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## Article

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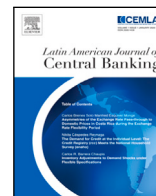
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# A diffusion index analysis of the Argentinean business economic cycle based on the “Survey of Business Economic Perspectives”<sup>☆</sup>

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## ABSTRACT

The Central Banks use diffusion indexes (*DI*s) to synthesize information from proprietary surveys that complement official statistics generating real-time proxies of the economically relevant variables. According to the evidence, the *DI*s closely follow the economic cycle reflected in those official statistics. In this paper, we calculate diffusion indexes to summarize relevant qualitative information on the economic situation of the firms participating in the *Survey of Business Economic Perspectives* collected by the Argentinean Central Bank [Banco Central de la República Argentina (BCRA)] and we evaluate their ability to track economic activity in real-time. The indexes are analyzed for the 2017–2022 period, a particularly volatile business cycle for Argentina and (given the impact of Covid-19) for the global economy. Using the qualitative data from the firms we calculate (i) the marginal diffusion index (*MDI*) proposed by the Federal Reserve Bank of Chicago (FRB-Chicago) and based on the *balance of answers* corrected by the averaged participant response and, (ii) the marginal fixed diffusion index (*MFDI*), a real-time variation of the latter. To contrast and validate the indexes' ability to summarize relevant information we introduce an econometric procedure aimed at assessing their relationships with official economic activity indicators. The results indicate that the *DI*s calculated with the qualitative BCRA's Survey information closely track and even anticipate the behavior of other official activity indicators both for the entire sample of firms and for the industrial sector.

## 1. Introduction

The BCRA collects a monthly *Survey of Business Economic Perspectives* from a sample of non-financial companies. This type of survey implemented by the BCRA and other central banks around the world, including the Federal Reserve in the US, is a valuable tool for obtaining real-time information about the economy and to maintain a direct liaison with non-financial companies. In a volatile economic environment like Argentina's<sup>1</sup> where conditions can change rapidly, having direct data is crucial. As indicated

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<sup>1</sup> As Fanelli (2002) indicated, in Argentina, “*periods of turbulence alternate with periods of tranquility*”. In fact, in considered period between 2017 and 2022, the economy was particularly volatile alternating different macroeconomic and monetary programs (including one with the IMF) and several currency depreciation episodes between 2018 and 2019 as well as political uncertainty and financial turmoil around a government election with a change in the government ruling party. In addition, in march 2020 the rapid and unexpected impact of the Covid-19 pandemic generated a strong and significant economic shock both globally

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by Pinto et al. (2020), the Central Banks and/or use the information to calculate synthetic indexes that provide closer to real-time and/or complement information not compiled in the aggregated official statistics. In fact, the sample includes more than 100 non-financial companies and a diverse range of participants from different sectors, including industrial, commercial, construction, services and energy. The non-financial companies included in the survey are dominant in their respective markets and represents more than 6% of total formal employment. The quantitative and qualitative questions in the Survey are complemented with *follow up* interviews to have a more comprehensive and accurate picture of the economic situation of the companies and their economic sectors. A challenge in this type of voluntary survey is to keep the companies' engagement and potentially increase the sample size. In order to maximize the usefulness of the data obtained, it becomes crucial to extract the highest quality and quantity of information using a minimal number of questions keeping the questionnaire concise and identifying key questions that are critical for understanding the economic outlook.

In this sense, the objective of the paper is to highlight how the data obtained from a qualitative question from the *Survey of Business Economic Perspectives* can be used to generate synthetic indicators that, in real-time, can help to extract reliable information to track the actual economic business cycle. Argentina's official economic activity information is compiled and published by the national statistical agency: *Instituto Nacional de Estadísticas y Censos (INDEC)*. Typically, the aggregated economic activity information is released with delay (one-month lag) and may be subject to revisions. Therefore, for the BCRA is helpful to have a real-time indicator tracking the actual economic activity to enhance the monetary policy decision-making process.

As emphasized by Brave et al. (2015), the qualitative information, as the one collected in the *Survey of Business Economic Perspectives*, is "by design anecdotal, but it is meant to provide context for understanding trends in actual quantitative data". Indeed, the BCRA's Survey includes a first qualitative question regarding the *economic situation of the firm* both for the last and the next six months. This question is open and subjective in terms of the various economic variables (sales, production, prices, etc.) that the qualified informant of the firm may consider when formulating the answer.<sup>2</sup> Precisely, this particular question is used to calculate different *DI*s for 2017 through 2022 period.

In general, traditional *DI*s are based on the "balance of responses". and, as highlighted by the literature,<sup>3</sup> may present "response bias" due to differences in the relative participant's optimism or pessimism and/or due to differences in sector's idiosyncratic cycles. Departing from the traditional index, two different *DI*s are calculated. First, the *DI* proposed (Brave et al., 2015) and used at the FRB-Chicago is introduced. The so-called *MDI* is also based on the "balance of the responses" but results from subtracting to each answer the average participant's response during the entire sample (for the whole period). As highlighted by the authors<sup>4</sup> the *MDI* has some attractive features comparing with the traditional *DI* including: (i) a higher variance and, (ii) a potentially lower "response bias". However, in the case of the *MDI* the past values may change as the average answer through the entire sample period changes.<sup>5</sup> As noted by Brave et al. (2015), the new information can certainly change during abnormally volatile periods (periods with sharp economic shocks) affecting the *MDI* past observations.<sup>6</sup> Second, the so-called, Marginal Fixed DI (*MFDI*) is introduced [See Elosegui et al. (2022)] aiming to solve the potential change in the *MDI* past observations due to ex-post volatile economic periods. The *MFDI* calculates the *MDI* in pseudo-real-time, considering the firm's average response until the current period and keeping the index value invariant to future economic changes. Therefore the *MFDI* complements the business cycle analysis derived from the *MDI*.<sup>7</sup> As we will see, the comparison of both indexes on a particular date complements the business cycle analysis that can be extracted from the original data.

Finally, the *DI*s are statistically and econometrically analyzed in order to assess how well they track the best available official monthly GDP indicator, the *Monthly Estimator of Economic Activity (MEEA)*.<sup>8</sup> Also, an analysis is performed for the sample of industrial companies and compared with the aggregated industrial production official indicator (*IPI*).<sup>9</sup>

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and in Argentina. The domestic economic activity dropped by 25% yearly in April 2020. In this context, the government implemented a series of economic policies focused on avoiding disruption of households' income, assisting companies to preserve employment and guaranteeing supply, and enhancing public health services. As result, after an annual change in GDP of -9.94% in 2020 the economy recovered 10.39% in 2021.

<sup>2</sup> As we describe next, the question has five different possible answers, including two positive (low or significant) and two negatives (low or significant) answers as well as one reflecting a neutral vision (no change) of the economic situation of the firm.

<sup>3</sup> See for instance Pinto et al. (2015).

<sup>4</sup> Brave et al. (2015)

<sup>5</sup> The answer provided at period  $t$  is included in the *MDI* after subtracting the average response of the firm until period  $T$ , ranging from period 0 to  $T$ , and including information from the period  $t+1$  up to  $T$  that was not available for the firm at  $t$ .

<sup>6</sup> For example, a firm may answer a low positive economic situation at period  $t$ . Provided the firm has an average neutral economic situation response the resulting *MDI* would give a low positive economic situation vision. But if in the future the economic situation improves (either because the aggregated or the particular industry business cycle improves) and the average response of the company changes on average to a low positive economic situation, then the particular result for the firm at period  $t$  would now become neutral contrasting with the vision the firm's had with the available information at the actual period  $t$  and may end up affecting the calculated *MDI* at period  $t$ .

<sup>7</sup> As we will show in our analysis, the calculated *MDI* changes for past observations as the average response of each firm is affected by the new and unexpected information arising from the Covid-19 shock. Similar to other business cycle filters, as the popular HP filter. See Orphanides and Norden (2002) for an interesting discussion. However, during the same period, the *MFDI* value is unaffected and allows us to keep track of the actual situation in the past periods as synthesized from the original qualitative information, without considering the then unexpected Covid-19 shock.

<sup>8</sup> The *MEEA* is a monthly index calculated by INDEC aiming at maintaining the quarterly Gross Domestic Product (GDP) estimation methodology. Then, the *MEEA* is a provisional indicator of the evolution of GDP at constant 2004 prices that according to INDEC is "released with a lag of 50 to 60 days after the end of the reference month".

<sup>9</sup> The industrial manufacturing production index (*IPI*) includes an exhaustive survey of all the manufacturing economic activities of the industrial sector, with national representative coverage. The indicator measures the evolution of the sector on a monthly basis and is calculated from the variables of production, sales, input use, and apparent consumption in physical units as well as the number of hours worked by personnel affected by the production process and sales at deflated current prices.

The results indicate that the *DI*s calculated with the *Survey of Business Economic Perspectives* information closely track and even anticipate the behavior of the main official economic activity indicators in the context of shocks as relevant as Covid-19 and in a very volatile economic environment as the one that characterized the Argentinean economy between 2017–2022. The results validate the auspicious statistical properties of the diffusion indexes and highlight the potential value of strengthening the *Survey of Business Economic Perspectives*. In particular, the calculated *DI*s required no seasonality adjustment indicating that the participant firms incorporate the actual seasonal variations in their individual assessments. In contrast, both *MEEA* and *IPI* indicators require seasonality adjustments. Also, both the *MDI* and the *MFDI* for the last six months are leading and contemporaneous indicators of the *MEEAsa*. The *MFDI* for the next six months shows simultaneity with the *MEEAsa* suggesting that the firms consider the economic activity level as a relevant input in their expectation formation process. In addition, the results for the *DI*s calculated for the industrial sector sample show similar behavior with respect to the main industrial sector production indicator. Finally, the results underscore the relevance and the close relationship between the anecdotal information extracted through the qualitative question from the *survey of Business Economic Perspectives* and the economic activity through the Argentinean economic business cycle both before and after the strong impact of the Covid-19 pandemic.

The rest of the paper is organized as follows. Section 2 describes the source of the proprietary information from the *Business Survey of Economic Perspectives*, and the question used to calculate the diffusion indexes. Section 3 introduces the different diffusion indexes proposed to analyze the participant's information. Section 4 introduces the statistic and econometric procedures used to analyze the relationship between the calculated *DI*s and the official economic activity series. Finally, Section 5 introduces the main conclusions and the next steps of this research agenda.

## 2. The business survey of economic perspectives

Since December 2016, the BCRA implements a monthly *Survey of Business Economic Perspectives* for non-financial companies. The survey is submitted online by companies from different economic sectors, including industrial, commercial, energy, construction, and services. The sample includes more than 100 non-financial companies that are economically relevant in their markets representing approximately 6% of total formal private employment. It should be noted that the sample is not statistically significant or random. Also, as is the case in many other Central Banks, participation in the survey is voluntary as the *Business Economic Perspectives Survey* for non-financial companies is not included in any information regime required by the BCRA as a financial regulatory agency.

The participant companies designate a qualified informant, with access to both the internal balance sheet and the company's planning information, responsible for submitting the survey. Additionally, the qualified informant is contacted for follow-up questions that aim to assess the economic situation of the company and its economic sector. This anecdotal information is aggregated to complement the quantitative and qualitative information revealed in the survey. The online survey includes a qualitative question about the company's economic situation both current (for the last 6 months) and expected (for the next 6 months) together with a set of quantitative questions<sup>10</sup> about the quarterly changes (past and expected) in several relevant economic variables from the balance and the statement of profit and loss books and the companies' planning projections.

Indeed, together with the first qualitative question, the firms complete a quantitative<sup>11</sup> survey with questions regarding the past and projected changes in domestic and foreign prices.<sup>12</sup> The Survey includes similar questions for following variables: domestic input costs, imported input costs, and unit labor costs. The survey questions include sales, inventories over sales and production. The quantitative information is aggregated and summarized using standard descriptive statistics (including the mean, median, and standard deviation) and used in internal confidential reports as well as in research analysis. Indeed, [Elosegui and Sangiácomo \(2022\)](#) performs an econometric analysis of the price and cost quantitative information and its relationship with inflation and other macroeconomic variables.<sup>13</sup>

The information is uploaded through a secure external application designed by the Central Bank, and it is processed and analyzed following strict confidential and secured procedures.

### 2.1. Dataset

The information used to calculate the different *DI*s corresponds to the first qualitative question of the *Survey of Business Economic Perspectives*. The question answered by the qualified informant inquires about the economic situation of the firm both for the last and the next 6 months. The qualitative question has five different possible ordered categorical answers, including a neutral and two positive (high/low) and negative (high/low) responses.<sup>14</sup> The actual question and the possible categorical answers are listed below:

- How do you evaluate the economic situation of your company compared to six months ago?

<sup>10</sup> These quantitative questions are also accompanied by the respective qualitative questions (with five possible answers).

<sup>11</sup> The firms have to answer with the average change in the variable during the last and the next three months.

<sup>12</sup> This variable is a weighted average change in the prices of goods and/or services sold by the company.

<sup>13</sup> See [Elosegui and Sangiácomo \(2022\)](#) for a comprehensive quantitative data description of the *Survey of Business Economic Perspectives*.

<sup>14</sup> This type of ordered categorical scale with a neutral middle category is commonly referred to as a *Likert* scale. In the present analysis, the calculated *DI*s summarize the ordinal answers collected by the categorical scale by using their quantitative nature. As highlighted by [Agresti \(2010\)](#) ordered categorical response variables can be analyzed through a quantitative scale or exclusively utilizing the ordering information of the categories. This distinction is not important for the current analysis, but may be useful to study the main determinants explaining the behavior of the categorical original variable through non-parametric methods utilizing ranks or models that estimate cumulative response probabilities.

- Significantly improved.
  - Moderately improved.
  - Did not change.
  - Moderately worse.
  - Significantly worse.
- And for the next six months?
    - Will improve significantly.
    - Will improve moderately.
    - Will not change.
    - Will get moderately worse.
    - Will get significantly worse.

To quantify the responses, a numerical value of 1 and 0.5 for significant and moderate improvement, 0 for no change, and -0.5 and -1 for moderate and significant worsening is applied to the answer of the firm  $i$  during a period  $t$ . Then the firm’s nominal responses are used to calculate the diffusion indexes, as detailed in the following section.

### 3. Diffusion indexes

Diffusion indexes are statistics derived from survey responses capable of providing summarized quantitative indicators even from originally qualitative information. The evidence shows that the calculated  $DI_s$  may provide real-time assessment and/or leading indicators of economic activity, aiming to capture changes in the direction of economic activity. The  $DI_s$  are usually defined in terms of the proportions of answers indicating opposed visions (or disagreements) around a given question (either qualitative or quantitative). As indicated by Pinto et al. (2020), by considering the discrepancy arising from the data, the  $DI_s$  “provide a measure of the breadth of change” in the corresponding aggregated series associated with the particular question.<sup>15</sup> In fact, the original  $DI_s$  have been extensively analyzed in terms of their ability to forecast economic activity indicators.

#### 3.1. The original (“Balance of Response”) diffusion index

The traditional diffusion index are based on the “balance of response”, as highlighted by the Board of Governors of the Federal Reserve System (1991).<sup>16</sup> Several Federal Reserves use these  $DI_s$  to capture the direction of change of different economic variables, like inventories or sales, that are not usually measured (at least in real-time) by the official statistics, see Pinto et al. (2015), Pinto and Waddell (2022) and Brave et al. (2015). Despite their usefulness, an interesting feature of this  $DI_s$  based on the balance of answers is that two different scenarios may lead to the same synthetic result. For instance, in the case of two participants with contrasted visions, one moderately positive and the other moderately negative, the  $DI$  is neutral and generates the same result as in the case where both firms have a neutral vision. Both cases can reflect a no-change economic situation. However, as indicated by Pinto et al. (2020) the implied uncertainty regarding the business cycle reflected in the polarized answers is not fully reflected by the original  $DI$  and the authors proposed an approximation of the  $DI$  distribution to allow considering a measure of uncertainty.

#### 3.2. The marginal diffusion index

The Federal Reserve Bank of Chicago, Brave et al. (2015) proposed a diffusion index used to calculate different Chicago Fed Survey of Economic Conditions (CFSBC) indicators.<sup>17</sup> As stated by the authors, this  $DI$  generates solid correlations “with other regional and national indexes of economic activity, as well as gross output growth”. The authors introduce an adjustment to the traditional diffusion index formula by measuring the individuals’ responses relative to their respective average responses. A response is positive

<sup>15</sup> In the case of the Board of Governors of the Federal Reserve System (1991), the information comes from a set of industrial production series that are synthesized as a unique industrial production index. In contrast, the information used in the calculated  $MDI$  and  $MFDI$  is qualitative and not directly related to any identifiable quantitative series.

<sup>16</sup> In order to introduce the notation we calculate the traditional or “original diffusion index”  $ODI$  by defining  $R_{i,t}$  as the “nominal response” for a firm  $i$  at the period  $t$ . We assume that the set of  $k$  possible nominal answers associated to the five possible qualitative responses. Then, an answer  $k = 1$  is  $R_i^1 = 1$  and

$$\frac{1}{N} \sum_{i=1}^N R_i^1 + \frac{1}{N} \sum_{i=1}^N R_i^{0.5} + \frac{1}{N} \sum_{i=1}^N R_i^{-1} + \frac{1}{N} \sum_{i=1}^N R_i^{-0.5} = \sum_k \frac{1}{N} \sum_{i=1}^N R_i^k.$$

Then  $ODI$  is a weighted average at  $t$  of the proportion of firms with positive (increasing) answers compared with the proportion with negative (decreasing) answers over the “span” (or period) ranging from -100 to 100. A value above (below) 0 is interpreted as an improvement (worsening) of the economic situation. The  $ODI$  is calculated as:

$$ODI_t = [\sum_k \frac{1}{N} \sum_{i=1}^N R_i^k] \times 100.$$

<sup>17</sup> Publicly available at Chicago Fed Survey of Economic Conditions (CFSEC).

(negative) if it is above or below their respective average answers. In that sense, the answer by each participant is re-scaled before applying a traditional DI “balance of response” formula. As highlighted by the authors, *the resulting diffusion indexes are adjusted for inherent biases in measurement and interpretation.*

The proposed index captures (what we call) the *marginal* response of each company with respect to its own average answer during the sample period. Therefore, the marginal diffusion index *MDI*, is calculated by subtracting the firm’s average response in the complete sample period. The re-scaling process helps to ameliorate (as claimed by the authors) several concerns associated with the traditional diffusion indexes (Pinto and Waddell, 2022). For instance, the *response bias* because participants: (i) may differently assess a given variation as a slightly and/or a significant variation<sup>18</sup> Overall, they indicate that *MDI “benefit from de-trending because it removes respondent- as well as firm (and sector)-specific trends”*. or (ii) may potentially have an optimistic (pessimistic) bias. In these cases, the individual participant responses would always fall within the same range. To deal with this concern the authors rely on the participant’s own assessment regarding the average change in the variable to determine how far the recent answer is from the *normal (long run)* value of the variable. The authors claim that *“moderately optimistic respondents are counted as having a positive outlook only when they are feeling very optimistic and our moderately pessimistic respondents are counted as having a positive outlook even when they are feeling slightly pessimistic”*. Furthermore, the procedure is particularly useful in cases (as the one analyzed here) of small samples or when the samples are not statistically significant or random and/or in samples with participants (firms) belonging to different sectors. In fact, the authors consider that a potential bias arises from the fact that the industries and firms represented in their data may have different growth trends compared to the overall economy. This can lead to biased indexes due to the lack of a random sample of respondents. Specifically, if the industry (as in our case) constitute a significant portion of the respondents, a traditional *DI* may disproportionately reflect trends in the industrial sector. By re-scaling the indexes relative to respondents’ average responses, the authors claim they effectively address the *“biases associated with individual respondents, firms, and industries”*. This allows for the safe combination of industrial and non-industrial (commercial, construction, energy and services) sectors in the same respondent pool, *“reducing potential bias from a nonrandom sample”*.<sup>19</sup> In addition, this procedure helps to increase variation on the marginal answer enhancing the aggregate variance as shown by Brave et al. (2015) for their sample and noted in Table 2 below for our case. In sum, the *MDI* considers the average quantitative response  $\hat{R}_{i,t}$  for each firm *i* and period *t* until the last period *T*.

$$\hat{R}_{i,T} = \frac{1}{T} \sum_{t=1}^T R_{i,t} \tag{1}$$

In every period *t* until *T* each firm’s response  $R_{i,t}$  is compared with the average trend  $\bar{R}_{i,T}$  and the sign is preserved:

$$R_{i,t}^* = 1 \iff \text{sign}(R_{i,t} - \hat{R}_{i,T}) > 0 \tag{2}$$

$$R_{i,t}^* = -1 \iff \text{sign}(R_{i,t} - \hat{R}_{i,T}) < 0 \tag{3}$$

As described before, the marginal index is calculated through a traditional DI formula applied to the modified (demeaned or re-scaled) data,<sup>20</sup>

$$MDI_t = \left[ \frac{1}{N} \sum_{i=1}^N R_{i,t}^* \right] \times 100 \tag{4}$$

As highlighted by Brave et al. (2015), in their analysis for the Midwest Region at U.S., the *MDI* presents a higher variance compared with the traditional *DI* and generates solid correlations *“with other regional and national indexes of economic activity, as well as gross output growth”*. However, there is a concern due to the fact that the index may change as the trend changes. As noted by the authors as the histories of firms’ responses increase *“their average responses evolve, sometimes changing whether we treat earlier responses as positive, neutral, or negative, which in turn changes earlier values of the CFSBC indexes”*. In order to address this issue we propose a variation of the *MDI* only considering the information available at any given date to avoid index changes for past periods.<sup>21</sup>

### 3.3. The marginal fixed diffusion index

The Marginal Fixed Diffusion Index (*MFDI*) is a variation of the *MDI* aimed to deal with the *MDI*’s changes in past observations as recent information modified the participant average response trend. Indeed, the average trend may change during

<sup>18</sup> The same qualitative answer may have different meanings (and different numerical scores) for different individuals. As stated by the authors, *individuals may interpret phrases such as “substantially increased” differently, so that our numerical scores have different meanings for different people*. To overcome this, the survey relies on individuals’ assessments of “average” growth to determine deviations from normal business conditions. Also, as they expressed, a *“second type of potential bias is that the industries and firms represented in our data may have different growth trends than the overall economy, which could bias the indexes because we do not have a random sample of respondents”*.

<sup>19</sup> Brave et al. (2015) recommend smoothing the average of repeated respondents, taking into account the change in the number of participants in the survey. The procedure requires a relatively balanced sample as correlative (and several) observations are needed in order to correctly re-scale the participant’s average response.

<sup>20</sup> *MDI* ranges from -100 to 100, with values above (below) zero indicating an improving (worsening) vision zone.

<sup>21</sup> See Elosegui et al. (2022).

volatile cycles modifying the *MDI* past observations.<sup>22</sup> In the *MFDI* each new observation is compared with the participant's average response calculated until the period under analysis. The actual assessment in period  $t$  is then saved (fixed) and does not change thereafter. Then *MFDI* uses the average participant answer  $\hat{R}_{i,t}$  considering the information available up to the  $t = \tau$ :

$$\hat{R}_{i,t} = \frac{1}{\tau} \sum_{r=1}^{\tau} R_{i,r} \tag{5}$$

At  $t = \tau$  the (marginal) participant answer is compared with its average answer up to the period  $\tau$ . Then the next period, the *MDI* is calculated again and replaced for period  $t + 1$ , with the corresponding average until  $\tau = t + 1$  and, again is fixed and saved. It should be noted that in the *MDI* the average was calculated until period  $T$ . In the *MFDI* case, the *MDI* is fixed after  $t$ . In contrast to the *MDI*, the *MFDI* in  $t$  is not recalculated in  $t + 1$  even if new information arises that could change the average until  $t + 1$  and, the *MDI* at  $t$  and/or in past periods.

$$R_{i,t}^{**} = 1 \iff \text{sign}(R_{i,t} - \hat{R}_{i,t}) > 0 \tag{6}$$

$$R_{i,t}^{**} = -1 \iff \text{sign}(R_{i,t} - \hat{R}_{i,t}) < 0 \tag{7}$$

$$MFDI_t = \left[ \frac{1}{N} \sum_{i=1}^N R_{i,t}^{**} \right] \times 100 \tag{8}$$

The *MFDI* indicator is calculated just like the *MDI* and the information for each period  $t$  is saved and then remains invariant.<sup>23</sup> In particular, the calculation and saving procedure is done using Stata's ROLLSTAT module designed by Panigo and Sangiácomo (2003).

The *MFDI* gives a slightly different and complementary business cycle interpretation with good predictive behavior. In particular, in any given current period *MDI* and the *MFDI* are equal. However, the past values for the latter stay fixed as time evolves whereas the *MDI* past values may change provided the participant's long-run trends are affected by new shocks and modified with new information. Therefore, the *MFDI* shows the real-time period valuation as measured by the diffusion index calculated with the actual information available up to the period. The *MDI* is not useful to analyze past periods. But, from a purely statistical point of view, the *MDI* should capture the long-run trend information characterizing the (invariant) participant characteristics. Therefore, the indexes are complementary, the *MFDI* solves the past changes in perspective as time pass while the *MDI* indicates the long-run participant's perspectives. In a context of highly volatile economic business cycles and in periods with sharp and unexpected shocks the past period's differences between both indexes are quite informative as analyzed in the Elosegui et al. (2022).

### 3.4. The Marginal and Fixed DI's calculation and analysis

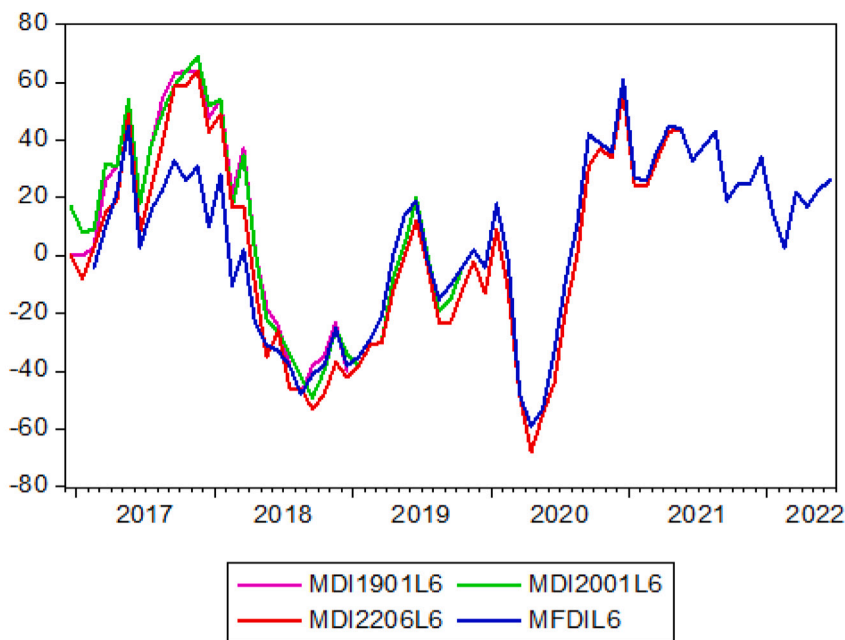
The calculated *MDI* and *MFDI* indexes can be seen in Fig. 1 both for the last and next 6 months. The main differences between both DI can be noted at the beginning of the sample period and after important shocks such as Covid-19. During such volatile period, the average trend changed modifying the perception registered by the participants with the information accrued at each given period. In fact, there is an important difference between the *MDI* and *MFDI* during 2017 and the difference becomes important again during the 2020's Covid-19 period. In the first case, the *MDI* clearly overestimates the positive perspective, as the long-run economic situation worsens for most of the participants. The responses of several participants changed from a neutral or negative perception at the time to a positive one just because their average response for the whole period (up to  $T$ ) changed. In this particular case, the change is due to an important and unexpected economic shock like Covid-19. The firms at that time  $t$  were indicating an economic situation that was not as good as the one they would have indicated if they knew about the Covid-19 shock. The actual economic perception with the information up to  $t$  is indicated by the *MFDI*.

In fact, Fig. 1(a) shows the *MDI* calculation considering different initial periods for the average response of each company and resulting in different *MDI* values that are in all cases above the *MFDI* calculated with the information up to the period. A similar situation arises during and immediately after the unexpected Covid-19 shock. In particular, the *MDI*s overestimate the extent of the crisis. After the initial shock in March and April, as the economy rapidly improves, participants' averages also improve and for some of them, the difference between the period's perception and the average, adjusted after the crisis, changes the perspective's sign. Indeed, participants' perceptions overestimate the actual perception during that period. The technical note by Elosegui et al. (2022) analyzes the economic business cycle comparative performance of both indexes (*MDIL6* and *MFDI6*). It is clear from the comparison in Fig. 1 that the *MFDI* does not change with time as the average perception for each company changes, reflecting participants' perspectives based on the available information during each given period.

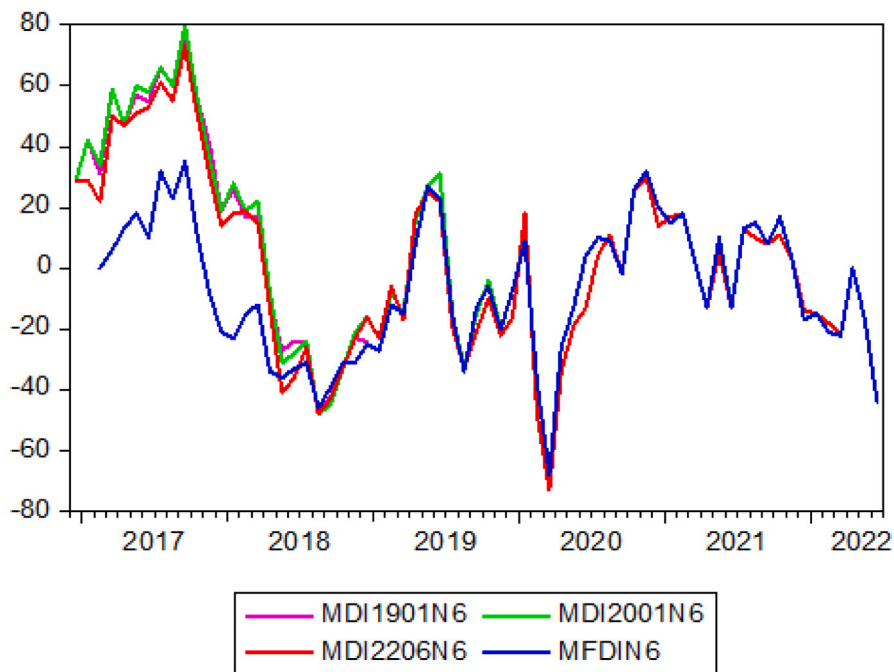
The variance and covariance matrix of the different DIs are summarized in Table 1. The comparison includes the *ODI* calculated as indicated in footnote 15. It should be noted that *ODI*'s variance (the diagonal of the variance-covariance matrix) is always the lowest value as indicated by Brave et al. (2015).

<sup>22</sup> The early values may change if the economy is not growing near its long-term trend or facing a sharp economic shock and/or when new firms are incorporated to the sample in different phases of the business cycle.

<sup>23</sup> A feasible alternative, is to define the mean using a rolling window of different  $k$  periods around  $t$ . This would imply calculating different averages (up to  $k \rightarrow T$ ) to re-scale the observation of the firm at  $t$ , resulting in intermediate values between the one used in the *MFDI* and *MDI*. In contrast with the *MFDI*, future information would be used to calculate the index in  $t$ .



(a) *MFDI* and *MDI*s for the last 6 months. The latter calculated with information up to 01-2019, 01-2020 and 06-2022.



(b) *MFDI* and *MDI*s for the next 6 months. The latter calculated with information up to 01-2019, 01-2020 and 06-2022.

Fig. 1. *MDI* (different periods) & *MFDI*.

**Table 1**  
Diffusion index variance and covariance matrix.

Series	<i>ODIL6</i>	<i>MDIL6</i>	<i>MFDIL6</i>	<i>ODIN6</i>	<i>MDIN6</i>	<i>MFDIN6</i>
<i>ODIL6</i>	<b>171,8</b>	389,5	335,0	60,8	157,4	168,6
<i>MDIL6</i>		<b>1152,0</b>	950,9	112,3	407,8	370,8
<i>MFDIL6</i>			<b>896,7</b>	38,2	147,3	252,2
<i>ODIN6</i>				<b>92,0</b>	254,6	167,7
<i>MDIN6</i>					<b>943,8</b>	590,8
<i>MFDIN6</i>						<b>509,6</b>

**Table 2**  
Mean correlation all and w.r.t. *MEEAsa*.

Series	Mean correlation	
	Pearson corr.	<i>p</i> -value
<i>All</i>	0.7619	0.001
<i>MDIL6</i>	<b>0.6125</b>	0.00
<i>MFDIL6</i>	0.5828	0.001
<i>MDIN6</i>	0.4148	0.003
<i>MFDIN6</i>	<b>0.5585</b>	0.001

Note: Own calculations with R Program. See Gouhier and Guichard (2014) for reference.

In order to analyze the comparative behavior of the diffusion indexes with respect to the actual economic business cycle information, the next section introduces a systematic econometric procedure. The procedure is applied to the *MDI* and *MFDI* calculated for the whole sample included in the *Survey of Economic Business Perspective*<sup>24</sup> in comparison with the economic activity index (*MEEA*). In addition, in the ANNEX the industrial sub-sample *DI*'s are compared to the industrial activity index (*IPI*).

#### 4. The *DI*s and the business cycle dynamics

In this section the comparative behavior of the different *DI*s is analyzed with an statistic and a *step by step* econometric procedure. The purpose of the analysis is to evaluate the *DI*s relationship with the economic business cycle-measured by the Monthly Estimator of Economic Activity, *MEEA*. In addition, the econometric analysis, allows modeling the *DI*'s dynamics. The analysis is aimed at understanding *DI*s ability as a lead/simultaneous indicator of economic activity level and assessing the *DI*s behavior during the business cycle highlighting their relevance as a policy-making decision tool.

##### 4.1. Synchrony analysis

A “standard” synchrony approach as proposed by Gouhier and Guichard (2014) is utilized to analyze the concordance between the analyzed variables.<sup>25</sup> The variables under analysis, *MEEAsa*, *MDI* and *MFDI* for the last and next six months, showed a joint significant concordance.<sup>26</sup> The results indicated a Kendall's *W* = 0.6527<sup>27</sup> with a statistically significant *W p*-value (one-tailed test [greater]) = 0.001, calculated with 999 Monte Carlo randomizations. In addition, the computed “Community Synchrony”<sup>28</sup> indicator equals 0.6381 with a “Mean pairwise correlation” of 0.5321 and a statistically significant Synchrony *p*-value [(one-tailed test [greater]) = 0.001.] The mean correlation analysis is summarized in Table 2.<sup>29</sup>

The analysis indicated that the five analyzed variables show a high concordance and synchrony through the business cycle with a relative higher correlation and significance between the *MAEAsa* and the *MDIL6* for the last 6 months and the *MFDIN6* for the next six months.

##### 4.2. Econometric analysis

In order to explore the underlying dynamic of the series we propose an econometric analysis that relies on a procedure with several steps highlighted in the specialized literature, see for instance Enders (2010) and Landro and González (2009). The procedure

<sup>24</sup> As mentioned before the only data requirement is for each company in the sample to have a minimum of eight consecutive observations.

<sup>25</sup> See the synchrony R package, that allows to analyze the concordance of a group of variables on the neighborhood of each point in time via Monte Carlo randomization.

<sup>26</sup> For reasons further developed in Section 4.2, we utilize the seasonally adjusted economic indicator, *MAEAsa*.

<sup>27</sup> The Kendall's *W* is a non-parametric statistic ranging between 0 and 1 and indicating the level of agreement between the analyzed variables.

<sup>28</sup> The Community-wide Synchrony statistic ranges between 0 and 1. If all the series show strong harmony, the community-wide synchrony is close to one. If the fluctuations are uncorrelated, the indicator approaches to zero.

<sup>29</sup> The statistic “peaks” was analyzed to determine the proportion of common local minima/maxima between the pair of variables, and the results were not statistically significant.

**Table 3**  
Series structural breaks and integration.

Series	Seasonality	Structural breaks	Integration order
<i>MDIL6</i>	Non-identifiable	April 2020	I(1)
<i>MDIN6</i>	Non-identifiable	September 2020	I(1)
<i>MFDIL6</i>	Non-identifiable	June 2020	I(1)
<i>MFDIN6</i>	Non-identifiable	September 2020	I(1)
<i>MEEA</i>	Identifiable	May 2019	I(1)
<i>MEEAsa</i>	Adjusted	April 2020	I(1)

Note: Own calculations with EViews Program. See [Enders \(2010\)](#) for reference.

involves modeling and evaluating the *DI*s temporal dynamic with respect to the economic activity level. The econometric procedure is applied to both the last and next 6 months.

The proposed econometric procedure for each series involves:

- A seasonality analysis, following the CENSUS X13 procedure.<sup>30</sup>
- A second-order stationary condition analysis.
- A unit root test analysis considering the presence of structural breaks. As indicated before, the breaks are actually important during the considered period, 2017 to 2022.
- A differentiation of the series according to the number of unit roots found with the extended Dickey–Fuller test for unit roots under the structural break.

**Table 3** summarizes the result of the initial steps of the proposed econometric analysis, including in each column: the seasonality, the date of identifiable structural breaks, and the integration order for each of the analyzed series.

In Argentina, the economic activity indicators as *MEEA* present a clear seasonality and are properly adjusted by the INDEC. The relevance of the seasonality in the Argentinean economy can be clearly seen in [Fig. 2\(a\)](#) below. The *MEEA* has a seasonal peak in the second quarter mainly explained by the agricultural sector influence. The agricultural sector impact is smoothed by the seasonal adjustment process.<sup>31</sup> In contrast, the *DI*s have non-identifiable seasonality. Interestingly, the latter result is informative, as it is reflecting that the participants consider their own seasonality judgment at the moment of assessing their economic situation.<sup>32</sup> Given the significant *MEEA* seasonality the relationship between the activity indicator and the *DI*s is analyzed using the index seasonally adjusted by the INDEC, the *MEEAsa*.

In addition, [Fig. 2\(b\)](#) shows the economic trend and cycle of the *MEEAsa* for different sub-periods. The trend calculated by INDEC is not linear nor stable and was clearly affected by the Covid-19 shock. Furthermore, the Figure shows different sub-periods trends that are clearly diverse and the *MEEAsa* indicator presents significant volatility throughout the period. There is an initial increasing trend, lasting until the beginning of 2018. Then, the economy can be better described by a decreasing trend that goes through 2018–2019 (after several exchange rate depreciation episodes) and clearly deepened during the Covid-19 shock. Subsequently, the recovery trend path after Covid-19 is clearly sustained until the end of the sample. These structural breaks, analyzed in **Table 3** certainly have an important effect on the appraisal of companies regarding their own averaged economic situation. As noted in the Figure, a company's average response may differ depending on the period of analysis and the information set available at that particular time.

Based on the previous analysis, the series are “whitened” identifying the actual data generating process to specify the “best” model for each of the series.<sup>33</sup> Then, the cross-correlation estimation between the (now) pure random residuals (or white-noise) models is performed. Finally, the transfer functions modeling and assessing the *DI*s ability as simultaneous/advanced indicators with respect to the economic activity level during the recent pandemic period are analyzed. The results are analyzed and discussed in the remaining sections, beginning by studying the relationship between the past (6 months) *MDI* and *MFDI* indicators with the *MEEAsa* and then analyzing the relationship with the prospective indexes.

#### 4.2.1. Relative performance of “observed” *MDIL6* & *MFDIL6* vs *MEEAsa*

As can be noted in [Fig. 3\(a\)](#) there is a close relationship between the *MDI* for the last 6 months *MDIL6* and the *MEEAsa*. It is interesting to observe that the *MDIL6* index captures the impact of the Covid-19 shock as well as the fast recovery.<sup>34</sup> In addition,

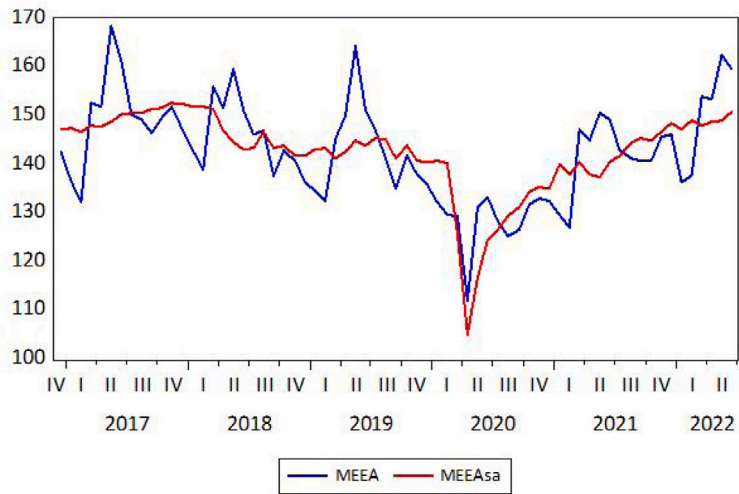
<sup>30</sup> The X-13 ARIMA-SEATS seasonal adjustment procedure was developed by the U.S. Census Bureau and can be applied using different statistical software. In this case, is used the [CENSUS X13 EViews Program](#).

<sup>31</sup> The *IPI* also has a seasonal behavior, not directly related, but influenced, by the agricultural sector.

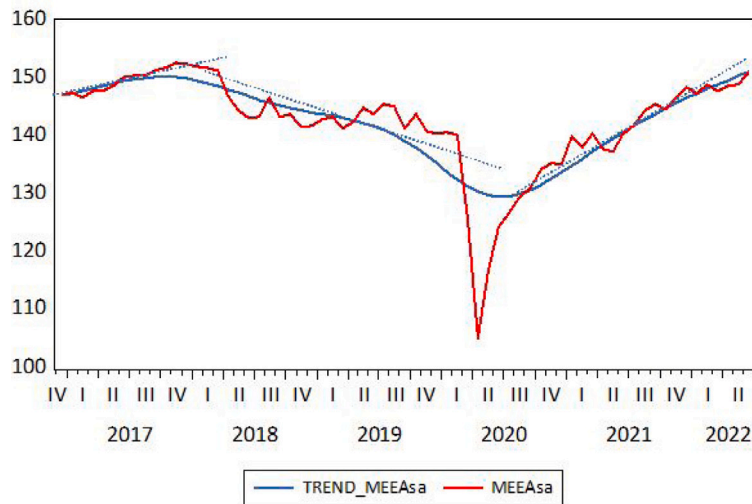
<sup>32</sup> It should be noted that the firm's sample in the survey is not comparable with the firms and sectors represented in the *MEEA* indicator.

<sup>33</sup> The pre-whitening process allowed the time series to be “cleaned” from their auto-regressive component. Therefore, the dynamic relationships between the different *DI*s and the *MEEAsa* can be inferred from the residuals cross-correlogram.

<sup>34</sup> It should be noted that there are two periods of time in which the *MDI* (and also the *MFDI*) appear not to have been synchronized with the *MEEAsa*. Indeed, between 2018-II to 2019-III the economy underwent a significant drought and several exchange rate and financial shocks as well as political uncertainty up to the 2019 elections. Both, the observed and expected *DI*s overestimated the economic recovery observed before the elections. On the contrary, between 2021-II and 2022-I, during the aftermath of the Covid-19 shock the *DI*s showed a rather pessimistic view comparing with the actual economic recovery indicated by the *MEEAsa*. As noted before, the qualitative question referred to the “firms' economic situation” is subjective and not uniquely related to the economic



(a) Economic activity seasonality - *MEEA* & *MEEAsa*. Source: INDEC.



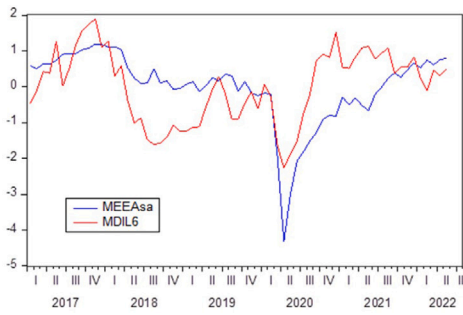
(b) Economic trend and cycle - *MEEAsa* & *MEEAsa – Trend*. Source: INDEC. The figure includes 3 different trends for the 2004-2017, 2017 - 2020 and 2020-2022 periods (own calculations).

Fig. 2. The monthly estimator of economic activity (*MEEA*).

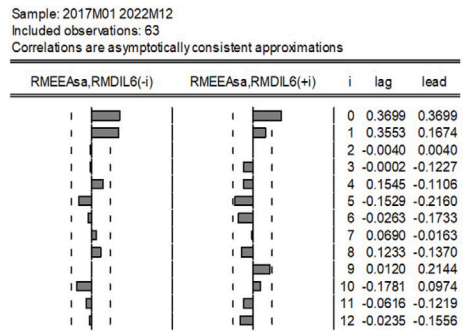
the *MDIL6* reveals a positive perspective of the participants after Covid-19, beginning in the third quarter of 2020 and up to the last observation.

The relationship is confirmed by the cross-correlation among the properly treated series as shown by Fig. 3(b). In particular, the cross-correlogram indicates that the series shows a significant lag correlation for two periods as well as a one-period lead with a simultaneous (positive) correlation. It should be underscored that the *MEEA* is calculated and published by the INDEC with 50 days and 35 days lag respectively. Whereas, the Survey is processed and the *MDI* and *MFDI* are calculated with no more than 30 days lag. Therefore, the *MDIL6* can be considered as a leading indicator (at least one month ahead) of the *MEEAsa*.

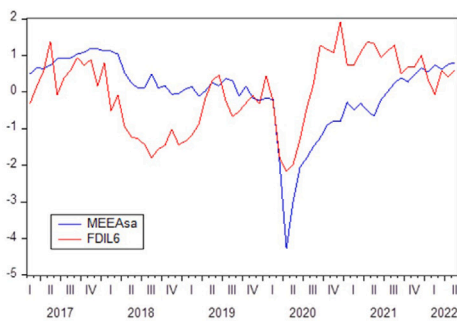
activity. Firm's may include other economic variables in their economic assessment rather than the overall economic activity as measured by *MEEAsa*, including the inflation rate, exchange rate depreciation, among others. Therefore, during periods of wide economic, financial and even political turmoil, the relevance of several macroeconomic variables can influence the economic situation assessments by the firms. However, in the entire period there is a strong correlation and synchronicity between the *DIS*s and the economic activity measured by the *MEEAsa*.



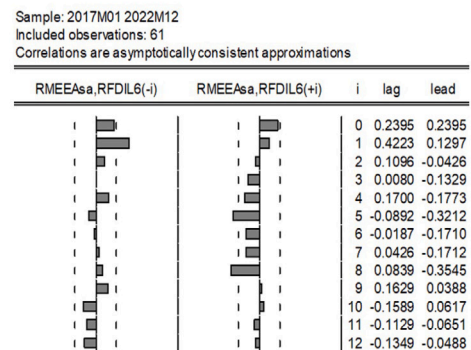
(a) *MEEAsa* & *MDIL6* (standardized)



(b) *MEEAsa* & *MDIL6* Cross correlation



(c) *MEEAsa* & *MFDIL6* (standardized)



(d) *MEEAsa* & *MFDIL6* Cross correlation

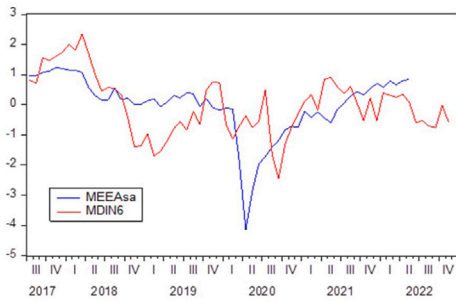
Fig. 3. *MEEAsa* vs *MDI* & *MFDI* for the last 6 months.

Then, Fig. 3(c) indicates the relationship between the *MEEAsa* and the *MFDI* for the last 6 months. It is interesting to note the close relationship observed during 2018 and 2019, as well as the recovery at the end of 2019 and the sharp decline in economic activity due to Covid-19. Also, the *MFDIL6* reveals the fast recovery after the initial pandemic shock and the participant’s positive perception during the latest periods.

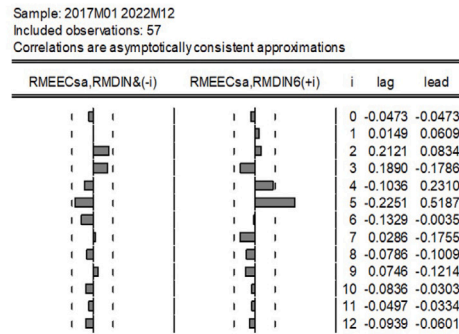
The econometric analysis indicates a strong and statistically significant relationship between the *MFDI* for the last 6 months and the *MEEAsa*. Fig. 3(d) reflects the cross-correlation analysis indicating a strong and statistically significant simultaneous as well as a one-lead relationship between the variables. Similarly to the *MDI*, and taking into account the relative lag between the indicators, the *MFDI* is a promising real-time predictor of economic activity. Also, the correlation value for the first lag is 0.4223 and it is statistically significant and stronger than the one corresponding to the *MDI*, that is 0.3553 as shown in previous Fig. 3(b). In addition, another difference with the *MDI* is the important feedback relationship between the *MFDI* and the *MEEAsa* as shown by the significant 5 and 8 months lead cross-correlations. The results indicate the relative relevance that the expectations regarding the economic activity have in defining the participant perceptions regarding the firm’s economic situation in the previous months. Again, the *MEEAsa* seems to play a significant role in the firm’s expectation formation (at least for the short run within a 6-month horizon), as we will see this relationship is captured as even stronger with the *MFDI* for the next 6 periods.

4.2.2. Relative performance of “prospective” *MDIL6* & *MFDIL6* vs *MEEAsa*

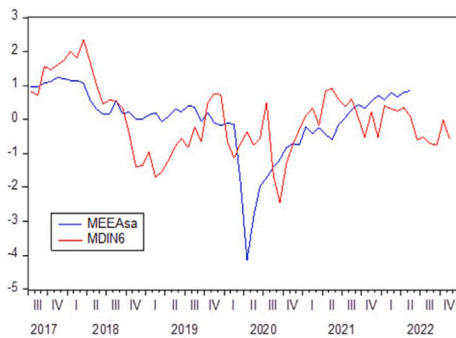
Fig. 4(a) displays the relationship between the participant perspectives for the next 6 months as captured by the *MDIN6* and the *MEEAsa*. The econometric analysis indicates a strong and statistically significant relationship between the *MDI* for the next 6 months and the *MEEAsa*. The cross-correlation analysis between the properly treated series, in Fig. 4(b), indicates a 5 periods statistically significant relationship between the perspective and the actual *MEEAsa*. The lag is reflecting that the firms consider the *MEEAsa* as a key ingredient in their 6 months expectations formation process. Indeed, the result indicates that the economic activity level, measured by the *MEEAsa*, plays a significant role in the firm’s planning process. It should be noted that a six months period may be short as a planning program and may reflect the firm’s reaction to the overall volatility of the Argentinean economy.



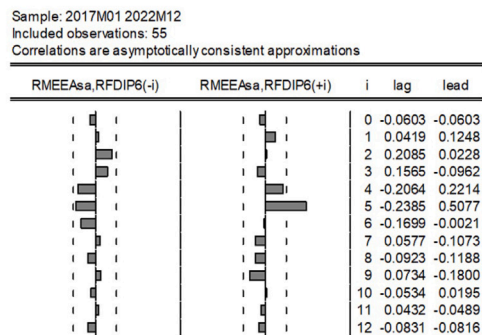
(a) *MEEAsa* & *MDIN6* (standardized)



(b) *MEEAsa* & *MDIN6* Cross correlation



(c) *MEEAsa* & *MFDIN6* (standardized)



(d) *MEEAsa* & *MFDIN6* Cross correlation

Fig. 4. *MEEAsa* vs *MDI* & *MFDI* for the next 6 months.

**Table 4**  
Transfer function model with white noise residuals.  
Dependent Variable: *MEEAsa* w.n. res.  
Sample (adjusted): 2017M01 2022M03.  
Included obs. 63 after adjustments.

Variable	Coefficient	Std. Error	t-statistic	Prob
<i>MDIL6</i> w.n. res.	0.0915	0.02676	3.4199	0.0011
<i>MDIL6</i> (-1) w.n. res.	0.0778	0.02708	2.8759	0.0055
R-squared	0.2743			
Adjusted R-squared	0.2624			
Durbin-Watson stat	1.8908			

In addition, the correlation confirms the fact that the firms answer the question regarding the economic situation of the firm by considering mostly the aggregate activity level captured by the *MEEAsa*.

In turn, Fig. 4(c) shows the relationship between the *MFDIN6* and the seasonally adjusted economic indicator, *MEEAsa*. As can be noted in the Figure, the *MFDIN6* seems to present sharper changes during recoveries compared with the *MDIN6*. The *MFDIN6* shows a stronger statistical relationship for the 5 period lead as compared with the *MDIN6*. See the cross-correlation between the series in Fig. 4(d). Again, the *MEEAsa* seems to play a significant role in a firm's expectation formation (at least for relatively short-run planning) and seems to be better captured, at least in relative terms, by the *MFDIN6* compared with the *MDIN6*.

In addition, Table 4 summarizes the transfer function model describing the close relationship between the adjusted white-noise residual of *MDI* for the last 6 months and the economic activity. The dependent variable is given by the white-noise adjusted *MEEAsa*, and the significant explanatory variables are the white-noise adjusted contemporaneous and one period lagged *MDIL6*.

**Table 5**  
 Transfer function model with white noise residuals.  
 Dependent Variable: *MF DIN6* w.n. res.  
 Sample (adjusted): 2017M01 2022M03.  
 Included obs. 60 after adjustments.

Variable	Coefficient	Std. Error	t-statistic	Prob
<i>RDMEEAsa</i> (-5) w.n. res.	2.0116	0.4480	4.4898	0.0000
R-squared	0.2541			
Adjusted R-squared	0.2541			
Durbin-Watson stat	2.2376			

Finally, the transfer model corresponding to the *MF DIN6* with the *MEEAsa* in Table 5, captures the two-way relationship between the economic activity indicator and the firm's perspectives for the next six months. It seems that the companies use the *MEEAsa* indicator as an important variable in the planning and forecasting process for their future operations.<sup>35</sup> The dependent variable in the model is the *white noise MF DIN6* residual whereas the explanatory variable corresponds to the *MEEAsa white-noise* residual. The statistically significant coefficient corresponds to five month's lag.

## 5. Conclusions

This paper analyzes the statistic and econometric properties of *DI*s based on the qualitative information from the *Survey of Business Economic Perspectives* in assessing the actual Argentinean business cycle behavior between 2017 and 2022 as reflected by the official economic activity statistics. The results indicate that the business cycle volatility was captured in real-time and with at least one month lead by the *DI*s. The results are based on a synchrony and concordance analysis as well as an econometric procedure including series seasonality and stationary analysis, whitening (considering structural breaks) as well as cross-correlation and synchrony analysis.

The analysis includes the Marginal Diffusion Index (*MDI*), proposed by the FED-Chicago, based on the "balance of responses" and re-scaled by the participant's average response during the business cycle. The index is particularly suitable for analyzing information from diverse companies and sectors. By updating the indicator backward each period, the proposed adjustment generate a *DI* that may overestimate past optimism during negative shock events or underestimate past pessimism under positive shocks. A variation of the *MDI*, called Fixed Marginal Diffusion Index (*MF DI*) adjust this potential bias by fixing the marginal comparison between the actual observation and the average trend in each period of time. The *MF DI* allows a more accurate perspective of the companies' vision in each period, complementing the conclusions derived from the *MDI*.

The results indicate that, in contrast to the *MAEE*, the *DI*s do not require seasonality adjustment reflecting that the seasonality is already incorporated in the answers completed by the companies.<sup>36</sup> Furthermore, the marginal and fixed marginal *DI*s show several interesting statistic and econometric properties including *synchrony* and a strong contemporaneous correlation with economic activity (one month ahead in real-time) as measured by *MEEAsa*.

The *MDI* and *MF DI* indexes show important discrepancies during some periods, reflecting the considerable changes in the mood of firms as new information arrives in a context of a particularly volatile economic environment. Indeed, for the early periods, the *MF DI* reflects a different estimation of the breadth of change compared with the *MDI* and should be considered, at least as complementary information, in the case of important volatility in the economic business cycle. Indeed, both indicators have similar significance with respect to the economic activity, especially in relation to the observed periods. The *MF DI* seems to have better forecasting properties compared with the *MDI*.

The global results indicate that the *DI*s based on a unique qualitative question from the *Survey of Business Economic Perspectives* are an important complement for the real-time assessment of the Argentinean business cycle. The future research agenda includes potentially increasing the Survey's sample size by incorporating randomly selected companies that only respond the first qualitative question. Furthermore, an analysis will be conducted to explore the feasibility of integrating these *DI*s into the now-casting indicators of the Argentinean Central Bank. Finally, a possible extension includes the use of the quantitative questions in the dataset to calculate composed *DI*s calculated from the combination of qualitative and quantitative questions concerned with production, sales and/or inventories.

## 6. Annex

### 6.1. Industrial sector analysis

The sub-sample corresponding to the industrial sector firms is analyzed with the same diffusion indexes formula and econometric tools. Table 6 shows the series of structural breaks and integration.

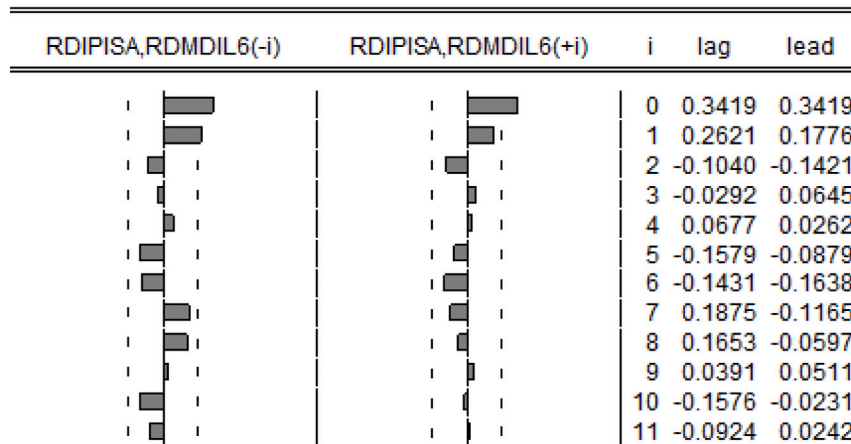
Fig. 5(a) displays the cross-correlogram between the *MD IL6* for the industrial sector and the *IPI sa*. The results indicates that the *MD IL6* anticipates the *IPI sa* in one period. The cross correlation between the properly treated *IPI sa* series and the *MF DI IL6* is shown in Fig. 5(b). Again, the *MF DI IL6* anticipates *IPI sa* by one period.

<sup>35</sup> In fact, this is also revealed during the Survey follow-up interviews with the companies.

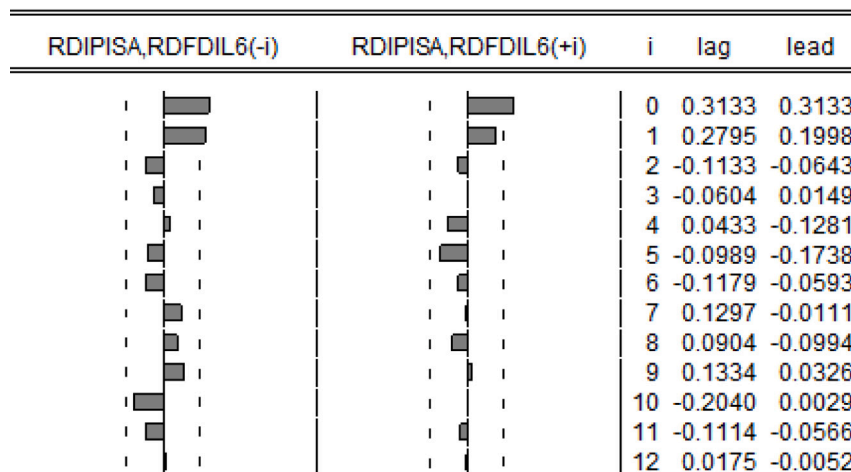
<sup>36</sup> It should be not a surprise that no one knows better the seasonality of their own business than the companies.

**Table 6**  
Series structural breaks and integration.

Series	Seasonality	Structural breaks	Integration order
<i>MDIL6</i> (ind)	Non-identifiable	March 2020	I(1)
<i>MDIN6</i> (ind)	Non-identifiable	September 2020	I(1)
<i>MFdil6</i> (ind)	Non-identifiable	March 2020	I(1)
<i>MFdin6</i> (ind)	Non-identifiable	September 2020	I(1)
<i>IPI</i>	Identifiable	August 2020	I(1)
<i>IPisa</i>	Adjusted	August 2020	I(1)



(a) *IPIsa* & *MDIL6* (ind.) Cross correlation



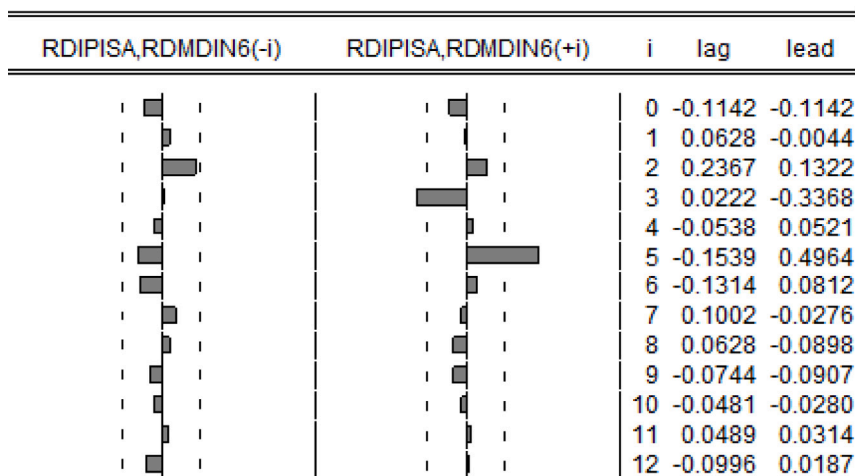
(b) *IPIsa* & *MFdil6* (ind.) Cross correlation

Fig. 5. Cross correlation.

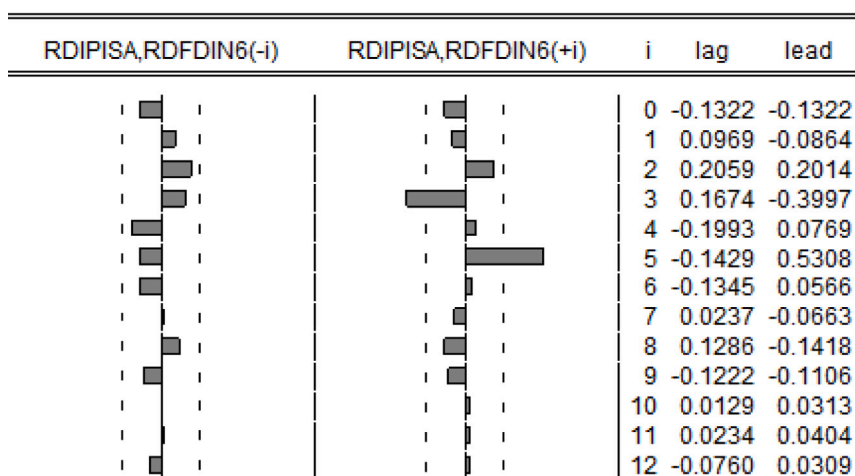
Meanwhile, Fig. 6(a) displays the cross-correlogram between the *MDIN6* for the industrial sector and the *IPIsa*. The results indicate a high correlation among the *MDIN6* and the *IPIsa* with 3 and 5 lags. The cross-correlation between the properly treated *IPIsa* series and the *MFdin6* is shown in Fig. 6(b). Again, the *MFdin6* significantly anticipates *IPIsa* by one period.

**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.



(a) *IPIsa & MDIN6 (ind.)* Cross correlation



(b) *IPIsa & MFDIN6 (ind.)* Cross correlation

Fig. 6. Cross correlation.

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