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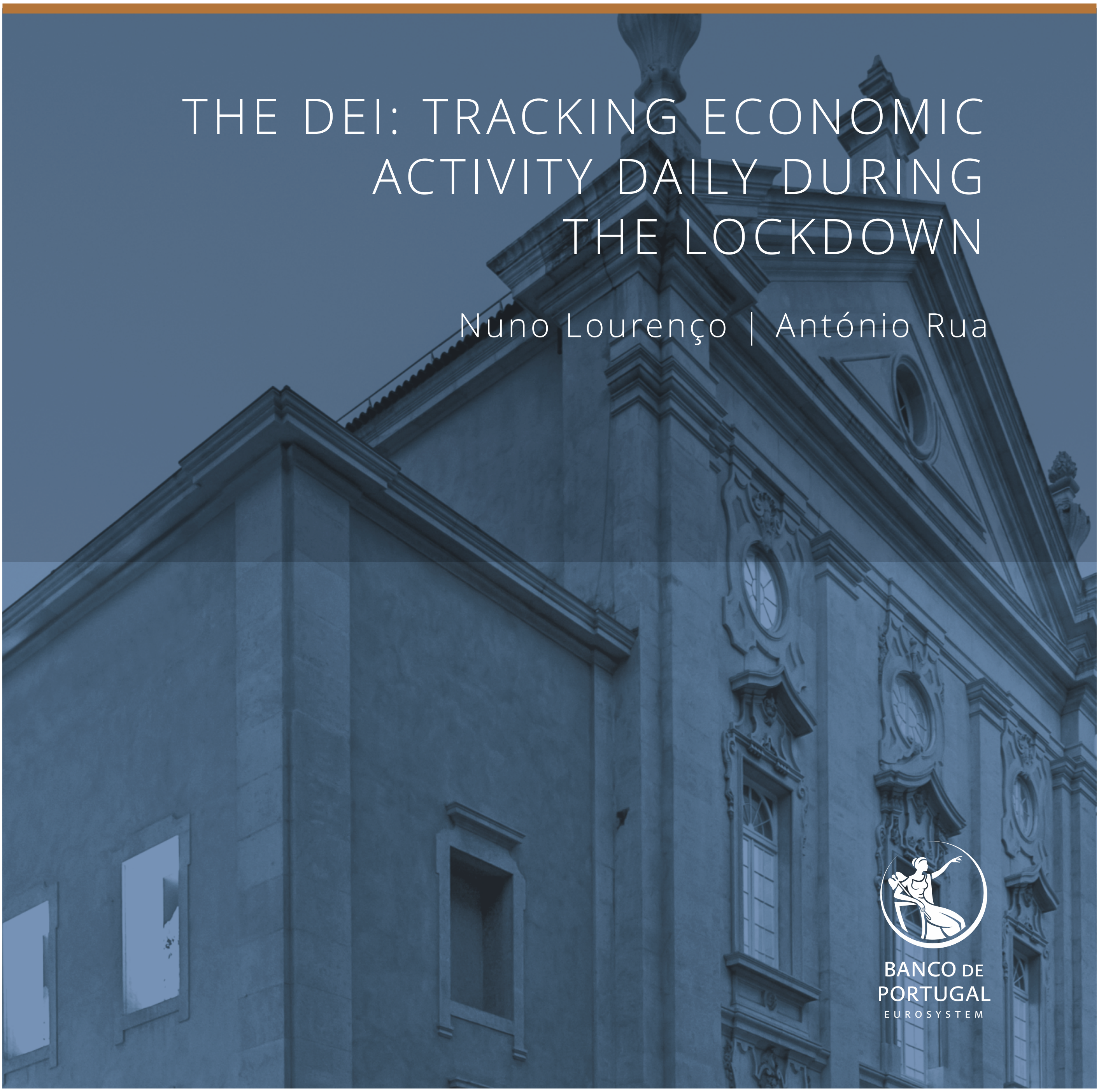

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Nuno Lourenço | António Rua

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Please address correspondence to
Banco de Portugal, Economics and Research Department
Av. Almirante Reis, 71, 1150-012 Lisboa, Portugal
Tel.: +351 213 130 000, email: estudos@bportugal.pt

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The DEI: tracking economic activity daily during the lockdown

Nuno Lourenço
Banco de Portugal
Nova SBE

António Rua
Banco de Portugal
Nova SBE

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Abstract
The SARS-CoV-2 outbreak has spread worldwide causing unprecedented disruptions in the economies. These unparalleled changes in economic conditions made clear the urgent need to depart from traditional statistics to inform policy responses. Hence, the interest in tracking economic activity in a timely manner has led economic agents to rely on high-frequency data as traditional statistics are released with a lag and available at a lower frequency. Naturally, taking on board such a novel data involves addressing some of the complexities of high-frequency data (e.g. marked seasonal patterns or calendar effects). Herein, we propose a daily economic indicator (DEI), which can be used to assess the behavior of economic activity during the lockdown period in Portugal. The indicator points to a sudden and sharp drop of economic activity around mid-March 2020, when the highest level of alert due to the COVID-19 pandemic was declared in March 12. It declined further after the declaration of the State of Emergency in the entire Portuguese territory in March 18, reflecting the lockdown of several economic activities. The DEI also points to an unprecedented decline of economic activity in the first half of April, with some very mild signs of recovery at the end of the month.

JEL: C22, C38, E32.

Keywords: Daily economic index, high-frequency, measurement of economic activity, factor model.

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E-mail: nalourenco@bportugal.pt; antonio.rua@bportugal.pt

1. Introduction

Monitoring economic developments in real-time is often grounded in the assessment of a large panel of variables available at a monthly or quarterly frequency. These indicators are also made available with a release lag, thus not proving to be suitable to track sudden changes of economic activity. The use of high-frequency data, i.e., data recorded at infra-monthly intervals, dates back to the 1920s. In fact, statisticians and econometricians at the time relied on weekly data to support policy analysis. Fisher (1923) pionereed this work, by proposing a weekly index number of wholesale prices, based on price quotations of 200 commodities. Early efforts to model the statistical properties of high-frequency data were remarkable. In this regard, Crum (1927) studied the series of weekly bank debits outside New York City from 1919 to 1926 and developed a seasonal adjustment based on the median-link-relative method suggested by Persons (1919).

Nowadays, with the rapid dissemination of statistical data that are being processed weekly, daily or even hourly, the information set available to economic agents has been made progressively larger. Nevertheless, there is still room to improve on data collection while making it available to economic policy agents as most of the data is typically owned by private firms. Furthermore, relying on high-frequency data poses challenges to empirical work (e.g., multiple seasonal patterns and non-integer periodicities, calendar effects, high volatility and a marked irregular component, existence of outliers). Therefore, taking on board such a high-frequency data into the analysis of short-term economic prospects is not straightforward which explains why its use has been rather limited.

The SARS-CoV-2 outbreak has made clear the urgent need to depart from traditional statistics and rely instead on high-frequency non-conventional data sources. One of the reasons behind this shift relates to the rapid change of economic conditions. The unprecedented nature of the shock makes it difficult to assess the impact of the COVID-19 pandemic on the real economy. In this regard, a lot of effort is being devoted to measure economic activity at a high-frequency so as to help designing sound economic policies. Recently, Lewis *et al.* (2020) proposed a weekly economic index (WEI) to track the rapid economic developments associated with the response to the novel coronavirus in the United States. It corresponds to the single factor estimated from ten weekly series. Similarly, the Bundesbank (2020) developed a weekly activity indicator (WAI) for the German economy based on a dataset comprising seven high-frequency indicators. Herein, in contrast with previous literature, we focus on developing a composite daily economic indicator.

The uselfulness of several non-conventional data sources to track economic developments has been documented in the literature. This can be particularly relevant in the face of sudden disruptions of economic activity that pose challenges to the more traditional statistics. A very promising data source refers to that of card-based payments, as these provide an encompassing view of transactions in the economy. The applications on the use of payments data to track economic activity are quite extensive and include, *inter alia*, Carlsen and Storgaard (2010) for Denmark, Barnett *et al.* (2016) for the United States, Duarte *et al.* (2017) for Portugal, Galbraith and Tkacz (2018) for Canada and Aprigliano *et al.* (2019) for Italy. In addition, transportation activites have also been used to gauge prospects on economic activity. In fact, as pointed out by Lahiri *et al.* (2004), transportation activities are very sensitive to the business cycle. However, their use to track business cycle fluctuations has been rather limited. One of the reasons behind this refers to a non-negligible release lag of these statistics, a situation that has been circumvented with the rise of systems with electronic toll collections that allow these statistics to be more promptly available (see also Lahiri and Yao (2012)). Moreover, Askitas and Zimmermann (2018) consider transportation activity performed by heavy transport vehicles across Germany to track the general state of the economy, while Fenz and Schneider (2009) use this type of data to predict Austrian exports. Interesting insights can also be derived from electricity consumption data due to its broad coverage and wide availability. In this respect, Arora and Lieskovsky (2014) show evidence of the usefulness of electricity consumption to trace GDP developments, which is also corroborated by the work of Aprigliano *et al.* (2019).

Herein, we develop a Daily Economic Indicator (DEI) to track economic activity in Portugal on a high-frequency basis. After an extensive data collection and a preliminary analysis, we end up with five daily series, namely card-based payments, road traffic of heavy commercial vehicles, cargo and mail landed, electricity consumption and natural gas consumption. These series present the strongest co-movement with GDP developments among the series assessed and allow to cover several important dimensions of economic activity as discussed above. Based on those series, a latent factor is estimated drawing on a factor model. However, prior to that step, a pre-treatment of the variables has to be performed to cope with data issues such as seasonality and calendar effects. For that purpose, we resort to STL (Seasonal-Trend decomposition based on Loess) and RegARIMA methods. We find marked seasonal intra-weekly patterns in the series that have to be accounted for as well as the presence of significant calendar effects.

The proposed composite indicator presents statistically significant information content about current GDP developments. In particular, the evolution of economic activity during the lockdown is analysed. We find that the DEI started to decrease substantially in mid-March, at the time the Portuguese government declared the highest level of alert due to the COVID-19 pandemic followed a few days after by the declaration of the State of Emergency in the entire Portuguese territory. Such analysis reinforces the usefulness of high-frequency indicators such as the DEI. Naturally, the use of high-frequency indicators is not limited to the analysis of particular events such as the lockdown, but can also be used for monitoring real activity in a timely manner and, thus, anticipating the path of low frequency variables.

The remainder of the paper proceeds as follows. In section 2, we present the econometric framework pursued. Section 3 describes the data. The daily economic indicator is put forward and discussed in section 4. Section 5 concludes.

2. Econometric framework

Despite the potential usefulness of considering high-frequency indicators, the use of such series involves tackling several issues. In fact, daily raw data typically presents strong seasonal patterns.[1] However, daily or weekly series are available for much shorter time spans than monthly or quarterly data. This implies that, for example, annual seasonality can be poorly estimated using such high-frequency data. To overcome this issue, one can consider year-on-year growth rates (as in, for instance, Lewis *et al.* (2020) for weekly data). Such data transformation is easily interpretable and allows to accommodate slowly moving annual seasonality.

However, although we are comparing a given date *vis-à-vis* the same date in the previous year, the weekday might differ. In fact, in many economic series, the behavior differs across the seven days of the week. Such distinction can be particularly marked between, for example, the weekend and working days. To account for intra-weekly seasonality we resort to STL (see also Bergmeir *et al.* (2016) and Hyndman and Athanasopoulos (2014)).[2]

Furthermore, there are specific events that occur every year which one should also take into account. In this respect, national holidays are often linked to a date but there are moving holidays such as Easter which do not always fall on the same date. Hence, after coping with intra-weekly seasonality, the impact of those calendar effects is purged resorting to seasonal RegARIMA models.

After the pre-treatment of the data, one can proceed with factor model estimation to obtain the daily economic indicator. In the remainder of the section, we run through the above-mentioned building blocks in detail.

2.1. STL

The STL is a non-parametric method proposed by Cleveland *et al.* (1990). It allows to decompose a seasonal time series (Y_t) into trend (T_t), seasonal (S_t) and remainder (R_t) components, i.e,

$$Y_t = T_t + S_t + R_t,\ t = \{1, ..., N\}\,. \tag{1}$$

STL is a very versatile and robust method for decomposing time series and it has several advantages over other decomposition methods. It can handle any type of seasonality, meaning that it is not restricted to monthly and quarterly data. The seasonal component is allowed to change over time, with the rate of change controlled by the parameter seasonal width. The smoothness of the trend-cycle is also user-defined. It can be specified to be robust to outliers, so that sporadic

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[1] For an overview of different seasonal adjustment procedures for daily and weekly data see, for example, Ladiray *et al.* (2018).

[2] Note that if one is interested in addressing multiple periodicities, one can use STL sequentially (see Cleveland *et al.* (1990) and Ollech (2018)).

unusual observations will not affect the estimates of the trend-cycle and seasonal components. Although the above model corresponds to an additive decomposition, a multiplicative decomposition can be obtained by first taking logs of the data.

The STL operates by iterating through smoothing of the seasonal and trend components where all smoothing is done resorting to Loess.[3] For the seasonal smoothing, observations are separated into cycle-subseries. These subseries are separately smoothed and then recombined. The trend smoothing is done after removing the previously estimated seasonal component. This is iterated until convergence. The STL also has an outer loop which, after each inner loop, computes robustness weights that are passed on to the inner loop, in order to cope with outliers.

2.1.1. Loess. Loess was initially proposed by Cleveland (1979) and developed further by Cleveland and Devlin (1988). Loess combines the simplicity of linear least squares regression with the flexibility of nonlinear regression. This is achieved by fitting, at each point in the data set, a low-degree polynomial to a localized subset of the data. The polynomial is estimated using weighted least squares, giving more weight to the data points nearer the point of estimation and less weight to the data points that are further away. The value of the regression function for a specific data point is obtained by evaluating the local polynomial at that data point. This is done for each of the N data points.

The usual weight function used for Loess is the tri-cube weight function

$$W(d) = \begin{cases} \left(1-d^3\right)^3 & 0 \leq d < 1 \\ 0 & d \geq 1 \end{cases} \tag{2}$$

where d is the distance of a given data point from the point of estimation, scaled to lie in the range from 0 to 1. Therefore, the weight for a specific point t_i in any localized subset of data is obtained by evaluating the weight function at the distance between that point and the point of estimation t, after scaling the distance so that the maximum absolute distance over all of the points in the subset of data is exactly one. That is,

$$w_i(t) = W\left(\frac{|t_i - t|}{|t_q - t|}\right). \tag{3}$$

This means that observations close to t have the largest weights while decreasing as the distance increases, becoming zero at the q^{th} farthest point. Note that the parameter q determines the number of neighbouring observations included in the local regression and therefore controls the smoothing degree. The choice regarding the degree of smoothing can be informed by diagnostic methods (see Cleveland and Terpenning (1982) and Cleveland *et al.* (1990)).

[3]Loess or Lowess stands for "LOcally WEighted Scatterplot Smoother".

2.1.2. Inner Loop. The inner loop is basically an iteration between seasonal smoothing (smoothing of the cycle-subseries) and trend smoothing. The inner loop iteratively updates the trend and seasonal components. This is done by subtracting the current estimate of the trend from the raw series. The time series is then partitioned into cycle-subseries. The cycle-subseries are Loess smoothed and then passed through a low-pass filter. The seasonal components are the smoothed cycle-subseries minus the result from the low-pass filter. The seasonal components are subtracted from the raw data. The result is Loess smoothed, which becomes the trend. What is left is the remainder. More formally, the k^{th} iteration of the inner loop is composed by the following steps:

1. *Detrending:* The first step is to detrend the series, calculating $Y_t - T_t^{(k)}$.
2. *Cycle-subseries smoothing:* The detrended time series is broken into cycle-subseries. For example, daily data with a weekly seasonality would yield seven cycle-subseries: all Sundays will be one time series, all Mondays a second, etc. Each cycle-subseries is smoothed by Loess with a span of q. The smoothed values yield a temporary seasonal time series $C_t^{(k+1)}$.
3. *Low-pass filtering of smoothed cycle-subseries:* To prevent low-frequency power from entering the seasonal component, a low pass filter is applied on $C_t^{(k+1)}$ yielding $L_t^{(k+1)}$. The filter is composed of moving average and Loess filters.
4. *Detrending of smoothed cycle-subseries:* $S_t^{(k+1)} = C_t^{(k+1)} - L_t^{(k+1)}$. This is the $(k+1)^{th}$ estimate of seasonal component.
5. *Deseasonalizing:* The original series is deseasonalized by subtracting the seasonal component computed in the previous step, that is, $Y_t - S_t^{(k+1)}$.
6. *Trend smoothing:* Smoothing by Loess the deseasonalized time series results in $T_t^{(k+1)}$, the $(k+1)^{th}$ estimate of the trend component.

2.1.3. Outer Loop. If outlying values are apparent in the time series, one may wish to run the outer loop to down-weight these values. In the outer loop, robustness weights are assigned to each data point depending on the size of the remainder. This allows for reducing or eliminating the effects of outliers.

After running the inner loop, given the estimates for the trend and seasonal components, the remainder can be obtained simply by

$$R_t = Y_t - T_t - S_t. \tag{4}$$

Let

$$h = 6 \times median\left(|R_t|\right). \tag{5}$$

Then the robustness weight at time t is calculated as

$$\rho_t = B\left(|R_t|/h\right) \tag{6}$$

where B is the bisquare weight function

$$B(u) = \begin{cases} \left(1-u^2\right)^2 & 0 \le u < 1 \\ 0 & u \ge 1 \end{cases} \tag{7}$$

For the Loess regressions in the steps 2 and 6 of the inner loop, the neighborhood weight is multiplied by the robustness weight, which allows to dampen the influence of outliers.

2.2. RegARIMA

To determine the impact of moving holidays on the time series, we consider a RegARIMA model (see, for example, Findley *et al.* (1998)):

$$\varphi_p\left(L\right)\Phi_P\left(L^s\right)\left(1-L\right)^d\left(1-L^s\right)^D\left[Y_t - \sum_{j=1}^{r}\beta_j Z_{jt}\right] = \theta_q\left(L\right)\Theta_Q\left(L^s\right)\varepsilon_t \tag{8}$$

where L is the lag operator, p, q, d, s, P, D, Q are non-negative integers $(s \geq 2)$ and Z_{jt}, $j = \{1,...,r\}$ are the set of independent variables. The parameters p, q, P, Q determine the order of the lag polynomials and d and D control for the non-seasonal and seasonal differencing, respectively. In the case of the daily series, $s = 365$.[4] The parameter β_j captures the impact of regressor Z_{jt} on Y_t. To capture the impact of moving holidays, regressors for these holidays are included in the set of independent variables. As the event may affect beyond the date of the event itself, a number of days preceding and/or following the event can also be considered in the set of regressors.[5]

2.3. Factor model

After the above pre-treatment of the data, one can proceed into the estimation of the factor model. Let X_t be a M-dimensional column vector of time series, observed for $t = \{1,...,N\}$, that is, $X_t = [Y_{1t} \cdots Y_{mt} \cdots Y_{Mt}]'$. The variables in X_t are represented as the sum of two orthogonal components: the common component, driven by a small number of unobserved common factors that accounts for most of the co-movement among the variables; and the idiosyncratic component, driven by variable-specific shocks.

The data generating process for X_t admits a static factor representation written as:

$$X_t = \Lambda F_t + \xi_t \tag{9}$$

[4] In this case, the leap day, February 29, has to be dropped.

[5] See, for example, Ladiray (2018) about impact models to estimate the before or after effect on the activity.

where $F_t = (f_{1t}, ..., f_{rt})'$ is a $(r \times 1)$ vector of latent factors, Λ is a $(M \times r)$ matrix of unknown factor loadings and ξ_t denotes a M-dimensional vector of idiosyncratic terms. This representation is without loss of generality as it can be shown that the dynamic factor model representation has an equivalent static factor formulation (see, for instance, Stock and Watson (2005)).

The space spanned by the latent factors can be estimated through the principal components estimator which has been shown to be consistent under relatively general assumptions (see Stock and Watson (1998, 2002b), Bai and Ng (2002) and Amengual and Watson (2007)).[6] The proposed DEI corresponds to the latent factor f_{1t} driving the co-movements of the variables in X_t (see also Lewis *et al.* (2020)).

3. Data

The lack of priors on which economic time series prove to be more relevant for tracking economic activity at a high-frequency basis motivated an unparalleled data collection effort. A comprehensive dataset comprising around two dozens of daily economic time series with a minimal sample period for in-sample analysis was built at the first place. The series were chosen to encompass several domains of the economy, thus signalling developments across different sectors.

We collected data on traffic from Instituto da Mobilidade e dos Transportes (IMT).[7] In addition to total traffic, we also gathered disaggregated data on traffic of heavy commercial vehicles and light passenger vehicles. These traffic statistics provide a measure of daily traffic intensity as they record the number of vehicles passing through tolls, adjusted for the number of miles travelled. As many goods across Portugal are transported by road and Spain is the country's main trading partner, these statistics may signal prospects on both the production and international trade. We considered daily traffic data since the beginning of 2012.

Also on transport activity, we gathered data on the movement of passengers at national airports, the number of aircrafts landed as well as freight movements (cargo and mail shipments) which are compiled by ANA Aeroportos de Portugal and the Portuguese Civil Aviation Authority (ANAC) and kindly provided by Statistics Portugal for the period since 2009.

Energy consumption developments are also of utmost relevance to assess the stage of economic activity in the industrial and domestic sectors. Therefore, we collected data on electricity consumption across different distribution grids (e.g. very high-voltage, high-voltage, medium-voltage) which was provided by EDP

[6] The typical assumptions allow for some heteroskedasticity and limited dependence of the idiosyncratic components in both the time and cross-section dimensions, as well as for moderate correlation between the latter and the factors.

[7] IMT currently manages 15 motorway concessions in Portugal from north to south, corresponding to the universe of existing concessions.

Distribuição. As these series are only available since the beginning of 2011, this set of information was complemented with aggregate electricity consumption (adjusted for temperature effects) released by Redes Energéticas Nacionais (REN). We also collected data on natural gas consumption in the conventional market for the period since the start of 2013, which has also been provided by REN.

An additional source of data aiming at tracking the consumer behavior and transactions in general refers to card-based payments and ATM cash withdrawals, carried out both with cards issued in Portugal and abroad. These series are compiled and have been provided by Banco de Portugal.[8] Although these series are available for a longer time span, we will restrict henceforth the analysis to the period from January 1, 2009 to April 30, 2020.

4. Results

4.1. Preliminary analysis

Given the composition of the initial dataset and to avoid over-representation of any particular economic activity dimension, we pursue a parsimonious approach regarding the number of variables considered. In this respect, one should mention the acclaimed work by Stock and Watson (1989) who proposed a composite economic indicator for the United States based on a factor model using just four series (in the same vein, Azevedo *et al.* (2006) developed a composite indicator for the euro area activity also resorting to a small number of series). More recently, focusing on weekly data, Lewis *et al.* (2020) consider ten high-frequency indicators whereas Bundesbank (2020) take on board seven weekly series.[9]

Having in mind the objective of obtaining a broadly based measure, we consider those variables that display more information content about the evolution of economic activity.[10] We end up with five daily series: road traffic of heavy commercial vehicles; electricity consumption; natural gas consumption; cargo and mail landed; card-based payments. As in Lewis *et al.* (2020) we disregard financial data as the aim is not to track financial conditions, but the real activity instead.

[8]For this type of data, there are two discontinuities. Until October 31, 2015 there is no split between operations with cards issued in Portugal and abroad. From November 1, 2015 onwards data is available for cards issued in Portugal whereas data regarding cards issued abroad is available only since January 1, 2018.

[9]In the former case, the high-frequency indicators include measures of same-store retail sales, steel production, fuel sales, railroad traffic, electricity consumption, an index of consumer sentiment, initial and continued claims for unemployment insurance, an index of temporary and contract employment and tax collections from paycheck withholdings. In the latter case, the series include electricity consumption, truck toll mileage, Google searches related to unemployment and short-time work, worldwide number of flights, air pollution and cash withdrawals.

[10]In particular, the co-movement between the year-on-year quarterly growth rate of each daily series and GDP growth has been assessed to pre-select the variables.

4.2. Intra-weekly seasonality

As described in section 2, we firstly estimate the weekly seasonality using the robust STL. In particular, we take logs of the series and set the value of the smoothing parameter to 151, as in Ollech (2018).[11] This means that around 3 years of data are used in Loess regressions. Such a value is high enough to avoid including annual periodic movements into the intra-weekly seasonal factors while leaving some room for variation of the seasonal factors.[12]

Following Ollech (2018), we compute the smoothed periodogram for both the differenced original series and the differenced seasonally adjusted series (see Figure 1). One can see that the spectral peaks associated with intra-weekly seasonality (at frequency $2\pi/7$ and its harmonics, denoted by the dashed lines in Figure 1) have been filtered out.

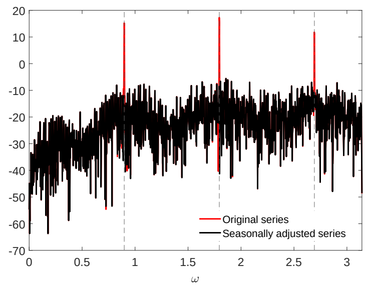
In Figure 2, we display the estimated seasonal factors for all indicators. For each variable, we plot the cycle-subseries of the weekly seasonal component. Each cycle-subseries is plotted separately against time. In particular, first the Sunday values are plotted, then the Monday values are displayed, and so forth. The midmean for each weekday corresponds to the horizontal line.

The immediate finding is that there is a strong weekly seasonal pattern in all series. As expected, in the case of the road traffic of heavy commercial vehicles, there is a striking difference between working days and the weekend. In particular, traffic on Sundays is 90 per cent lower than on an average day, while on Saturdays it is almost 60 per cent lower. One can also conclude that such magnitudes have fallen somewhat during the period under analysis. Concerning electricity consumption, usage on Sundays is 15 per cent lower while on Saturdays it is near 10 per cent lower than the average day. One should also mention that electricity consumption on Mondays seems to be a bit below the observed for the remaining working days, most probably reflecting the gradual resume of production activity after the weekend. The natural gas consumption presents a relatively similar seasonal pattern to the observed for electricity consumption. Both series are reflecting, to a large extent, the intra-weekly seasonality of industrial activity. In particular, gas consumption on Sundays is around 20 per cent lower while on Saturdays it is close to 15 per cent lower than the average day. Regarding cargo and mail landed, Sundays record a value 45 per cent below the average day but this figure has been decreasing over time. On Saturdays, cargo and mail landed are also below average and the gap has been widening. Mondays and Tuesdays correspond basically to an average day, while the remaining weekdays are characterized by cargo and mail landed above

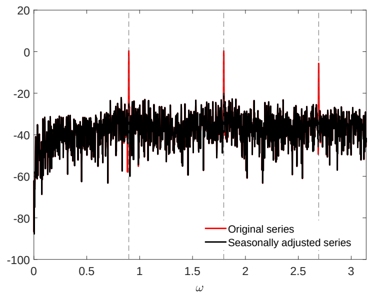
[11]In this respect, Cleveland *et al.* (1990) argue that it should be an odd number and at least 7, but beyond that there is no unique choice.

[12]One should bear in mind that STL, as well as other well-established seasonal adjustment procedures such as X-12-ARIMA, TRAMO-SEATS and unobserved component models, despite their advantages, are not free of caveats when applied to daily data and may not be completely effective on removing intra-weekly seasonality (see, for example, Ladiray *et al.* (2018)).

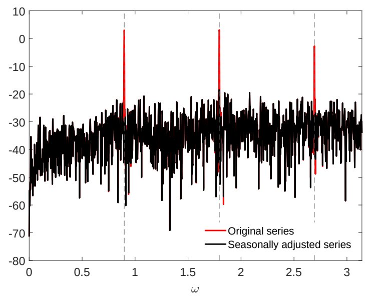
average. In what concerns card-based payments, purchases are 25 per cent lower on Sundays and 10 per cent higher on Fridays and Saturdays. The remaining weekdays behave close to an average day.



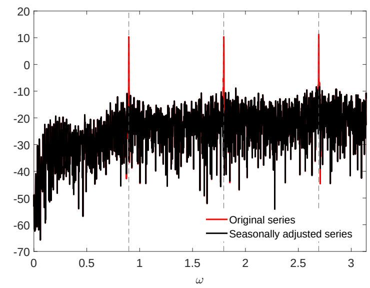
(a) Road traffic of heavy commercial vehicles



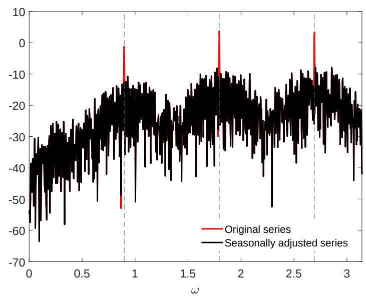
(b) Electricity consumption



(c) Natural gas consumption

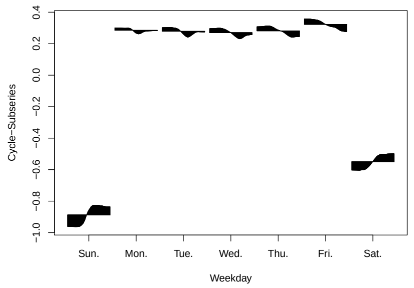


(d) Cargo and mail landed

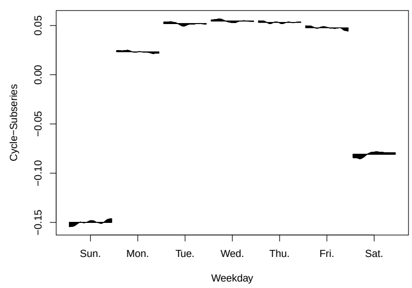


(e) Card-based payments

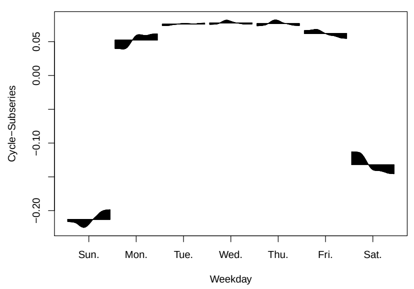
Figure 1: Smoothed periodogram.



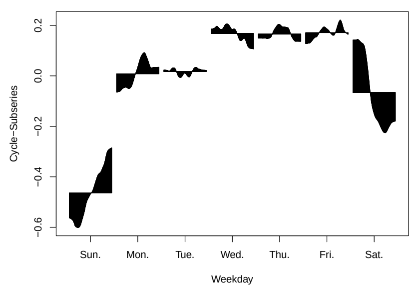
(a) Road traffic of heavy commercial vehicles



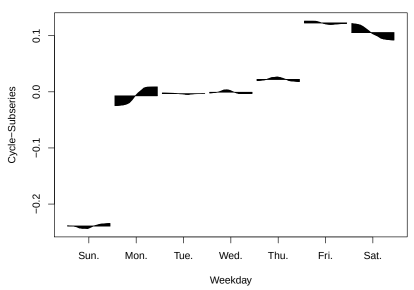
(b) Electricity consumption



(c) Natural gas consumption



(d) Cargo and mail landed



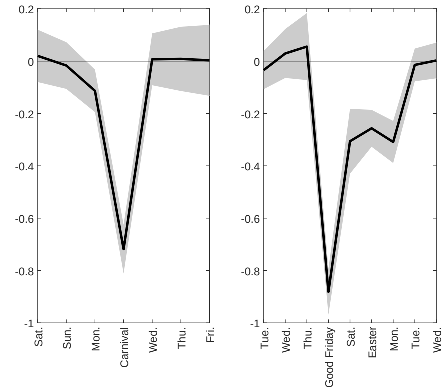
(e) Card-based payments

Figure 2: Cycle-subseries of the weekly seasonal component.

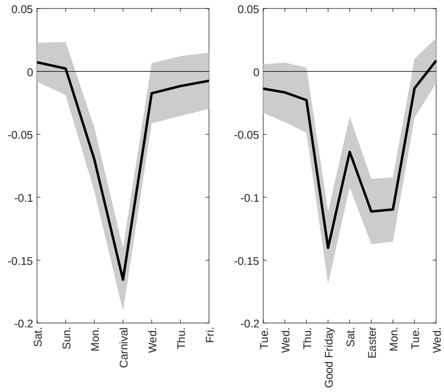
4.3. Calendar effects

After removing the intra-weekly seasonality, one proceeds with the estimation of the effects of Carnival and Easter (which involves two national holidays, the Good Friday and the Easter Sunday). Besides considering regressors for each of those days, to capture potential effects in the activity during the days before or after those events, we also consider regressors for these periods. In particular, we consider a window width of one week, that is, we consider three days before and after each event. In the case of Carnival, this means considering the period from Saturday to Friday (as Carnival occurs on a Tuesday) whereas for Easter the period ranges from Tuesday to Wednesday next week. Regarding the specification of the RegARIMA model, the polynomial lag orders are determined by minimizing the BIC criterion.

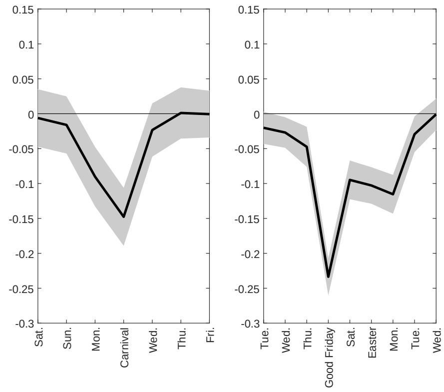
The estimated effects are reported in Figure 3 along with the 95 per cent confidence intervals. Regarding the road traffic of heavy commercial vehicles, there is a substantially decline of traffic on Carnival, by around 70 per cent, and a reduction of 10 per cent on the previous day. In the remaining days, the impact is not statistically different from zero. In what concerns Easter, the major effect is on Good Friday with a negative impact of 90 per cent and around 30 per cent in the subsequent three days. A very similar pattern is found for both electricity and natural gas consumption, but with smaller magnitudes. In the case of Carnival day, the negative impact on electricity and natural gas consumption is estimated to be around 15 per cent. For Good Friday, the effect is close to 15 per cent for electricity and near 25 per cent for natural gas consumption. For cargo and mail landed, the Carnival effect is close to 15 per cent and there is also a statistically significant effect on the following day of around 20 per cent. It is also found a significant impact throughout the Easter period, with the major effect being recorded on Good Friday (almost 60 per cent). Regarding card-based payments, there are no significant effects during the Carnival period. For Easter, it is observed a positive impact on the days immediately before Good Friday, a negative effect between Good Friday and Monday with the largest impact recorded on Sunday (close to 50 per cent).



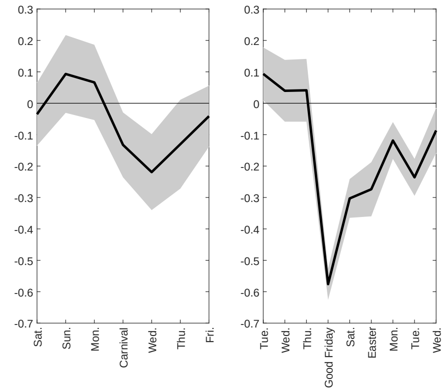
(a) Road traffic of heavy commercial vehicles



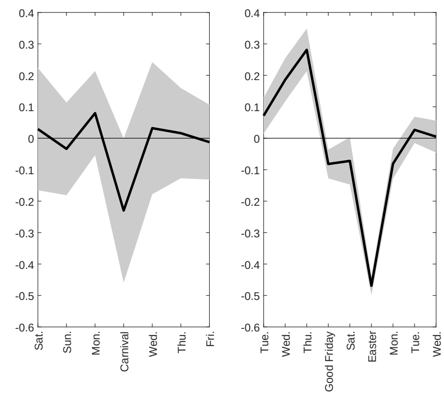
(b) Electricity consumption



(c) Natural gas consumption



(d) Cargo and mail landed



(e) Card-based payments

Figure 3: Carnival and Easter effects on the daily series.

4.4. The Daily Economic Indicator

After the series have been corrected for the above effects, year-on-year growth rates are computed. As usual, prior to factor model estimation, the series are outlier-adjusted following Stock and Watson (2005) and normalized to a common scale. To cope with missing values and unbalanced datasets in the context of a factor model one can draw on the EM algorithm as suggested by Stock and Watson (2002a).

Considering data until the end of 2019, the resulting weights attached to each variable are as follows: road traffic of heavy commercial vehicles (0.25), cargo and mail landed (0.15), natural gas (0.27), electricity consumption (0.18) and card-based payments (0.17). The road traffic of heavy commercial vehicles and natural gas consumption present a slightly higher weight whereas cargo and mail landed record the lowest weight. The variance explained by the latent variable amounts to 53 per cent.[13]

Through the recursive computation of the weights, one can also conclude that most of the weights have been relatively stable over the last years. Only the weight attached to electricity consumption seems to have decreased slightly whereas the weight for card-based payments has moved in the opposite direction.

Figure 4 displays the estimated latent factor from January 1, 2014 to April 30, 2020.[14] Such a daily economic indicator is certainly prone to some irregular movements, which reflect its high-frequency nature. In fact, if one takes the centered weekly average of the DEI, that is, the seven-day centered moving average, one rapidly obtains a much smoother indicator. This is, of course, even truer for the centered quarterly average of the DEI.[15]

[13] For example, in the case of the weekly economic index developed by Lewis *et al.* (2020), the variance explained is around 54 per cent.

[14] Note that this is the period for which all the constituent series are available. For the period which goes back to the beginning of 2010, the results should be read with caution as the information set is more limited.

[15] In the case of Lewis *et al.* (2020), they consider the year-on-year growth rate of weekly frequency data, whereas in Bundesbank (2020) 12-week growth rates are computed from the rolling 12-week averages for each high-frequency indicator.

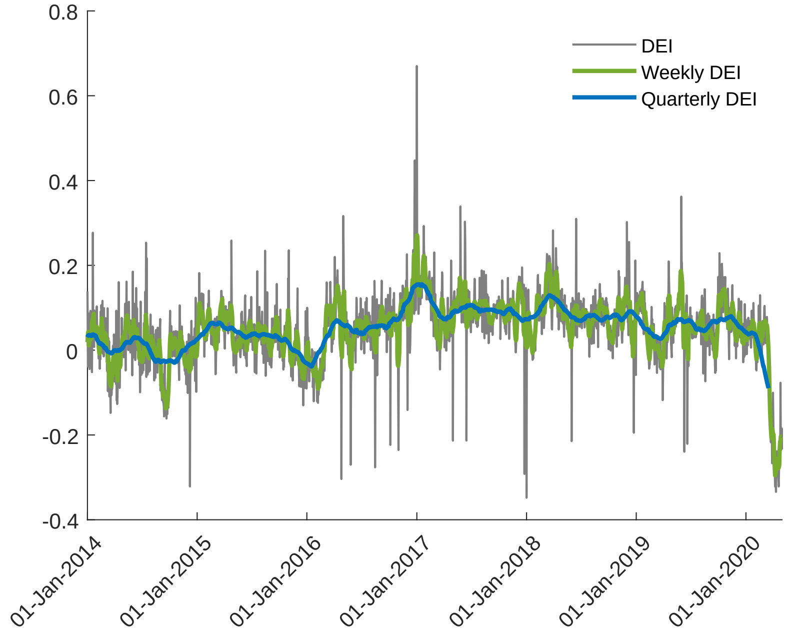


Figure 4: The Daily Economic Indicator.

In Figure 5, we narrow the analysis to the latest period covering the lockdown of economic activity due to the coronavirus pandemic. In particular, we plot the DEI along with the year-on-year growth of quarterly GDP. One should note that, due to the estimation method, the scale of DEI is not interpretable. Therefore, to compare it more directly with the recent evolution of GDP growth, DEI has been normalized so that its quarterly counterpart has the same mean and standard deviation of GDP growth over the last years.

The DEI started to fall on March 12, when the Portuguese government declared the highest level of alert due to the COVID-19 pandemic. It sharpened the decline immediately after the declaration of the State of Emergency in the entire Portuguese territory on March 18, which led to the lockdown of several economic activities. In April, the figures point to an unprecedented decline of economic activity during the first half, with some very mild signs of recovery at the end of the month. Hence, this type of analysis emphasizes the usefulness of high-frequency indicators such as the DEI.

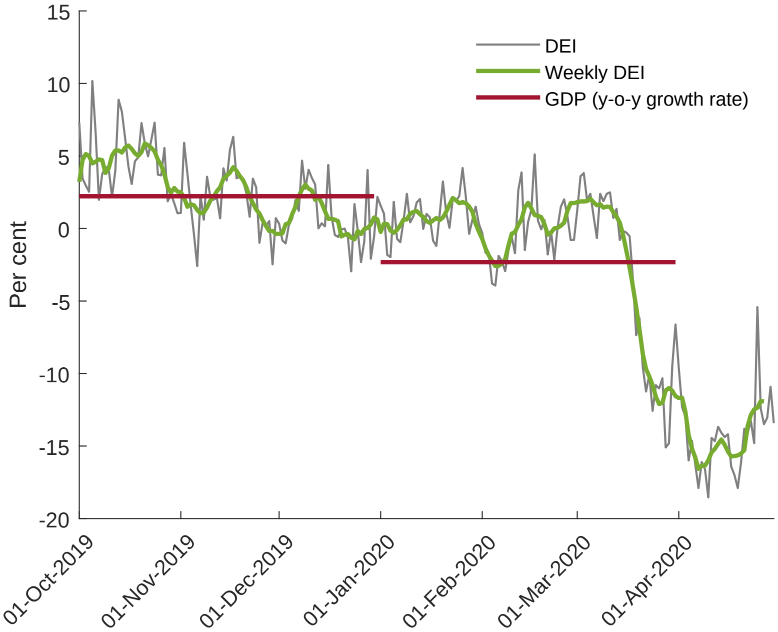


Figure 5: Economic activity during the lockdown period.

Finally, as in Lewis *et al.* (2020) we also assess the information content of the DEI to track current GDP developments. We start by regressing GDP growth on the quarterly average of the DEI, i.e.,

$$y_t = \beta_0 + \beta_1 x_t + \sum_{s=1}^{S} \gamma_s y_{t-s} + u_t \tag{10}$$

with the number of autoregressive lags selected according to BIC criterion. The estimation results are presented in Table 1.

The results reveal that the quarterly average of the DEI conveys significant information about current GDP growth, even after controlling for its past behaviour.[16]

We also investigate the usefulness of the high-frequency availability of the DEI in a regression context. For that purpose, we consider a Mixed-Data Sampling (MIDAS) approach. The MIDAS approach, which has been put forward by Ghysels *et al.* (2004), allows series y_t sampled at lower-frequencies (such as quarterly GDP), to be regressed on a variable $x_t^{(m)}$ sampled at frequency m, say daily (see,

[16]We also assessed the impact of excluding one series at a time from the DEI to evaluate the deterioration of the performance of the composite indicator with a more limited set of data. We find that the informational content of the composite indicator tends to decrease, although not substantially, with the largest drop recorded when electricity consumption is excluded.

	Quarterly data regression	Mixed frequency regression	
		Beta polynomial	Almon polynomial
Low-frequency regressors			
Constant	0.356***	0.413***	0.397***
	(0.116)	(0.122)	(0.113)
y_{t-1}	0.550***	0.400***	0.410
	(0.079)	(0.100)	(0.094)
Quarterly DEI	10.684***		
	(1.845)		
Parameters associated with DEI			
β_1		15.192***	
		(2.479)	
θ_1		2.375*	0.005
		(1.232)	(0.060)
θ_2		1.450*	0.004**
		(0.768)	(0.002)
R-squared	0.938	0.949	0.950
Adjusted R-squared	0.935	0.940	0.942

Table 1. GDP regression results.
Notes: *,**,*** denote statistical significance at the 10, 5 and 1 per cent significance levels, respectively. The standard errors are reported within brackets.

for example, Andreou *et al.* (2013), for a comprehensive overview). Consider the following MIDAS model:

$$y_t = \beta_0 + \beta_1 B(L^{1/m};\theta)x_t^{(m)} + u_t \tag{11}$$

where $B(L^{1/m};\theta) = \sum_{k=0}^{K} B(k;\theta)L^{k/m}$ and $L^{1/m}$ is a lag operator such that $L^{k/m}x_t^{(m)} = x_{t-1/m}^{(m)}$, and the lag coefficient in $B(k;\theta)$ of the corresponding lag operator $L^{k/m}$ is parameterised as a function of a small-dimensional vector of parameters θ. Thus, $B(k;\theta)$ is a weighting scheme used for aggregation. As the number of lags of $x_t^{(m)}$ can increase quite substantially, in particular when the frequency of the variables is very different, say quarterly and daily, the use of a convenient parametric function of $B(L^{1/m};\theta)$ allows to cope with parameter proliferation. In particular, we consider the Beta polynomial which is characterised by two parameters, $\theta_1$and θ_2, and the traditional Almon polynomial (of degree two). The model has also been augmented with lags of the dependent variable. From Table 1, one can conclude that both mixed-frequency models present a quite high explanatory power and slightly higher than in the previous case.

5. Concluding remarks

During rapidly evolving economic conditions, traditional statistics fail to provide timely signals on the state of the economy. The outbreak of the novel coronavirus at the end of 2019 and its lightning-fast spread across continents led economists to depart from traditional statistics and rely on high-frequency data instead. In fact, alternative data sources have become an increasingly important tool to track economic activity in the aftermath of the COVID-19 pandemic, due to the lack of relevant up-to-date data. This effort in collecting timely data has been particularly notable in central banks and other major institutions. Such a line of research can greatly benefit from the engagement of private firms, which typically own this type of data.

In this paper, we carried out an extensive data collection of non-traditional statistics from several sources at a daily frequency to assess which time series prove to be more relevant for tracking economic activity. However, when dealing with high-frequency data, there are relevant issues that have to be addressed, including marked seasonal patterns and calendar effects, which are expected to influence the dynamics of the time series. In this respect, we estimated the intra-weekly seasonal pattern by means of the STL method, while calendar effects have been addressed through RegARIMA models.

After a preliminary analysis and bearing in mind a widespread coverage of economic activity, we selected five daily series. These series cover electronic payments, transportation activity and energy consumption. The latent factor underlying the evolution of those series constitutes the proposed daily economic indicator. The analysis of the recent behaviour of DEI during the lockdown period in Portugal reveals a sudden and sharp drop of economic activity from mid-March 2020 onwards. In particular, when the Portuguese government declared the highest level of alert due to the COVID-19 pandemic on March 12, the DEI started its downward path. It declined further after the declaration of the State of Emergency in the entire Portuguese territory on March 18, which led to the lockdown of several economic activities. Moreover, the DEI points to an unprecedented decline of economic activity in April during the first half, with some very timid signs of recovery at the end of the month.

Lastly, we also assess the information content of the DEI to track current GDP developments. The results reveal that the quarterly average of the DEI conveys significant information about current GDP growth, even after controlling for its past behaviour. These findings are corroborated in a Mixed-Data Sampling regression approach, hence highlighting the usefulness of the DEI in tracking economic activity.

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