PERUVIAN ECONOMIC ASSOCIATION

Consumption dynamics and the expectation channel in a Small Open Economy

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This version: April 2019

Abstract:

The transmission mechanism between consumption and its fundamentals has been under reviews in the literature from Friedman's permanent income hypothesis to household's liquidity constraints. One particular angle to explain consumption is focused on the role of consumer expectations as a determinant of consumption spending. Here we explore alternative measures for consumer expectations (captured by surveys to households) by taking into account general manager expectations and by using imports of durable consumption goods (which capture consumer confidence about future economic conditions). We argue that, for a small open economy, the expectations channel is well captured by alternative measures; find that even though there is a pass-through from expectations to consumption, this effect tends to have a short-period effect; and also report those values and periods of time for which the alternative measures have a significant impact on consumption.

JEL Classification: C16, F31, F41

Key words: Consumption, Durable goods, Business expectations, Households expectations.

1. INTRODUCTION

The transmission mechanism for private consumption usually works in channels that link the observed outcome in consumption for a given behavior in its fundamentals. Here the literarture goes from Friedman's permanent income hypothesis (long term view) to household's liquidity constraints (short term dynamics). One particular channel takes into consideration consumer expectations as an important driver for explaining consumption because surveyed households tend to answer according to their view about the future path on their incomes. Here we explore an alternative measure by taking into account general manager expectations about doing business and, in doing so, reading the future demand for their products (Carrera, 2012). We also argue in favor of durable consumption goods because consumers only engage in purchasing this type of goods when they feel confident about their current economic situation and their expected incomes.

In order to explain the dynamics observed in consumption, we estimate a VAR that includes a system for current and past values of its fundamentals. Here, the literature discusses whether variables such as income, wealth, unemployment, inflation, and consumer's expectations capture the dynamics of those fundamentals. This approach usually deals with the endogeneity problem between consumption and its fundamentals and allows the introduction of a shock in expectations.

Based on a New Keynesian model, Barsky and Sims (2012) introduce a shock in consumer's expectations for future incomes that is associated with three components: consumer's own productivity in the future, changes in technology induced by ongoing investment process, and a pure noise from news around the households. This view tries to disentangle the source of the shock and complement the work in Carroll et al. (1994).[1]

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[1] See also Blanchard et al. (2013), Baudry et al. (2014), and Ilur et al. (2014) for a follow up on this expectation channel for RBC models.

The focus of the empirical literature on the expectations channel is whether consumer confidence measures have any statistical significant power in predicting consumption outcomes once information from the proxy variables for fundamentals is used (Carroll et al., 1994; Howrey, 2001; Dees and Soares, 2011; Barsky and Sims, 2012). In particular, some works highlight the importance of correctly forecasting some components in consumption expenditure for predicting strong fluctuations in the economy such as recessions and recoveries. In that regard, confidence indicators may contain information that goes beyond fundamentals.

The inclusion of a business confidence index in step of a consumer sentiment index is based on an alternative supply view. General managers are in constant search for how the demand for their products looks like. By correctly having good forecasts, they can anticipate the up-and-downs in each particular market. The question we pick is the one made to a general manager regarding his expectations about the group of companies that belong to his particular sector. This time serie in particular seems to capture the eagerness from the part of the firms to invest in each sector in response to an increase in demand and, if so, income must increase and consumption must rise. In line with Carroll et al. (1994), we argue that this is an alternative way to incorporate the expectations channel into the mechanism behind the drivers for consumption.

On the other hand, durable consumption goods (or durable goods) are also key for understanding the future path on private consumption. On one side, this type of goods does not need to be purchased frequently because they are made to last for a long time (usually lasting for at least three years). On the other hand, durable goods tend to have larger sticky prices so during bad times, households may not replace or update their durable goods and may wait until they have better expectations about their future income. Here, it is usually assumed that individuals have better information about their own income growth and, based on that information, take shopping decissions.

One strategy to approach the consumption on durable goods for a small open economy (SOE) is by using the imports of durable consumption goods. For those economies with a limited industry on supplying this type of goods, imports seem to be an effective choice for approaching the consumption behavior for durable goods.

In the case of Peru, those measures of expectations seem to be highly correlated with the observed growth in private consumption. In line with Carrol et al. (1994), we argue that those comovements observed in the data correspond to an expectations channel and may be important when fundamentals rank short in explaining strong variations in private consumption (see Figure 1).

If expectations grow (by any of the measures), private consumption has a good chance to growth as well. If a crisis shocks this small open economy, the expectations channel seems to be way ahead of most fundamentals. The international crisis in 2008 – 2009 seems to be a good example in which different measures for expectations quickly reacts.

According to Carroll et al. (1994) and Bram and Ludvigson (1998), the task at hand is to reveal which measure of expectations does a better job in terms of explaining the observed dynamics in consumption. The correlation between changes in Indicca and the business confidence index is relatively large (0.36) and relatively low between Indicca and imports of durable goods (0.20). Part of our argument is that differences in these series are associated with the problem of correctly measure consumer expectations, even though clear comovemente are observed (see Figure 2).

We show that a measure based on the expectations of general managers outperforms other measures. We find that a shock in expectations has statistically significant effects in consumption. And when a threshold value is identified, expectations tend to significantly add to the fit of models explaining consumption behavior.

FIGURE 1 – CONSUMPTION GROWTH (LHS) AND CHANGE IN EXPECTATIONS (RHS)

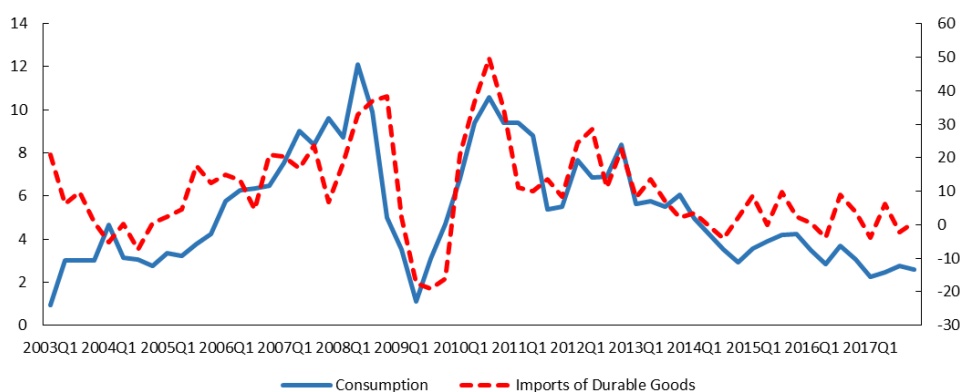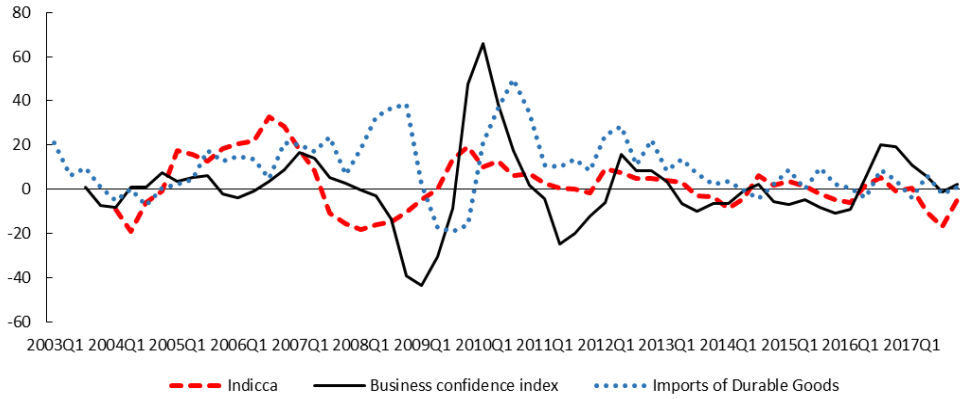## A: INDICCA
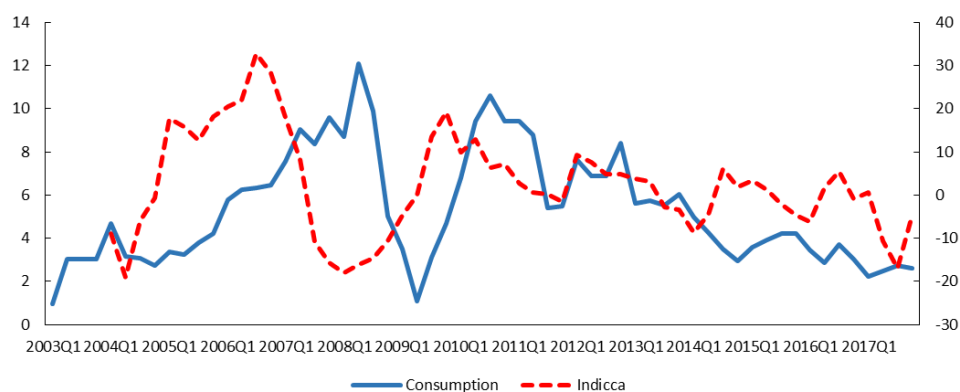
B: BUSINESS CONFIDENCE INDEX (BCI)

C: IMPORTS OF DURABLE GOODS (MDG)

NOTES: GROWTH AND CHANGE ARE MEASURED IN ANNUAL TERMS. INDICCA IS BASED ON A SURVEY TO HOUSEHOLDS AND THE BUSINESS CONFIDENCE INDEX (BCI) IS BASED ON A SURVEY TO GENERAL MANAGERS.

FIGURE 2 – CHANGE IN MEASURES FOR EXPECTATIONS

NOTES: GROWTH AND CHANGE ARE MEASURED IN ANNUAL TERMS. INDICCA IS BASED ON A SURVEY TO HOUSEHOLDS AND THE BUSINESS CONFIDENCE INDEX IS BASED ON A SURVEY TO GENERAL MANAGERS.

The rest of this paper is organized as follows. Section 2 describes the data. Section 3 presents our time-series estimations on consumption as a function of fundamentals. Section 4 includes forecasting exercises using a threshold model. Section 5 concludes this paper.

2. DATA CHARACTERISTICS

In this paper, the dataset covers the period from the first quarter of 2002 to the fourth quarter of 2017.[2] It is important to mention that during this time frame Peru was exposed to a commodity boom (2002 – 2007), a global financial crisis (2008 – 2009), and Peru has had one-single monetary policy regime: inflation targeting.

The consumption time serie is the real value of the expenditure made by private households in goods and services that is estimated in the Input-Output table for different years and is consistently reported by the National Institute of Statistics of Peru (INEI) in every quarter.

The measures for consumer expectations are the Consumer Confidence Index (Indicca), the Business Confidence Index (BCI), and imports of durable goods for consumption (MDG). Indicca is estimated by a private consultant company and is based on a survey to households

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[2] The data is seasonally adjusted with TRAMO – SEATS.

in Lima, the capital city of Peru.[3] BCI is based on a survey conducted by the central bank to a sample of general managers of the most important firms in Peru.[4] As for MDG, the selection of items corresponds to those imported goods that are classified according to the Standard Classification by Economic Use or Destination (CUODE by its initials in Spanish) of the Economic Comission for Latin America and the Caribbean. Those imports are measured in real terms.

In order to capture habits in consumption, we consider past values of consumption as a determinant of current consumption. The fundamental for income is approached by the real GDP (and disposable income for robustness analysis). For wealth, we use the measure estimated in Davies et al. (2017) for Peru.[5] In terms of equity prices, we use the index for prices by squared meter in Lima, reported by the central bank of Peru.

The interbank interest rate in domestic currency is used as the short-term interest rate because it allows us to have an idea of monetary policy given the inflation targeting regime followed by the central bank.

For the unemployment rate we use the percentage of the economically active population who are searching for a job and do not find it. Given the importance of copper in Peru's export portfolio, international copper prices are part of the set of fundamentals because it reflects improvement in competitiveness. These variables are reported by the central bank of Peru.

Finally, in order to evaluate a possible overseas transmission in terms of consumer confidence, we use the University of Michigan's Consumer Sentiment Index for the U.S. as a foreign confidence indicator. This choice is made because the U.S. is one of Peru's greatest trading partners.

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[3] For example, the University of Michigan's Consumer Index and the Conference Board's Consumer Confidece Index are also constructed with current and prospective questions. Although Indicca is constructed with current and prospective questions, we prefer to use the whole indicator because of data availability.

[4] Regarding BCI, we focus on the question about doing business in the following 3 months by firms that belong to the same sector.

[5] We extrapolated the anual terms such that we get quarterly data based on a linear and quadratic trend. Here we argue that wealth has smooth transitions and then has few large changes within a year, during the sample period under study.

3. PASS-THROUGH FROM EXPECTATIONS TO CONSUMPTION

Our empirical approach begins with traditional unit root and causality tests, results that remain very partial. For the dynamic analysis, we estimate consumption as a linear function of different expectation indicators in addition to standard variables that are identified as fundamentals for consumption in the empirical literature. We close this section with the estimation of VAR models in order to derive impulse response functions and historical decompositions that provide insights between consumption and our proxies for expectations.

3.1 Granger causality test

We use the Granger causality test and report the p-values for the probability of no Granger-causality from the variables in the column to the variables in the raw. Rejections of the null hypothesis are set for 5% significance level (see Table 1).[6]

Consumption is Granger-caused by some stylized fundamentals in the literature: income, wealth and, at a lesser extend, interest rate. Out of our three measures, only BCI seems to Granger cause consumption. We also perform the Granger causality test for our expectations variables. Indicca is Granger-caused by foreign expectations and equity prices; BCI is Granger-caused by consumption, income, copper prices, foreign confidence, and interest rate; and MDG is Granger-caused by consumption, income, and copper prices.

These results of the Granger causality tests might lead to some ideas about the relationship between consumption and our alternative measures for expectations. Other than the expected effect from income and consumption over expectations, there is some evidence of recursiveness between consumption and BCI. Copper prices might have a stronger effect in the confidence

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[6] We first perform the Augmented Dickey-Fuller test and find that our variables are integrated of order one or I(1). The lag for the Granger causality test is 4.

for doing business as well as in importing more durable goods for consumption, and in doing so, drive some confidence to consumers as well. Interest rate also seems to have an important effect on expectations, measured by BCI. While better international prices in general tend to improve the purchasing power of the economy as a whole, it seems to have two-sided effects in actual consumption through a direct income effect and better expectations about future conditions. In terms of a lower interest rate, the increase in consumption and in more opportunities for business may be associated with a sound monetary policy given the lower levels of inflation and the consistent inflation targeting regime followed by the central bank.

TABLE 1 – GRANGER CAUSALITY TEST

From\To	$\Delta \ln C_t$	$\Delta Indicca_t$	ΔBCI_t	$\Delta \ln MDG_t$
$\Delta Indicca_t$	0.43			
ΔBCI_t	0.06			
$\Delta \ln MDG_t$	0.80			
$\Delta \ln C_t$		0.56	0.00	0.00
$\Delta \ln Y_t$	0.04	0.35	0.00	0.00
$\Delta \ln W_t$	0.00	0.35	0.15	0.20
$\Delta \ln q_t$	0.25	0.17	0.74	0.31
Δi_t	0.17	0.57	0.05	0.91
Δu_t	0.59	0.23	0.52	0.20
$\Delta \ln cp_t$	0.48	0.91	0.00	0.02
$\Delta \ln Expectation_t^*$	0.71	0.09	0.02	0.33

NOTES: INDICCA, BUSINESS CONFIDENCE INDEX (BCI) AND IMPORTS OF DURABLE CONSUMPTION GOODS (MDG) ARE DIFFERENT MEASURES THAT PROXIES EXPECTATIONS. C IS REAL CONSUMPTION EXPENDITURE; Y IS REAL GDP; W IS WEALTH; Q IS REAL EQUITY PRICES; I IS A SHORT-TERM INTEREST RATE; U IS THE UNEMPLOYMENT RATE; CP IS REAL COPPER PRICE; EXPECTATION* IS FOREIGN CONFIDENCE. Δ REFERS TO FIRST DIFFERENCES. REPORTED P-VALUES FOR THE PAIRWISE GRANGER CAUSALITY TEST, FOR 4 LAGS.

3.2 Uniequational models

The estimation of uniequational linear models allows us to measure the contribution of our expectations variables to three set of variables that capture the main fundamentals for consumption. To take into account the marginal contribution to the additional variable, we use

the adjusted R^2. Here we move from a simple model to one that takes into account all fundamentals (the last set of variables). In each round, a variable for expectations is considered.

The first model is a simple one in which the log change in consumption ($\Delta ln C_t$) only depends on the change in the confidence indicator ($\Delta Expectation_t$),

$$\Delta \ln C_t = \alpha + \sum_{i=1}^{4} \beta_i \, \Delta \, Expectation_{t-i} + \varepsilon_t \tag{1}$$

where ε_t is an i.i.d. error term.[7]

We then estimate a linear model in which consumption depends on past changes in consumption together with past changes in income ($\Delta ln Y_t$). For simplicity, we define $Z_t^1 = (\Delta ln C_t, \Delta ln Y_t)$. With this first group of fundamentals, we estimate

$$\Delta \ln C_t = \alpha + \sum_{i=1}^{4} \gamma_i \, Z_{t-i}^1 + \varepsilon_t \tag{2}$$

The first round concludes with the estimation of a model in which the variable that approaches expectations is added to Z_t^1,

$$\Delta \ln C_t = \alpha + \sum_{i=1}^{4} \beta_i \, \Delta \, Expectation_{t-i} + \sum_{i=1}^{4} \gamma_i \, Z_{t-i}^1 + \varepsilon_t \tag{3}$$

For the second round, we include wealth (W_t) to the list of fundamentals. So the new control set of fundamentals is $Z_t^2 = (Z_t^1, \Delta ln W_t)$ and the regressions estimated are,

$$\Delta \ln C_t = \alpha + \sum_{i=1}^{4} \gamma_i \, Z_{t-i}^2 + \varepsilon_t \tag{4}$$

$$\Delta \ln C_t = \alpha + \sum_{i=1}^{4} \beta_i \, \Delta \, Expectation_{t-i} + \sum_{i=1}^{4} \gamma_i \, Z_{t-i}^2 + \varepsilon_t \tag{5}$$

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[7] The lag order (4) that is found to be optimal for all estimated models is determined using standard information criteria.

As mentioned by Barsky and Sims (2012), Dees and Soares (2011), and Carroll et al. (1994), there is a group of variables that might influence consumption behavior even though no theory includes them directly as fundamentals but allows a more compelling story, especially in a SOE. These variables are equity prices (q_t), the short-term interest rates (i_t), the unemployment rate (u_t), and copper prices (cp_t). The third set of fundamentals is defined as $Z_t^3 = (Z_t^2, \Delta \ln q_t, \Delta i_t, \Delta u_t, \Delta \ln cp_t)$ and closes the third round by estimating,

$$\Delta \ln C_t = \alpha + \sum_{i=1}^{4} \gamma_i Z_{t-i}^3 + \varepsilon_t \qquad (6)$$

$$\Delta \ln C_t = \alpha + \sum_{i=1}^{4} \beta_i \Delta Expectation_{t-i} + \sum_{i=1}^{4} \gamma_i Z_{t-i}^3 + \varepsilon_t \qquad (7)$$

The last case we evaluate is whether adding a confidence indicator from abroad improves the fit of previous models,

$$\Delta \ln C_t = \alpha + \sum_{i=1}^{4} \beta_i \Delta Expectation_{t-i} + \sum_{i=1}^{4} \gamma_i Z_{t-i}^3 + \sum_{i=1}^{4} \rho_i \Delta Expectation_{t-i}^* + \varepsilon_t \qquad (8)$$

Table 2 reports our results based on adjusted R squared. By estimating Equation (1), BCI seems to explain over 10 percent of observed data of consumption. When Indicca and MDG are considered, past values of expectations have few explanatory power.

Results from the first round are defined as the difference in adjusted R^2 between estimating Equations (3) and (2). In the case of BCI, it improves the fit by 10 percent points. Indicca also improves the fit (in 4 percentage points). MDG seems to decrease the fit when expectations are considered.

For the second round, estimations of Equations (5) and (4), we find that BCI again improves the fit by 8 points. Indicca adds 11 more points to the fit, and MDG adds 2 points only. The third round between Equations (7) and (6) seems to be the most challenging test for expectations. Here BCI adds just 1 point while Indicca adds 8 points, and MDG does not add

points to the fit. In this round, it is Indicca the variable that clearly explains the most among expectation variables.

Finally, when we add the foreign confidence index, the model improves its fit in 11 points (for Indicca), in 2 points (for BCI), and in 5 points (for MDG). Once more, Indicca is the variable that induces the higher fit.

From the regression based analysis, we conclude that there is some evidence of an expectations channel in the dynamics for consumption. On the other hand, we also find that other fundamentals seem to be the main drivers in explaining changes in aggregate consumption.

TABLE 2 – UNIVARIATE SPECIFICATIONS

Equation	Consumption equation	Adjusted R^2		
		$Indicca_t$	BCI_t	MDG_t
(1)	$C_t = f(Expectation_t)$	0.01	0.1	0.00
(2)	$C_t = f(Z_t^1)$	0.19	0.19	0.19
(3)	$C_t = f(Expectation_t, Z_t^1)$	0.23	0.29	0.16
(4)	$C_t = f(Z_t^2)$	0.33	0.33	0.33
(5)	$C_t = f(Expectation_t, Z_t^2)$	0.44	0.41	0.35
(6)	$C_t = f(Z_t^3)$	0.53	0.53	0.53
(7)	$C_t = f(Expectation_t, Z_t^3)$	0.61	0.54	0.53
(8)	$C_t = f(Expectation_t, Z_t^{3\,*})$	0.72	0.56	0.58

NOTES: $Z_t^1 = (\Delta lnC_t, \Delta lnY_t)$, $Z_t^2 = (Z_t^1, \Delta lnW_t)$, $Z_t^3 = (Z_t^2, \Delta \ln q_t, \Delta i_t, \Delta u_t, \Delta \ln cp_t)$, $Z_t^{3*} = (Z_t^3, Expectation_t^*)$. $Expectation_t$ EQUALS $Indicca_t$, BCI_t, AND MDG_t, RESPECTIVELY. FOR THE DEFINITION OF THE VARIABLES, SEE TABLE 1 NOTES.

3.3 VAR analysis

Here we explore the response in terms of dynamics of consumption given a shock in expectations. We first estimate VAR models using the same variables as in the univariate estimations in order to test for how many periods a shock in expectations lasts. We then compute the historical forecast error decomposition for a better understanding of the contribution of expectations shocks over time.

We estimate the preferred model for consumption in Equation (7) as a part of a VAR setting, using the largest set of fundamentals (Z_t^{3*}). The VAR model is defined as:

$$y_t = \sum_{i=1}^{q} A_i y_{t-i} + u_t \tag{9}$$

where u_t is a vector of orthogonalised shocks and y_t is a vector defined as:

$$y_t = \begin{pmatrix} \Delta\, Expectation_t \\ Z_t^{3*} \\ \Delta ln\, C_t \end{pmatrix}$$

We follow Bram and Ludvigson (1998) and Dees and Soares (2011) for the structural orthogonolasition, according to a Choleski ordering, such that: confidence expectations, financial variables, interest rate, wealth, consumption, and income. The Foreign confidence index is considered as an exogenous variable in the system.[8]

Figure 3 reports the impulse response functions from expectations to consumption which have mixed results. On one hand, a one standard deviation shock to either BCI or MDG seems to have significant effects for only one period ahead but insignificant at the 95% level for future periods. While for MDG the impact on consumption occurs almost contemporaneously, for BCI it occurs after one quarter after the shock is induced. On the other hand, there is no significant response from consumption given a shock in Indicca.

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[8] The optimal lag order, q in Equation (9), is equal to 1 for Indicca and BCI and 4 for MDG. We perform different tests criteria for the lag order and use Schwarz information criteria.

FIGURE 3 – RESPONSE OF CONSUMPTION GROWTH TO A 1 SD INNOVATION IN EXPECTATIONS

A: INDICCA

B: BUSINESS CONFIDENCE INDEX (BCI)

C: IMPORTS OF DURABLE GOODS (MDG)
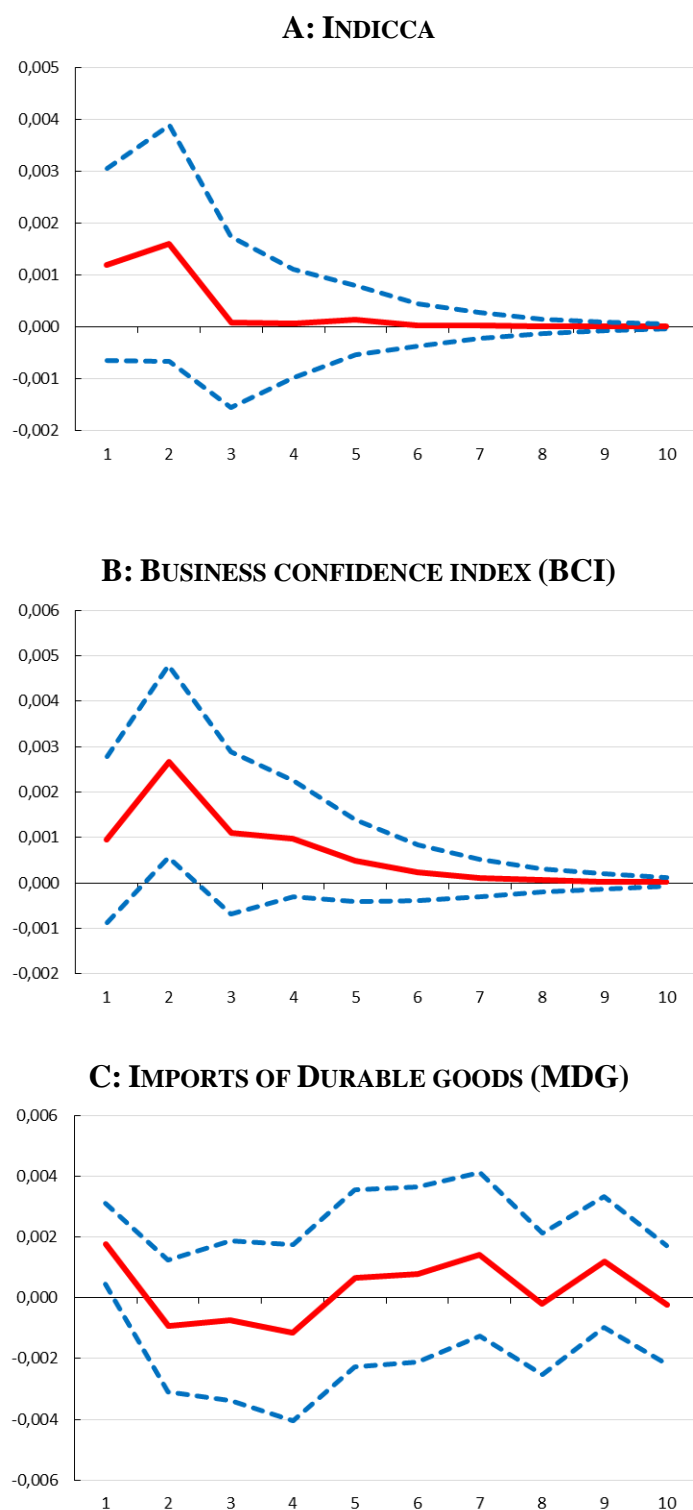
NOTES: INNOVATIONS ARE ESTIMATED USING CHOLESKY (DEGREES OF FREEDOM ADJUSTED) FACTORS. INDICCA IS BASED ON A SURVEY TO HOUSEHOLDS AND THE BUSINESS CONFIDENCE INDEX IS BASED ON A SURVEY TO GENERAL MANAGERS.

In order to make the innovation accounting, we decompose the observed time series into those components corresponding to each structural shock, in particular the ones associated to our measures of expectations. Burbidge and Harrison (1985) propose a historical forecast error decomposition by transforming observed residuals to structural residuals.[9]

Figure 4 shows respectively the historical decomposition for Indicca, BCI, and MDG. In other words, the contribution to the deviations between actual consumption and its VAR-based forecasts of shocks. In our setup, those shocks are tied up to expectation and the largest set of fundamental variables (Z_t^{3*}). Independently of the measure of expectations, confidence shocks play a small role on average relative to other shocks.

We identify some periods in which a confidence shock seems to have an important contribution. At some points in time, one measure of expectations is more important than the other two. It is important to mention, however, that BCI and MDG have larger negative influence to forecast errors during 2008 – 2009. This period coincides with the international crisis which in turn leads to an important desaceleration in the growth rate in private consumption. For the case of Indicca, its negative effect on consumption in the final months of 2016 and the whole of 2017 is remarkable. During this time, private consumption was affected by the negative wealth effect generated by the El Niño Costero event and also by the slow recovery of the labor market.

As preliminary conclusion, the impulse response and the historical decomposition suggest some limited reach for the expectations channel. If anything, it favors BCI over the other two measures of expectations and seems to matter in some specific episodes. Those episodes usually correspond to periods in which consumption has larger changes as in the presence of international financial crisis.[10]

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[9] For each observation beyond some point in the estimation sample, it is computed the contribution of the different accumulated structural shocks to each observed variable based on the reorganization of the moving average representation.

[10] Our results are robust to the use of alternative measures for fundamentals. We use disposable income rather than GDP and also consider the basket for export prices and real exchange rate in order to robust those results for

FIGURE 4 – HISTORICAL FORECAST ERROR DECOMPOSITION

A: INDICCA

B: BUSINESS CONFIDENCE INDEX (BCI)

C: IMPORT OF DURABLE GOODS (MDG)
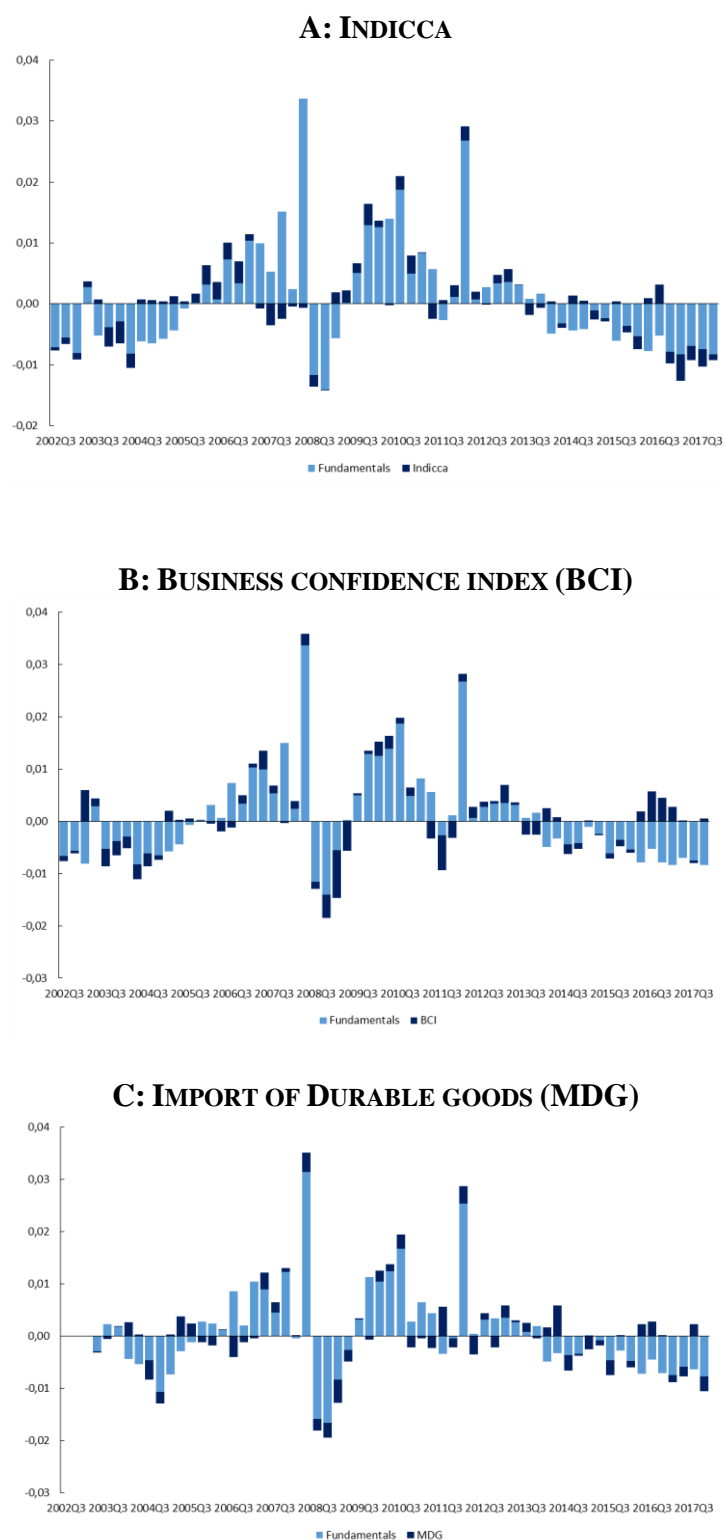
NOTES: INNOVATIONS ARE ESTIMATED USING CHOLESKY (DEGREES OF FREEDOM ADJUSTED) FACTORS.

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copper prices. Regarding equity prices, we also considered the S&P / Lima Stock Exchange General Index as an alternative for the price by squared meter for real estates in Lima.

4. THRESHOLDS IN EXPECTATIONS

4.1 Threshold models

The historical decomposition suggests that an expectation shock matters during moments of high volatility. The literature usually highlights the role of this type of events in periods of uncertainty (Garner, 1991; Throop, 1992). We test this statement by estimating a threshold model in order to isolate periods in which expectations (for any of the three indicators proposed) have significant effects over consumption. The non-linear estimation of consumption removes low frequency observations for those variables that capture the expectation channel. In line with Desroches and Gosselin (2002) and Dees and Soares (2011), the rule of removing or not a value is given for a threshold value which is estimated following the next criterion:

$$\Delta\, Expectation_t^C = \begin{cases} 0 \;\; if \;\; |\Delta\, Expectation_t| < \theta \\ \Delta\, Expectation_t \;\; otherwise \end{cases}$$

where $Expectation_t$ is one of the following: BCI_t, MDG_t or $Indicca_t$.

Under this rule, the set of possible values for the vector $\Delta\, Expectation_t^C$ goes from 0 to its highest value (max $|\Delta\, Expectation_t|$). Therefore, there are as many vectors as the total number of observations. Vectors are similar between each other with the only difference that some observations are set to zero.

We estimate the models using each one of the vectors. The model with the best performance in terms of Schwarz information criteria is selected. If so, the optimum θ is the one that maximizes the fit of the model by setting zero to all changes in expectation below this value.

From a particular value (threshold value), changes in expectations have a significant impact on consumption dynamics. In other words, if the vector related with the optimum

threshold contains a big number of censored observations (set to zero), then it is possible to argue that only big changes in expectations (above the threshold) affect consumption behavior.

The forecasting exercises is made for each of the three indicators of expectations. We estimate the Final Prediction Error (FPE) for in-sample forecasting and Root Mean Square Error (RMSE) for out-of-sample projections.

We compare the performance of each expectation indicator and also test the marginal contribution for each indicator by estimating different alternatives of the model: without the expectation indicator, with the expectation indicator, and with the censored expectation indicator. The following equations are estimated:

$$\Delta \ln C_t = \alpha + \sum_{i=1}^{\eta} \delta_i \, \Delta \ln C_{t-i} + \beta \, \Delta \, Expectation_{t-1} + \, \varepsilon_t \qquad (10)$$

$$\Delta \ln C_t = \alpha + \sum_{i=1}^{\eta} \delta_i \, \Delta \ln C_{t-i} + \beta \, \Delta \, Expectation_{t-1} + \sum_{i=1}^{4} \gamma_i \, Z_{t-i}^{3*} + \, \varepsilon_t \qquad (11)$$

where $\eta = 4$ for BCI and MDG, $\eta = 3$ for Indicca, and $Z_t^{3*} = (Z_t^3, \Delta \, Expectation_t^*)$.

4.2 In-sample forecasting

Table 3 presents the estimations for Equations (10) and (11), in terms of FPE. The first row shows results for estimations without the corresponding expectations indicator. The second row includes estimations with the expectations indicator. The third row reports the same specification as the second row, but with censored data for the expectations indicator (observations are set to zero according to a threshold value). Table 3 also considers if fundamentals are necessary for forecasting consumption by excluding and including them in the corresponding columns.

TABLE 3 – FINAL PREDICTION ERROR FOR IN-SAMPLE FORECAST

A: INDICCA

Models	Without Z_t^{3*}	With Z_t^{3*}
Without $INDICCA_t$ (1)	0.0000697	0.0000915
With $INDICCA_t$ (2)	0.0000712	0.0000909
With $INDICCA_t^C$ (3)	0.0000700	0.0000896
(2) / (1) x 100	102.03	99.35
(3) / (2) x 100	98.39	98.57
Coefficient (β)		
With $INDICCA_t$	0.0005810	0.0006890
(t-stat)	(1.3239720)	(1.6335300)
With $INDICCA_t^C$	0,000742	0,000811*
(t-stat)	(1.6382260)	(1.7889050)
θ^*	1.7885067	1.7885067
censored observations for θ^*	30	30

B: BUSINESS CONFIDENCE INDEX (BCI)

Models	Without Z_t^{3*}	With Z_t^{3*}
Without BCI_t (1)	0.0000741	0.0000985
With BCI_t (2)	0.0000653	0.0001051
With BCI_t^C (3)	0.0000651	0.0000961
(2) / (1) x 100	88.13	106.66
(3) / (2) x 100	99.80	91.47
Coefficient (β)		
With BCI_t	0.0008800***	0.0002220
(t-stat)	(3.2246940)	(0.7697780)
With BCI_t^C	0.0008850***	0.0011450*
(t-stat)	(3.2447010)	(1.7264670)
θ^*	1.1135320	7.433120
censored observations for θ^*	15	58

C: IMPORTS OF DURABLE GOODS (MDG)

Models	Without Z_t^{3*}	With Z_t^{3*}
Without MDG_t (1)	0.0000741	0.0000985
With MDG_t (2)	0.0000780	0.0001031
With MDG_t^C (3)	0.0000768	0.0000951
(2) / (1) x 100	105.25	104.65
(3) / (2) x 100	98.56	92.18
Coefficient (β)		
With MDG_t	-0.0054370	0.0194350
(t-stat)	(-0.2891600)	(1.0406480)
With MDG_t^C	-0.0596780	0.0356580*
(t-stat)	(-0.9257670)	(1,8156620)
θ^*	0.1872429	0.0702121
censored observations for θ^*	62	48

NOTES: *STATISTICALLY SIGNIFICANT AT 90 % LEVEL OF CONFIDENCE, **STATISTICALLY SIGNIFICANT AT 95 % LEVEL OF CONFIDENCE, ***STATISTICALLY SIGNIFICANT AT 99 % LEVEL OF CONFIDENCE. Z_t^{3*} IS A VECTOR OF FUNDAMENTAL VARIABLES. FOR THE DEFINITION OF THE VARIABLES, SEE TABLE 1 NOTES.

The model for BCI without fundamentals has the expectation indicator that is statistically significant at 99% confidence level with either censored or uncensored data. The gains in the model with fundamentals for censoring data are also important: with a θ^* of 7.4, 58 observations are set to zero.[11] Therefore, the specification with BCI seems to fit better the data for consumption and capture the channel of expectations.

Our results also show that the impact of any of the expectations indicator is greater when we consider fundamentals and censor observations by a threshold value. All the threshold models with censored data have statistically significant parameters for the expectation variable.

Furthermore, when fundamentals are included, the optimal threshold and the number of censored observations are higher for BCI (58 out of 63 observations are censored) and for MDG (48 out of 63 observations are censored). For the estimations with Indicca, less than half of observations are censored (only 30 out of 63 observations). Therefore, the impact of movements above certain threshold value in expectations is more important over the behavior of consumption for the cases of BCI and MDG.

Figure 5 shows those periods in which values for the expectations indicator are censored. Periods in which the indicator is not censored (red areas) imply that there are large movements in expectations. Moreover, it is worth noting that the time period where these indicators are uncensored repeatedly coincides with that of the great fall and recovery occured between 2008 and 2010 (international financial crisis). Regarding the censored values for Indicca's case, the idea of "large movements only matter to explain future consumption behavior" seems not to be completely justified.
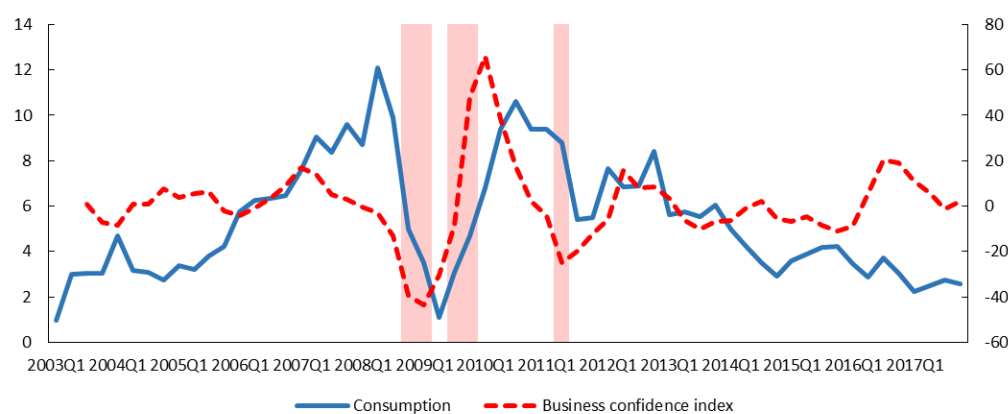
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[11] Dees and Soares (2011) find that the threshold value increases when economic fundamentals are included for the case of the United States.
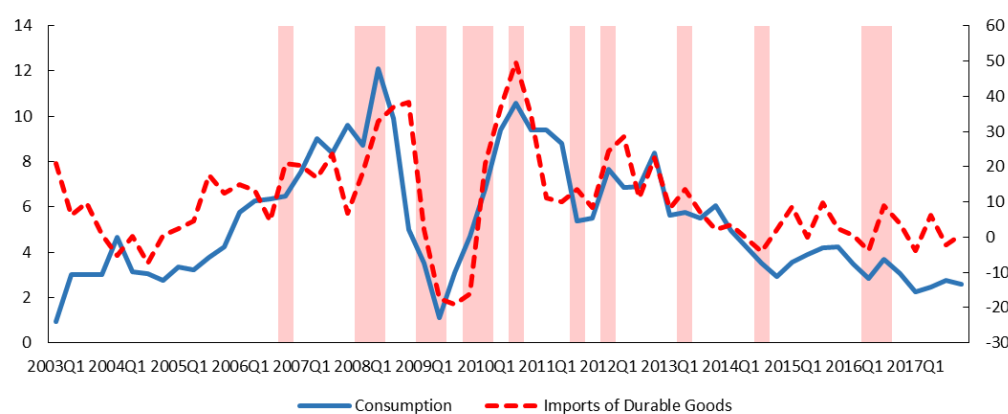
FIGURE 5 – CENSORED AND UNCENSORED PERIODS

A: INDICCA

Consumption —— Indicca - - -

B: BUSINESS CONFIDENCE INDEX

Consumption —— Business confidence index - - -

C: IMPORTS OF DURABLE GOODS

Consumption —— Imports of Durable Goods - - -

NOTES: RED AREAS SHOW PERIODS WHERE EXPECTATIONS VALUES UNDER A THRESHOLD ARE UNCESORED.

Out-of-sample forecasting

In this section, we perform out-of-sample estimations based on the estimation of Equation (11). Each of them consists of one-step ahead forecasts over the period 2015Q1-2017Q4. Figure 6 presents three types of specifications: without expectations indicator, with expectations indicator, and with censored expectations indicator.

For the Indicca's case, the model without the expectation indicator outperforms most of the time the other models, while the censored data seems to produce the largest forecast errors. For BCI, the three results seem to be very similar so it is difficult to discern which has the smallest forecast errors. Finally, the model with censored data for MDG has the smallest absolute forecast errors.

Table 4 reports the RMSE for each model. In line with the graphic analysis, models with expectations indicator present a smaller RMSE than models without this variable when BCI or MDG is considered. The model with MDG presents the greatest gain (0.92) when it is compared with the model without this variable. BCI also presents gains when it is incorporated (0.96). However, only the threshold model for MDG has the smallest RMSE i.e. has gains for introducing MDG with censored data.

FIGURE 6 – ABSOLUTE FORECAST ERRORS FOR OUT-OF-SAMPLE FORECAST

A: INDICCA

B: BUSINESS CONFIDENCE INDEX (BCI)

C: IMPORTS OF DURABLE GOODS (MDG)
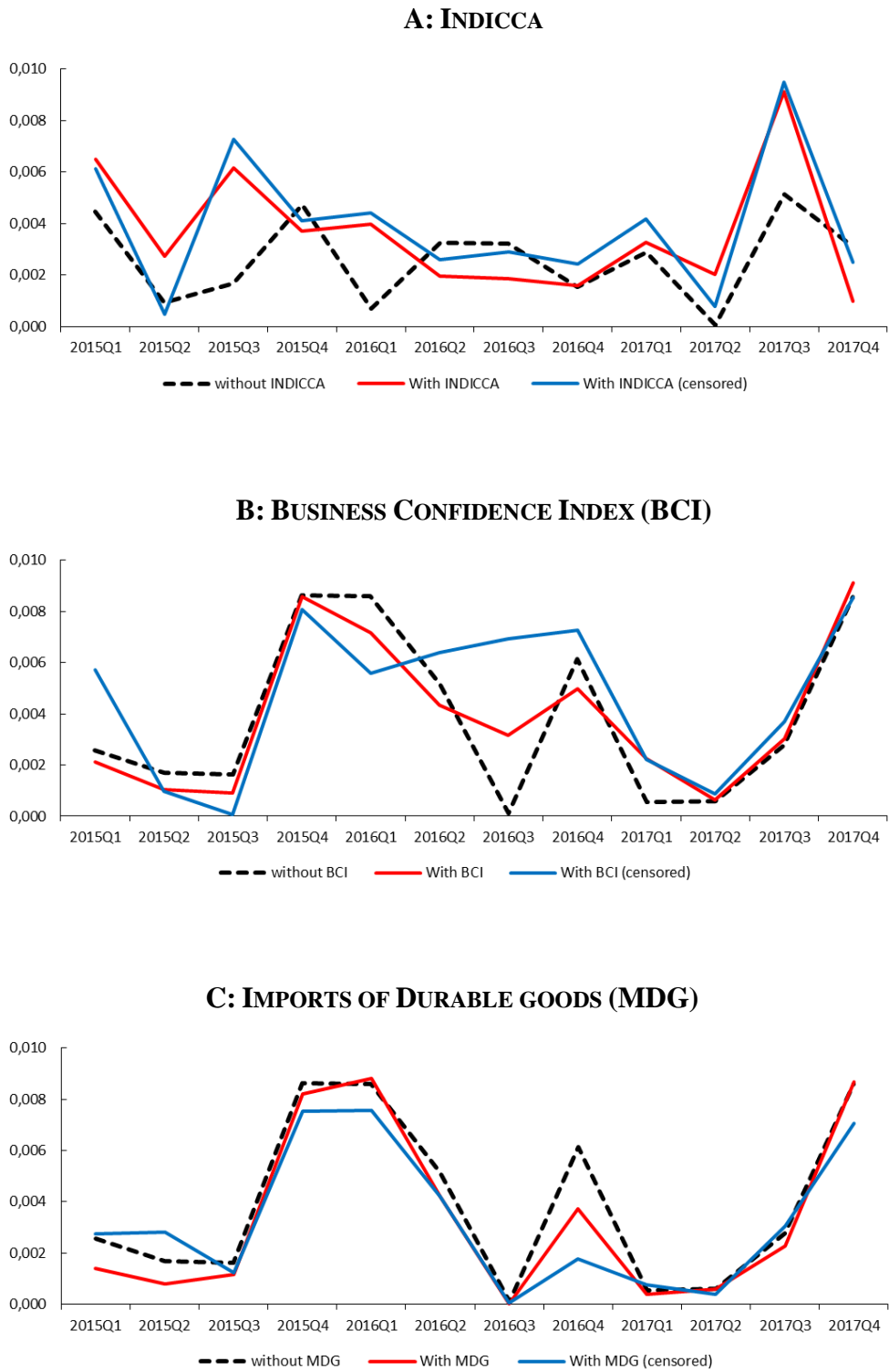
TABLE 4 – ROOT MEAN SQUARE ERRORS FOR OUT-OF-SAMPLE FORECAST

Equation	$INDICCA_t$	BCI_t	MDG_t
Without indicator (1)	0.0031	0.0051	0.0051
With indicator (2)	0.0043	0.0049	0.0047
With censored indicator (3)	0.0047	0.0055	0.0042
(2) / (1)	1.4062	0.9596	0.9232
(3) / (1)	1.5151	1.0886	0.8317

NOTES: RATIOS BELOW 1 INDICATES GAINS FOR INCLUDING A NEW VARIABLE IN TERMS OF RMSE. IN EQUATION (11), IT IS ESTIMATED WITH 3 LAGS FOR $Indicca_t$, AND 4 LAGS FOR BCI_t AND MDG_t .

5. CONCLUSIONS

We evaluate the importance of the expectations channel in private consumption dynamics. While in general it has a small contribution relative to other traditional fundamentals, it seems to have periods in which such contribution becomes important.

While the Business Confidence index captures the implicit dynamics in consumption when a shock in expectations occurs, imports of durable consumption goods seem to do a better job in forecasting consumption based on an expectation channel. This result is in line with those in Barsky and Sims (2012) under the argument of "animal spirits" on the side of the firms, and with that in Carroll et al. (1994) in which expectations from forward-looking life-cycler consumers are better for understanding the underlying dynamics in consumption.

We also find that the variable associated with the expectation of general managers tends to anticipate big swings in consumption i.e. managers seem to anticipate future changes in the behavior of households which in time also impact the aggregate consumption. This result is consistent with an expectations channel at work.

In agenda remains to build a model that identifies the source of the change in expectations, in line with Barsky and Sim (2012).

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