Composite leading indicators of economic activity: An application to Rio de Janeiro's upstream oil and gas industry

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Abstract This paper proposes a monthly composite leading indicator (CLI) to anticipate turning points in the economic activity of Rio de Janeiro's upstream oil and gas industry, from January 2002 to May 2019. First, we build a database with 61 series, and categorize each of them into i) rapidly responsive to economic activities; ii) expectation-sensitive; or iii) prime movers indicators. Next, we remove the seasonality of the series through the X-13 ARIMA-SEATS method and use the Bry-Boschan algorithm to identify the cycles. Then, we evaluate the components' fit to integrate the composite leading indicator through four statistical tests: cross-correlation, quadratic probability score, Granger causality, and probit. The assessment of the composite leading indicator demonstrates that it leads 67% of the peaks and 100% of the troughs in the target series (5/6 of the turning points). The average leading period is 8.4 months, the median is 9 months and the standard error is 2.8 months. Diebold-Mariano tests confirm that adding lags to our CLI improves predictive accuracy. We contribute to the literature by creating, to our knowledge, the first leading indicator for the oil and gas industry in Brazil.

Keywords: Business cycles; Rio de Janeiro; Oil and gas; Composite leading indicator; Cross-correlation; Quadratic probability score

JEL Code: E3, C41, C43, C53.

1. Introduction

Anticipating upturns and downturns in business cycles is a key competitive advantage for companies and a powerful tool for policymakers. Since Mitchell and Burns (1938 and 1946), economic forecasting has attracted attention. A vast literature covers the measurement and the anticipation of economic activity in global, national, and sectoral levels. However, as Lucas (1977) defines, business cycles are easily misunderstood since they commonly refer to co-movements in different forms of economic activity, not just fluctuations in Gross Domestic Product (GDP).

In this paper, we construct a composite leading indicator (CLI) to the upstream oil and gas economic activity in the state of Rio de Janeiro. The

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starting point for a composite leading indicator is the choice of the target variable. In this sense, we choose IBGE's *Pesquisa Industrial Mensal – Produção Física* (Monthly industrial survey – physical production) for Rio de Janeiro's extractive industry as the target. The *Pesquisa Industrial Mensal – Produção Física* (PIM-PF) provides short-term fluctuations for extractive and transformation industries' real products since 1970. Since May 2014, PIM-PF has followed a new methodology; however, there was no break for the series dated back since 2002.

The upstream oil and gas sector is Rio de Janeiro's primary extractive industry and plays a key role in the state's economy. The sector is responsible for direct jobs, tax revenues, and investments, and provides a strategic raw material for economic and social development. Petroleum production royalties represented 18% of Rio de Janeiro's state revenue in 2018 (*Secretária da Fazenda do Rio de Janeiro*, 2019). At the same time, it is also a multiplier for the state's economy, since service industries are intertwined with the upstream oil and gas sector. That said, anticipating changing business cycles in Rio de Janeiro's upstream oil and gas economic activity may contribute positively to a significant number of stakeholders.

The composite leading indicator in this paper follows the OECD's (2012) recommendation. The construction method has five steps: series pre-selection, seasonal adjustment, cycle identification, evaluation, and aggregation. First, we classify the potential leading indicators into three categories: rapidly responsive to economic activities, expectation-sensitive, and prime movers. We benefit from multiple public sources to gather the candidate leading series, such as ANP, BCB, CBOE, CNI, Eletrobras, EIA, FGV, Firjan, IBGE, OECD, Yahoo Finance, and others. Second, we remove seasonal patterns in the series and identify the cycles. Then, we evaluate the series best fit to integrate the composite leading indicator through four statistical tests: (i) cross-correlation (Hollauer, Issler, and Notini, 2009; Oliveira, 2016; NYU, 2017; Issler and Pimentel, 2019); (ii) quadratic probability score (Chauvet, 2000; Issler, Notini, and Rodrigues, 2009); (iii) Granger-causality (Issler, Notini, and Rodrigues, 2009; Oliveira, 2016); and (iv) probit (Morais and Chauvet, 2011). Finally, we use The Conference Board's (2001) aggregation method. Finally, we compare the predictive accuracy of autoregressive (AR) and vector-autoregressive (VAR) models – the latter includes lags of the CLI – using the Diebold-Mariano Test (Diebold and Mariano, 2002).

Our paper connects to the literature on measuring and analyzing business cycles in Brazil (see, for example, Chauvet, 2000; Picchetti and Toledo, 2002; Issler, Notini, and Rodrigues, 2009; Hollauer, Issler, e Notini, 2009; Morais and Chauvet, 2011; Oliveira, 2016; Campelo Jr., Issler and Pimentel,

2019; Ozyildirim, Sima-Friedman, Picchetti, and Lima, 2019). Specifically, we contribute to a more scarce literature that measures and analyzes cyclical aspects of specific sectors and industries, which has been done for industrial activity (Hollauer, Issler, and Notini, 2009), the capital goods industry (Chauvet and Morais, 2011), and the construction sector (Cruz and Colombo, 2018). To our knowledge, there is still a gap for the extractive industry. This paper provides the first composite leading indicator to Rio de Janeiro's upstream oil and gas industry economic activity.

The sections in this paper are organized as follows. Section 2 contains a brief review of international and Brazilian literature regarding composite leading indicators. Section 3 describes the methodology. Section 4 analyzes the main results of the paper and reports the assessment of the composite leading indicator constructed. Finally, Section 6 concludes with the main findings and further studies.

2. Review of literature

2.1 Composite leading indicators in the global landscape

Composite leading indicators research began back in the 1930s when Burns and Mitchell (1938 and 1946) developed a pioneering work concerning business cycles. They developed a list of leading, coincident and lagging series of economic activity in the United States in an effort to explain the recession that began in 1937. As stated by Mitchell and Burns:

“Business Cycles are a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises. A cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years.” (Burns and Mitchell, 1946, p 3)

Early attempts to explain business cycles were not unanimously approved. Koopmans (1947) considered Mitchell and Burns' work excessively empirical, but the authors disagreed and re-affirmed that the work was fundamentally based on the economic theory.

Moore (1961) added other series to the initial list proposed by Mitchell and Burns in the context of the post-war business transformation. Following

this idea, Moore and Shiskin (1967) developed composite leading, coincident, and lagging indicators by a combination of the series. Recessions and expansions do not have a single explanation, as economic theory and experience have demonstrated. That said, a combination of series into a composite indicator may better explain signals from different sectors of the economy.

New methods for composite indicators have appeared successively, from heuristical to more complex models. The Conference Board (TCB) has published composite leading, coincident, and lagging indicators of economic activity in the United States since 1995, through a methodology that requires no estimation based on formal econometric models. Alternatively, Stock and Watson (1988a, 1988b, 1989, 1993) propose construction methods using sophisticated econometric and statistical techniques. However, a major failure in Stock and Watson's model was the missing US recession in 1990-1991 (Issler, 2009). Chauvet and Piger (2008) compare the real-time performance of business cycle dating methods and find that both the Bry-Boschan algorithm and a Markov-switching dynamic-factor model have accurately identified the NBER business cycle chronology over the past 30 years. Duarte, Issler and Spacov (2004) compare the state of the economy dating abilities from TCB's method and a series of alternative econometric-based models. Despite the simplicity present in TCB's method, the results are notably satisfactory.

Finally, since the 1970s, OECD has provided a system of composite leading indicators. OECD (2012) details the construction process in four steps: pre-selection, filtering, evaluation, and aggregation. This paper follows those steps, and they will be further described in Section 3. For further reading on leading indicators, we recommend Lahiri and Moore (1992) and Marcellino (2006). For in-depth analyses of business cycles, we suggest Diebold and Rudebusch (1999).

2.2 Composite leading indicators in Brazil

Contador (1977) and Contador and Ferraz (1999) developed pioneering work on coincident and leading indicators in Brazil, followed by Chauvet (2001, 2002) and Picchetti and Toledo (2002). In 2002, IBGE redesigned the *Pesquisa Mensal do Emprego* (Monthly Employment Survey) which characterized a major drawback in composite indicators research, since long-term series are crucial for business cycle analysis. Research and development of composite indicators in Brazil face major challenges regarding the frequency, timeliness, revision, and length of the series. Data should be available in monthly frequency, shortly after the period to which it refers, with no significant revision and no breaks in the life span. Despite these challenges, Duarte,

Issler, and Spacov (2004) compare three alternative indicators for Brazilian economic activity and establish a recession chronology. Ellery Junior (2002) analyzes the empirical relationship between GNP and key factors, such as investment, work hours, consumption and productivity. Chauvet and Morais (2008) construct a composite leading indicator to anticipate downturns in the Brazilian business cycle through a time-varying autoregressive probit model.

Other business cycle studies have been developed for Brazil in order to understand sector specificities. Hollauer, Issler and Notini (2009) construct a composite coincident indicator for Brazilian industrial activity through a comparison of The Conference Board's (TCB) method, linear dynamic models and the Mariano-Murasawa approach. They conclude that TCB's method is superior for this purpose. Morais and Portugal (2008) develop a composite coincident indicator of industrial activity in the state of Rio Grande do Sul.

Even though composite coincident indicators have already been exhaustively studied in Brazil, there is still room to advance in composite leading indicators for sectoral analysis. To address this, Campelo Junior (2008) develops a composite leading indicator for Brazilian industrial activity; Morais (2005) studies business cycles of industrial activity in the state of Bahia; Chauvet and Morais (2011) construct a composite leading indicator for the Brazilian capital goods industry through a time-varying autoregressive probit model; and Morais (2013) analyzes cycles and leading indicators of Rio Grande do Sul's industrial activity. As far as we know, a composite leading indicator to the petroleum extractive industry of the state of Rio de Janeiro has not previously been constructed.

3. Methodology

In this paper, the business cycle is defined by the turning points in the level of aggregate economic activity (Harding and Pagan, 2002). In this manner, we identify the cycles through the classical approach. Eliminating trends from economic aggregates is difficult, and inadequate estimations may cause significant mistakes (Zarnowitz and Ozyildirim, 2006). The studies of the National Bureau of Economic Research (NBER) follow the classical cycle approach, analyzing expansions and contractions in the level series without trend adjustments. Harding and Pagan (2002) explain that classical business cycle studies do not require a de-trending operation. Additionally, Hamilton (2018) provides evidence that the HP Filter, a widely-used tool for de-trending, produces series with spurious dynamic relations. The resulting series have no basis in the true data-generating process. Phillips (2015) also states that the HP Filter fails to eliminate stochastic trends when used as a decomposition device to estimate growth cycles.

Following OECD (2012), constructing the composite leading indicator to upstream oil and gas economic activity in the state of Rio de Janeiro follows five steps: pre-selection, seasonal adjustment, cycle identification, evaluation, and aggregation.

3.1 Pre-selection

First, pre-selection considers the best practices for the choice of reference and component series. The reference series in this article is the PIM-PF for Rio de Janeiro's extractive industry, which is a proxy for business cycles in the upstream oil and gas economic activity in the state. The series is available monthly without breaks since 2002. We select over 60 indicators as potential components, according to their economic relevance and practical considerations. Table A1, in the appendix, describes each potential leading series, including any adjustment used. We classify all potential component indicators as rapidly responsive to economic activities, expectation-sensitive, or as prime movers. Additionally, we assess them according to frequency, length, timeliness, and revision. The series should have monthly frequency and long life span. Besides, it should also be available as fast as possible with no significant revision in past data.

3.2 Seasonal adjustment

The second step considers the seasonal adjustment method. The series are seasonally-adjusted when necessary, followed by outlier detection to avoid discrepancies in the analysis. We use the X-13 ARIMA-SEATS method provided by the US Census Bureau to adjust seasonal patterns and detect outliers. If the series was seasonally adjusted by the source provider, no modification is made in this sense. The target variable, PIM-PF for Rio de Janeiro's extractive industry, is seasonally-adjusted through X-13 ARIMA-SEATS in this paper. Then, the observations of each series ($Y(t)$) are transformed by its natural logarithm form, except for those that may be expressed by negative numbers (i.e. monthly inflation).

3.3 Cycle identification

The cycles in this paper are identified through turning points detection without any de-trending. We use the algorithm developed by Bry and Boschan (1971) to identify business cycles turning points in each time series. First, the algorithm detects peaks and troughs in the series as follows (NCER, 2019).

- A *peak* occurs at time t if

$$y_{t-k}, \dots, y_{t-k+1} < y_t > y_{t+1}, \dots, y_{t+k}. \quad (1)$$

- Similarly, a *trough* happens at time t when

$$y_{t-k}, \dots, y_{t-k+1} > y_t < y_{t+1}, \dots, y_{t+k}. \quad (2)$$

The variable k is known as the turn phase parameter or symmetric window, and is defined as 5. After the identification of each peak and trough, the series are divided into expansion and contraction phases. However, other restrictions are also introduced to establish a minimum phase and a minimum cycle (expansion + contraction). The minimum phase is set as 5 and the minimum cycle is specified as 15. In this way, we transform series into binary variables, denoting expansions as 1 and contractions as 0.

The last procedure in the seasonal adjustment step is normalization, which aims to equalize the series regarding the scale and units. Normalization is carried out by subtracting the mean of the series from each filtered data, dividing the result by the absolute mean deviation and, finally, by adding 100 to each observation (OECD, 2012).

$$s_t = \frac{(y_t - \mu)}{\sigma} + 100 \quad (3)$$

3.4 Evaluation

We evaluate the potential leading series through four statistical tests: cross-correlation, quadratic probability score, Granger causality, and probit. Following the four tests, a selection criterion defines a set of components that are fit to the composite leading indicator.

3.4.1 Cross-correlation

Cross-correlation function (CCF) expresses a measure of the correlation between two time series, ranging in value from -1 to 1. CCF between R_t (target variable) and s_t (potential leading series) is defined by the ratio of covariance to root-mean variance (Boyd, 2001).

$$CCF = \frac{\sum_{t=1}^K (R_t - \bar{R})(s_t - \bar{s})}{\sqrt{\sum_{t=1}^K (R_t - \bar{R})^2 \sum_{t=1}^K (s_t - \bar{s})^2}} \quad (4)$$

The cross-correlation widens the concept of correlation to the timing of two series, $CCF = \text{corr}(R_t, n_{t+k})$. If k assumes a negative value, the correlation between the two time series is analyzed in the past, while a positive value for k refers to the correlation in the future. We analyze the CCF between the target variable and each potential leading series graphically for k

ranging from -24 to 24. Thus, we can observe the leading and lagging characteristics of the series. Countercyclical series, such as the benchmark interest rate, are inverted ($y_t^* = -y_t$).

3.4.2 Quadratic Probability Score

The second test applied to evaluate the potential leading series is the Quadratic Probability Score (QPS), originally proposed by Diebold and Rudebusch (1989). This test has also been used by Zhang and Zhuang (2002), Gallardo and Pedersen (2007), Campelo Junior and Issler (2008), Issler, Notini and Rodrigues (2009) and Chauvet and Morais (2011). The objective of the test is to score the candidate leading series according to its capacity to anticipate the state of the economy (expansion or recession) of the reference series. The score is calculated by

$$\text{QPS} = \frac{\sum_{t=1}^N (R_t - s_{t-k})^2}{N}. \quad (5)$$

We state the reference series (R_t) and the candidate leading series (s_t) as binary variables according to the Bry Boschan algorithm results, where 1 is given to expansion phases and 0 refers to recessions. Therefore, the QPS results range from 0 to 1 by construction, with 0 indicating a perfect fit between the series. We apply the test for lags (k) ranging from 1 to 16 and identify the best performers, as well as the optimum lag.

3.4.3 Granger-causality

The third test applied in this paper to evaluate potential leading series is Granger-causality. Granger (1969) examines whether forecasts of future values of a reference series may be better explained if the present and lagged values of another series are also considered. In this sense, Granger proposes the following definitions for causality between two series denoted as X and Y :

- (i) **Granger-causality.** X Granger-causes Y if past values of X help predict Y , given the information contained in the lagged values of Y .
- (ii) **Feedback.** Feedback happens if X Granger-causes Y and Y Granger-causes X .

We apply the Granger-causality test to the series in level and in the stationary form. Therefore, prior to the causality test, we verify the stationarity of each series through the Augmented Dickey-Fuller (ADF) test and adjust

when necessary. Next, we use the Akaike Information Criteria (AIC) test to identify the optimum lag between the reference and leading candidate series. Then, we verify the Granger-causality in the optimum lag. The series is only accepted if the Granger-causality test points to a performance in the direction expected for a leading indicator (Definition (i)). Definitions (ii) and (iii), feedback and instantaneous causality, respectively, are not accepted, following Campelo Junior and Issler (2008) and Issler, Notini and Rodrigues (2009).

3.4.4 Probit

The last test is the probit approach. This model is adopted by Estrella and Mishkin (1998) to evaluate the leading characteristics of series. It aims to compute probabilities that a contraction (Y_t) will occur at given values of a leading indicator candidate (s_t). The variable Y_t is defined as follows:

$$Y_t = \begin{cases} 1, & \text{recession phase} \\ 0, & \text{otherwise} \end{cases}.$$

The probability of obtaining $Y_t = 1$ is linked to a latent variable, I . In this article, the variable I represents the business cycle phases. In the probit model it may be defined as $I = \beta_0 + \beta s_{t-k}$.

β_0 and β are the regression coefficients, while k is the leading period. Next, it is necessary to set a threshold value, I^* , to indicate the occurrence of a recession phase. If the unobservable variable I is greater than I^* , it means $Y_t = 1$. Therefore, the probit model can be characterized as

$$\Pr(Y_t = 1 | s_{t-k}) = \Pr(I^* \leq I) = \phi(\beta_0 + \beta s_{t-k}). \quad (6)$$

The recession prediction is obtained from the conditional probability of a contraction occurrence, with k months ahead, given a cumulative normal distribution represented by $\phi(\cdot)$.

3.4.5 Selection criteria

There is no unique and obvious way to reach an optimum set of leading indicators. Therefore, after the four tests above are applied, we establish the following selection criteria to identify a set of leading indicators that are fit to integrate the composite leading indicator to the economic activity of the extractive industry of the state of Rio de Janeiro.

- (i) Absolute maximum correlation between 0 and -12 months in the CCF test.

Table 1
Selected series for the composite leading indicator

code	series	classification
prod_rj	crude oil production - Rio de Janeiro	rapid responsive
exp_pet	crude oil exports - Brazil	rapid responsive
elet_cons_SE	electricity consumption in Brazilian southeastern region	rapid responsive
petr4	Petrobras preferential stocks	expectation sensitive
Fdi	foreign direct investment	expectation sensitive
di_pre_360	swap DI x pre 360 (inverted)	prime mover

- (ii) QPS lower than 0.4, following one of the thresholds established by Issler, Notini and Rodrigues (2009).
- (iii) Candidate indicators that Granger-cause the reference series and not vice-versa, at the 10% significance level, using the lag structure suggested by the Akaike information criterion (AIC).
- (iv) p -value lower than 10% in the bivariate probit model for the optimum lag defined by the QPS.
- (v) Retain only series that satisfy (i), (ii), (iii) and (iv).

Starting with a database of 61 candidate series for leading, and following the above criteria, we end up with six different leading series: crude oil production in Rio de Janeiro, crude oil exports in Brazil, electricity consumption in Brazil's southeastern region, Petrobras preferential stocks, foreign direct investment, and swap DI x Pre 360 days. Table 1 presents the components of the composite leading indicator according to the established method.

The first test, cross-correlation, approves 32 series out of the 61 that composed the initial list. The quadratic probability score accepts 9 out of the 32 remaining series. Next, Granger-causality approves 6 series. And finally, probit validates the 6 remaining series. The individual results of the selected series for each statistical test are presented in the appendix as follows. Figures A1, A2, and A3 report the cross-correlation results. Tables A2 and A3 demonstrate the results from the quadratic probability score. Tables A4 and A5 show the Granger-causality results. Finally, Table 6 presents the probit results, and Table A7 shows the descriptive statistics of the selected series for the composite leading indicator.

3.5 Aggregation

The last step of the composite leading indicator construction is to aggregate the selected series. We use the aggregation method proposed by The

Conference Board (2001) in this paper. The procedure has four stages, as follows (p. 47).

- (i) The month-to-month variation, $r_{i,t}$, is calculated through a symmetric percent change formula for each series.

$$r_{i,t} = 200 \frac{(x_{i,t} - x_{i,t-1})}{(x_{i,t} + x_{i,t-1})} \quad (7)$$

- (ii) The month-to-month variations are adjusted by the components' standardization factor, $w_{i,t}$. The standard deviation, μ_i , of each component is calculated, followed by the sum of the inverse of each one.

$$k = \sum_i \frac{1}{\mu_i} \quad (8)$$

These factors aim to give each component an equal opportunity to contribute to the composite indicator.

$$c_{i,t} = w_i r_{i,t} = \frac{r_{i,t}}{k \cdot \mu_i} \quad (9)$$

- (iii) The sum of each month-to-month variation adjusted through the standardization factor is calculated.

$$s_t = \sum_i c_{i,t} \quad (10)$$

- (iv) Finally, the composite indicator is computed through the symmetric percent change formula recursively, starting from 100 in the first month, $S_1 = 100$.

$$S_t = S_{t-1} \cdot \frac{(200 + s_t)}{(200 - s_t)} \quad (11)$$

Following TCB's (2001) recommendations, to account for changes in the standardization factors over time, we update it annually by recalculating the standard deviation of each component.

4. Results

In this section, we present the performance of the composite leading indicator, according to the methodology proposed in this article, and analyze the

Figure 1
Comparison between the composite leading indicator (CLI) and PIM-PF for Rio de Janeiro's extractive industry, seasonally adjusted

Table 2
Selected series for the composite leading indicator

#	turning point type	target series turning point's date	CLI turning point's date	lead (-) / lag (+)
1	peak	June 2002	February 2003	+8
2	trough	May 2004	April 2004	-1
3	peak	November 2006	January 2006	-10
4	trough	October 2007	June 2006	-16
5	peak	August 2009	August 2008	-12
6	trough	August 2011	April 2009	-28
7	peak	February 2012	January 2011	-13
8	trough	March 2013	January 2013	-2
9	peak	March 2015	March 2015	0
10	trough	April 2016	February 2016	-2
11	peak	April 2018	November 2016	-17
12	trough	August 2018	December 2017	-8

results. Figure 1 shows the composite leading indicator and the target variable (PIM-PF extractive industry RJ, seasonally adjusted), with its recession phases shaded.

The reference series presents six recessions (shaded areas) and seven expansion phases, totaling twelve turning points in the analyzed period. Table 2 compares the turning points of both series and assesses the leading capacity of the indicator proposed in this article. Both series have twelve turning points from January 2002 to May 2019.

Table 2 shows the composite leading indicator misses two turning points: the recessions beginning in June 2002 and March 2015. Meanwhile, the sixth

Table 3
Composite leading indicator performance:
Timing measures

state of the economy	lead (-) / lag (+)		
	average	median	standard error
recession	-7.3	-11.0	3.8
expansion	-9.5	-8.0	4.3
overall	-8.4	-9.0	2.8

Table 4
Composite leading indicator performance: False signals and leading ratio

state of the economy	leading	coincident	lagging	false signal	leading ratio
recession	4	1	1	0	67%
expansion	6	0	0	0	100%
overall	10	1	1	0	83%

turning point, the trough in August 2011, has an excessive leading period (28 months), which is an unsuitable indication. Tables 3 and 4 report the leading performance of the composite indicator for recessions, expansions, and overall phases.

Based on the above results, we observe an asymmetric performance for recessions and expansions. Even though the composite leading indicator demonstrates a satisfactory leading ratio (83%) for the overall analysis, the capacity to predict downturns is 67%. On the other hand, the composite leading indicator has a perfect score anticipating expansions from January 2002 to May 2019.

Interpreting signals from the leading index is a key aspect of business cycle study. TCB (2001) recommends the Three Ds analysis – duration, depth, and diffusion – to avoid misinterpretation in the short term. According to TCB, reasonable criteria to assess the likelihood of a recession are a 2% decrease in the index over six months, coupled with downward movements in more than half of the components. Table 5 demonstrates if the recession signals from the composite leading indicator constructed in this article follow the Three Ds criteria suggested by TCB.

Table 5 reports that the recession signals of the composite leading indicator adhere precisely to the Three Ds criteria. Afterward, we compare the composite leading indicator and the target variable adjusted by a three-month moving average. Thus, we verify the performance of the leading indicator followed by a smoothing technique.

Figure 2 demonstrates that the target variable adjusted by a three-month

Table 5
Three Ds analysis for the composite leading indicator

Date - 6 months after peak	Depth - 6 months after peak	Diffusion
August 2003	-4%	67%
July 2006	-8%	100%
February 2009	-7%	67%
July 2011	-4%	67%
September 2015	-5%	67%
May 2017	-7%	83%

Figure 2
Comparison between the composite leading indicator (CLI) and PIM-PF for Rio de Janeiro's extractive industry adjusted by a three-month moving average

moving average has five recessions and five expansion phases, which results in nine turning points. On the other hand, the adjusted composite leading indicator has seven expansions and six recessions in the period, adding to twelve turning points. The adjusted composite leading indicator misses the beginning of the first recession, has an extra cycle from September 2008 to April 2009, and coincides with the target recession in May 2015. Therefore, we can affirm that the smoothing technique does not improve the assessment of the composite leading indicator proposed.

Finally, a robustness check is done to analyze the performance of the composite leading indicator without Rio de Janeiro's crude oil production component. Even though the indicator was approved with the selection criteria proposed, one may affirm it should be a coincident, instead of a leading indicator. Therefore, we aggregate the other five components into an adjusted composite leading indicator (ACLI) and assess the performance, as reported in Table 6.

Table 6
Comparison between the adjusted composite
leading indicator and the target variable

#	turning point type	target series turning point date	ACLI turning point date	lead (-) / lag (+)
1	peak	June 2002	September 2002	+5
2	trough	May 2004	April 2004	-1
3	peak	November 2006	January 2006	-10
4	trough	October 2007	October 2006	-12
5	peak	August 2009	June 2008	-14
6	trough	Null	April 2009	false signal
7	peak	Null	January 2011	false signal
8	trough	August 2011	November 2011	+3
9	peak	February 2012	April 2012	+2
10	trough	March 2013	January 2013	-2
11	peak	March 2015	June 2015	+3
12	trough	April 2016	February 2016	-2
13	peak	April 2018	November 2016	-17
14	trough	August 2018	December 2017	-8

Results in Table 6 demonstrate that the adjusted composite leading indicator performs poorly as a tool to anticipate the changing cycles in the target variable. Therefore, we may affirm that crude oil production in Rio de Janeiro contributes positively to the composite leading indicator.

5. Is the leading indicator useful to forecast the target variable? A reference VAR model to compare predictive accuracy

Our last empirical step is to analyze the usefulness of the composite leading indicator (CLI) to predict the PIM-PF for Rio de Janeiro's extractive industry (our target variable). In particular, we want to estimate the marginal effect of the lags of the CLI on predicting the current PIM-PF for Rio de Janeiro's extractive industry, after controlling for the lags of the target variable itself. Following Diebold and Rudebusch (1991), we estimate

$$\begin{aligned}
 \text{PIM-PF Extractive Industry in Rio}_t &= \\
 &= \beta_0 + \sum_{i=1}^p \beta_i \cdot \text{PIM-PF Extractive Industry in Rio}_{t-i-k+1} + \varepsilon_t \quad (12)
 \end{aligned}$$

and

$$\begin{aligned} \text{PIM-PF Extractive Industry in Rio}_t = \\ = \beta_0 + \sum_{i=1}^p \beta_i \cdot \text{PIM-PF Extractive Industry in Rio}_{t-i-k+1} \\ + \sum_{i=1}^p \gamma_i \cdot \text{Leading Indicator}_{t-i-k+1} + \varepsilon_t, \quad (13) \end{aligned}$$

where (12) and (13) stand for the AR(p) and VAR(p) models used to forecast the PIM-PF for Rio de Janeiro's extractive industry. Specifically, PIM-PF Extractive Industry in Rio is the level of the target variable, Leading Indicator is the level of the composite leading index (CLI), t refers to the time period (year-month), k refers to the number of months ahead of the prediction, and p refers to the lag length of the estimated regression. Because we use monthly data, we choose $p=12$.

By estimating (12) and (13), we get two forecasts: $\{\hat{y}_{1t}; t = 1, \dots, T\}$ (from the AR[12] model) and $\{\hat{y}_{2t}; t = 1, \dots, T\}$ (from the VAR[12] model). We compare both $\hat{y}_{1t}$ and $\hat{y}_{2t}$ with the actual values of the PIM-PF for Rio de Janeiro's extractive industry (y_t). Our question is: is the prediction of y_t better when we add lags of our composite leading indicator (i.e., are the forecast errors of the VAR model lower than those from the AR model)? Figure 3 shows the forecasts from the AR(12) and VAR(12) models, for both the PIM-PF for Rio de Janeiro's extractive industry in levels (Panel A) and change in natural logarithm (i.e., percentage changes, Panel B).

From Figure 3, it seems that the forecast using the VAR(12) model is closer to the actual series of the target variable than the AR(12) model. However, it is nearly impossible to assess predictive performance only graphically. Thus, to compare both predictions with and without the lagged values of the CLI, we define the forecast errors as $e_{it} = \hat{y}_{it} - y_t$, $i = 1, 2$. The loss associated with each forecast is a function of the forecast error: $g(e_{it})$. Such a loss function ($g[\cdot]$) is typically the square (squared-error loss) or the absolute value (absolute error loss) of e_{it} . We use the Diebold-Mariano test (Diebold and Mariano, 2002) to infer whether the loss differential between the two forecasts ($d_t = g(e_{1t}) - g(e_{2t})$) is statistically different from zero. The "equal accuracy" null hypothesis is equivalent to the test that the population mean of the loss-differential series is 0 (Diebold and Mariano, 2002). Table 7 shows the results from the Diebold-Mariano test of predictive accuracy, using three different loss functions: mean squared errors (MSE), mean absolute errors (MAE), and mean absolute percentage errors (MAPE).

Figure 3
PIM-PF for Rio de Janeiro's extractive industry and AR(12) and VAR(12) forecasts

Forecasts with the AR(12) [VAR(12)] model start in Jan. 2003 [Feb. 2003]. VAR(12) model is the AR(12) plus twelve lags of the the composite leading indicator (CLI). In Panel A the target variable – PIM-PF for Rio de Janeiro's extractive industry – is measured in levels and equals 100 in Jan. 2002. In Panel B, the target variable is measured as changes in natural logarithms (i.e., percentage changes), and thus the y-axis is interpreted as percentage points (p.p.).

As we can infer from Table 7, the VAR forecasts (i.e., those that include the lags of our CLI) outperform the AR forecasts in the point estimates (i.e., lower errors), regardless of the loss function (MSE, MAE, MAPE). More importantly, these differences in predictive accuracy are statistically meaningful, according to the Diebold-Mariano test (all p -values < 0.05). Thus, we conclude that marginally adding lags of our CLI to the model containing lags of the target variable itself (PIM-PF for Rio de Janeiro's extractive industry) improves predictive performance.

6. Conclusion

In this paper, we construct a monthly composite indicator to anticipate the business cycles in Rio de Janeiro's extractive industry using OECD's recommendations and TCB's aggregation technique. The proposed indicator leads business cycle turning points by 8.4 months on average, with two failures characterized by one lagging and one coincident recession signal, from January 2002 to May 2019. We observe an asymmetric behavior in the leading

Table 7
Diebold-Mariano comparison of predictive accuracy

This table shows the Diebold and Mariano (1995) tests for predictive accuracy. The two competing predictions (AR and VAR) are compared using different loss criteria (MSE, MAE, MAPE). The null hypothesis is that the accuracy of both predictions is the same. MSE stands for mean squared errors; MAE, mean absolute errors; MAPE, mean absolute percentage errors. We implement the test using the “DMARI-ANO” user-written command for Stata (Baum, 2003). MAPE statistics in Panel B are not calculated because the underlying series is already in percentage changes.

Panel A: Levels			
	MSE	MAE	MAPE
forecast (AR)	12.73	2.754	0.2371
forecast (VAR)	11.48	2.656	0.2279
difference	1.25	0.098	0.0092
p-value	0.0074	0.047	0.0336
better forecast:	forecast(VAR)	forecast(VAR)	forecast(VAR)
Panel B: Change in natural logarithms			
	MSE	MAE	MAPE
forecast (AR)	9.282	2.338	-
forecast (VAR)	8.317	2.235	-
difference	0.965	0.103	-
p-value	0.0012	0.072	-
better forecast:	forecast(VAR)	forecast(VAR)	-

indicator since it is able to anticipate all expansions, whereas recessions have a 67% leading ratio. Regarding the overall performance, the composite leading indicator is able to anticipate 83% of the turning points. Furthermore, tests comparing the predictive accuracy of AR and VAR models confirm that adding lagged values of our CLI improves the forecast of Rio de Janeiro’s extractive industry physical production. To our knowledge, this is the first attempt to create an indicator with this purpose for the oil and gas industry in Brazil.

Composite leading indicators have been studied extensively to enable a timely analysis of business conditions and assist companies, economists, and policymakers to anticipate changing cycles in economic activity. Decision-makers are continually struggling with the possibility of a sudden downturn shifting the expected direction of the market. Thus, composite indexes may be a powerful tool, since the aggregation of series in one indicator may reveal common turning points from a wide range of data in a more convincing manner than a single component. However, like any other forecasting tool, business-leading indicators should be analyzed cautiously, and enhanced with additional data and information (TCB, 2001).

We suggest that future studies explore more sophisticated econometric

techniques to refine the series selection criteria proposed in this paper. The upstream oil and gas industry plays a vital role in Rio de Janeiro's economy, through tax revenues, investments, and direct and indirect jobs. Therefore, a leading indicator of the sector may benefit a wide range of stakeholders.

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A. Additional tables and figures

Figure A1
Cross-correlation results for crude oil export Brazil
and crude oil production Rio de Janeiro

Figure A2
Cross-correlation results for electricity consumption in Brazilian
southeastern region and Petrobras preferential stocks

Figure A3
Cross-correlation results for foreign direct investment and
SWAP DI x Pre 360 days

Table A1
Potential leading series database

#	series	source	seasonally adjusted	stationary
01	Crude oil export Brazil	ANP	X-13 ARIMA SEATS	1 st diff.
02	Crude oil import Brazil	ANP	X-13 ARIMA SEATS	Level
03	Crude oil production Brazil	ANP	X-13 ARIMA SEATS	1 st diff.
04	Crude oil production Rio de Janeiro	ANP	X-13 ARIMA SEATS	1 st diff.
05	Oil products import Brazil	ANP	X-13 ARIMA SEATS	1 st diff.
06	Oil processing in refinery	ANP	X-13 ARIMA SEATS	1 st diff.
07	Oil products sale Brazil	ANP	X-13 ARIMA SEATS	1 st diff.
08	Benchmark interest rate – SELIC overnight	BCB	-	1 st diff.
09	CDI overnight	BCB	-	1 st diff.
10	Brazilian broad money supply (MO)	BCB	X-13 ARIMA SEATS	1 st diff.
11	Brazilian broad money supply (M1)	BCB	X-13 ARIMA SEATS	1 st diff.
12	Brazilian broad money supply (M2)	BCB	X-13 ARIMA SEATS	1 st diff.
13	Foreign Direct Investment	BCB	X-13 ARIMA SEATS	1 st diff.
14	IBC-Br	BCB	Source	1 st diff.
15	Foreign exchange rate (R\$/US)	BCB	-	1 st diff.
16	SWAP DlxPre 180	BCB	-	1 st diff.
17	SWAP DlxPre 360	BCB	-	1 st diff.
18	CDS Brazil – 5 years	Bloomberg	-	Level
19	CDS PETR4 – 5 years	Bloomberg	-	1 st diff.
20	Volatility index (VIX)	CBOE	-	Level
21	Oil volatility index (OVX)	CBOE	-	Level
22	Real industry's revenue - Brazil	CNI	Source	1 st diff.
23	Work hours in the industry – Brazil	CNI	Source	1 st diff.
24	Employment level in the industry - Brazil	CNI	Source	1 st diff.
25	Confidence index in the extractive industry	CNI	X-13 ARIMA SEATS	1 st diff.
26	Confidence index in the transformation industry	CNI	X-13 ARIMA SEATS	1 st diff.
27	CPB world trade monitor	CPB	X-13 ARIMA SEATS	1 st diff.
28	Electricity consumption in Brazilian southeastern region	Eletrobras	X-13 ARIMA SEATS	1 st diff.
29	Brent spot price	EIA	X-13 ARIMA SEATS	1 st diff.
30	WTI spot price	EIA	X-13 ARIMA SEATS	1 st diff.
31	Nymex contract 4	EIA	X-13 ARIMA SEATS	1 st diff.
32	Spread Nymex contract 4 and WTI spot	EIA	-	Level
33	Global oil production	EIA	X-13 ARIMA SEATS	1 st diff.
34	OECD oil consumption	EIA	X-13 ARIMA SEATS	1 st diff.
35	OECD oil stocks	EIA	X-13 ARIMA SEATS	1 st diff.
36	Consumer confidence index	Fecomércio	X-13 ARIMA SEATS	1 st diff.
37	Consumer expectation index	Fecomércio	X-13 ARIMA SEATS	1 st diff.
38	Current economic condition index	Fecomércio	X-13 ARIMA SEATS	1 st diff.
39	Inflation – IGP	FGV	-	Level
40	Industry capacity utilization level	FGV	Source	1 st diff.
41	Real industry's revenue – Rio de Janeiro	Firjan	X-13 ARIMA SEATS	Level
42	Industry utilization capacity index	Firjan	X-13 ARIMA SEATS	1 st diff.
43	Employment level in the industry – Rio de Janeiro	Firjan	X-13 ARIMA SEATS	1 st diff.
44	Industry salary level	Firjan	X-13 ARIMA SEATS	1 st diff.
45	Work hours in the industry – Rio de Janeiro	Firjan	X-13 ARIMA SEATS	1 st diff.
46	Export prices	FUNCEX	X-13 ARIMA SEATS	1 st diff.
47	PIM-PF Capital Goods	IBGE	Source	1 st diff.
48	PIM-PF Intermediate goods	IBGE	Source	1 st diff.
49	Inflation – IPCA	IBGE	-	Level
50	CAGED Admissions	Government	X-13 ARIMA SEATS	1 st diff.
51	Capital goods import	Government	X-13 ARIMA SEATS	1 st diff.
52	Composite leading indicator - Brazil	OECD	-	Level
53	Composite leading indicator – China	OECD	-	Level
54	Composite leading indicator – G7	OECD	-	Level
55	Composite leading indicator - OECD	OECD	-	Level
56	Business confidence index – Brazil	OECD	X-13 ARIMA SEATS	Level
57	Business confidence index – G7	OECD	X-13 ARIMA SEATS	Level
58	Business confidence index - OECD	OECD	X-13 ARIMA SEATS	Level
59	Ibovespa	Yahoo Finance	-	1 st diff.
60	New York Stock Exchange (NYSE)	Yahoo Finance	-	1 st diff.
61	Petrobras preferential stock (PETR4)	Yahoo Finance	-	1 st diff.

Table A2
Quadratic probability score for the composite
leading indicator components from lags –1 to –8

series	lag –1	lag –2	lag –3	lag –4	lag –5	lag –6	lag –7	lag –8
prod_rj	0.21	0.19	0.23	0.26	0.27	0.30	0.32	0.35
exp_pet	0.36	0.36	0.35	0.36	0.36	0.37	0.38	0.40
cons_elet_se	0.51	0.49	0.49	0.46	0.44	0.40	0.37	0.35
PETR4	0.38	0.38	0.36	0.37	0.37	0.37	0.37	0.38
FDI	0.46	0.44	0.42	0.41	0.39	0.38	0.37	0.37
di_pre_360	0.47	0.47	0.46	0.46	0.45	0.45	0.45	0.45

Table A3
Quadratic probability score for the composite
leading indicator components from lags –9 to –16

series	lag –9	lag –10	lag –11	lag –12	lag –13	lag –14	lag –15	lag –16
prod_rj	0.39	0.40	0.43	0.45	0.45	0.47	0.47	0.47
exp_pet	0.41	0.42	0.44	0.46	0.49	0.49	0.51	0.51
cons_elet_se	0.33	0.30	0.30	0.29	0.30	0.31	0.32	0.32
PETR4	0.38	0.39	0.39	0.38	0.37	0.37	0.37	0.37
FDI	0.39	0.39	0.39	0.40	0.41	0.44	0.46	0.48
di_pre_360	0.43	0.41	0.40	0.39	0.38	0.38	0.38	0.39

Table A4
Granger causality results for the composite
leading indicator components in level

null hypothesis	F-statistic	Probability	AIC
PROD_RJ does not Granger Cause REFERENCE	2,06537	0,0868	4
REFERENCE does not Granger Cause PROD_RJ	1,31329	0,2392	
EXP_PET does not Granger Cause REFERENCE	2,24975	0,051	6
REFERENCE does not Granger Cause EXP_PET	0,70247	0,648	
CONS_ELET_SE does not Granger Cause REFERENCE	2,48385	0,086	2
REFERENCE does not Granger Cause CONS_ELET_SE	0,71487	0,4905	
PETR4 does not Granger Cause REFERENCE	1,52559	0,0965	3
REFERENCE does not Granger Cause PETR4	0,86157	0,3544	
FDI does not Granger Cause REFERENCE	9,00582	0,0002	2
REFERENCE does not Granger Cause FDI	1,40765	0,2044	
DI_PRE_360 does not Granger Cause REFERENCE	3,46359	0,0642	5
REFERENCE does not Granger Cause DI_PRE_360	1,51499	0,2198	

Table A5
Granger causality results for the composite
leading indicator components stationary

null hypothesis	F-statistic	Probability	AIC
PROD_RJ does not Granger Cause REFERENCE	5,02483	0,0022	3
REFERENCE does not Granger Cause PROD_RJ	0,13818	0,9371	
EXP_PET does not Granger Cause REFERENCE	1,99982	0,0804	7
REFERENCE does not Granger Cause EXP_PET	1,39292	0,2194	
CONS_ELET_SE does not Granger Cause REFERENCE	2,75286	0,0986	1
REFERENCE does not Granger Cause CONS_ELET_SE	0,15718	0,6922	
PETR4 does not Granger Cause REFERENCE	2,01437	0,0171	2
REFERENCE does not Granger Cause PETR4	1,35978	0,2247	
FDI does not Granger Cause REFERENCE	4,42009	0,0367	2
REFERENCE does not Granger Cause FDI	0,05651	0,8123	
DI_PRE_360 does not Granger Cause REFERENCE	4,15609	0,0428	4
REFERENCE does not Granger Cause DI_PRE_360	1,38686	0,2403	

Table A6
Bivariate probit model results for the composite
leading indicator components

variable	optimum lag QPS	Z-Statistic	Probability
prod_rj	2	-2.0685	0.0386
exp_pet	3	2.517864	0.0118
cons_elet_SE	12	1.915566	0.0554
Petr4	3	-1.98859	0.0467
FDI	7	-1.94946	0.0512
di_pre_360	13	2.705671	0.0068

Table A7
Descriptive statistis of the series selected for the final
composite leading indicator (CLI)

variable	mean	p50	sd	min	max	skewness	kurtosis
petr4	16.314	16.358	8.12	3.275	40.512	0.403	2.648
prod_rj	4.80E+07	4.80E+07	6.20E+06	3.40E+07	6.40E+07	-0.051	2.478
ied	844.554	514.94	1198.227	14.37	1.30E+04	5.588	52.545
cons_elet	1.80E+04	1.90E+04	2334.772	1.20E+04	2.10E+04	-0.762	2.252
di_pre_360	-13.127	-12.02	5.053	-31.18	-6.35	-1.287	4.882
exp_pet	1.70E+07	1.50E+07	9.60E+06	1.10E+06	5.60E+07	1.083	4.382

Note: number of observations for all variables equals 209 (year-month).