

The daily urban dynamic indicator: Gauging the urban dynamic in Porto during the COVID-19 pandemic

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ABSTRACT

The SARS-CoV-2 outbreak motivated the development of a myriad of weekly and daily indicators that track economic activity to estimate and predict the consequences of the pandemic. With some exceptions, these indicators are calculated at the country level and are mainly focused on tracking economic factors, disregarding local urban phenomena. To address this, we present the Urban Dynamic Indicator (UDI), a novel composite indicator designed to measure a city's daily urban dynamic. The UDI is applied to Porto municipality, in Portugal, and it corresponds to a latent factor obtained through a factor analysis over seasonal adjusted daily data regarding traffic intensity, public transportation usage, internet usage in public buses, NO₂ emissions and noise level. The UDI's values show that, by the end of 2020, despite the approach of economic activity to its pre-pandemic values, as suggested by the Portuguese Daily Economic Indicator (DEI), Porto urban dynamic did not recover completely. The UDI enriches the information available for Porto city planners and policymakers to respond to crisis situations and to gauge the application of local policies that contribute to urban sustainable planning. Furthermore, the methodology defined in this work can be followed for the development of daily urban dynamic indicators elsewhere.

1. Introduction

Achieving smart and sustainable cities has become one of the main concerns of most countries, regions and policy makers, being considered one of the seventeen goals of the United Nations' 2030 Agenda for Sustainable Development (United Nations General Assembly, 2015). Smart cities incorporate a wide range of technologies, namely information and communication technologies (ICT) and Internet of Things (IoT), in their infrastructures and services, leveraging on urban activity data to provide their citizens better transportation and mobility, healthcare, waste management, and economic competitiveness, all of these in a sustainable manner (Silva et al., 2018). The application of policies and strategies to promote the development of smart and sustainable cities requires the continual monitoring and gauging of their impacts on the urban tissue at different levels (Feleki et al., 2018). In this note, the European Commission (2018) has made clear the importance of urban indicators as key components for decision makers to monitor socio-economic impacts of transformations on public infrastructures,

services and citizen behaviour. Hence, different urban indicators that compile information from multiple variables of interest into a single global value, have been proposed and implemented in Europe and worldwide (for a review regarding these indicators and their methodology see Sharifi (2020) and Backhouse (2020)).

The rise of smart cities has also progressively led to the dissemination of high-frequency data (i.e., weekly, hourly, and daily data) resulting in an increase in the timeliness and amount of information available generated from cities' technological equipment - such as cameras and sensors - that track human and environmental phenomena (Rathore et al., 2018). In this respect, the recent SARS-CoV-2 virus (also named COVID-19) outbreak and the consequent rapid changes in economic and social behaviours, proved the imperativeness of the quick availability of high-frequency urban data. Accordingly, the year of 2020 was marked by the emergence of studies that resort to weekly, daily, and even hourly data to measure the impact of the pandemic on urban life, as well as a myriad of weekly and daily composite indicators developed by Central Banks to measure economic activity and support the process of

; UDI, Urban Dynamic Indicator; DEI, Daily Economic Indicator; APD, Associação Porto Digital; PSI20, Portuguese Stock Index of 20 largest listed companies.

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short-term decision making and policy design. Notwithstanding the usefulness of these studies, they either focus on a single phenomenon, such as air pollution, urban noise, and mobility, or, in the case of the composite indicators, are calculated at the country level, thus disregarding the variations that occur at the local level, and are mainly concerned with measuring economic activity, discounting, at least directly, important phenomena of urban dynamic that play a crucial role in the city's quality of life and sustainability, like mobility, public services availability and usage, pedestrian intensity, pollution, and urban events frequency and attendance.

To address this, we propose the Urban Dynamic Indicator (UDI), a composite indicator designed to create a holistic and daily view of a city by measuring its daily urban dynamic. The UDI was implemented in the Porto municipality in Portugal. Porto is an appropriate locale to develop this work since it has a rich recent history of studies in the field of smart cities. In 2015, Porto was selected to work in close cooperation with GrowSmarter,¹ a project from the European Commission for the development of smarter European cities and, in 2016, it was considered by the Portuguese Smart Cities Index as the Portuguese city with better results regarding vectors of urban intelligence (Guerra et al., 2017). Today, the city of Porto has a pivotal role in the context of European Strategy for cities and communities, for instance, through the "Living-in.Eu – Join, Boost and Sustain" initiative² that aims to leverage the European market of services and digital platforms for cities, or even "100 Intelligent Cities Challenge" Initiative³ which goal is to promote the use of digital technologies for the sustainable development of over 100 European cities, and in which Porto is one the European cities selected as mentor city.

To the best of our knowledge, the UDI is the first high-frequency composite indicator monitoring the urban dynamic of Porto, that is, the daily dynamic of people regarding mobility, services usage, and intensity of outside activities in the urban context. The indicator is composed of several time series selected after an extensive analysis, that contain daily data regarding traffic intensity, public transportation usage, internet usage in public buses, NO₂ emissions and city noise level. We describe the methods applied to cope with the data issues present in the time series, namely seasonality and calendar effects, and estimate the composite indicator using a factor model (Spearman, 1904). To analyse the UDI, we start by looking at how its values evolved with the COVID-19 pandemic and the following states of emergency. We then compare the UDI's evolution with Google's Mobility report data and with relevant economic indicators, such as Portugal's GDP and Banco de Portugal's DEI (Lourenço & Rua, 2021). These comparisons reveal that the UDI can keep track of urban dynamic phenomena, such as mobility, and that despite the approach of the economic activity to pre-pandemic values by the end of 2020, that is not the case for the urban dynamic in Porto. These results reinforce UDI's potential applicability in supporting responsible authorities in a timely manner and in anticipating the results from low-frequency indicators, in Porto and other cities worldwide. Hence, our contributions with this work are the following:

- 1 We develop the first high-frequency indicator to track urban dynamic at the municipality level by combining data from multiple urban phenomena.
- 2 We provide a framework for the development of similar indicators in other regions.
- 3 We enrich the information available for city planners and policy-makers to diagnose problems and respond to crisis situations in a short span of time.
- 4 Our indicator can support the design of local policies that effectively contribute to urban sustainable planning, by identifying areas that

would profit from interventions and by helping to monitor the success and impact of these policies at a daily level.

- 5 The application in Porto complements the DEI, developed by Banco de Portugal, and other high-level economic indicators, such as the GDP, with a more spatially detailed indicator, one that captures features of Porto's urban activity, which allows for comparability between the country markers with the more granular reality of the municipality.

The remainder of the paper proceeds as follows. In Section 2, we review the recent relevant literature regarding usage of high-frequency data to analyse phenomena of urban dynamic. In Section 3 we present, and describe the data used. Section 4 describes the methodology followed to cope with the data issues and compute the UDI. In Section 5 we benchmark the UDI with other relevant indicators and discuss the results. We conclude the work in Section 6.

2. Literature review

The data generated by ICT and IoT has become the bedrock of smart, resilient, and sustainable cities (Ahad et al., 2020). These data, originated from citizen smart devices and city infrastructures, like sensors, allow for high-frequency data processing, opening the possibility for real-time analytics and inference (Malik et al., 2018), enabling to perceive and solve urban challenges, prescribing solutions and more general or concrete actions (Castro Neto & Melo Cartaxo, 2021). Despite this, Sharifi (2020) noted that, over the past several years, the surge of tools and indicators for smart city assessment, sustainability evaluation and measurement of urban phenomena, has rarely considered the use of real-time data sources. Most recently, the outbreak of the SARS-CoV-2 virus shed a light on the crucial need for the availability of urban data to support a real-time understanding of the quick changes in the urban socio-economic tissue, as well as to assist decision making and help calculate the impacts of the measures implemented to combat the pandemic.

In response, since mid-2020 different studies have dealt with the application of high-frequency data to measure urban dynamic phenomena. In this regard, Benita (2021) and Shokouhyar et al. (2021) summarized the impact of the pandemic on human mobility behaviour, reporting the acute reduction of public transportation usage and urban traffic volumes, and the disruption of the aviation sector, greatly impacting citizens movement, and the importation and exportation of goods. Also within the scope of human mobility, Google has published the COVID-19 Community Mobility Reports⁴ - a set of indexes that resort to Google users' location data to track mobility trends in locations from different categories, namely retail and recreation, grocery and pharmacy, transportation stations, parks, workplaces, and residential places. The reports demonstrate the influence the pandemic has had on reducing the amount of people outdoors and in their work locations, increasing the number of people staying at their residential place.

Changes in the concentration of the major air pollutants in urban areas have also been the focus of attention of recent literature on COVID-19 impacts. While studying these chemicals is of the utmost importance to understand air quality and the impacts it has on the health of cities, it is also the case that levels of transportation and industrial activity in cities are typically correlated with concentrations of air pollutants, such as Nitrogen dioxide (NO₂). Thus, these activities' behaviour can be extrapolated from the analysis of changes in the emissions of pollutants. On this behalf, Benchrif et al. (2021) summarized the most recent studies addressing the evolution of air pollutants during the pandemic, concluding that the lockdown lead to a drastic reduction of air pollution levels at the cost of the normal functioning of urban activity, including road traffic and industry. Likewise, Wang and Li (2021) looked at the

¹ <https://grow-smarter.eu/home/>

² <https://living-in.eu/>

³ <https://www.intelligentcitieschallenge.eu/>

⁴ <https://www.google.com/covid19/mobility/>

non-linear relationship between the impact of the COVID-19 lockdown and four pollutants in eight cities worldwide (Wuhan, New York, Milan, Madrid, Bandra, London, Tokyo and Mexico City), showing that the global lockdown reduced concentrations of NO₂ in these cities, up to 50% during 2020.

Urban noise level is another factor of urban dynamic that has been addressed in the pandemic context, namely by Lee and Jeong (2021), who studied the evolution of noise levels in London, concluding through citizens' tweets that perceived outdoor noise level decreased but neighbour noise level increased during the lockdown. Similarly, Rumppler et al. (2020) resorted to noise monitoring devices installed in buildings to measure the variation of city noise levels in different locations in Stockholm, Sweden, where the restrictive measures were, in general, lighter than in other European countries. Their study relied on the assumption that urban noise implies outdoors human activity to provide a monitoring method for the implementation of regulations during the pandemic. Rumppler et al. (2020) concluded that the decrease in urban noise levels due to COVID-19 restrictions is equivalent to those seen during public holidays.

Central Banks have also contributed to the analysis and monitoring of the impacts of the pandemic, with a multitude of weekly and daily composite indicators developed in 2020 to measure economic activity. The first of this sequence, the weekly economic indicator (WEI), proposed by Lewis et al. (2020) was developed to track economic rapid changes caused by the COVID-19 pandemic in the United States. The composite indicator corresponds to one factor aggregated from ten time series that record different economic phenomena, such as retail sales, unemployment, tax collections, industrial production, electricity consumption and goods transportation, and has shown to provide an accurate nowcast of the US GDP growth. The WEI was followed by Eraslan and Götz (2021) German weekly activity indicator (WAI), Lourenço and Rua, (2021) Portuguese daily economic indicator (DEI), Fenz and Stix (2021) Austrian weekly GDP indicator, Wegmüller et al. (2021) Swiss weekly real economic activity (WEA), Delle Monache et al. (2021) Italian weekly economic growth indicator (ITWEI), and other indicators developed by other country central banks.

Some of the high-frequency series used in these composite indicators to measure economic activity can be extrapolated to capture other informative phenomena regarding urban dynamic. In this regard, transportation activity data in its different types has played a central role in most indicators. Fenz and Stix (2021) use time series of transportation activities to capture goods exports in Austria, namely they resort to truck mileage, pointing out the correlation between freight growth and economic growth. Truck mileage is also used by Eraslan and Götz (2021) in the weekly economic activity index for Germany, as a proxy to capture the performance of the production sector, by Lourenço and Rua, (2021) in the construction of the Portugal daily economic indicator, and by Delle Monache et al. (2021), which consider traffic flow of cargo and trucks for the Italian weekly economic indicator. Looking at other types of transportation, in the WEI, Lewis et al. (2020) resort to railroad traffic to measure intermediate inputs of production, and Wegmüller et al. (2021) consider rail freight transport net tonne kilometres to capture production activity in the weekly economic indicator for Switzerland.

Likewise, air pollution was also considered by Wegmüller et al. (2021) and Eraslan and Götz (2021), that used NO₂ as a variable for the weekly economic indicator in Switzerland and Germany, respectively, to capture mobility patterns and the production activity of the manufacturing sector.

In summary, the SARS-CoV-2 virus outbreak led to the development of studies that resort to high-frequency data produced in cities to evaluate the local impacts of the pandemic and the following lockdowns on one factor of urban dynamic, such as mobility, pollution, or noise levels. Since the aim of these studies is to analyse a single phenomenon, they do not provide an overarching view of the urban environment and its dynamic. In parallel, Central Banks focused on measuring economic activity at the country level, by modelling the data of different economic

indicators into a single composite indicator. In this case, despite the multidimensionality of the studies, they are predominantly interested in economic factors measured at the country level, failing to address most factors of urban dynamic at the local level. This way, we believe there is an opportunity to build on what was done by modelling the data produced in the day-to-day activities of a city, into a composite indicator that captures and synthesizes the city's overall dynamic.

3. The data

In this Section, we present the input variables used to compute Porto's daily Urban Dynamic Indicator. We explain the criteria followed to select our variables and describe them at different levels, including seasonality and calendar effects.

3.1. Variables

To collect the necessary data, we depended on its availability and the willingness of the institutions owning the data to provide it, as most urban activity data is not public. Hence, all data considered was made available by Associação Porto Digital⁵ (APD), a leading institution in the promotion of information and communication technologies projects in the city of Porto. Namely, we collected urban data regarding traffic, public transportation usage, air pollution and noise. The selected variables are grounded on the data used in the works reviewed in Section 2, which are related with the impact of the pandemic on urban environments and human activity, and therefore can capture phenomena of the urban dynamic.

Besides considering the relevance of the variables to our task and their availability, we defined a simple set of criteria for variable selection to ensure the indicator has the adequate time and location granularity: (i) variables need to have a daily frequency – we rely on genuinely daily indicators that capture the day-to-day variation and noise that is reflective of the high frequency urban changes; (ii) the series should span over at least the year of 2020 so that we could understand the variable's behaviour a few months before and during the COVID-19 pandemic (ideally the series should consider at least two or three years in order to properly address seasonality and holidays); (iii) the data should consider only locations inside the Porto municipality and be captured at a sufficient number of different locations to provide information for the whole municipality. Given these criteria, we arrived at a total of five time series.

Table 1 describes the time series used, their time frame, frequency, aggregation, and source. The "Traffic Flow" series records the number of vehicles that circulate in Porto streets in a specific day, offering information regarding human mobility, namely commuting, but also transportation of goods. The "Public Transportation Users" also covers human mobility and provides additional information about the volume of public services usage, namely train, subway, and bus. "Public Bus Wi-Fi Logins" records the number of logins to the public bus Wi-Fi, informing about the number of people that resort to the public bus transportation and use the bus Wi-Fi network. "Air Pollution" measures the average level of NO₂ and offers both information about mobility and industrial production. Finally, "Noise Level", besides expressing traffic intensity, also captures pedestrian intensity, urban events, construction work and overall human outdoors activity.

The values for each variable were recorded at different locations in the Porto municipality. This is exemplified in Fig. 1, which shows the locations where sensors that measure levels of noise and NO₂ are placed in Porto. The data for the other three series is also measured in different locations. Nevertheless, these locations either do not intercept between series, or use different geo-political nomenclatures. For this reason, we aggregate each series at the level of the municipality using the

⁵ <https://www.portodigital.pt/>

Table 1
Variables used in the DUI, description, time frame, frequency, aggregation, and source.

Variables	Description	Time Frame	Frequency	Aggregation	Source
Traffic Flow	Vehicle count on highways and streets.	01/01/2016 to 31/03/2021	daily	sum	APD
Public Transportation Users	Number of validations, by railway and bus operator, of the <i>Andante</i> tickets and monthly pass.	01/01/2020 to 31/01/2021	daily	sum	APD
Public Bus Wi-Fi Logins	Count of accesses to public bus Wi-Fi network.	01/01/2019 to 31/12/2020	daily	sum	APD
Air Pollution	NO ₂ micrograms per cubic metre (µg/m ³) as measured by sensor.	01/01/2018 to 30/04/2021	daily	mean	APD
Noise Level	noise level (dB) as measured by sensor.	30/06/2018 to 30/04/2021	daily	mean	APD

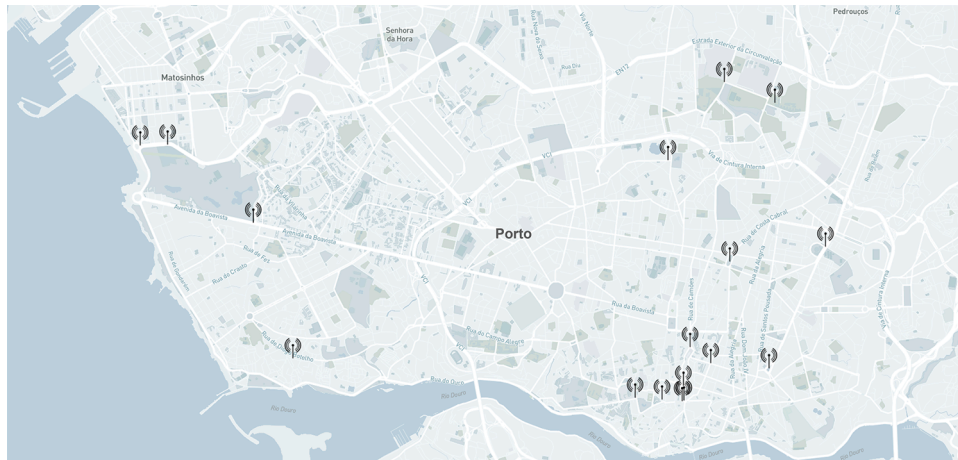


Fig. 1. Location of sensors measuring noise and NO₂ levels in the Porto municipality.

aggregations described in [Table 1](#).

4. Methodology

In this section, we present and explore the existing issues in the input time series, and explain the methods applied for the adjustment of these data prior to the construction of the daily indicator. Moreover, we explain and describe the process followed to compute the values for the UDI.

4.1. Time series adjustment

To the best of our knowledge and despite recent efforts in that direction, namely [Dominique et al., \(2018\)](#), there is not a consistent body of work that clearly indicates how studies addressing daily time series should be conducted in order to correctly adjust the data for issues such as missing values, seasonality and calendar effects. Moreover, most of our time series consider a short period of time (some less than two years), which restricts the use of standard econometric methods. Nevertheless, we based our approach on the methodology employed in the related work, namely [Lourenço and Rua, \(2021\)](#), while at the same time resorting to a more “data-driven” approach.

We start by addressing the missing values, which are present in all five series used as input for the composite indicator. Although not in a substantial amount, missing values appear scattered along the time frame of each series, sometimes in sequences. To fill the missing data, we calculate a seven-day rolling mean of previous dates and use those values as the placeholders for the missing values.

Furthermore, daily time series typically present strong seasonal patterns. Besides yearly and monthly effects, daily series require the adjustment of the series for weekly seasonality and holiday effects. Likewise, daily series suffer from lack of periodicity – the position of

weekends and holidays varies across the years, namely due to changing month length and moving holidays. We decompose our time series using the Prophet solution developed by [Taylor and Letham \(2018\)](#), which is based on the structural time series model proposed by [Harvey and PETERS \(1990\)](#). The decomposable time series model considers three main components: trend, seasonality, and holidays. This model is presented in the following equation:

$$Y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{1}$$

The trend component is represented in the equation by $g(t)$ and models non-periodic changes in the time series; $s(t)$ captures the periodic changes, namely yearly, monthly and weekly seasonality; the $h(t)$ component represents the holiday effects - the model considers regressors for days of holidays and for the two previous and two next days; ϵ_t represents the error term, and it captures the remainder components consisting of unique changes not accommodated by the model.

The decomposed series reveal a pronounced weekly seasonality and holiday effects as shown in [Fig. 2](#) and [Fig. 3](#), respectively. Regarding weekly seasonality, “Traffic Flow”, “Air Pollution”, “Public Transport Users” and “Public Bus Wi-Fi Logins” display stable values throughout the week, peaking on Friday and dropping 0.5 to 1.5 points below the mean on weekends. As for “Noise Level”, it peaks on Saturday and displays lower values on Sunday. Concerning holiday effects, [Fig. 3](#) displays the average and standard deviation values for each series for the Easter holidays week. In this case, all series exhibit values below the mean during this week. The values start to drop on Wednesday or Thursday prior to Good Friday, reaching their lowest point on Easter Sunday (in the case of “Air Pollution”, the values of NO₂ increase on Saturday before decreasing on Easter Sunday). On the Monday after the Easter holiday, values for each series start returning to normality, except for “Traffic Flow”, whose Monday values are like the Easter Sunday ones.

Applying an augmented Dickey-Fuller (ADF) test ([Cheung & Lai,](#)

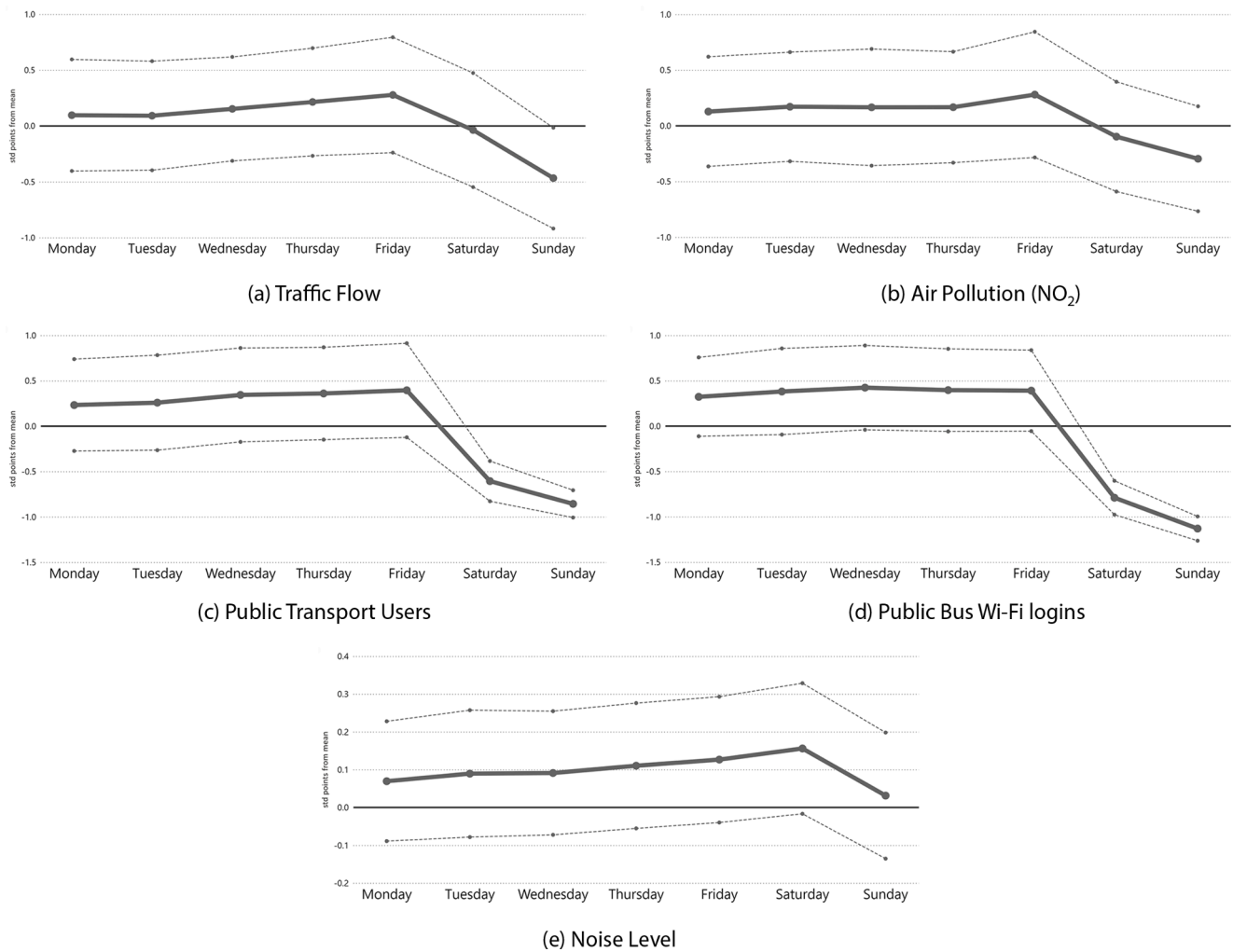


Fig. 2. Weekly average (solid line) and standard deviation (dashed lines) values for each input series. Values were standardized so that the y-axis indicates standard deviation points away from mean.

1995) led us to confirm the null hypothesis that each original series is non-stationary (i.e. time series properties depend on the time at which the series is observed). The autocorrelation plots also pointed to the same conclusion, confirming the need for seasonal adjustment.

After adjusting for the seasonal and holiday effects by extracting the monthly and weekly seasonality, and holiday components, we applied again the augmented Dickey–Fuller test (ADF) which led us to reject the null hypothesis that each series was non-stationary (i.e., time series properties do not depend on the time at which the series is observed) and autocorrelation plots indicate that the series became stationary.

4.2. Factor analysis

With the adjusted series, we proceed with a Factor Analysis model estimation to obtain the daily urban dynamic composite indicator. Factor Analysis is a technique for identifying latent variables, called factors, that drive the co-movement of observed variables. This approach can be summarized by the following equation:

$$X = \Lambda F + \xi \quad (2)$$

Here, $X = [X_1, \dots, X_n]$ is a set of n observed time series (variables) represented by two orthogonal components: the common component, composed by F and Λ , and the idiosyncratic component ξ . The common component considers $F = (f_1, \dots, f_i)$, a vector of i latent factors, and $\Lambda = (\Lambda_{11}, \dots, \Lambda_{ni})$, a matrix of factor loadings that quantifies the extent to

which a variable is related with a given factor; the idiosyncratic component considers $\xi = (\xi_1, \dots, \xi_n)$, a vector of specific indicator features. Simply put, each time series is the sum of one or more common factors, not correlated among themselves, with the idiosyncratic component.

Before beginning the factor analysis, we restricted the values used to compute the composite indicator to the year of 2020, since this is the period where the different time series intercept and guarantees that the indicator values always comprise all variables. This time frame also allows us to benchmark the results with other data already available for 2020. In addition, all variables are normalized to a common scale.

We applied the Kaiser-Meyer-Olkin (KMO) goodness of fit test (Kaiser, 1981) and the Bartlett’s test of sphericity (Bartlett, 1950) to measure the adequacy of the Factor solution. The KMO test indicates the proportion of variance in a set of variables that might be caused by underlying factors; typically, values close to 1.0 indicate factor analysis is useful, while values below 0.5 indicate the opposite. The Bartlett’s test of sphericity tests the hypothesis that the variables’ correlation matrix is an identity matrix. Therefore, if the significance level is higher than 0.05 variables are unsuitable for factor analysis. A KMO value of 0.667 and a Bartlett’s test of sphericity with significance level <0.05 lead us to conclude that the sampled variables were adequate for the factor analysis.

We estimated the latent factors performing a factor analysis through a principal components’ estimator using a varimax rotation, which

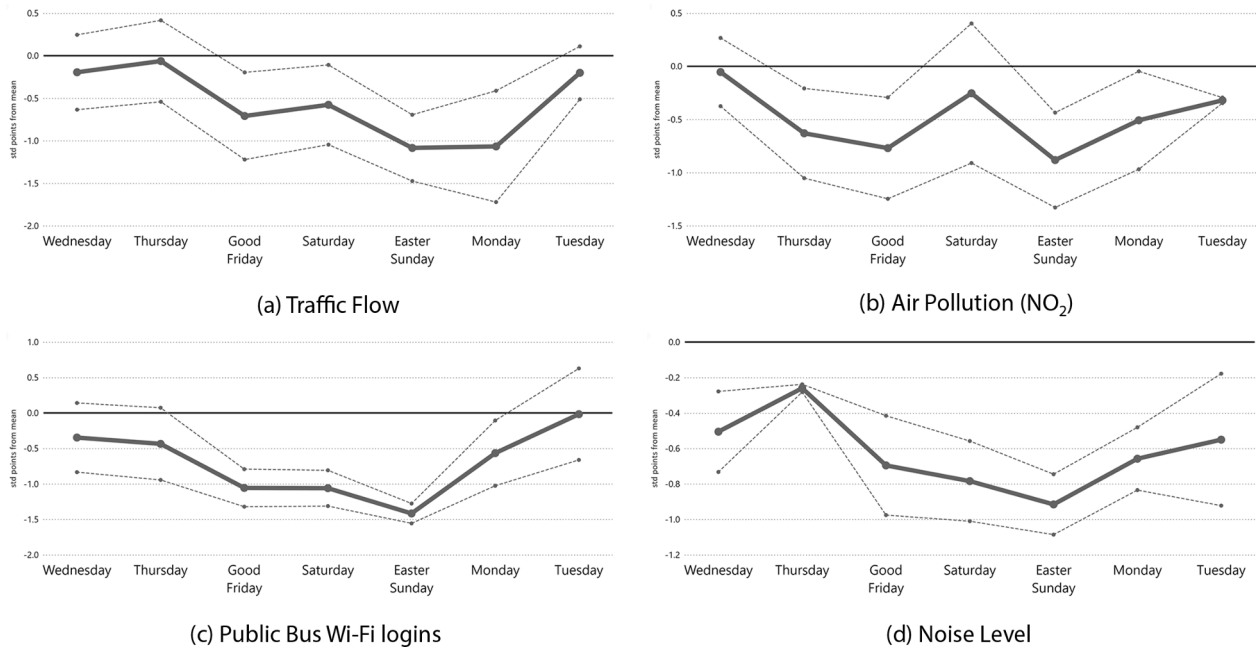


Fig. 3. Easter week average (solid line) and standard deviation (dashed lines) values for each input series. Values were standardized so that the y-axis indicates standard deviation points away from mean. Values for “Public Transport Users” are not displayed since this series only contains a single year of data.

rotates the orthogonal basis to maximize the sum of the variances of the squared correlations between variables and factors. The scree plot of eigenvalues⁶ and factors is shown in Fig. 4. The Kaiser’s criteria (Kaiser, 1960) for deciding the number of factors to retain, determines that one should retain the factors with eigenvalues greater than one. This way, we consider only one factor that amounts to 49 per cent of the variance in the data, a value close to the one seen in the factor analysis performed by Lewis et al. (2020) and Lourenço and Rua, (2021), with 54 per cent and 53 per cent, respectively. This factor represents the Porto daily Urban Dynamic Indicator (UDI).

The relationship of each variable X_n with the UDI is expressed by the factor loading - the regression weight Λ_{n1} attached to the factor f_1 , from Eq. (2). The loadings attached to the input variables are as follows: traffic flow (0.74), public transport users (0.74), Wi-Fi logins (0.76), air

pollution (0.52) and noise level (0.70).

5. Results and discussion

In this section, we present the daily Urban Dynamic Indicator for Porto. We describe the UDI values, then check the indicator’s evolution during the pandemic, and evaluate its ability to keep track of urban mobility and economic phenomena by comparing it with other relevant indicators.

Fig. 5 displays the UDI values from January 1, 2020, to December 31, 2020. The daily indicator shows noisy movements that reflect the high frequency nature of the data. These values can be smoothed by calculating a seven-day rolling mean of the daily UDI.

The UDI is standardized so that it fluctuates around the mean, which is 0. This way, positive values indicate above-average growth in urban dynamic, while negative values signal a below-average decline. Likewise, because the standard deviation of the index is 1, the magnitude of the change can be interpreted as follows: a value of x above or below the mean indicates a x standard deviation change compared to the average of the index.

To benchmark and discuss our results, we resort to other time series and key indicators that were not included in the estimation of the UDI but can track developments in urban dynamic in Porto and Portugal, using them for plausible checks on the measurement ability of the UDI, as done by Celgin and Gunay (2020) and Eraslan and Götz (2021), Fenz and Stix (2021) in their composite indicators. The time series used for comparison are summarized in Table 2.

The evolution of the daily UDI across the year of 2020 is clearly affected by the COVID-19 pandemic and the subsequent national lockdowns. Fig. 6 demonstrates this pattern. As of mid-March, the UDI records an acute decline of two standard deviation points below the mean, that coincides with the start of the pandemic in Portugal, the emergence of the first COVID-19 cases in Administração Regional de Saúde (ARS) do Norte - the health administration region where Porto is included -, as well as the first lockdown. Later, as the measures to contain the pandemic were easing and cases stabilizing, urban dynamic grew slightly and maintained constant values around its mean until the weeks before the fourth lockdown on the 9th of November, that were marked by an abrupt increase in COVID-19 cases. By the end of the year, the

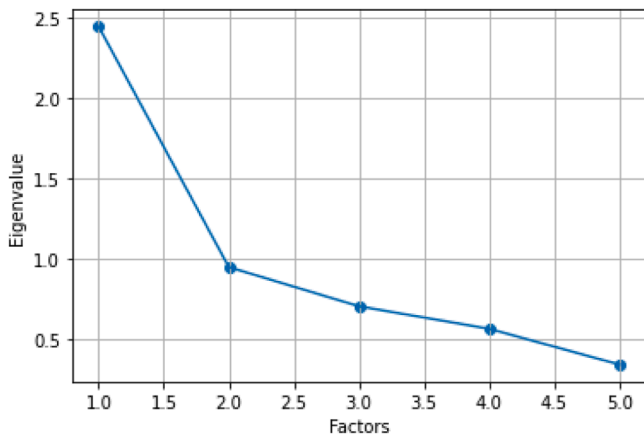


Fig. 4. Scree plot of eigenvalues and factors.

⁶ An eigenvalue is an index that indicates how good a factor is as a summary of the input data.

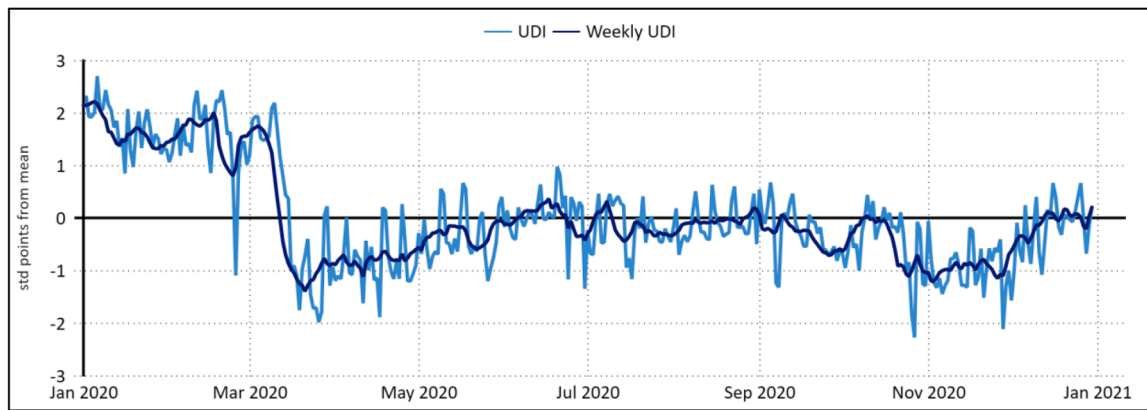


Fig. 5. The daily and the weekly Urban Dynamic Indicator.

Table 2
Indicators used to benchmark the UDI.

Indicator	Description	Frequency	Level	Source
New Covid-19 cases ARS Norte	Number of new Covid-19 cases.	daily	ARS do Norte	Data Science for Social Good Portugal ^a
Google Mobility	Google Mobility Index - average of the standardized Google subindices “retail and recreation”, “grocery and pharmacy”, “parks”, “public transport” and “workplaces”, that measure percentage change of phenomena compared to baseline day.	daily	Porto	Google ^b
	Google Residential Index - percentage change of people staying home compared to a baseline day.	daily		
Daily Economic Indicator (DEI)	Composite indicator used to assess the real economic activity.	daily	Portugal	Banco de Portugal ^c
GDP	Gross domestic product.	trimestral		
PSI20 stock market open value	Lisbon Euronext open value of the top 20 highest Portuguese listed companies.	daily	Portugal	Yahoo! Finance ^d
Number of card-based transactions	Number of transactions recorded by SIBS ^e .	monthly	Porto	APD

^a <https://github.com/dssg-pt/covid19pt-data>.
^b <https://www.google.com/covid19/mobility/>.
^c <https://www.bportugal.pt/comunicado/banco-de-portugal-lanca-indicador-diario-de-atividade-economica-0>.
^d <https://finance.yahoo.com/quote/PSI20.LS/history?p=PSI20.LS>.
^e <https://www.sibs.com/>.

indicator returned to values closer to the mean, as the lockdown was producing the desired effects to mitigate the rise in the number of cases. Nevertheless, the urban dynamic did not return to its pre-pandemic values.

Next, in Fig. 7 we compare the evolution of the UDI with the Google Mobility Report indexes, used by Fenz and Stix (2021) to benchmark the Austrian weekly indicator. In Fig. 7(a), we calculate an aggregated Google mobility index at the level of Porto, by standardizing and then averaging the Google subindexes “retail and recreation”, “grocery and pharmacy”, “parks”, “public transport” and “workplaces”. At the short and long-term, both indicators exhibit movements in the same direction and with close values. It is also interesting to observe that prior to the pandemic and after the second lockout in November, the values for both indicators are noisier, but the Google index becomes smoother in between these dates in contrast to the UDI. In Fig. 7(b) we plot the UDI against another Google subindex, “residential”, that measures the percentage change of people staying home compared to a baseline day. In this case, the indicators display clear opposite movements - since urban dynamic is directly dependent on the amount of activity outdoors, less activity will result in lower levels of urban dynamic.

To investigate the extent to which Porto urban dynamic and overall Portuguese economic activity are correlated, in Fig. 8 we compare the UDI with the DEI and GDP percentage year-on-year rate of change. The UDI values and its evolution are very similar to the ones displayed by the DEI and GDP. Nevertheless, while the UDI’s values stay closer to the mean as the year progresses, the DEI and GDP return to values closer to the ones during the beginning of the year, a pattern that points to the restore of the economic activity to its normality, in contrast to urban dynamic that was still deeply affected by the pandemic and the preventive measures.

Likewise, in Fig. 9 we benchmark the UDI against an indicator of real economic activity in Porto - the monthly number of card-based transactions. This is a variable used as one of the input variables for the DEI, as well as other recent indicators, such as Wegmüller et al. (2021) and Celgin and Gunay (2020). The monthly trend is similar between both indicators, but like the DEI, from July to November the number of card transactions gets closer to pre-pandemic values, although decreasing by the end of the year, when the UDI returns to its mean value.

Finally, to assess the degree of relationship between urban dynamic and financial changes, in Fig. 10 we compare the UDI with the PSI20 open values. Even though this indicator works at the national level,

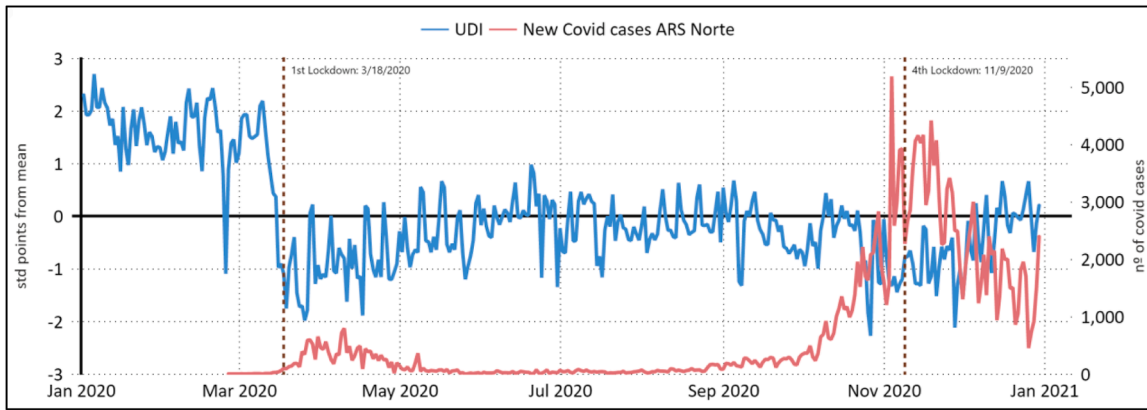
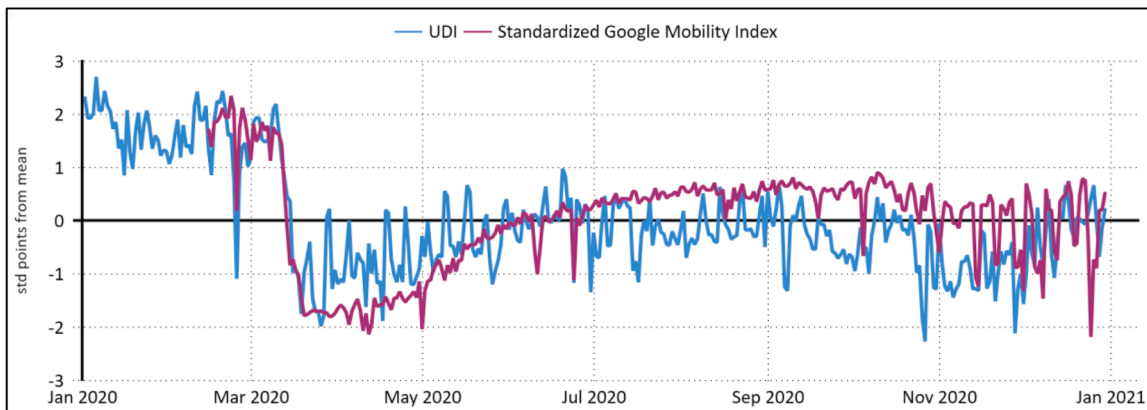
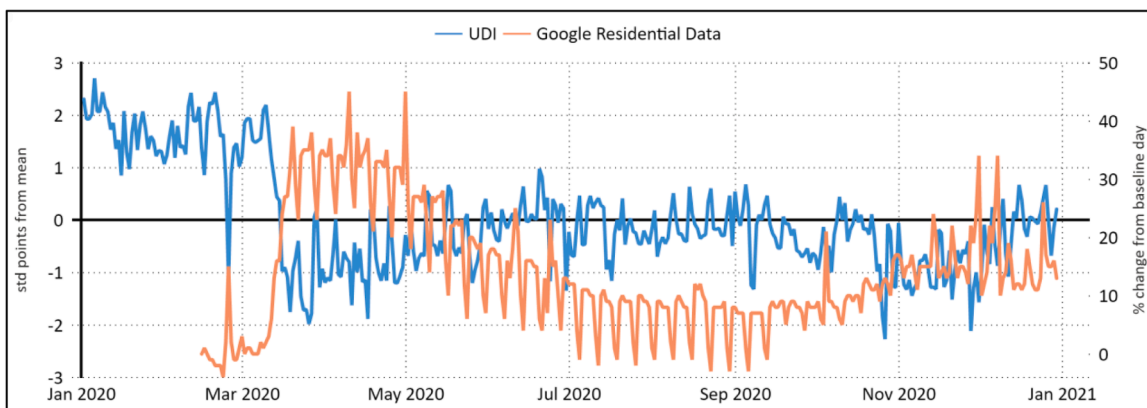


Fig. 6. Comparison between UDI and evolution of the number of new covid cases in Área Regional de Saúde (ARS) do Norte.



(a) UDI vs standardized Google Mobility Index (average of the standardized Google subindices “retail and recreation”, “grocery and pharmacy”, “parks”, “public transport” and “workplaces”).



(b) UDI vs Google “Residential” Index.

Fig. 7. Comparison between UDI and Google Mobility Report Indexes for Porto.

Porto’s economy is deeply dependent on the activity of the companies contemplated by it. It seems that the PSI20 and the UDI generally display similar values, although with less delay on the part of the PSI20.

6. Conclusions and future work

The year of 2020 was marked by a depart from traditional low-frequency statistics to more high-frequency ones, mostly due to the

emergence of the SARS-CoV-19 pandemic, but also because, progressively, more timely data is being recorded and made available as the attention towards smart and sustainable cities grows, and so does the technologies they entail. Recently these high-frequency data have been used successfully by studies that analyse a single phenomenon of the urban environment (mobility, air pollution and noise levels) to measure the impact of the pandemic, and by Central Banks for the development of composite indicators that predominantly track country-level



Fig. 8. Comparison between UDI, the Daily Economic Indicator (DEI) and trimestral GDP. The DEI and GDP measured at national level.

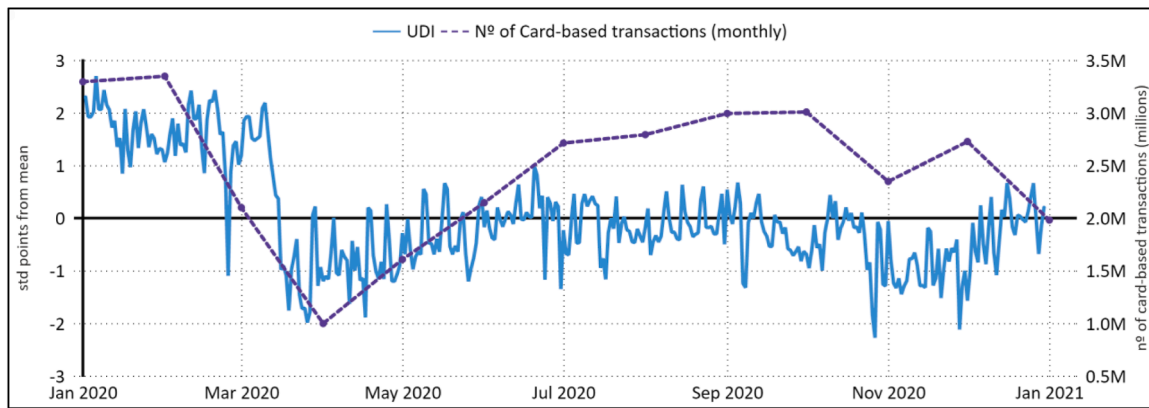


Fig. 9. Comparison between UDI and monthly Number of Card-based transactions in Porto.

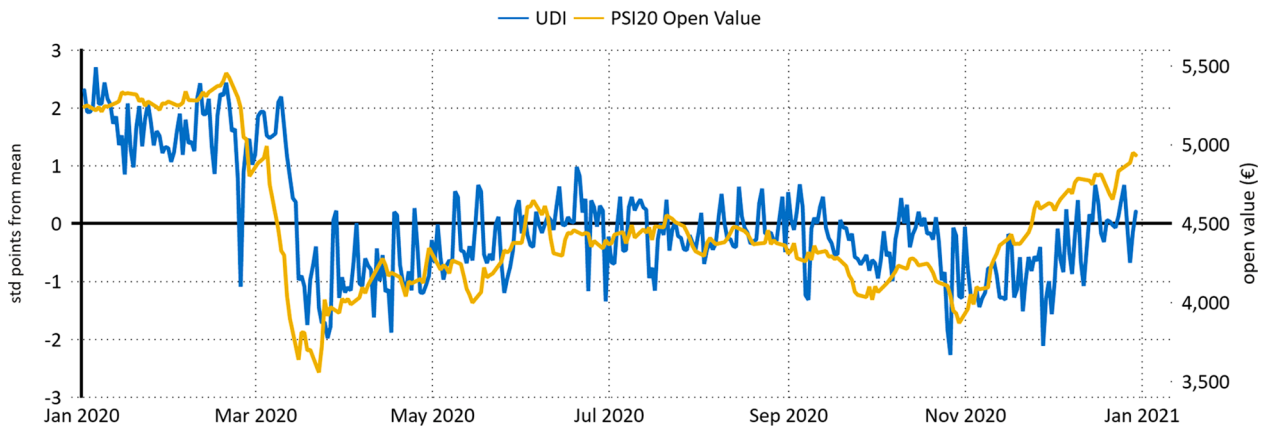


Fig. 10. Comparison between UDI and PSI20 open value.

economic activity. We argue these studies either lack an overarching view of a city’s urban dynamic or, in the case of the country economic composite indicators, disregard phenomena of local urban environments, and thus the differences between cities that belong to the same country. The importance of synthesizing and measuring urban phenomena is also made evident by the contrasting measures applied during the COVID-19 pandemic - since these measures varied across cities, a return of the country economy to normality does not mean the local economy has also returned to normality. Moreover, even if the local economic indicators present “healthy” values, this does not mean that the urban dynamic of the city is working as before.

In this work, we focused on the Portuguese municipality of Porto and collected daily data that captures phenomena of the urban dynamic, that is, the daily dynamic of people regarding mobility, services usage, and intensity of outside activities in the urban context. After a preliminary analysis and being constrained by the availability of such high-frequency data spanning over relatively long periods of time, we ended up with five series. These series cover traffic flow, public transportation users, Wi-Fi logins in public bus, air pollution and noise level. All series presented marked seasonal patterns, more evidently weekly seasonality, and calendar effects, that may negatively influence later inferences and lead to wrong conclusions. In this note, we resorted to the

Prophet method to estimate and remove the monthly and weekly seasonality, as well as holiday effects. We then estimated a latent factor to those series that explains 49% of the variance in the data and constitutes the proposed urban dynamic indicator.

The analysis of the UDI behaviour suggested that, during 2020, urban dynamic in Porto was severely affected by the COVID-19 pandemic. UDI's values acutely dropped during the first lockdown in March, slightly growing after May and maintaining stable values until October, decreasing again until December and then returning to the values displayed after May – which indicates that the urban dynamic in Porto did not return to the pre-pandemic values. This is in line with the mobility indicators that are part of the Google Mobility Reports, but contrasts with the DEI and GDP, as well as the number of card-based transactions in Porto, whose values during 2020 approximate pre-COVID-19 ones. Moreover, the evolution of the stock market open values for the 20 most important Portuguese companies seems to be in line with the UDI, despite the differences in the nature of the phenomena being tracked.

Based on these comparisons, we strongly believe that the UDI represents an effective tool to measure the level of daily urban dynamic in Porto, allowing authorities to quickly track changes during crisis situations and understand how urban dynamic evolves during normal periods of activity. As well, the UDI can support city planners and policymakers on the application of local policies, by gauging the impact of these policies on the urban dynamic of a city. This way, it effectively contributes to urban sustainable planning, as it allows to evaluate policies based on their real impact on the urban environment and the community, at the level of traffic, public transportation, air quality and noise.

Since this study considers only the year of 2020, the similarity between the evolution of the values displayed by UDI and the other indicators is obviously influenced by the COVID-19 pandemic. Nevertheless, it also seems to be applicable for times of normal activity; in fact, one can see that the values of the UDI and other indicators were very alike in the first two months of the year, before the pandemic impacted Portugal, and, in the case of the Google indicators and the PSI20, even when the measures to retain the pandemic were easing, by the end of the same year. Even so, UDI's reliability will also depend on its capacity to keep track urban phenomena on the long term. Likewise, the availability of other macro indicators for Porto will allow us to compare the UDI and see whether it consistently performs accurately.

We must say that this work was naturally limited by the availability of high-frequency data regarding urban phenomena, which is increasingly being recorded, but is not so commonly made publicly available. If this is the case in Porto, the second largest city in Portugal, which has a rich history of involvement with smart city initiatives, one can presume the difficulty to collect these kinds of data on less urbanized regions. However, once similar data is collected, researchers can follow the methodology proposed on this work to implement a daily urban dynamic indicator for other cities, in Portugal and elsewhere. Moreover, other variables which record urban phenomena can serve the purpose of tracking urban dynamic. Thus, we hope that in the future we can enrich the UDI's capacity to capture urban dynamic by considering more input variables, as they are made available by local authorities and other institutions.

Finally, we note that *Associação Porto Digital* intends to have the UDI in production and that efforts are being made in this direction. These include the continuous collection of data for each of the variables that make up the UDI, to ensure that the indicator is updated, and the increase in spatial detail, to allow for a more granular geographical analysis of the urban dynamic.

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.

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