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Are business tendency surveys useful to forecast private investment in Peru? A non-linear approach

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Are business tendency surveys useful to forecast private investment in Peru? A non-linear approach[1]

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Abstract:

We use the results of business tendency surveys (BTS) to forecast private investment growth in Peru, exploring the possible non-linear link between the BTS and private investment for forecasting purposes. We find that business confidence indices extracted from BTS, in particular the one calculated by the Central Reserve Bank of Peru (CRBP), are useful to forecast private investment growth in Peru. Moreover, models constructed only with indices extracted from BTS have a higher predictive power than models including control variables such as lagged GDP growth, inflation or interest rates. We also find that non-linear models are not superior to linear ones in forecasting Peruvian private investment. Additionally, the linear model finally selected would allow us to estimate real private investment growth for the current quarter with a 75-day lead with respect to the official publication date, almost twice the lead associated with the estimation methodology used by practitioners.

JEL Classification : E22, E27, E32, E37.
Keywords : Business Tendency Surveys, Business cycles, Private Investment, Forecasting.

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1 Introduction

Short-term business cycle surveillance is key for government officials and private sector participants. To the former, it allows them to determine the correct timing to implement or withdraw measures of economic stimulus. To the latter, it helps them to adjust their market strategies in order to reduce losses on the verge of recessions or to achieve great profits when facing the beginning of a recovery phase.

From all the variables comprising GDP in the expenditure side, the one that portrays the most valuable information on business cycle turning points is private investment due mainly to its sudden and violent shifts when an economy moves from a recovery to a recession phase or vice versa (Ramos and Serra, 2008). This can be seen in the case of the Peruvian economy in Figure 1 in Annex 1, where we show the annual growth rate of Peruvian private investment and GDP. We can see that not only is the growth rate of private investment larger than that of GDP, but also that it changes with more violence with respect to GDP growth as seen in the case of the 2008-2009 global recession associated to the international financial crisis.

Although private investment provides important information regarding business cycle phase shifts in historical terms, it is not very useful for everyday business cycle monitoring conducted by private sector analysts and policy-makers. This is due to the contemporaneous relationship between GDP and private investment as shown in Figure 2 in Annex 1, where we portray the dynamic correlation of the cyclical component of these variables. The latter eliminates the possibility to use private investment as a leading index of changes in GDP, given the fact that both variables for the current quarter are published with a two-month delay.

Thus, in order to use private investment for short-term business cycle monitoring it is necessary to find a new tool which allows us to forecast its evolution. One way to proceed is to find the determinants of private investment in order to anticipate its evolution and, with that, anticipate business cycle phase shifts. In this line, theoretical and empirical literature have focused on private investment determinants[1] which are not useful to detect possible business cycle shifts in real-time since they are published also with delay. Additionally, the large number of possible determinants proposed by the theoretical and empirical literature complicates the task of predicting private investment since we would require many forecasts of the explanatory variables to predict the dependent variable, which, in turn, increases the forecast uncertainty.

Therefore, Naboulet and Raspiller (2004), and Ramos and Serra (2008) proposed business tendency surveys (BTS) as useful tools to overcome the previously mentioned problems and, thus, anticipate the evolution of private investment. As mentioned by Pindyck (1991), one of the main features which differentiate private investment from other GDP components is its irreversibility. That means that the cost of investing in machinery, equipment or infrastructure cannot be fully recovered in a subsequent sale. Hence, investment decisions require a careful analysis, especially regarding key variables such as expected sales and costs which are surrounded by great uncertainty or incomplete information. In this regard, expectation variables extracted from BTS could reflect the true intention to invest which is the result of the unknown process of decision-making of businessmen. From this, it would only be necessary to monitor variables extracted from BTS since they already synthetize the information contained in the possible determinants of private investment, be them current or expected. Moreover, the fact that these series are not revised backwards and are published with a very short delay makes them

[1] See Section 2.

potentially useful to anticipate the evolution of private investment with promptness and reliability in short-term business cycle analysis.

In Peru, there are two business confidence indicators available. One calculated by the Central Reserve Bank of Peru (CRBP) and the other calculated by Apoyo Consultoría, a local business consulting firm. As shown in Figure 3 and 4 in Annex 1, both indexes seem to have a very close evolution with private investment growth. First, this close relationship can be observed in the period from mid-2003 to mid-2008 characterized by a buoyant world economy, rising commodity prices[2], declining financial costs and large FDI inflows to emerging markets. This context allowed private investment growth to move from almost 10% year on year (YoY) at the beginning of 2003 to almost 30% YoY in mid 2008, an acceleration that was accompanied by increasing business confidence. Second, in the 2008-2009 period associated to the international financial crisis, business confidence indicators anticipated the sharp drop in private investment growth and also its recovery. Indeed, after a clear business confidence collapse, the Peruvian economy experienced a 25% YoY drop in private investment; and after a rapid pick-up in business confidence, private investment returned to pre-crisis growth rates of 30% YoY. And third, this phenomenon of co-movement seems to be observed once more at the end of the sample in a period characterized by falling business confidence during a period of local political uncertainty generated by the presidential election process in early 2011. In this case, private investment growth moved from almost 30% YoY in mid-2010 to just 8% YoY in the fourth quarter of 2011. However, the upward correction seen in business expectations in the third and fourth quarter of 2011 seems to herald a possible recovery in private investment after almost three quarters of deceleration.

Based on this apparent predictive power of BTS on private investment under different scenarios such as international crisis or local political uncertainty, Peruvian policy-makers and private sector analysts monitor these variables closely. However, the relationship of these variables with private investment in terms of predictive power has not been yet analyzed in applied literature. In this regard, private investment analysis in Peru has been only limited to its long-term determinants[3], with no particular focus on short-term analysis of the business cycle. In contrast, international literature has found extensively the usefulness of indicators extracted from BTS for private investment forecasting. This can be seen in Cademyr and Karabudak (1994) for Turkey; Larsen (2001), and Barnes and Ellis (2005) for England; Ferrari (2005) for France; Abberger (2005) for Germany; Friz and Gayer (2008) for the Eurozone; Ramos and Serra (2008) for Portugal; and Schenker (2011) for Switzerland.

The last important feature worth mentioning regarding private investment is its non-linear character. For example, although interest rates remain unchanged, the movement from tranquility to uncertainty (recovery to recession) would make this variable less important in an investment decision. This would imply that the parameters which link private investment to its main determinants can change according to business cycle phase shifts as suggested by Ghassan and Al-Dehailan (2007), Naboulet and Raspiller (2004) as well as Ramos and Serra (2008). However these authors do not propose a non-linear model to characterize private investment with explanatory or predictive purposes. In this regard, we state that business confidence indicators could also be useful to characterize the possible non-linear nature of private investment. Therefore, non-linear models would turn out to be more suitable for private investment modeling.

[2] Especially copper, zinc and gold, the main exporting products of Peru.
[3] See Loyola (2009) and Mendiburu (2010).

From this discussion, three questions naturally arise which will be the focus of this paper: (i) Are business confidence indexes useful to forecast private investment in Peru? If the answer to the latter is affirmative, (ii) are business confidence indexes enough to explain private investment or more determinants must be included for the Peruvian case? And finally, (iii) are non-linear models superior to linear ones to predict the evolution of Peruvian private investment?

We find that business confidence indexes extracted from BTS, in particular the one calculated by the CRBP, are useful to forecast private investment growth in Peru. Moreover, models constructed only with indexes extracted from BTS have a higher predictive power than models augmented with control variables such as lagged GDP growth, inflation or interest rates. We also find that non-linear models are not superior to linear ones to forecast the evolution of private investment growth in Peru. Finally, the non-linear model finally selected would allow us to estimate current real private investment growth with a 75-day lead with respect to the official publication date, almost twice with respect to the lead gained from the current estimation methodology used by practitioners.

The structure of this paper is as follows. Section 2 deals with the relationship between BTS and private investment according to theoretical and empirical economic literature. Section 3 presents the econometric methodology and the main results. Finally, Section 4 shows the main conclusions.

2 What does economic literature say about the relationship between business tendency surveys and private investment?

2.1 Business Tendency Surveys and Private Investment in the theoretical literature.

According to Ghura and Goodwin (2000), there are four general approaches to model private investment in existing literature. These four categories include the accelerator model of Keynes (1936), the neoclassical model associated to Jorgenson (1963), the Tobin Q model associated to Tobin (1969) and the model of expected profits which shows different variants following Zebib and Moughalu (1998). From these four approaches, we can make a summary, following Mlambo and Oshikoya (2001), of the existing theories of investment in the following equation: $I_t = I(\Delta m, r, q, \mu)$, where Δm is the conditional expectation on future market conditions, r represents the financial conditions facing the firm, q is the value of the firm in the capital market and μ is the political and economic uncertainty.

In empirical terms, among the variables that reflect Δm we can mention lagged GDP growth (Blejer and Kahn, 1984; and Greene and Villanueva, 1991), inflation (Greene and Villanueva, 1991) and real exchange rate (Serven and Solimano, 1989). Indeed, if the overall economy is more dynamic, the private investment outlook will improve and private investment growth will accelerate. Also, as inflation rises, private investment project's costs increase. This affects negatively the ability of the firm to generate internal funds and also the profitability of the backlog of investment projects, thus reducing private investment. Finally, an increase in the real exchange rate raises real costs of imported goods, in particular capital goods, which increases the costs of acquisition of new capital. Besides, in the case of highly dollarized economies such as the Peruvian economy (Armas and Grippa, 2006)[4], an increase in the real exchange rate increases the real cost of debt servicing in foreign currency of firms whose revenues are expressed in local currency, thus reducing their profits. This process is called "balance sheet effect". All these channels imply a negative relationship between real exchange rate and private investment.

[4] Credit dollarization ratio reached 45% in June 2012, while deposit dollarization ratio reached 43%.

Among the variables that reflect r we can mention credit volume (Wai and Wong, 1982; Greene and Villanueva, 1991; and Ndikumana, 2000) and interest rates (McKinnon and Shaw, 1989). In the case of credit volume, this variable represents the main financial source of firms in emerging markets given the low development of capital markets in those economies, so its relationship with private investment is expected to be positive. In the case of the interest rate, it should have a negative relationship with private investment since it represents the financing cost of an investment project.

Even though Δm and r have been analyzed in empirical studies in international literature, μ has been mostly neglected given the difficulty to approximate this variable notwithstanding the fact that μ could be the most important factor to explain private investment dynamics in the short-run. Moreover, while all the studies revised up to this point have been based on theoretical models constructed or assumed in order to explain private investment performance, the truth is that the actual decision-making process is a non-observable phenomenon. As stated by Ramos and Serra (2008) the identification of the structural interactions that explain investment decisions is always a complex task. This complexity does not only reflect the difficulty to capture μ, but also the fact that expectation formation mechanisms of economic agents may be sector-dependent. For instance, Ramos and Serra (2008) mention that "*some firms may invest as a reaction to a favorable economic situation, possibly unexpected, while others invest because they expect higher demand over the medium or long run. This may co-exist with firms that do not invest at all simply because they have already achieved their desired capital stock. In addition, the driving forces among different sectors may be rather different, for example between residential and productive investment*".

Therefore, Naboulet and Raspiller (2004), and Ramos and Serra (2008) proposed a more pragmatic approach based on surveys conducted on investment decision-makers. In this regard, BTS would represent more plausibly the actual investment intention of businessmen based on an unknown process which must take into consideration all or part of the variables discussed above, including μ and even other variables unexplored by the theoretical literature. Hence, this type of indicators is useful for private investment forecasting since they synthesize all the information necessary for this task, bearing in mind as well the fact that BTS are published with promptness and are not revised backwards.

Finally, Ghassan and Al-Dehailan (2007), Naboulet and Raspiller (2004) as well as Ramos and Serra (2008) point to the fact that the determinants of private investment can affect it differently throughout time. That means that private investment may have a non-linear relationship with its determinants, that is, the relationship between these variables changes across regimes or states in the economy. However, these authors neither do they propose a theoretical model to explain this non-linear relationship nor a variable that could potentially trigger the regime change.

2.2 Business Tendency Surveys and Private Investment in the empirical literature.

Following the suggested theoretical relationship between private investment and BTS explored in Section 2.1, several efforts have been conducted in the empirical field to confirm this relationship. In a first stage, these efforts were focused on analyzing the degree of correlation between these variables as seen in Cademyr and Karabudak (1994) for Turkey and Barnes (2005) for England. Not surprisingly, these authors found that BTS and private investment have a very high degree of correlation which, in some cases, reaches 0.8.

In a second stage, econometric efforts were placed to explore the possible predictive ability of BTS with respect to private investment. In this regard, Larsen (2001) evaluates the predictive ability of BTS regarding private investment in England using linear autoregressive models and Mean Squared Prediction Error (MSPE). Abberger (2005) includes in the econometric approach used by Larsen (2001) the use of additive autoregressive models to explore the relationship between BTS and private for Germany. These models assume linearity in the relationship between private investment and its lag structure as seen in autoregressive models, but estimates parameters using non-parametric techniques, not OLS. Ferrari (2005) analyzes the relationship between BTS and private investment using a special survey conducted in France. In this survey, businessmen are first asked about their investment intentions at the beginning of the year, and then asked about the changes on their initial investment plans on a quarterly basis. Given that in the Portuguese economy there are many BTS available, Ramos and Serra (2008) use principal component analysis in order to aggregate the information contained in this indexes into one series. Then, they explore the predictive ability of this synthetic business confidence indicator with respect to private investment using linear autoregressive models and Root Mean Squared Prediction Errors (RMSPE). Finally, Schenker (2011) explores the same relationship for Switzerland accounting for the possible model selection uncertainty in the forecasting process. To achieve this objective, the author used the Bayesian Model Averaging (BMA) method and the Least Absolute Shrinkage and Selection Operator (LASSO) method in order to find the optimal aggregation of linear models to produce forecasts which were analyzed using RMSPE. Although this entire previous work deploys different econometric approaches to evaluate the relationship between BTS and private investment, the conclusion is unique and straightforward: the inclusion of BTS enhances the predictive ability of models to forecast private investment.

As seen in Section 2.1, many authors have suggested the possible non-linear nature of the theoretical relationship between BTS and private investment. However, these authors have not proposed a non-linear model to characterize private investment. In this regard, we state that business confidence indicators could also be useful to characterize the possible non-linear nature of private investment. That is, business expectations shifts (from pessimism to optimism and vice versa) could potentially capture turning points in private investment behavior as we move from one phase of the business cycle to another (recovery to recession and vice versa).

3 Econometric methodology and main results

Our econometric methodology will undergo four steps. First, we will review the two business confidence indexes to be used. Second, we will conduct stationarity tests on these indexes and private investment, as well as causality tests between these indexes and private investment. Third, we will present the linear and non-linear models to be used and its results. Finally, we will present the superior predictive ability tests and their main results.

3.1 The Business confidence indicators

In Peru, there are two available business confidence indicators. The first one is developed by the CRBP based on monthly surveys conducted on about 600 firms about their appraisal of state of the economy in three months[5]. The three possible answers: “Better”,

[5] BTS indexes calculated by the CRBP include: expected sales in three months, expected demand in three months, business financial situation, access to credit, business environment, business inventories, and appraisal of the economy in three months. Among these, the BTS index regarding the appraisal of the state of the economy in three months is the most

“Same” or “Worse” are tabulated and transformed into a diffusion index, where a value of 100 indicates that all firms expect a better economic situation, a value of 0 indicates that all firms expect a deterioration of economic conditions and a value of 50 indicates a neutral balance of answers .

The second is developed by the business consulting firm Apoyo Consultoría on a quarterly survey to about 250 businessmen (managers and company executives) in which they are asked directly on their prospects about the pace of investments in their companies in the next 6 months. In this survey, there are three possible answers: “Accelerate”, “Maintain” or “Reduce” the pace. The final expectations index is made of the net balance of responses; i.e. the difference between the percentage of those who will accelerate the pace of investment projects and the percentage of those who want to reduce this pace.

An important feature worth reviewing regarding these indexes is their possible bi-modality. In this case, central tendency indicator of responses in each point in time would not reflect well the distribution of answers to the survey. As pointed out in Carrera (2012), the business confidence indicator elaborated by the CRBP shows symmetric and unimodal responses, so central tendency indicators of these series are a good approximation to the distribution of answers in the survey. Given limited availability of date regarding the decomposition of the business confidence index elaborated by Apoyo Consultoría, we have not been able to confirm the uni-modality hypothesis on theses series. However, we would expect that they also share the same pattern as the CRPB’s business confidence index.

Additionally, it is worth mentioning that the business confidence index constructed by the CRBP has a response rate of 50%, which is statistically significant given the population of 8500 companies considered (CRBP, 2011). Surveys conducted by Apoyo Consultoría have a response rate of 90%. Although this survey is conducted on Apoyo’s clients so it does not have a matching population, Apoyo’s clients belong to the largest companies in several sectors. Hence, we would expect Apoyo’s business confidence index to be representative of the population of Peruvian firms in terms of investment decisions.

Taking into consideration the starting date of both series, the period of analysis will be established from 2003Q2 to 2011Q4. This span may seem short in order to test the explanatory and predictive power of business tendency surveys on private investment. However, as stated by Katona (1968), agents in the economy can’t be forever optimistic or pessimistic. Hence, the only time frame where expectations can affect private investment is in the short-run.

Before proceeding with the description of the methodology, we must take into account the difference in frequency between private investment and the series of expectations. There are two options: convert into quarters the monthly series of expectations (in particular the one calculated by the CRBP), or convert into months the quarterly series of private investment. Following Jonson 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 from month to month[6]. It should be mentioned that real private investment was taken from the statistical series of CRBP and corresponds to real private fixed investment.

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adequate to capture the μ component discussed in Section 2.1, given the fact that we will include control variable to capture the impact of financial conditions (r) and expected economic conditions (Δm).

[6] This same method of quarterly averaging was applied to the series of expectations of Apoyo Consultoría which began to be held monthly since April 2011 to capture changes in business expectations due to the increasing electoral uncertainty.

3.2 Stationarity and causality tests

Before proceeding to specify the models to be used, it is convenient to conduct a stationarity analysis on our variables of interest. Therefore, we apply different unit root tests on our variables: the ADF test, Phillips & Perron (PP), KPPS, Ng & Perron and Zivot & Andrews. These tests are used in our main variables: private investment and business expectations. In Table 1 we can observe that the results based on unit root tests without structural breaks show us that the annual percentage change in private investment (Private_investment) and expectation variables in levels (expect_apoyo and expect_pcb) are both I(1) variables.

However, these results could be biased. From a graphical inspection, we can observe in Figure 3 and 4 that these variables may have experienced a structural break in 2008, which is a direct effect of the international financial crisis; besides, there may be another structural break in the first quarters of 2011; this is due to a context of political risk associated with the last presidential election. To verify this suspicion, we analyzed our series under the Zivot & Andrews test. The results verified that our variables are stationary but with a structural break in the year 2008 (see Table 1) and not for the first months of 2011. Hence, we can conclude that annual percentage of private investment and BTS variables in levels are stationary, therefore we will include these variables in our models. These results support the idea of stationarity on the variables under study, because we consider private investment in annual percentage change (YoY) and expectations variables in levels. The latter are by construction stationary given the fact that firms or consumers cannot be permanently optimistic or pessimistic (Katona, 1968), so business confidence indexes must have a mean-reverting process.

Table 1. Unit root tests results, 2003Q2-2011Q4

Variable	ADF		PP		KPSS	NP				Zivot & Andrews
	statistic	p-value	statistic	p-value	statistic	Mza	Mzt	Msb	Mpt	Break point
Private Investment Growth	-2.052	0.553	-2.522	0.316	0.084*	-24.513***	-3.493***	0.142***	3.761***	H1-2008Q2
d_Private Investment Growth	-3.94	0.020**	-3.739	0.032**	0.040*	-23.339**	-3.415**	0.146**	3.905**	
Expect Apoyo	-2.51	0.321	-2.628	0.271	0.108*	-9.425	-2.142	0.227	9.782	H1-2008Q3
d_Expect Apoyo	-5.694	0.000***	-6.057	0.000***	0.076*	-16.332*	-2.854*	0.144**	5.599	
Expect PCB	-2.225	0.461	-2.649	0.262	0.073*	-32.646***	-4.033***	0.123***	2.830***	H1-2008Q2
d_Expect PCB	-3.794	0.028**	-3.359	0.073*	0.050*	-29.041***	-3.790***	0.130***	3.252***	
Critical Values										
1%					0.216	-23.8	-3.42	0.143	4.03	
5%					0.146	-17.3	-2.91	0.168	5.48	
10%					0.119	-14.2	-2.62	0.185	6.67	

ADF test with trend and intercept term, lag length selected using Modified Schwarz, PP test with trend and intercept term using Barlett Kernel and Newwy-West Bandwidth, KPSS test with trend and intercept term using Barlett Kernel and Newey - West Bandwith, Ng Perron test with trend and intercept term (four statistic Mza, Mzt, Msb and Mpt) lag length selected using Modified Schwars with special AR Gls-detrended.
*** Significance at 99% confidence level.
** Significance at 95% confidence level.
* Significance at 90% confidence level.
d_.... : indicates first difference of the variable included.

To complement the stationarity analysis shown above, we will perform a Granger causality analysis. This analysis was conducted over the whole available sample (2003-2011). The results are presented in Table 2, which contains p-values for F-statistic of redundancy test. In the column denoted with "$x\ not\ \rightarrow y$" there are estimations of the probability that a BTS variable is not a cause – in Granger`s sense - of the annual change of real private investment. In the column "$y\ not\ \rightarrow x$" you may find probabilities that the annual change of private investment is not a cause of BTS variables.

Table 2: Granger Causality test between expectations indicators (x) and private investment growth (y), 2003Q2-2011Q4[7]

	y not → x	x not → y	Period of max correlation with private investment growth	Maximum correlation
Expectations PCB	0.000	0.470	-1	0.831
Expectation Apoyo	0.000	0.265	-1	0.774

We find that both BTS variables Granger cause annual changes in real private investment. This result leads us to think that these variables may be potential candidates for forecasting models of real private investment. Furthermore, we include in this analysis a simple dynamic cross-correlation exercise to assess the maximum correlation level between the business confidence variables and real private investment growth, as well the lag/lead period where this maximum correlation occurred. We found that the maximum correlation for both business confidence variables and real private investment growth was registered in period t-1, that is, business confidence indexes lagged one quarter.

This implies that business confidence variables may be potentially useful for private investment forecasting. Moreover, we found that these maximum correlations are high (greater than 0.7), and in particular, the business expectations variable calculated by the PCB has the highest correlation. This may imply that this variable may be the optimal business confidence index in terms of explanatory and predictive power of real private investment growth.

Finally, it is important to note that although the business confidence index elaborated by Apoyo is constructed based on the firm's appraisal for its pace of investment in the next six months, the maximum correlation is found in period t-1, that is, only 3 months since we are dealing with quarterly data. This may imply that respondents of Apoyo's surveys actually have a 3-month investment horizon which they use in order to respond to the survey.

3.3 The models

3.3.1 The linear models

The first step in the evaluation of the impact business expectations on private investment is to develop linear models. In this line, we will first develop a "naïve" model which will serve as benchmark to compare the explanatory and predictive power of more complex models going forward. The naïve model is an AR(p) model:

$$I_t = v + \sum_{i=1}^{p} \alpha_i I_{t-i} + e_t , \tag{1}$$

where v_t is the intercept, the variable I_t $I_t$represents private investment, and ε_t is and i.i.d. white noise.

Second, we will develop a model that incorporates the variables extracted from BTS, which will allow us to identify the impact of investment expectations on investment decisions of firms and, thus, respond to question (i) *Are business confidence indexes*

[7] 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.

useful to explain and forecast private investment in Peru? in Section 2. The model is as follows:

$$I_t = v + \sum_{i=1}^{p} \alpha_i I_{t-i} + \sum_{j=1}^{q} \beta_j \text{expect}_{t-j} + e_t, \tag{2}$$

where the variable expect_t represents business expectations. It is important to note that we do not assume a particular value for the lag of the expectations variable. That is, we will estimate the best specification for the lag structure of the expectations variables which will let us assess if BTS can lead private investment.

Third, we will develop a model that incorporates control variables instead of variables extracted from BTS. This model will allow us to assess if variables extracted from BTS have a greater explanatory power than private investment determinants identified by applied literature (question (i) in Section 2).

$$I_t = v + \sum_{i=1}^{p} \alpha_i I_{t-i} + \sum_{k=1}^{k} \gamma_k X_{t-k} + e_t, \tag{3}$$

where X_t is a matrix containing the short-term private investment determinants identified in Section 2. Having defined the matrix X_t, it is necessary to review its components, their sources and transformations. Credit volume is approximated by the growth of financial system credit to the private sector deflated by inflation. The interest rate will be proxied by the interest rate of commercial credit in a 360-day term or longer, taken from the database of the Superintendence of Banking and Insurance (SBI). We will use the 360-day term or longer, because such term is the most appropriate to evaluate investment financing for firms in the medium and long-term, unlike the working capital credit to firms that would be represented by the interest rate of commercial credit less than 360 days. Inflation will be proxied by the annual change in Metropolitan Lima CPI (Capital of Peru) taken from the statistical series of the PCB. The real exchange rate corresponds to the annual percentage in index of multilateral real exchange rate series taken from the Central Bank statistics. Finally, GDP corresponds to the annual growth of real quarterly GDP taken from the PCB statistics.

Fourth, we will estimate a final model that contains short-term private investment determinants and variables extracted from BTS. This model will allows us to respond to question (ii) *are business confidence indexes enough to explain private investment or more determinants must be included for the Peruvian case?* in Section 2.

$$I_t = v + \sum_{i=1}^{p} \alpha_i I_{t-i} + \sum_{k=1}^{k} \gamma_k X_{t-k} + \sum_{j=1}^{q} \beta_j \text{expect}_{t-j} + e_t. \tag{4}$$

To choose the best specification for each of the 4 proposed models, we will compare the results of different specifications having as decision criteria normality and autocorrelation tests of residuals, individual significance of explanatory variables and information criteria.

Finally, the estimation of these linear models will allow us to identify, based on information criteria, which of the two indicators of investment expectations existing in Peru has a greater explanatory power of private investment. Since the business confidence indicator calculated by Apoyo is taken directly from managers and chief executives (unlike the business indicator calculated by the PCB which is calculated through e-mailed surveys), it could provide us with a more accurate approximation of the true intentions of the firm's investment plans.

Table 3: Linear models, 2003Q2-2011Q4

	Model 1'	Model 2'	Model 3'	Model 4'	Model 5'	Model 6'
Private Investment Growth (-1)	0.763***	0.559***	0.550***	0.273	0.413**	0.336*
	(6.776)	(6.253)	(6.773)	(1.470)	(2.236)	(1.996)
Expect Apoyo (-1)		0.258***			0.139	
		(5.584)			(2.259)	
Expect PCB (-1)			0.740***			0.487***
			(6.585)			(2.842)
Interest Rate - National currency (-1)				-2.939***	-2.156**	-1.213
				(3.727)	(2.639)	(1.298)
GDP growth (-1)				2.948***	1.607*	1.598*
				(3.990)	(1.761)	(1.957)
Adjus. R squared	0.569	0.777	0.811	0.793	0.818	0.832
Jarque-Bera	0.072	0.741	0.930	0.969	0.894	0.844
AIC	7.196	6.587	6.397	6.540	6.437	6.353
BIC	7.285	6.772	6.530	6.720	6.661	6.578
RSS	2439	1211	1035	1089	926	852

Absolute value of t-statistic in parenthesis.
*** Significance at 99% confidence level.
** Significance at 95% confidence level.
* Significance at 90% confidence level.

In Table 3 we can observe the results of the estimations of the linear models discussed above. Model 1' corresponds to the best specification of model depicted in equation (1) discussed above. Although this models shows a good fit to the data (high adj. R squared), it depicts non-normal residuals as seen in the results of the Jarque-Bera test. Model 2' and Model 3' show the best specification for model depicted in equation (2) discussed above using as proxies of expect_{t-j} the business confidence indicators calculated by Apoyo and the PCB, respectively. We can see that business confidence affects private investment growth with a lag of 1 quarter. That is, business confidence leads private investment growth as found in the dynamic cross-correlation analysis conducted in Section 3.2. Moreover, Model 3' which includes the business confidence indicator calculated by the PCB performs marginally better than Model 2' which includes the business confidence indicator calculated by Apoyo. This can be seen in the fact that Model 3' depicts a higher adj. R squared, lower information criteria and a lower residual sum of squares. It is worth noticing that both Model 2' and Model 3' show a better fit to the data than Model 1'. This implies that the inclusion of business confidence indicator improves the explanatory power of models of private investment.

Model 4' shows the best specification of model shown in equation (3) discussed above. We can see that the best control variables to explain private investment growth are lagged interest rates and lagged GDP growth. Real credit volume growth, inflation and real exchange rate variations are non-significant. In the case of real credit growth, this is possibly due to the fact that interest rates already contain the information regarding overall financial conditions facing the firm. In the case of inflation, this is possibly due to the fact that it remained relatively under control even during the pre-crisis period characterized by rising oil and food commodity prices. And in the case of real exchange rate variations, this is possibly due to the fact that it did not affect private investment since the ample PCB's net international reserves avoided a sharp real exchange rate depreciation during the international financial crisis of 2008-2009[8]. This means that in Peru, financial conditions and the improvement in the business outlook caused by a buoyant economy are important drivers of private investment. Finally, Model 5’ and Model 6’ shows the best specification for model depicted in equation (4) discussed above. We can see in Model 5’ that business confidence calculated by Apoyo is non-significant in the presence of control variables. However, we can see that business confidence calculated by the PCB is not only significant in the presence of control variables (see Model 6’); but also that in its presence, all other control variables are non-significant. First, this means that business confidence variables alone, in particular the one calculated by the PCB, are enough to explain the dynamics of private investment since they contain all the information gathered in other control variables regarding the unknown process of private investment decision-making. And second, this means that the business confidence indicator calculated by the PCB has a larger explanatory power of private investment than the one calculated by Apoyo. This may respond to the fact that the business confidence indicator calculated by the PCB, despite the fact that it is not constructed from direct surveys to chief executives of firms, gains explanatory power on its large coverage (600 firms). Therefore, the best linear explanatory model of private investment growth selected is Model 3’.

3.3.2 The non-linear Threshold Autoregressive Model (TAR)

As suggested by Ghassan and Al-Dehailan (2007), Naboulet and Raspiller (2004) as well as Ramos and Serra (2008), determinants of private investment can affect it differently throughout time. This possible non-linear nature requires non-linear econometric models for private investment modeling. Moreover, given the fact that private investment depicts sudden and violent movements when an economy moves from a recovery to a recession phase or vice versa, we need econometric models which suppose abrupt regime shifts to model private investment.

In this regard, Threshold Autoregressive Models (TAR) introduced by Tong (1990) meet the objectives described above[9]. These models are piecewise autoregressive linear models defined by a particular variable called transition variable. This variable is the one that marks regime shifts in the model. For expository purposes, if we want to redefine Model 4 in Section 3.3.1 as a non-linear TAR model, then following Krolzig (2002):

$$I_t = \left(v_1 + \sum_{i=1}^{p} \alpha_{1i} I_{t-i} + \sum_{k=1}^{k} \gamma_{1k} X_{t-k} + \sum_{j=1}^{q} \beta_{1j} \mathrm{expect}_{t-j} \right) \left(1 - L\left(\mathrm{expect}_{\mathrm{t\text{-}n}}, c\right)\right) +$$

$$+ \left(v_2 + \sum_{i=1}^{p} \alpha_{2i} I_{t-i} + \sum_{k=1}^{k} \gamma_{2k} X_{t-k} + \sum_{j=1}^{q} \beta_{2j} \mathrm{expect}_{t-j} \right) \left(L\left(\mathrm{expect}_{\mathrm{t\text{-}n}}, c\right)\right) + e_t ,$$

where$\mathrm{L}(\mathrm{expect}_{\mathrm{t}}; \mathrm{c})$ $L\left(\mathrm{expect}_{\mathrm{n}}, c\right)$ is defined as follows:

$L\left(\mathrm{expect}_{\mathrm{t\text{-}n}}, c\right) = 1$, if $\mathrm{expect}_{\mathrm{t\text{-}n}} > c$;

$L\left(\mathrm{expect}_{\mathrm{t\text{-}n}}, c\right) = 0$, if $\mathrm{expect}_{\mathrm{t\text{-}n}} \leq c$.

[8] The PCB sold almost US$10 bn. (3% of GDP) in mid 2008 to mid 2009 to dampen exchange rate depreciation and to avoid the negative balance sheet effect on the Peruvian economy.

[9] We also estimated a Logistic Smoothed Transition Autoregressive Models (LSTAR) which supposes a smooth transition for the indicator function (logistic). However, we verified that goodness-of-fit indicators of TAR models were superior to those of the LSTAR models estimated. These results can be obtained from the authors upon request.

$L(\text{expect}_{\text{t-n}}, c)$ is known as the transition function, expect_{n} is known as the transition variable (the variable that marks the regime shifts in the model), and c is known as the threshold. We state that variables extracted from BTS could be potential transition variables given the fact that business confidence indicators could be useful to explain the possible non-linear nature of private investment.

As seen in the expression above, TAR models are characterized by two sets of parameters proposed to explain the behavior of the dependent variable. The suitability of each set of parameters depends on the values taken by the indicator function as follows: when expectations are below the threshold (c), the indicator function will take the value zero and "turn on" the set of parameters with subscript 1 and "turn off" the set of parameters with subscript 2. And once expectations cross the threshold (c), the indicator function will take the value one and "turn off" the set of parameters with subscript 1 and "turn on" the set of parameters with subscript 2. Using this mechanism, these models incorporate abrupt regime changes, i.e. changes in the relationship of private investment with its determinants occur immediately. In others words, we can say that according to these models, the changing behavior of private investment from a recession to a recovery phase (or vice versa) occurs when expectations cross the threshold c c.

To chose the best specification for the non-linear TAR model we rely on Tsay (1994) who proposes a four step procedure: the first step is to determine the best specification for the linear model[10], then select the transition variable (in our case, business expectations), then locate the threshold value and finally check for non-linearity. The estimation procedure will rely on the grid search method (see, Krolzig 2002) over the optimal lag of the transition variable and the optimal threshold value that minimizes the overall residual sum of squares (RSS). Then the estimation method can be represented as follows: $(c,n)^* = \arg\min_{c,n} RSS(c,n)$

A final remark on these models relates to testing for non-linearity. Due to the fact that standard tests that attempt to test the suitability of non-linear models vs. linear models - that is, the number of regimes (1 regime for linear models vs. 2 for our TAR model) - do not have a standard distribution (see Hansen, 1992), Humala (2005) proposes as an alternative to use goodness-of-fit indicators in order to select the best model. We followed this criterion and evaluated the suitability of non-linear models using the AIC, BIC and RSS.

[10]The model was estimated taking the best linear specification.

Table 4: Non-Linear TAR models, 2003Q2-2011Q4

	Model A		Model B		Model C		Model D	
	Regime 1	*Regime 2*	*Regime 1*	*Regime 2*	*Regime 1*	*Regime 2*	*Regime 1*	*Regime 2*
Private Investment Growth (-1)	0.627***	0.878***	0.774***	0.247**	0.729***	0.081	0.550**	0.152
	(4.517)	(6.669)	(8.889)	(2.373)	(3.656)	(0.408)	(2.507)	(0.713)
Expect PCB (-1)			0.973***	1.005***			0.770***	0.790***
			(6.530)	(7.997)			(3.564)	(3.403)
Interest Rate - National currency (-1)					-4.173***	-0.370	-1.213	-0.152
					(4.908)	(0.338)	(0.973)	(0.155)
GDP growth (-1)					1.544*	1.346*	1.461	0.692
					(2.041)	(1.298)	(1.432)	(0.509)
c* from Expect PCB t-1	69		63		67		63	
Adjus. R squared	0.558		0.872		0.857		0.881	
Jarque-Bera	0.104		0.199		0.981		0.099	
AIC	7.176		6.052		6.241		6.098	
BIC	7.309		6.274		6.555		6.502	
RSS	2258		654		677		522	

Absolute value of t-statistic in parenthesis.
*** Significance at 99% confidence level.
** Significance at 95% confidence level.
* Significance at 90% confidence level.

Table 4 shows the results of the best specifications of the non-linear TAR models. We verified that models including business confidence indicators calculated by Apoyo as the transition variable have lower goodness-of-fit indicators. Therefore, we only display the specifications of models estimated using business confidence indicators calculated by the PCB as the transition variable. For each model, the best specification was achieved with Expect PCB lagged one quarter, that is, the optimal transition variable for every model was $\text{Expect PCB}_{t\text{-}1}$ in line with the results of our dynamic cross-correlation analysis performed in Section 3.2. Overall, the results of the non-linear TAR models follow what we found in linear models. The inclusion of business confidence indicator (model B and D) improves the explanatory power of simpler models (model A and C). Furthermore, the inclusion of business confidence indicators, in particular the one calculated by the PCB, is enough to explain the evolution of real private investment growth, since all other control variables turn out to be non-significant (model D). Therefore, we choose model B as the best non-linear model for real private investment growth, since this model also portrays normal errors unlike model D (see Jarque-Bera test). Finally, a point to consider is the selection of the optimal model from the best non-linear and linear models. When compared by the RSS criteria, we can observe that the best non-linear Model B has a lower RSS than its linear counterpart (Model 3'). Hence, we will choose the non-linear Model B as the best overall model to explain the evolution of private investment.

3.3.3 Tests of superior predictive ability[11]

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 portrays the highest predictive power with respect to private investment. 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 2003Q2 to 2008Q2, that is a quarter before the beginning of the international financial crisis. Thus, the initial sample includes R=21 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

[11] Following Dudek (2008).

by one quarter forward and we forecasted one point (quarter) also. 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 unrestricted regression model are significantly superior to the forecasts from restricted one, we used: the Theil's ratio (called in some papers as a U statistic), the McCracken (2004) MSE-F and Clark and McCracken (2001) ENC-NEW statistics.

Theil's U statistic is defined as the ratio of the square roots 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 business expectations indexes are superior to the forecasts 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 statistics have two key advantages over the original one. First, they account for the parameter uncertainty inherent in estimating the unrestricted and restricted models that are used to form the competing forecasts. Second, Clark and 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 business confidence indexes have additional predictive power for modeling private investment (they reduce forecasting error). Clark and McCracken (2005) demonstrated that the MSE-F statistics shares a non-standard limiting distribution. Critical values fort that test are taken from Clark and McCracken tables (2001). The MSE-F test is constructed as follows:

$$MSE - F = P \times \frac{MSE_R - MSE_U}{MSE_U},$$

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 BTS variables included in the unrestricted model provides no useful additional information for predicting changes in real private investment relative to the restrictive model which excludes the BTS variables. If the restricted model forecasts do not encompass the unrestricted model forecasts, then the BTS indicators do contain information useful for predicting changes in real private investment beyond the information already contained in a model that excludes the BTS 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:

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

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 5: Assessment of the Predictive Power of the Linear Models

Statistic	Model 1'	Model 2'	Model 3'	Model 4'	Model 5'	Model 6'
MSPE	115.814	42.514	28.928	34.762	26.738	22.936
U-Theil		0.367	0.250	0.300	0.231	0.198
MSE-F		24.138***	42.048***	32.642***	46.641***	56.691***
ENC-NEW		20.242***	38.282***	33.279***	47.505***	55.125***

*** Significance at 99% confidence level.

** Significance at 95% confidence level.

* Significance at 90% confidence level.

Table 5 shows the statistics to assess the predictive ability of linear models discussed in Section 3.3.1. We can clearly see that models 2' – 6' have a superior predictive ability in comparison to the naïve model. These models not only have a U-Theil statistic lower than 1, but also significant MSE-F and ENC-NEW tests at a 99.9% significant level. Additionally, models which include expectations variables have a superior predictive power than previous who do not. In the case of models without control variables, this can be seen when comparing MSPE and U-Theil statistics of Model 2' and Model 3' versus Model 1'; and in the case of models with control variables, this can be seen when comparing MSPE and U-Theil statistics of Model 5' and Model 6' versus Model 4'. Furthermore, within models with expectation variables, those which include Expect PCB have a superior predictive ability relative to those who include Expect Apoyo (Model 3' versus Model 2' and Model 6' versus Model 5'). Finally, although Model 6' has the lowest MSPE and U-Theil statistic, we will choose Model 3' as the best predictive model given the fact that Model 6' shows non-normal errors as shown in 3.3.1.

Table 6: Assessment of the Predictive Power of the Non-Linear Models

Statistic	Model A	Model B	Model C	Model D
MSPE	189.351	35.283	101.769	83.083
U-Theil		0.186	0.537	0.439
MSE-F		61.133***	12.048***	17.906***
ENC-NEW		57.691***	18.625***	26.680***

*** Significance at 99% confidence level.
** Significance at 95% confidence level.
* Significance at 90% confidence level.

Table 6 shows the statistics to assess the predictive ability of non-linear models discussed in Section 3.3.2. We can observe that, as seen in the case of linear models, the inclusion of business confidence surveys improves the forecasting power of non-linear models. In particular, model B has a superior predictive ability than the naïve model A. Likewise, model D has a superior predictive ability than model C, both models augmented with control variables. Among the predictive models, we can observe that the model which includes only the business confidence index calculated by the PCB (model B) has the best predictive power, as suggested by its MSPE and U-Theil statistic.

When comparing these results with those of linear models in order to find the best predictive models, we find that the best predictive non-linear model (model B) performs slightly worse than the best predictive linear model (model 2'). This seemingly counterintuitive result is in line with the findings of applied literature related to linear and non-linear forecast comparison (Terasvirta and others, 2003). Therefore, we will select model 2' as the best forecasting model for private investment growth in Peru.

A final remark of this forecasting exercise is its usefulness for short-term surveillance of the business cycle depending on its prompt availability. The Peruvian Central Bank calculates real fixed investment for the current quarter using first a weighted average of real imports of capital goods, construction GDP and real production of local capital goods. Then, from this weighted sum, real public investment is subtracted, thus obtaining real private investment. Practitioners usually try to replicate this methodology in order to estimate private investment in every-day macroeconomic analysis. Although real imports of capital goods and construction GDP are published for the current month in the first week of the next month, real production of local capital goods is published with a 45-day delay for the current month. Moreover, even though public investment for the current month is published with a 30-day delay, it is subject to significant revisions as public investment from regional governments and municipalities are added to the preliminary data. Thus the final print is known along with quarterly GDP and, hence, with the final official figure of private investment which are known with a 80-day delay for the current quarter. Therefore, this methodology allows practitioners to estimate private investment for the current quarter with a lead of 35 days with respect to the official data publication date and even with great uncertainty.

In contrast, business expectations calculated by the PCB are published for the current month in the first week of the next month. This means that business expectations for the current quarter as a whole are known 75 days before the publication date of private investment for the current quarter. Moreover, it is worth reiterating that this variable is not subject to revisions. Additionally, private investment for the previous quarter, the second input of our final model, is known in the 80-th day in the current quarter. Therefore, our model would be able to estimate private investment growth more accurately with a 75-day lead with respect to the official publication date, more than twice the current methodology used by practitioners.

4 Conclusion

From all the variables comprising GDP in the expenditure side, the one that portrays the most valuable information on business cycle turning points is private investment. This is mainly due to its sudden and violent shifts when an economy moves from a recovery to a recession phase or vice versa. However, private investment is not useful for everyday business cycle surveillance given its contemporaneous relationship with the business cycle and its large publication delay. To overcome these setbacks, we aim at constructing a forecasting model for private investment in Peru, exploring the possible non-linear nature of this variable. This non-linear nature has been suggested by Naboulet and Raspiller (2004), Ghassan and Al-Dehailan (2007), and Ramos and Serra (2008), but it has not yet been incorporated in econometric modeling with forecasting purposes. In this process, we pay special attention to the explanatory and predictive power of variables extracted from business tendency surveys (BTS), variables which are published with very short delay, are not revised backwards and could potentially synthesize the unknown investment decision process of businessmen.

We find that business confidence indexes extracted from BTS, in particular the one calculated by the CRBP, are useful to forecast private investment growth in Peru. Moreover, models constructed only with indexes extracted from BTS have a higher predictive power than models augmented with control variables such as lagged GDP growth, inflation or interest rates. We also find that non-linear models are not superior to linear ones to forecast the evolution of private investment growth in Peru. Finally, the non-linear model selected would allow us to estimate current real private investment growth with a 75-day lead with respect to the official publication date, almost twice with respect to the lead gained from the current estimation methodology used by practitioners.

REFERENCES

[1] Abberger, K. (2005). "The Use of Qualitative Tendency Surveys for Forecasting Business Investment in Germany". Ifo Working Paper N° 13.

[2] Armas, A. and Grippa, F. (2006). "Metas de inflación en una economía dolarizada: la experiencia de Perú". Dolarización financiera: la agenda de política. Lima: FMI and BCRP, pp. 135-162.

[3] Barnes, S. and C. Ellis (2005). "Indicators of short-term movements in business investment". Quarterly Bulletin - Spring, Bank of England.

[4] Blejer, M. and Khan, M. (1984). "Government policy and private investment in developing countries". IMF Staff Papers, 31:379-403.

[5] Cademyr, H. and H. Karabudak (1994). "The Search for Business and/or Investment Confidence Index in Turkey"**.** Central Bank of Turkey. Discussion Paper N° 9405.

[6] Carrera, C. (2012) "Estimating Information Rigidity Using Firms' Survey Data". The B.E. Journal of Macroeconomics: Vol. 12: Iss. 1 (Topics), Article 13.

[7] Clark T. and McCracken M. (2001), "Tests of equal forecast accuracy and encompassing for nested models", *Journal of Econometrics*, **105**, pp. 85-110.

[8] Central Reserve Bank of Peru (2011), "Metodología de la Encuesta de Expectativas Macroeconómicas del BCRP", available at http://www.bcrp.gob.pe/docs/Publicaciones/Notas-Estudios/2011/Nota-de-Estudios-35-2011.pdf

[9] Diebold F. and Mariano, R. (1995), "Comparing predictive accuracy". *Journal of Economics and Business Statistics*, **13**, pp. 253-263.

[10] Dudek, S. (2008), "Consumer Survey Data and short-term forecasting of households consumption expenditures in Poland", 29th CIRET Conference October 2008. The Research Institute for Economic Development (RIED).

[11] Ferrari, N. (2005), "Forecasting corporate investment - An indicator based on revisions in the French investment survey". DESE Working Paper, October.

[12] Friz, R. and Gayer, C. (2008). "The Harmonised EU Investment Survey: What can it tell us about investment growth in the Euro area?". Preliminary Draft available at: http://www.oecd.org/dataoecd/63/48/39610674.pdf .

[13] Ghassan, H. and Al Dehailan, S. (2009), "Does public investment determine private investment?: A non Linear Cointegration Approach". 14th Annual Conference of the African Economic Society.

[14] Ghura, D. and Goodwin, B. (2000). "Determinants of Private Investment: A Cross Regional Empirical Investigation". *Applied Economics.* **32** (14), pp. 1819-1829.

[15] Greene, J. and Villanueva, D. (1991). "Private Investment in Developing Countries". IMF Staff Papers. **38**, pp. 33-58.

[16] Hansen, B. (1992), "The Likelihood Ratio Test Under Non-Standard Conditions: Testing the Markov Switching Model of GNP", *Journal of Applied Econometrics* **7**, 61-82.

[17] Harvey D., Leybourbe S. and Newbold, P. (1998), "Test for forecast encompassing". *Journal of Business and Economic Statistics*, **16**, pp. 254-259.

[18] Humala, A. (2005), "Modeling interest rate pass-through with endogenous switching regimes in Argentina". Doctoral thesis. Not published.

[19] Jonsson, A. y Lindén, S. (2009), "The Quest for the Best Consumer Confidence Indicator", European Commission, Working Paper N° 372.

[20] Jorgenson, D. (1963). "Capital theory and investment behavior". American Economic Review, 247-274.

[21] Katona, G. (1968), "Consumer behavior: Theory and findings on expectations and aspirations" Brookings Papers on Economic Activity, 58, p. 19-30.

[22] Krolzig, H-M. (2002). "Regime–Switching Models", Department of Economics and Nuffield College, University of Oxford.

[23] Larsen, J. (2001). "Using Surveys of Investment Intentions". Quarterly Bulletin - Summer, Bank of England.

[24] Loyola, J. (2009). "Comportamiento de la Inversión Privada Durante Ciclos Económicos". XXVII Economist's Meeting organized by the PCB.

[25] McCracken, M. (2004), "Asymptotics for out-of-sample tests of Granger Causality", *Journal of Econometrics*, **66**.

[26] Mendiburu, C. (2010). "La Inversión Privada y el Ciclo Económico en el Perú". *Moneda*, **143**, pp 20-24.

[27] Mlambo, K. and Oshikoya, W. (2001). "Macroeconomic Factors and Investment in Africa". *Journal of African Economics*. **10**, AERC Supplement 2. pp12-47.

[28] Naboulet, A. and Raspiller, S. (2004). "Determinants of Investment Decisions: What Can We Learn from Business Investment Surveys?" 27th CIRET Conference.

[29] Ndikumana, L. (2000). "Financial Determinants of Domestic Investment in Sub-Saharan Africa: Evidence from Panel Data". *World Development*, **28** (2), pp. 381-400.

[30] Oshikoya, T. (1994). "Macroeconomic Determinants of Domestic Private Investment in Africa: An Empirical analysis". *Economic Development and Cultural Change.* **42** (3), pp. 573-596.

[31] Pindyck, R. (1991). "Irrevesibility, uncertainty, and investment". *Journal of Economic Literature*, **29** (3), pp.1110-49.

[32] Ramos J. and M. Serra (2008) "Forecasting Investment: A Fishing Contest Using Survey Data". Banco de Portugal. Working Paper N° 18/2008.

[33] Schenker, R. (2011). "Investment Indicator for Switzerland". In "Analyzing Capital Investment and Unemployment Using Modern Statistical Methods", pp 36-76.

[34] Serven, L. and Solimano, A. (1989). "Private investment and macroeconomic adjustment: Overview". PPR Working Paper WP 339. Washington D.C.: World Bank.

[35] Shafik, N. (1992). "Modelling Private Investment in Egypt". *Journal of Development Economics*. **39**, pp. 263-277.

[36] Terasvirta, T., D. Van Dijck and M. Medeiros (2003). "Smooth Transition Autoregressions, neural networks and linear models in forecasting macroeconomic time series: A re-examination". Available at: http://ideas.repec.org/p/hhs/hastef/0561.html

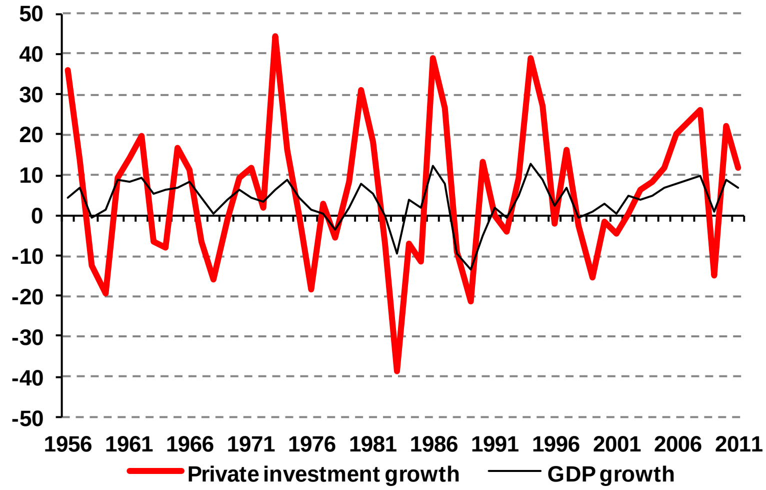
[37] Tong, H (1990). "*Non-linear Time Series. A Dynamical System Approach"*, Oxford University Press.

[38] Wai, T. and Wong, C. (1982). Determinants of Private Investment in Developing Countries. Journal of Development Studies. **19** (1), pp. 19-36.

[39] Zebib, M. and Muoghalu, M. (1998). "Dynamic nature of private investment and its determinants in developing countries". *Studies in Economics and Finance*. **18** (2), pp. 100-110.

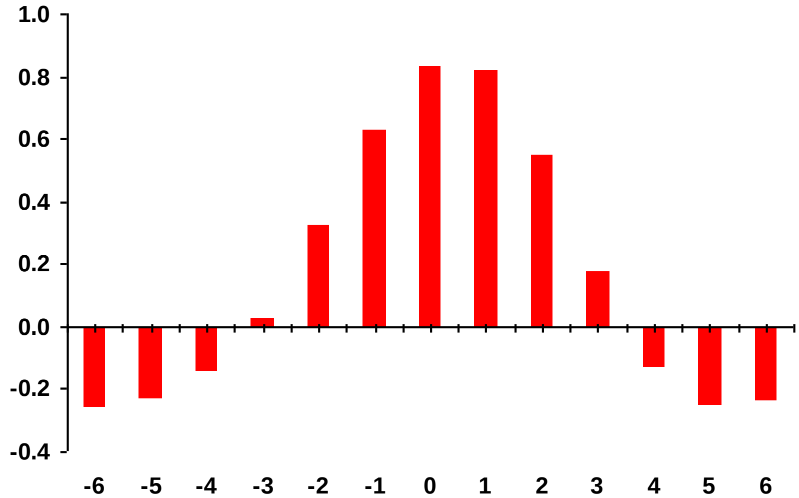
Annex 1

Figure 1: Private Investment and GDP
(YoY growth)



Source: Central Reserve Bank of Peru

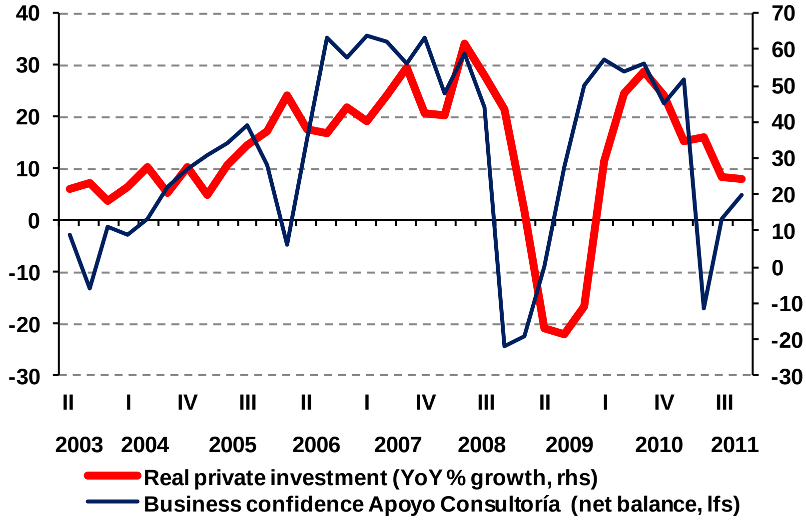
Figure 2: Dynamic cross-correlations between the cyclical component of GDP in t and the cyclical component of private investment in t+i



Using the Baxter and King filter.

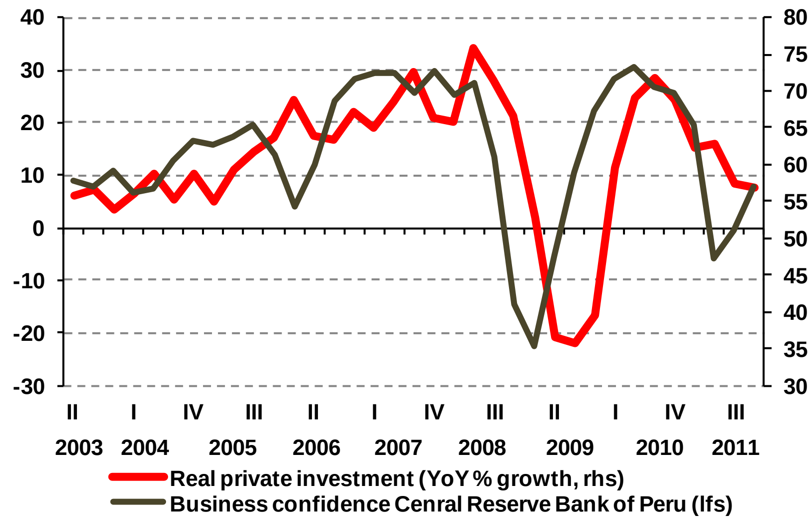
Source: Central Reserve Bank of Peru and own calculations

Figure 3: Private investment YoY growth and business expectations index constructed by Apoyo Consultoria



Source: Apoyo Consultoría, Central Reserve Bank of Peru

Figure 4: Private investment YoY growth and business expectations index constructed by the Central Reserve Bank of Peru



Source: Central Reserve Bank of Peru