, and the MSE-F and ENC-New tests.

Model estimation is performed with quarterly data since 1Q2001 to 4Q2011 (41 observations). The relatively reduced data sample is explained by the availability of control variables (employment growth is available since 1Q1998) and by reductions to the data sample made by the authors in order to obtain well-behaved models[7]. This data sample may look insufficient to test that confidence indicators improve real-time forecasting for private consumption models. However, as mentioned in Al-Eyd, Barrell and Davis (2007), by construction, consumer confidence cannot determine consumption growth in the long run, since consumers cannot permanently be excessively optimistic or excessively pessimistic. So, the only possibility for consumer confidence to affect private consumption is in the short-run (Al-Eyd, 2008). Therefore, our sample estimation is adequate to test the hypothesis of interest.

4.3.1 Purely autoregressive models.

One of the main characteristics of macroeconomic series is their high persistence. This makes purely autoregressive models highly suitable to explain and predict macroeconomic series. For this reason, we first evaluate a series of purely autoregressive models for the growth of private consumption. The first model includes the best purely autoregressive specification (AR(1)) and the second group of models (7 in total) incorporates confidence indicators.

We estimated a number of purely autoregressive models of the form AR(p) and the model with the best goodness-of-fit indicators was AR(1).

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[7] First we estimated models from 1Q1998 to 4Q2011 but the residuals did not behave as normal residuals under any specification of the models due to some outliers at the beginning of the sample. Therefore, we had two options: (i) to include dummy variables, or to (ii) shorten the estimation sample. We selected the second option in order to maintain the transparency of the results.

$$C_t = \alpha_1 C_{t-1} + u_t \,, \qquad (8)$$

where C_t is year on year annual growth rate of private consumption**.** This naïve model (model 1 in Table 3) shows a high Adjusted R^2, around 0.76.

We add different specifications of consumer confidence indicators to the naïve model (equation 9). This analysis seeks: (i) to determine whether the addition of confidence indicators improves the predictive ability of purely autoregressive models for private consumption growth, and (ii) to find the best specification of consumer confidence.

$$C_t = \alpha_0 + \alpha_1 C_{t-1} + \alpha_2 confidence_t + u_t \qquad (9)$$

Consumer confidence indicators are incorporated in the estimation in their original levels that range from 0 to 100 (see INDICCA description for further details). This is because we have shown in stage 2 of our methodology that consumer confidence series are stationary in levels. An important topic to bear in mind is that INDICCA is elaborated to assess consumer confidence from the consumer of Metropolitan Lima, while private consumption captures household spending nationwide. However, our estimations still hold since close to 55% of household expenditure in Peru is represented by households in Lima, so including information about consumer confidence in Lima represents a good proxy for the national consumer confidence dynamics.

When we estimate the models with consumer confidence indicators (models 2-8), we find that the incorporation of confidence indicators improves the fit of the model measured through the Adjusted R^2 and AIC and BIC statistics. However, not all the confidence indicators are significant. Indeed, only in models 2, 4, 7 and 8 are the consumer confidence indicators significant. In all these models, the residuals are homoscedastic and not serially correlated, but they are not normal. The lack of normality in the residuals can be explained by the absence of a relevant variable in the regression.

The model with the best explanatory power among the eight models evaluated is model 2, which includes the consumer confidence indicator for socio-economic level A (SEL A). Indeed, this model has an Adjusted R^2 of 0.8. However, as mentioned before, this model still has non-normal residuals.

Table 3: Autoregressive models without control variables

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Consumption (-1)	0.99***	0.85***	0.9***	0.88***	0.87***	0.95***	0.81***	0.78***
Constant					0.08*			1.21***
INDICCA SEL A		0.07***						
INDICCA SEL B			0,06					
INDICCA SEL C				0.07*				
INDICCA SEL D					-0,02			
INDICCA SEL E						0,03		
TOTAL INDICCA							0.03***	
INDICCA DFM								0.13*
Information Criteria								
Akaike	3,09	2,9	3,09	3,07	3,09	3,12	3	3,14
Schwartz	3,14	3	3,17	3,15	3,21	3,2	3,08	3,06
Adjusted R^2	0,76	0,8	0,77	0,77	0,77	0,76	0,78	0,79
Residual diagnostics [9]								
Normality test (H_0 : Normality)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Mean Square Error [0]	4,37	1,79	2,10	2,14	1,93	2,71	1,76	1,7
Heroskedasticity (H_0 : Hereroskedasticity)	0,73	0,24	0,99	0,75	0,13	0,27	0,70	0,17
Autocorrelation coefficient	0,45	0,35	0,47	0,49	0,46	0,46	0,46	0,44

***Null hypotheses rejected at 1%
**Null hypotheses rejected at 5%
*Null hypotheses rejected at 10%

Although the previous steps in our econometric methodology have allowed us to determine the model with the highest explanatory power, this model does not necessarily provide the highest predictive power with respect to private consumption. Therefore, in order to evaluate the predictive ability of the models we searched for a “turning point” period in the sample. The initial sample selected covered the period 2Q2001 to 2Q2008, that is, a quarter before the beginning of the international financial crisis. Thus, the initial sample includes R=29 observations. We will calculate P=14 point forecasts estimated recursively with re-estimation of the models. That is, at each recursion the estimation sample was increased by one quarter forward and we forecasted one point (quarter) as well. For all models we calculated forecast errors and average measures like root mean squared error (RMSE) and mean squared error (MSE).

In order to formally investigate whether the forecasts from an unrestricted regression model are significantly superior to the forecasts from a restricted one, we used the Theil’s ratio (also known as the U-statistic), the McCracken (2004) MSE-F test and the Clark and McCracken (2001) ENC-NEW statistic[8].

Theil’s U statistic is defined as the ratio of the square root of the mean squared forecasting errors (RMSE) of the unrestricted model and the restricted one. If Theil’s U statistic is smaller than one, then the forecasts based on the consumer expectations indexes are superior to those of the restricted models.

The second statistic (MSE-F) is a variant of the Diebold and Mariano (1995) and West (1996) statistic designed to test for equal predictive ability, and the third statistic is a variant of the Harvey, Leybourne and Newbold (1998) statistic designed to test for forecast encompassing. This statistic has two key advantages over the original one. First, it accounts for the parameter uncertainty inherent in estimating the unrestricted and restricted models that are used to form the competing forecasts. Second, Clark and

[8] Following Dudek (2008).

McCracken (2001) find that the MSE-F and ENC-NEW statistics have good size properties and are typically more powerful than the original statistics in extensive Monte Carlo simulations with nested models.

The MSE-F statistic is used to test the null hypothesis that the unrestricted model forecast mean squared error (MSE) is equal to the restricted model forecast MSE against the one sided (upper-tail) alternative hypothesis that the unrestricted model forecast MSE is less than the restricted model forecast MSE. A significant MSE-F statistic indicates that the unrestricted model forecasts are statistically superior to those of the restricted model. In other words it means that consumer confidence indices have additional predictive power for modeling private consumption (they reduce forecasting error). Clark and McCracken (2005) demonstrated that the MSE-F statistics share a non-standard limiting distribution. Critical values for that test are taken from Clark and McCracken tables (2001). The MSE-F test is constructed as follows:

$$MSE - F = P * \frac{MSE_R - MSE_U}{MSE_U}, \tag{10}$$

where MSE_R indicates the Mean Squared Error of the restricted model and MSE_U refers to the Mean Squared Error of the unrestricted model.

The second out-of-sample statistic, ENC-NEW, relates to the concept of forecast encompassing. Forecast encompassing is based on optimally constructed composite forecasts. Intuitively, if the forecasts from the restricted regression model encompass the unrestricted model forecasts, the consumer confidence variables included in the unrestricted model provide no additional useful information for predicting changes in real private investment relative to the restrictive model which excludes the consumer confidence variables. If the restricted model forecasts do not encompass the unrestricted model forecasts, then the consumer confidence indicators do contain information useful for predicting changes in real private consumption beyond the information already contained in a model that excludes those confidence variables. In general, forecast encompassing tests consist in testing whether the weight attached to the unrestricted model forecast is zero in an optimal composite forecast composed of the restricted and unrestricted model forecast. In the Clark and McCracken ENC-NEW test under the null hypothesis, the weight attached to the unrestricted model forecast in the optimal composite forecast is zero, and the restricted model forecasts encompass the unrestricted model forecasts. Under the one sided (upper tail) alternative hypothesis, the weight attached to the unrestricted model forecast in the optimal composite forecast is greater than zero, so that the restricted model forecasts do not encompass the unrestricted model forecasts. Similarly to the case of the MSE-F statistics, the limiting distribution of the ENC-NEW statistic is non-standard and pivotal when comparing forecasts from nested models. Critical values fort that test are taken from Clark and McCracken tables (2001). The ENC-NEW test is constructed as follows:

$$ENC - NEW = \frac{\sum_{t=1}^{P} \left(\hat{e}_{R,t+1}^2 - \hat{e}_{R,t+1} * \hat{e}_{U,t+1} \right)}{MSE_U} \tag{11}$$

where $\hat{e}_{R,t+1}$ is the one-step ahead prediction error of the restricted model and $\hat{e}_{U,t+1}$ is the one-step ahead prediction error of the unrestricted model.

Table 4 shows the estimation of the proposed statistics to test the superior predictive ability of models without control variables. In general terms, according to Table 3, confidence indicators do increase the predictive power of purely autoregressive models such as the naïve model initially proposed. The model with the best predictive power at this stage is the naive model augmented with the INDICCA SEL A, since it has the lowest U-Theil statistic and its MSE-F and the ENC-NEW statistics are significant at the 99.9% confidence level. This model is better in forecasting private consumption growth relative to the naïve model. It is worth mentioning that this model was also selected as the model with the best explanatory power as mentioned above.

Table 4: Assessment of the Predictive Power of the Models estimated without Control Variables

Statistic	Naive	Naive + INDICCA SEL A	Naive + INDICCA SEL B	Naive + INDICCA SEL C	Naive + INDICCA SEL D	Naive + INDICCA SEL E	Naive + INDICCA Total	Naive + INDICCA DFM
MSPE	2.616	2.140	2.720	2.599	2.817	3.014	2.356	2.260
U-Theil		0.818	1.039	0.993	1.077	1.152	0.900	0.864
MSE-F		3.113***	-0.531	0.095	-0.996	-1.847	1.551**	2.205**
ENC-NEW		2.687***	0.481	0.381	-0.113	-0.637	1.353**	3.064***

***Null hypotheses rejected at 1% **Null hypotheses rejected at 5% *Null hypotheses rejected at 10%.

4.3.2 Autoregressive models with control variables.

The main conclusion of the former section is that the best confidence indicator in terms of explanatory and predictive power is INDICCA SEL A. However, this conclusion has been arrived at through the estimation of purely autoregressive models without control variables. There is a possibility that the confidence indicator is capturing part of the variance associated with other explanatory variables such as employment of credit growth. Indeed, the non-normality of the residuals in the purely autoregressive models is a warning signal about the exclusion of relevant variables. To overcome this problem, we estimate models with control variables.

The literature on private consumption acknowledges that this variable depends on the purchasing power of consumers. This purchasing power depends positively on variables such as employment, the availability of consumer credit, and negatively on inflation, interest rates, and other variables. In this paper, we evaluate the addition of this kind of explanatory variables in a model for private consumption growth in the following way:

$$C_t = \alpha_0 + \alpha_1 C_{t-1} + \alpha_2 X_t + u_t \qquad (12)$$

Following Carrol (1994), and considering the availability of the variables for the Peruvian economy, we evaluate the following control variables: formal employment, consumer price index, consumer credit and interest rates. In addition, an important contribution of this paper is that we will not only evaluate the explanatory and predictive power of the levels of consumer confidence indexes, but also their volatility.

Formal employment is represented by the quarterly average of the urban employment index in medium and big companies extracted from the database of the Labour Ministry. This variable is included in annual growth rates. The consumer price index is represented by the quarterly average of the Metropolitan Lima consumer price index extracted from Central Bank´s databases and included in annual growth rates. Credit is represented by the quarterly average of the consumer credit stock, reported by Banking regulatory agency (SBS by its initials in Spanish). This variable is included in annual growth rates. Interest rate is represented by the quarterly average of consumer interest rates reported by SBS.

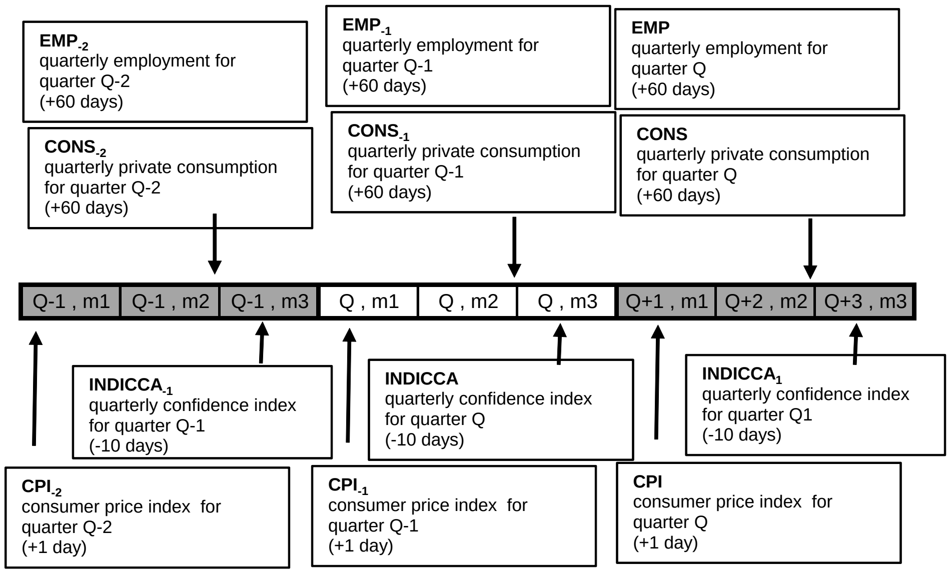
Additionally, we include consumer confidence volatility. The inclusion of this variable is an important contribution of this paper and aims to capture the precautionary savings motive developed by Leland (1968). After all, if consumer confidence indices are more volatile – that is, there is more uncertainty -, consumers should tend to consume less (save more). This variable is constructed as the cross-section variance of the consumer confidence (question ii) among the five SEL. In particular, we construct two different variances. One is the variance of the subcomponent of the consumer confidence (question ii) at a given period of time among the different five SEL´s. The other is the variance of the net confidence indicator based on question ii (percentage of people who expect that their household economic situation will improve in the next twelve months - percentage who expect their household economic situation to worsen) among the five SEL´s. In both cases, what we want to capture is the uncertainty of consumer confidence among different consumers at a given point of time (t). This is different from the traditional time series variance (variance of the consumer confidence along time). The first best was to calculate the cross-section variance of the consumer confidence based on the 800 people surveyed every month. However, we were not able to obtain the original databases and we had to construct this variance only for the average result for each of the five SEL. The short sample used to calculate this variance (five observations per each period) is a limitation that makes us cautious regarding the results of the estimations that include the volatility of consumer confidence.

One important issue stated above is that we intend to perform real-time forecasting. So the methodological approach described above has to take into account the availability of all time series just at the moment of performing the forecast or at the time of testing conditional Granger causality. As we can see in Figure 2, consumer confidence results are published very promptly, since the survey is conducted during the second week of the surveyed month. Hence, the results are published at the beginning of the next month. In a quarterly basis, this means that consumer confidence information is available at the beginning of the next quarter. So, this is a good reason to take advantage of consumer confidence indicators.

The consumer price index for the current month (a potential control variable) is published the first day of the next month. On a quarterly basis, this means that the information about a particular quarter will be available in the first day of the next quarter, similar to the information of INDICCA.

On the contrary, private consumption and employment (other potential control variables) are published with a two-month delay. This means that on a quarterly basis, the information about a particular quarter will be available at the end of the next quarter. This poses an important limitation to the estimation. Indeed, if we want to real-time forecast private consumption, we cannot use contemporary information of employment since it will not available by the time of the forecast.

Figure 2: Publication schedule of real private consumption and potential explanatory variables



Remarks: Q, Q-1, Q+1 - current, previous, next quarter; m1,m2,m3 - first, second and third month of the quarter.

Thus, if we want to perform a real-time forecasting exercise for private consumption in quarter t-1 at the beginning of quarter t, we have to use lagged employment information. However, we can use contemporary information on confidence indicators and the consumer price index. These limitations will be taken into account in the estimations of the models. Although these adjustments may diminish the predictive capacity of our models, they will provide us with available forecasts two months before the official private consumption data release.

We estimated different specifications with the control variables mentioned above. We find that the volatility of consumer confidence turned out to be non-significant[9]. However, we cannot reject the theory of precautionary savings for the case of Peruvian consumers based on these regressions since they have multiple limitations (time span, construction of variance, etc.). Furthermore, consumer credit growth and interest rates also turned out to be non–significant at the lowest level of significance, which may represent a rejection to a role of financial variables in the determination of Peruvian private consumption. As a consequence of the non-significance of these variables, we do not report models with these variables.

On the contrary, employment and the consumer price index (both lagged one period in order to perform real time forecasting) are highly significant: both have coefficients around 0.3 and -0.3, respectively. We present the results of 8 models in Table 5. The first model is

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[9] Results are shown in annex 2.

the best model without confidence indicators and will be considered the naive model in this section. This model includes lag 1 and lag 3 of private consumption, one lag of employment and consumer confidence and a constant. The model has a high goodness of fit (an Adjusted R^2 of 0.85) and the residuals are normal, homoscedastic and not serially correlated.

We add consumer confidence indicators to the best model with control variables. The aim of this exercise is to capture the component of willingness to buy mentioned by Katona (1951, 1975). According to Katona, this willingness to buy responds to psychological factors that can be summarized in the consumer confidence indicator.

$$C_t = \alpha_0 + \alpha_1 C_{t-1} + \alpha_2 X_t + \alpha_3 confidence_t + u_t \qquad (13)$$

Models 2-8 show the results of the naive models augmented by confidence indicators. The results prove that the incorporation of confidence indicators improve the explanatory power of the naive model since the statistics of goodness of fit are better and the confidence indicators are significant. Furthermore, the residuals are normal, homoscedastic and not serially correlated (with one exception).

In general, all the models with consumer confidence show a greater explanatory power and the differences in the explanatory capacity (measured through the Adjusted R^2 and AIC and BIC statistics) are too small to select a unique best model. Therefore, we will select the model by its predictive ability.

Table 5: Assessment of the Predictive Power of the Models estimated Including Control Variables

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Consumption (-1)	0.68***	0.69***	0.62***	0.67***	0.66***	0.62***	0.74***	0.68***
Constant	2.44***	1.99***	2.07***	2.04***	2.18***	2.29***		2.83**
INDICCA SEL A		0.04**						
INDICCA SEL B (-3)			0.09***					
INDICCA SEL C				0.07**				
INDICCA SEL D (-3)					0.07*			
INDICCA SEL E						0.06**		
TOTAL INDICCA							0.07***	
INDICCA DFM								0.12**
Employment(-1)	0.31***	0.27***	0.33***	0.30***	0.33***	0.37***	0.17**	0.25***
CPI(-1)	-0.31***	-0.29***	-0.29***	-0.29***	-0.30***	-0.29***	-0.22**	-0.26**
Consumption (-3)	-0.23***	-0.23***	-0.28***	-0.28**	-0.28***	-0.29***	-0.27**	-0.28***
Information Criteria								
Akaike	2.54	2.47	2.45	2.59	2.52	2.48	2.5	2.5
Schwartz	2.75	2.72	2.7	2.84	2.77	2.73	2.71	2.75
Adjusted R^2	0.85	0.87	0.87	0.87	0.86	0.87	0.86	0.87
Residual diagnostics								
Normality test (H : Normality)	0.74	0.75	0.68	0.8	0.94	0.81	0.99	0.75
Mean Square Error ^{0}	1.13	1.04	0.97	1.11	1.08	1.04	1.11	1.21
Heroskedasticity (H : Hereroskedasticity)	0.45	0.21	0.23	0.56	0.29	0.43	0.16	0.22
Autocorrelation coefficient	0.23	0.15	0.04	0.16	0.14	0.15	0.18	0.22

***Null hypotheses rejected at 1%
**Null hypotheses rejected at 5%
*Null hypotheses rejected at 10%

Despite the fact that we have not chosen a unique best model, we conclude that the addition of consumer confidence improves the explanatory power of models for private consumption growth, even after the incorporation of control variables.

Table 6: Assessment of the Predictive Power of the Models estimated Including Control Variables

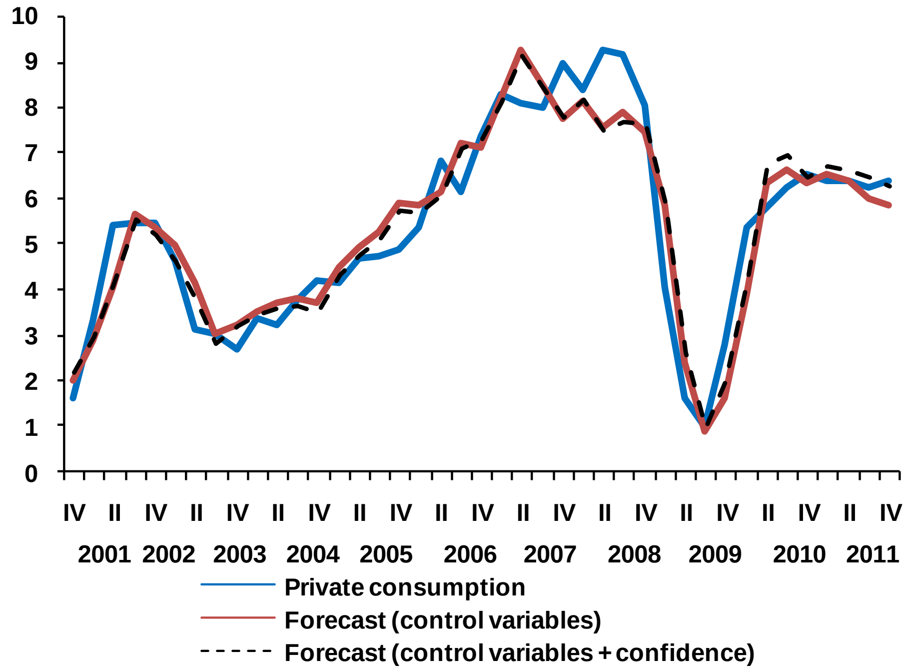
Statistic	Naive + controls	Naive + INDICCA SEL A	Naive + INDICCA SEL B	Naive + INDICCA SEL C	Naive + INDICCA SEL D	Naive + INDICCA SEL E	Naive + INDICCA Total	Naive + INDICCA DFM
MSPE	1.169	1.460	1.166	1.089	0.975	1.134	1.008	0.968
U-Theil		1.249	0.997	0.931	0.834	0.970	0.862	0.829
MSE-F		-2.788	0.035	1.032*	2.781**	0.429	2.233**	2.896***
ENC-NEW		-0.111	2.638***	0.784*	2.248***	0.342	1.461**	2.652***

***Null hypotheses rejected at 1% **Null hypotheses rejected at 5% *Null hypotheses rejected at 10%.

Table 6 shows the estimation of the proposed statistics to test the superior predictive ability of models without control variables. Unlike what can be seen in Table 4, Table 5 shows that the model including INDICCA DFM is the one with the highest predictive power since it carries the lowest U-Theil statistic and MSE-F and ENC-NEW statistics significant at the 99% confidence level. Moreover, the model including INDICCA SEL A portrays a lower predictive ability as seen in its U-theil, MSE-F and ENC-NEW statistics. In contrast, models including INDICCA SEL B, C and D, which had a low predictive power in the estimation of models without control variables, have a higher predictive power at this stage. This may be due to the fact that the control variables included in the model share information with the variable INDICCA SEL A which render the latter non-significant. Thus, a variable such as INDICCA DFM (or even INDICCA total) which aggregates information of more variables performs better in terms of predictive power. Given the fact that model including INDICCA DFM shows the lowest MSPE and U-Theil, we will select this variable as the ideal consumer confidence index for explaining and forecasting real private consumption in the short-term.

Figure 3 shows private consumption growth and the static forecast made by the best model with control variables and by the best model with control variables and consumer confidence. Indeed, the forecast made by the model with consumer confidence indicator (DFM) is closer to the actual value of private consumption; however, the difference of this forecast with the forecast of the model with control variables is small.

Figure 3: Private consumption forecast models
(Annual growth rates)



Source: APOYO Consultoria, BCR

5. Conclusions.

Ipsos APOYO conducts a monthly survey intended to gauge perceptions and expectations of consumers in the city of Lima. Apoyo Consultoría uses that information and calculates the Consumer Confidence Index of Apoyo Consultoría (INDICCA) as a weighted average of the responses to ten questions. This index still has a very short history. We choose the subcomponent with the largest span in order to evaluate its explanatory and predictive power over private consumption. In this process, we will also evaluate the disaggregation on socioeconomic levels of this index and a synthetic indicator of confidence based on dynamic factor models as an alternative way to combine the information contained in the sub-components of this index.

In addition, an important contribution of this paper is that we will not only evaluate the explanatory and predictive power of the levels of consumer confidence indexes, but also of their volatility, in line with the theory of precautionary savings developed by Leland (1968). It is worth mentioning that this is the first attempt -to our knowledge- that consumer confidence indexes are evaluated in terms of explanatory and predictive power on private consumption. Related work on surveys for Peru includes Carrera (2012) that estimate the information rigidity between two groups of people and Mendoza and Morales (2012) that uses the central bank survey for predicting investment.

Although the inclusion of consumer confidence indexes increases the explanatory and predictive power of models of private consumption in Peru, this improvement is small when other control variables are added. In particular, the optimal consumer confidence indicator is the synthetic indicator constructed with the dynamic factor model procedure based on question (ii) of INDICCA.

Additionally, the volatility of consumer confidence turned out to be non-significant. However, we cannot reject the theory of precautionary savings for the case of Peruvian consumers based on these regressions, since they have multiple limitations (time span, construction of variance, etc). Finally, as time passes, we will be able to better evaluate the overall INDICCA in order to exploit the explanatory and predictive power of its different subcomponents and its combinations for private consumption in Peru. Thus, the results presented in this paper, although valid for question (ii) in the overall INDICCA survey, are still inconclusive for the overall index.

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ANNEX

1. Assessing the stationarity of the variables of interest

Before searching the best consumer confidence indicator based on autoregressive models, it is useful to make a stationarity analisys of all variables. First, we will apply the Augmented Dickey Fuller test (ADF) and ADF-ERS. The ADF is a convencional test that has as null hypothesis that the variable is non-stationary. While the ADF-ERS shows the same null hypothesis as the ADF test, it removes the trend of the analized variable and evaluates stationarity using the Elliot Rothenberg and Stock metodology (1996) which gives more power/potency to the test avoiding to acceptance of the null hypothesis when it is false.

However, these tests lose power in the presence of structural breaks, tending to accept the null hypothesis when it is false. Therefore, in a second place, we will apply the unit root test developed by Lee and Strazicich (2003) that incorporates two structural breaks and that is based on the Lagrange Multiplier (LM) procedure. This test has three great advantages. First, it is more flexible than other conventional unit root test, since it admits two structural breaks. Therefore, it is based on an asymptotic distribution that does not diverge in the presence of structural breaks. And second, it has a better specification of the null and alternative hypothesis because in both hypothesis it considers stationarity with breaks and non-stationarity with breaks.

The unit root test proposed by Lee and Strazicich follows the scheme proposed by Perron (1989) where he considers models with three structural breaks. However, this test only considers two models: the first one considers a structural break on the intercept and the second one considers two changes in the intercept and trend. In these manner, the test incorporates two hypothesis:

<u>Model 1</u>

$$H_0 : y_t = u_0 + d_1 B_{1t} + d_2 B_{2t} + \beta y_{t-1} + v_{1t}$$

$$H_1 : y_t = u_1 + \alpha t + d_1 D_{1t} + d_2 D_{2t} + v_{2t}$$

Where D_{jt} is a *dummy* variable that takes the value of 1 when $t \geq T_{Bj} + 1$ $t \geq T_{Bj} + 1$ and shows the structural break in the variable.

<u>Model 2</u>

$$H_0 : y_t = u_0 + d_1 B_{1t} + d_2 B_{2t} + d_3 D_{1t} + d_4 D_{2t} + \beta y_{t-1} + v_{1t}$$

$$H_0 : y_t = u_1 + \alpha t + d_1 D_{1t} + d_2 D_{2t} + d_3 DT_{1t} + d_4 DT_{2t} + v_{2t}$$

Where DT_{jt} DT_{jt} is a variable that is equal to $(t - T_{Bj})$ $(t - T_{Bj})$when $t \geq T_{Bj} + 1$ $t \geq T_{Bj} + 1$ and shows the trend breaks of the variable.

Also, it includes the *dummy* B_{jt} following Perron (1989) in order to avoid that the asymptotic distribution of the statistic does not depend on the magnitude of the structural breaks.

Under this procedure, we will obtain an estimation of the unit root test using the principle of Lagrange Multiplier from which we obtain the t statistic of the null hypothesis[10]. The statistic obtained will be contrasted with the tabulated critic values that do not diverge on the size of the breaks. In order to calculate the critical values, we must estimate the coefficients $\lambda_j = \frac{T_{Bj}}{T}$. Although this estimation depends softly from the location of the breaks, it does not diverge in the presence of structural breaks.

Thus, we can test the null hypothesis of unit root with structural change against the alternative hypothesis of stationary with structural change[11]. The next table is a summary the unit root tests presented and how they differ in terms of null and alternative hypothesis. This point is crucial because the specification of the hypothesis for Lee and Strazicich's test provides more flexibility than the specification of a conventional test.

Table 7: Null and alternative hypothesis for unit root test

		Augmented Dickey-Fuller	Phillips-Perron	Zivot-Andrews	Perrón (1997)	Lee-Strazicich
Null hypothesis	Unit root without structural break	YES	YES	YES	YES	
	Unit root with structural break					YES
Alternative hypothesis	Stationary without structural break	YES	YES			
	Stationary with structural break			YES	YES	YES

Source: Rodríguez, Adolfo (2009) "Pruebas de raíz unitaria con cambio estructural de Lee y Strazicich"

The conventional unit root test as ADF and ADF-ERS shows that the variables are no stationary for the span considered. In Table 7, it is not possible to refuse the null hypothesis for almost all the variables at least in 10% of probability, considering the three types of specifications. This has qualitative implications because it implies that the consumers' confidence does not return to an average confidence in time.

[10] Fort the aim of this paper, we only consider the t test; however, the test based on the Lagrange Multiplier produces two statistics: t and $\hat{p}$.

Table 8: Conventional unit root test

Variable 1/	Augmented Dickey Fuller			Elliot-Rothenberg-Stock	
	Constant	Constant & Trend	None	Constant	Constant & Trend
Private consumption	-1.91	-1.88	-0.21	11.1	15.66
Inflation	-1.76	-2.15	-0.15	4.90	16.05
Employment	-2.47	-0.51	-0.5	21.91	73.17
Credit: National Currency (NC)	-0.86	-2.85	-1.29	6.57	12.83
Credit: Foreing Curency (FC)	*-3.83	-3.73	-1.8	9.33	14.22
Interest rate NC	-2.37	-1.02	-1.37	45.08	40.39
Interest rate FC	-1.79	0.16	-0.03	1.28	45.21
INDICCA SEL A	-1.7	-5.71	-0.73	4.83	*4.16
INDICCA SEL B	-1.39	-2.51	0.34	7.29	9.99
INDICCA SEL C	-0.94	-3.26	-0.15	13.13	7.91
INDICCA SEL D	-2.09	*-4.82	-0.03	-3.39	4.49
INDICCA SEL E	-0.84	*-5.46	-0.51	10.02	4.50
INDICCA DFM	-1.21	-2.14	-1.16	16.47	11.49
INDICCA	-1.23	-2.02	1.14	33.11	12.82

** Null hypotheses rejected at 10%*

*** Null hypotheses rejected at 5%*

**** Null hypotheses rejected at 1%*

1/ Sample size 2001Q1 to 2011Q4

However, if we implement the unit root test that allows structural breaks, we can refuse the null hypothesis of the unit root test. Applying the unit root test proposed by Lee and Strazicich (2003), we find that almost all the variables are stationary in the presence of two structural breaks even in 1% of probability as can be observed in Table 8. These results have important qualitative implications because it tells us that the confidence and private consumption return to an average confidence and an average growth in the long term.

Table 9: Unit root test with Structural Breaks

Variables 1/	Lee & Strazicich			
	Breakpoint 1	Breakpoint 2	Model	t- stat
Consumption	1T2008	4T2009	2	-6.75***
Inflation	4T2007	3T2008	2	-6.38***
Employment	4T2005	3T2008	2	-8.40***
Credit: National Currency (NC)	4T2003	3T2007	2	-6.36***
Credit: Foreing Curency (FC)	4T2004	2T2006	2	-8.01***
Interest rate NC	4T2003	1T2009	2	-13.2***
Interest rate FC	1T2007	1T2009	2	-7.67***
INDICCA SEL A	3T2006	3T2009	2	-6.81***
INDICCA SEL B	4T2006	2T2010	2	-6.87***
INDICCA SEL C	3T3006	4T2010	2	-7.67***
INDICCA SEL D	3T2006	3T2010	2	-6.48***
INDICCA SEL E	4T2003	4T2007	2	-6.24**
INDICCA DFM	3T2005	4T2007	2	-5.47*
INDICCA	3T2005	3T2009	2	-6.46***

**Null hypotheses rejected at 10%*

***Null hypotheses rejected at 5%*

****Null hypotheses rejected at 1%*

1/ Sample size

Also, we have considered the loss of power for the test when the sample is relatively small. In order to solve this problem, we have increased the sample size for the variables which have available information and the results point to stationarity for all the analyzed variables. As a way to contrast that our estimated models presented in the next section are consistent, we have analyzed the residuals that we obtain of each model. These results signal that all of these variables (the residuals) are stationary, which validates our results even if we have the problem of small sample when we apply the unit root test.

2. Regressions with volatility of INDICCA among consumers.

Table 10: Regressions with volatility as a control variable

Variable	Model 1	Model 2
Constant	2.31 ***	
Consumption (-1)	0.68 ***	0.67 ***
Consumption (-3)	-0.24 **	-0.24 ***
Emplyment (-1)	0.27 ***	0.28 ***
CPI (-1)	-0.27 ***	-0.29 ***
Variance better	0.00 *	
Variance difference		0.00
Information criteria		
Akaike	2.42	2.45
Schwartz	2.66	2.69
Adjusted R2	0.89	0.89
Residual diagnostics		
Normality test (H0: Normality)	0.81	0.69
Heteroskedasticity (Ho: Homocedasticity)	0.00	0.00
Autocorrelation test (Ho: no autocorrelation)	0.08	0.07

*** Null hypotheses rejected at 1%.

** Null hypotheses rejected at 5%.

* Null hypotheses rejected at 10%.

Variance better: refers to the variance of the percentage of consumers who think their family economic situation will improve in the next twelve months compared to their current situation. This variance is a cross-section calculation among the different SEL.

Variance difference: refers to the variance of the percentage of consumers who think their family economic situation will improve in the next twelve months compared to their current situation minus the percentage who their their situation will deteriorate. This variance is a cross-section calculation among the different SEL.