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معهد عصام فارس للسياسات العامة والشؤون الدولية

AN ECONOMIC POLICY UNCERTAINTY INDEX FOR LEBANON

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RESEARCH REPORT

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ABSTRACT

This paper constructs a weekly and monthly Twitter-based Economic Policy Uncertainty (TEPU) index for Lebanon, covering the period from January 1, 2011, to January 18, 2023.[1] We create and employ Python scripts that interact with the official Twitter API to fetch and transform tweets into actionable data. We adopted an online text-searching methodological approach and further extended it to suit the context of Lebanon. This extension was necessary to address the challenges presented by the unavailability and lack of reliability of data in Lebanon. We observe that our TEPU index significantly spikes during major political and economic events that occurred in Lebanon, effectively tracking the evolution of economic policy uncertainty. Furthermore, the Index has significant correlations with a set of demographic and labor market outcomes, which suggests important channels for the transmission of uncertainty to the Lebanese economy.

INTRODUCTION

Ever since the end of its civil war in 1990, Lebanon has undergone episodes of severe uncertainty and turbulence that have little parallels with the experience of other middle-income countries. One of these is undoubtedly the assassination of Prime Minister Rafic Hariri in 2005. The civil war that erupted in Syria in 2011, as part of wider Arab Spring protests, is also another event that had considerable negative effects on the Lebanese economy and society. More recently, Lebanon has been in the throes of a financial crisis that broke out in 2019 – considered as one of the worst economic crises in Lebanon's history. This crisis was further described by the World Bank as one of the top three most severe crises globally since 1850.[2] [3] Combined with the unsustainability of Lebanon’s fixed exchange rate, large external and fiscal deficits, and mounting losses in the banking sector, the country experienced an abrupt reduction of capital inflows – deemed a “Sudden Stop” by economists, and usually accompanied by economic recessions (Arellano and Mendoza, 2003) and defaulted on its government debt in March 2020, the first sovereign default in its history. The outbreak of the COVID-19 pandemic only worsened Lebanon’s economic and social outlook in 2020. However, the August 2020 Beirut port explosion was perhaps the culmination of an entire string of uncertain events that have little precedent in modern societies.

The purpose of this paper is to create a Twitter-based Economic Policy Uncertainty (TEPU) index for Lebanon to track the evolution of economic policy uncertainty and relate it to some salient events occurring in Lebanon. Moreover, we will demonstrate that our TEPU index contains information, which helps in understanding the uncertainty prevailing in Lebanon. This uncertainty has significantly contributed to the decline of economic outcomes in the country. To the best of our knowledge, this paper represents the first attempt to construct an Economic Policy Uncertainty

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[1] Work on this Index started before the platform formerly known as Twitter, changed its name to X in July 2023. This paper will use the platform’s former name for the purposes of simplicity and until a new more appropriate name for the Index is identified.
[2] See the World Bank’s Lebanon Economic Monitor (2021): https://www.worldbank.org/en/country/lebanon/publication/lebanon-economic-monitor-spring-2021-lebanon-sinking-to-the-top-3.
[3] Combined with corruption and political wrangling among Lebanon’s elite, this crisis led to staggeringly high current account deficits (21.7% of GDP in 2019) and one of the highest debt-to-GDP ratios in the world (155.1% of GDP in 2019), sustained by a fixed exchange rate system (LBP 1505 to the US Dollar since 1997).

index for Lebanon to monitor and track developments in the country's economic and political landscape. We present a detailed approach to constructing a weekly and monthly TEPU index for Lebanon, covering the period from January 1, 2011, to January 18, 2023, by exclusively using Twitter-collected data. Twitter data contains an abundance of information that may have crucial insights by capturing the beliefs and opinions of a broad cross-section of social media users worldwide. The construction of our TEPU index differs from the previous literature in several ways. First, we gather global data from Twitter to broaden the search space beyond Lebanon, allowing for a more comprehensive analysis. Second, we expand our data collection beyond certain populations previously defined in the existing literature, such as expert opinion tweets utilized by Yeşiltaş et al. (2022).

To generate the weekly and monthly TEPU index for Lebanon, we follow the approach of Baker et al. (2016) and Baker et al. (2021), in which they count the frequency of newspaper articles and tweets, respectively, that are related to economic policy uncertainty. In this paper, we create and employ Python scripts that interact with the official Twitter application programming interface (API) to fetch and transform tweets into actionable data. This curated data forms the basis for generating a TEPU index for Lebanon. Specifically, we search for all global tweets related to Lebanon from various locations worldwide, containing at least one keyword from the following four categories: (1) "Lebanon," (2) "Economic," (3) "Policy," and (4) "Uncertainty." The keywords in categories 1 and 4 are straightforward. To construct the keyword sets for categories 2 and 3, we use manual annotation to choose the words deemed important for the case of Lebanon. Our approach aligns with the "Let the data speak for themselves" approach utilized by Lee et al. (2023).

Our paper is related to other papers in the literature that have developed Twitter-based Economic Policy Uncertainty (TEPU) indices for countries such as the US (Baker et al., 2021), Turkey (Yeşiltaş et al., 2022), Chile (Becerra & Sagner, 2020) and China (Lee et al., 2023). However, in this paper, we have adopted a methodological approach based on the work of Baker et al. (2016) and Baker et al. (2021) and extended it to suit the context of Lebanon. This extension was necessary to address the challenges presented by the unavailability and lack of reliability of data in Lebanon. While our work does not introduce a new methodological contribution, we have extended the existing methodology to better fit the Lebanese case. Through this extended methodology, we were able to create a reliable and effective TEPU index for Lebanon.

The remainder of this paper is as follows. Section 2 presents a literature review. Section 3 presents the methodology. Section 4 presents an event analysis based on the monthly TEPU indices constructed through different scaling methods while Section 5 relates the constructed TEPU index to a set of real indicators for Lebanon. Section 6 concludes with some final thoughts on the index.

LITERATURE REVIEW

Understanding people's perceptions, attitudes, and emotions across various online platforms has become crucial with the increasing use of social media. Fortunately, researchers can access the data from many online platforms, including Twitter, which offers historical archives of opinionated data from public conversations. We obtained Twitter data from the digitalized Twitter archives through Twitter API for Academic Research. To analyze this massive amount of data, researchers have utilized sentiment analysis or opinion mining, which involves using computational methods to study people's opinions, sentiments, emotions, and attitudes toward various topics, such as products, organizations, services, and their attributes (Liu, 2015).

Sentiment analysis has been one of the most active and important research fields in natural language processing (NLP) since the early 2000s, with applications in data mining, text mining, web mining, and information extraction (Zhang et al., 2018). Given the significant impact of sentiment analysis, it has spread into management and social sciences, including marketing, finance, economics, political science, and even history. This spread is due to the fact that opinions have a crucial impact on our beliefs, behaviors, and perceptions of reality, affecting almost all human actions. Consequently, whenever individuals or organizations need to make a decision, they often seek the opinions of others.

The concept of uncertainty has been a prominent theme in economics, particularly in macroeconomics where it was referred to as macroeconomic uncertainty. Recently, the literature has specifically focused on the concept of economic policy uncertainty, as opposed to general macroeconomic uncertainty. Renowned economist Frank Knight's 1921 definition of uncertainty has shaped the modern understanding of this concept. Knight (1921) starts by defining risk, which is a related concept of uncertainty, as a known probability distribution over a specific set of events, while uncertainty pertains to the inability of individuals to forecast the likelihood of specific events occurring. This distinction between risk and uncertainty has been explored across several fields, including finance, psychology, philosophy, and economics. Bloom (2014) explores the concept of uncertainty, which he describes as an “amorphous concept.” On the one hand, it “reflects uncertainty in the minds of households, firms, and policymakers about possible futures.” On the other hand, it is a broad concept in that uncertainty exists regarding macro phenomena like GDP growth, micro phenomena like the evolution of firms, or geopolitical uncertainty regarding war and climate change.

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Bloom (2014) investigates the frequently asked question of how economic agents such as households, policymakers, and businesses adjust their economic behaviors in response to fluctuations in uncertainty. Uncertainty plays a significant role in shaping investment and consumption decisions at the micro level. In fact, when uncertainty is high, economic agents tend to delay making these decisions (Pindyck, 1988; Rodrik, 1991).

Developing Empirical Measures for Uncertainty

The recent literature focuses explicitly on the impact of economic policy uncertainty, as opposed to general macroeconomic uncertainty (Rodrik, 1991; Hassett & Metcalf, 1999; Altug et al., 2009; Baker et al., 2016; Baker et al., 2021; Lee et al., 2023). In recent years, many empirical studies have placed great emphasis on developing accurate measures for uncertainty. The field of measuring economic policy uncertainty has been expanding rapidly, with researchers utilizing text search methods to create new indices.[4] A prominent example is the economic policy uncertainty (EPU) index created by Baker et al. (2016). This EPU index is based on the frequency of articles in ten leading U.S. newspapers since 1985 that contain specific economic policy uncertainty keywords. In recent years, various other indices have emerged to measure economic uncertainty. For example, the World Uncertainty Index (WUI), created by Ahir et al. (2018), measures uncertainty by tracking the frequency of the word "uncertainty" in country reports released by the Economist Intelligence Unit for 143 countries quarterly since 1996. Moreover, Baker et al. (2021) develop daily, weekly, and monthly Twitter-based Economic Uncertainty indicators.

Becerra & Sagner (2020) develop a daily-frequency measure of economic uncertainty for Chile by scraping Twitter data. Yeşiltaş et al. (2022) create a high-frequency Twitter-based Economic Policy Uncertainty (TEPU) index for Turkey using a select group of Twitter user accounts deemed to reflect an expert opinion on the subject. Additionally, Lee et al. (2023) develop novel daily and monthly frequency "censorship-free" Twitter-based indices to measure Chinese economic policy uncertainty from 2010 onwards. Other studies also built economic policy uncertainty indices based on news coverage and examined their impact on domestic firms (Jirasavetakul & Spilimbergo, 2018). It is important to highlight that all these indices were developed using text search methods based on online platforms or newspaper articles that depend on specific words. The technique used in the newspaper-based economic policy uncertainty index developed by Baker et al. (2016) is based on the frequency of newspaper articles and served as the foundation for this keyword search approach. This novel approach guarantees the dependability and significance of the economic policy uncertainty index and has been shown to be effective.

METHODOLOGY

The TEPU Index for Lebanon is the new variable we aim to construct by gathering data from Twitter. To gather this data in an efficient and quick way, we utilize the Twitter API. Unlike other applications that use Twitter data, we address some unique issues to ensure the reliability of our index. Firstly, Lebanon is a relatively small country with a limited number of well-known Twitter influencers, and Twitter is not the most-commonly used social media platform in Lebanon.[5] Secondly, the issue of plagiarism and automated accounts, or "bots," poses a challenge as it has made Twitter data very noisy. We observe that many people copy-paste another person's tweet on their page without retweeting it, while some bots and fake accounts upload the same tweet multiple times on the same day to create distractions. Controlling this behavior is challenging due to the limited options offered by Twitter API. We wish to avoid counting tweets more than once to prevent bias. In literature, the second issue is not addressed in a proper way. During our manual

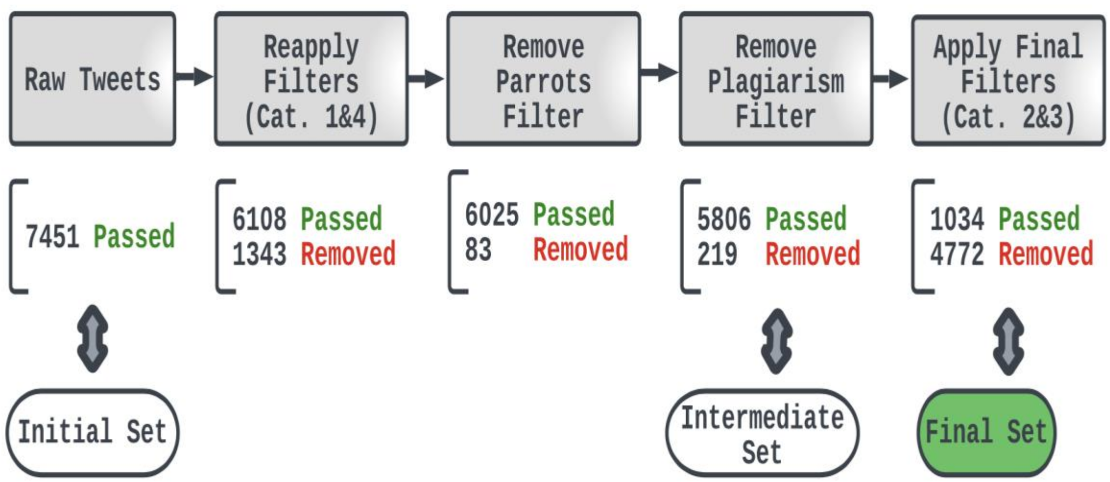
[4] These include Castelnuovo & Tran (2017), Donadelli & Gerotto (2019), Bilgin et al. (2019), Huang & Luk (2020), Angelico et al. (2022), Caldara & Iacoviello (2022) among others.

[5] According to recent data from Internet World Stats, Facebook and WhatsApp are the most popular social media apps in Lebanon, followed by Twitter and Instagram. https://medialandscapes.org/country/lebanon/media/social-networks.

annotation process, we discovered that the Twitter API is not as efficient as desired.[6] Consequently, we decided to address this issue without the help of Twitter API to ensure the accuracy of our data. Therefore, we developed a simple Python algorithm to control plagiarism and bots.

To start, our methodology is based on the work of Baker et al. (2016) and Baker et al. (2021), in which they count the frequency of newspaper articles and tweets respectively, which are related to economic policy uncertainty. To generate our weekly and monthly TEPU index, we search for all global tweets related to Lebanon from various locations worldwide, containing at least one keyword from the following four categories: (1) "Lebanon," (2) "Economic," (3) "Policy," and (4) "Uncertainty." When doing this, we widen our search to include global tweets, including those from the MENA region, Gulf countries, Egypt, Europe, the US, and others that provide jobs and investment funds for a small, open economy like Lebanon. This approach addresses the first issue and ensures an inclusive way of capturing economic policy uncertainty in Lebanon through the lens of global public tweets. Unlike other recent analyses (e.g., Yesiltas et al, 2022), we also consider tweets from a broad cross-section of the population and incorporate their opinion into our constructed TEPU index.

Figure 1. An Outline of the Methodology for Developing the TEPU Index for Lebanon



According to our methodology, our "Initial Set" contains 7,451 original global tweets sent by a total of 4,933 distinct users from January 1, 2010, to August 1, 2022. The tweets in this set are raw data obtained from Twitter API. We apply controls for retweets, capitalization, and language used to ensure a high-quality dataset. Therefore, we exclude all retweets from our search to ensure that we only select the original tweets. Additionally, we standardize capitalization to avoid distinguishing between words based on capital-small letters. For example, "Lebanon" is treated in the same way as "LEBanon," "lebanoN," or "LeBaNoN." Lastly, we restrict our search to English tweets and exclude Arabic Tweets from our analysis. This is because extracting and analyzing Arabic Tweets is extremely difficult due to the complex nature of the Arabic alphabet and the use of additional characters when writing Arabic words.

[6] We observed that the Twitter API matched the relevant keywords we provided with tweet data fields beyond the tweet body itself. Specifically, the Twitter API was identifying tweets as relevant if it found any of the relevant keywords in the body of the tweet, the account's username, the bio, or even the user's location, which was not what we wanted.

To address the second issue regarding plagiarism and bots, we develop a simple Python code to ensure the accuracy of our dataset and eliminate any repeated tweets by bots or users. Initially, we input the raw tweets into our Python code and apply various layers of checks to ensure their accuracy as shown in Figure 1. The first step involves reapplying Twitter API filters using our Python code, just like what Twitter API does, to ensure that Twitter API retrieved the relevant tweets that aligned with our requirements. The second step involves implementing our "Remove Parrots" algorithm to eliminate repeated tweets by the same user, whether posted at the same or different times, from our previous set of 6108 tweets. We only select the original relevant tweet posted by the user based on the tweet timestamp. The third step involves implementing our "Remove Plagiarism" algorithm to detect any plagiarized tweets with identical characters posted by different users. The algorithm retains the original tweet as relevant.[7] After we reach our "Intermediate Set," we proceed to build Economic and Policy categories. Our primary approach for creating these categories is to manually annotate all the tweets from the Intermediate Set. This process involves identifying the most frequent and important keywords in each tweet of our Intermediate Set that could be used for building these categories.[8] We then manually select the relevant and significant terms to distribute them into the Economic and Policy categories. We opt for the manual annotation process since we want to ensure that we are using the precise English terms used by the Lebanese people as well as Arabs, and people from other parts of the world when discussing specific economic policy events related to Lebanon. Since Arabic is the primary language of Lebanon, we are concerned that selecting keywords randomly for our categories might not cover all the relevant terms used in public Twitter conversations. It is important to note that these keywords are also selected based on their actual meaning as found in the tweets, which is helpful in assigning them to their appropriate categories. Therefore, we complete the first draft of each of the four categories shown in Table A.1 (see the Appendix). Following that, we copy all the keywords from the four categories into our Python code and let Python do the remaining work. Python generates a subset from the Intermediate Set, which is our "Final Set." This Final Set is filtered to contain relevant tweets that had at least one keyword in each of the four following categories: (1) "Lebanon," (2) "Economic," (3) "Policy," and (4) "Uncertainty."

We adopt two scaling methods in constructing our TEPU index for Lebanon. The first is proposed by Baker et al. (2021), which involves computing the mean, M, of our updated sample from January 1, 2011, to January 18, 2023, and then multiplying each weekly or monthly series by its own $\frac{100}{M}$ to renormalize our index to a mean of 100. The second scaling method is also proposed by Baker et al. (2021) as a variant of their main index and adopted by Lee et al. (2023) as their primary scaling method. It is based on the evolution of the total number of tweets worldwide containing the words "Lebanon" or "Lebanese" each month or week.[9] After using the Twitter API count service, we determine that there was a total of 39,506,906 tweets containing the words "Lebanon" or "Lebanese" between January 1, 2011, and January 18, 2023. Hence, our second scaling method is as follows: We scale the number of tweets in each month by the total number of tweets that mention "Lebanon" or "Lebanese" (we denote the resulting ratio by $R_{0,t}$). Then, we standardize the ratio $R_{0,t}$ to a unit standard deviation to obtain what we called $R_{1,t}$ using the standard deviation of our updated sample from January 1, 2011, to January 18, 2023. Finally, we compute the mean M of $R_{1,t}$ from January 1, 2011, to January 18, 2023, and multiply $R_{1,t}$ by $\frac{100}{M}$ to renormalize our index to a mean of 100.

[7] We intentionally removed the repeated tweets by the same user first, whether posted at the same or different times to gain accurate statistics on each step of our methodology and better understand how bots and automated accounts work.

[8] The manual annotation process is time consuming as it took approximately 1.5 months.

[9] Baker et al. (2021) used the total number of tweets containing the word "have."

EVENT ANALYSIS

In what follows, we conduct an event analysis to demonstrate how our TEPU index links to significant political and economic events that occurred in Lebanon throughout the sample period from January 1, 2011, to January 18, 2023. Table A.2 (see the Appendix) presents a timeline of significant economic policy uncertainty events in Lebanon.

Figure 2 shows the monthly TEPU index based on the first scaling method. Figure 3, on the other hand, shows the monthly TEPU index based on the second scaling method.[10] While both scaling methods are effective in identifying periods of high economic policy uncertainty in Lebanon over the past decade, there are some real differences between the two graphs presented in Figures 2 and 3. The most noticeable difference between them is the magnitude of the spikes in each index for August 2020.[11]

While Figure 2 assigns a large role in economic policy uncertainty due to the August 4, 2020, Beirut port explosion, Figure 3 also tracks uncertainty in earlier parts of the sample associated with the Syrian refugee crisis beginning in January 2012 and in 2015, the third postponement of the general elections in May 2017, and the decision of Prime Minister Saad Hariri to step down in July 2021.

Despite this difference, the two graphs share many common points, such as the general trend of the economic policy uncertainty index over time. The correlation between the two indices is 0.539. This analysis shows that Beirut's catastrophic port explosion, and the subsequent resignation of the Lebanese government, were among the most significant economic policy uncertainty events in the last decade. Figure 3 shows the increased level of economic policy uncertainty beginning in mid-2017 more clearly relative to Figure 2 and it assigns larger weight to the Syrian refugee issue, which is clearly a major economic and political problem for Lebanon.

Figure 2. Monthly TEPU Index for Lebanon from January 2011 to January 2023 with Major Economic Policy Uncertainty Events

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10 The weekly TEPU indices are not shown in this paper since they convey the same information as our monthly TEPU indices but are "noisier."

11 This has to do with the scaling approach used to construct the two different indices. In the first scaling method, we scale the number of relevant tweets for each month by the constant sample average. In the second scaling method, we scale the number of tweets in each month by the number of tweets that mentioned "Lebanon" or "Lebanese" (we denoted the resulting ratio by $R_{0,t}$). The relevant tweets associated with August 2020 are the highest relative to all other months (167 tweets). According to the first scaling method, this number is divided by the constant average of the relevant tweets in the sample, while according to the second scaling method, it is divided by the total number of tweets that contain "Lebanon" or "Lebanese" which is 5,097,894 for August 2020! Therefore, $R_{0,t}$ equals $\frac{167}{5{,}097{,}894}$ for the month of August 2020 and similarly, it is $\frac{73}{330{,}713}$ for the month of July 2021. Then, we standardize the ratio $R_{0,t}$ to a unit standard deviation to obtain what we call $R_{1,t}$, using the standard deviation from January 1, 2011, to January 18, 2023. Therefore, using the first scaling method, the largest spike emerges for August 2020. By contrast, in the second scaling method, a larger value of $R_{0,t}$ will lead to a higher value of $R_{1,t}$ resulting in a higher spike magnitude. Thus, for the TEPU index with the second scaling method, the calculations above show that the July 2021 spike is much larger than the August 2020 spike.

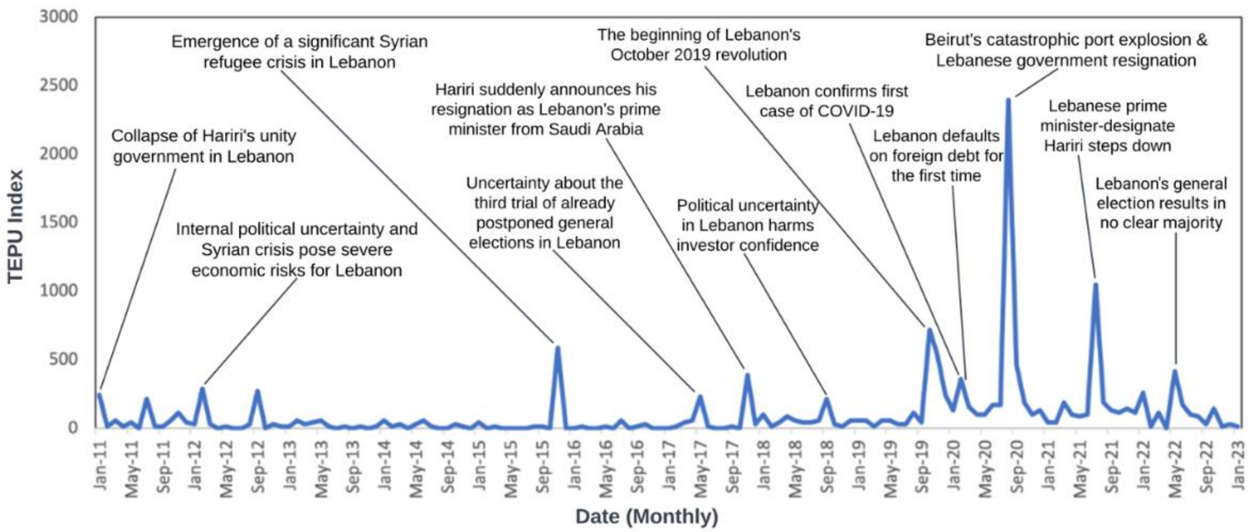
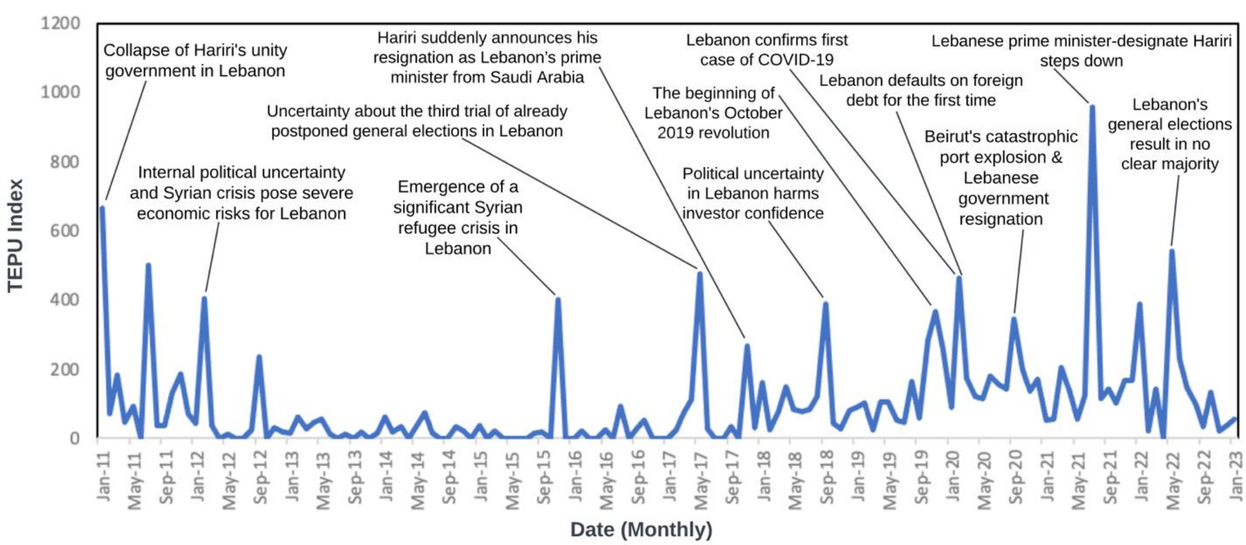


Figure 3. Monthly TEPU Index (Alternative Scaling Method) for Lebanon from January 2011 to January 2023 with Major Economic Policy Uncertainty Events



THE TEPU INDEX AND A KEY SET OF ECONOMIC INDICATORS FOR LEBANON

In our analysis up to this point, we have documented the sources of uncertainty for the Lebanese economy since 2011 and described how different scaling methods help to convey the evolution of this uncertainty. Undoubtedly, this uncertainty has been a major contributing factor to the deterioration of economic outcomes in Lebanon, with GDP growth registering declines of 7.16% in 2019, 21.4% in 2020, and 7% in 2021. The reasons for such a drastic collapse of economic activity are described more fully in Altug and Dagher (2023). Additionally, our analysis shows that the port explosion was a major determinant of the uncertainty faced by Lebanon over the sample period, which is better captured by the TEPU index according to the first scaling method. While contributing to the slowdown in economic activity and the loss of property and infrastructure, this event is known to have contributed to a new Lebanese exodus. Following the explosion, many with the means to do so left, thus further depriving the country of its educated workforce, including its academics, doctors, artists, and others, adding to the already negative effects of the ongoing financial crisis since October 2019.[12]

In this section, we present some correlations of our TEPU index constructed according to the first and second scaling methods with data on net migration, personal remittances received as a percentage of GDP, and total unemployment as a percent of the total labor force, as a way of capturing this phenomenon. The data we use for net migration and personal remittances are collected annually from the World Bank. The annual data that we use for the unemployment rate comes from two sources. One source is data from the World Bank, which are derived from ILO-estimates based on a regression model used to fill gaps for countries with missing observations. However, this regression model does not fully account for significant economic shocks such as COVID-19 and financial crises and hence, underestimates the unemployment rate in Lebanon. Therefore, for the post-2020 period, we use a second source for obtaining the unemployment rate in Lebanon which accounts for such shocks. This source is provided by the ESCWA-published surveys on economic and social developments in the Arab region. All our collected data for Lebanon is available only on an annual basis. Therefore, we need to convert our TEPU index, which is measured monthly, into an annual format. To achieve this, we take the average across all months in a given year, enabling us to obtain an annual series for our TEPU index. This step ensures that all our variables have a consistent annual frequency, allowing us to proceed with the correlation analysis.

Table 1. Correlation of TEPU Indices with Economic Indicators

	Net Migration-Population Ratio	**Personal Remittances-GDP Ratio**	**Unemployment Rate**
TEPU1	-0.31	0.59	0.73* (0.87)**
TEPU2	-0.41	0.62	0.62* (0.68)**

TEPU1 denotes the TEPU index based on the first scaling method. TEPU2 denotes the TEPU index based on the second scaling method.
These numbers show the correlation between TEPU1 and TEPU2 with the World Bank unemployment rate series.
**These numbers show the correlation between TEPU1 and TEPU2 with the ESCWA survey data substituted for the World Bank estimates of the unemployment rate for the years 2020-2022.*

Table 1 shows the correlations with our chosen TEPU index and a set of indicators for Lebanon that we view as being particularly pertinent for understating the effects of uncertainty and the

[12] https://www.aljazeera.com/news/2020/8/22/a-new-exodus-from-lebanon-after-deadly-beirut-blast
https://www.france24.com/en/20200817-beirut-blast-prompts-new-exodus-from-lebanon
https://storage.kuwaittimes.com/pdf/2020/aug/19/p05.pdf.

August 4 port explosion.[13] First, we note that the different TEPU indices that we calculate are positively correlated with the unemployment rate. While the World Bank data measures the unemployment rate slightly over 12% between 2020-2022, the data from the ESCWA surveys indicate unemployment rates of 40%, 25.8%, and 29.2% for these years, leading to the highest rate of unemployment in the world.[14] Hence, we calculate the correlation of the TEPU indices with two different unemployment rate series. The first is just the unemployment rate series based on the ILO estimates from the World Bank, while the second series substitutes the ESWCA survey estimates for the years 2020-22 into the World Bank series. Table 1 shows that the unemployment rate is positively correlated with the TEPU indices over the sample period based on both unemployment rate series. However, the association of the TEPU indices with the second constructed unemployment rate series is higher, given the higher unemployment rates indicated by the ESCWA estimates in the latter part of the sample.

Second, Table 1 provides evidence of two interrelated phenomena that are peculiar to Lebanon. These are the correlation of the TEPU indices with personal remittances and the net migration rate. Our results show that as uncertainty increases in Lebanon, outward migration increases (so that net migration becomes negative) while personal remittances increase as a fraction of GDP. Both phenomena are well documented in the Lebanese economy. As a recent report by UNDP (2023) makes clear, remittances have always been an important source of income in Lebanon and their role in providing basic sustenance has increased since the financial crisis. On the other hand, the negative rate of net migration since 2015 provides an indication that uncertainty is affecting the Lebanese economy through its effect on the productive labor force. While these results provide some preliminary evidence on the channels through which uncertainty affects the Lebanese economy, further studies using micro-level data on unemployment rates, net migration, and the nature of remittances and their evolution appear warranted.

CONCLUSION

In this paper, we construct a weekly and monthly Twitter-based Economic Policy Uncertainty (TEPU) index for Lebanon, covering the period from January 1, 2011, to January 18, 2023. Our objective is to develop a TEPU index that best fits Lebanon and can effectively identify and uncover significant economic policy uncertainty events that have taken place in the country since 2011. We observe that our TEPU index significantly spikes during major political and economic events that occurred in Lebanon, effectively tracking the evolution of economic policy uncertainty. We show that the August 2020 Beirut port explosion was an extreme event even by the standards of a country like Lebanon, which has undergone uncertainty and turbulence over several decades. The fact that it also led to a new exodus from a country that historically has a diaspora in the millions is just another example of its impact. However, we may also argue that the port explosion itself was the culmination of many unresolved issues that have plagued Lebanese political and economic life over many years. On its third anniversary, many Lebanese came out to protest the

[13] We tried estimating vector autoregression model for GDP in Lebanon jointly with the TEPU index, as well as constructing a forecasting model for GDP using a mixed-data sampling (MIDAS) methods that combine data measured annually such as GDP for Lebanon with quarterly and monthly measures of the TEPU indices. However, we were unable to generate a set of consistent and meaningful results from such analyses given the short samples available, such as annual GDP data (2011-2021) as well as the impact of extreme events like the port explosion.

[14] See the labor force survey conducted by Lebanon's Central Administration of Statistics with the ILO https://www.ilo.org/beirut/media-centre/news/WCMS_844831/lang--en/index.htm.

fact that no culpability had been assigned for this tragedy.[15] Indeed, the Lebanese polity has also lacked the resolve to deal with the causes of the financial crisis, accused of playing “a waiting game” in enacting credible solutions to overcome its effects.[16] In our analysis, we highlighted demographic and labor market outcomes as a key channel through which uncertainty affects Lebanese society. In our mind, any future work must tackle the transmission of uncertainty through this channel.

[15] https://www.aljazeera.com/gallery/2023/8/4/photos-hundreds-protest-as-lebanon-marks-third-anniversary-of-beirut-blast; https://today.lorientlejour.com/article/1345548/lebanese-in-paris-mark-third-anniversary-of-port-explosion.html.
[16] https://theforum.erf.org.eg/2023/02/14/the-grand-waiting-game-why-lebanons-elites-postpone-compromise/.

REFERENCES

Ahir, H., Bloom, N., & Furceri, D. (2018). The World Uncertainty Index. Technical Report, Stanford University 2018.

Altug, S. & L. Dagher (2023). A Tale of Two Crises: Turkey of the Early Aughts and Today's Lebanon MPRA No. 11760 https://mpra.ub.uni-muenchen.de/117600

Altug, S., Demers, F., & Demers, M. (2009). The Investment Tax Credit and Irreversible Investment. *Journal of Macroeconomics*, *31*(4), 509–522.

Arellano, C., & Mendoza, E. (2003). Credit Frictions and 'Sudden Stops' in Small Open Economies: An Equilibrium Business Cycle Framework for Emerging Markets Crises. In S. Altug, J. Chadha, & C. Nolan (Eds.), *Dynamic Macroeconomic Analysis: Theory and Policy in General Equilibrium, (pp. 335-405).* Cambridge: Cambridge University Press.

Angelico, C., Marcucci, J., Miccoli, M., & Quarta, F. (2022). Can we measure inflation expectations using Twitter? *Journal of Econometrics*, *228*(2), 259–277.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty. *Quarterly Journal of Economics*, *131*(4), 1593–1636.

Baker, S. R., Bloom, N., Davis, S. J., & Renault, T. (2021). Twitter-Derived Measures of Economic Uncertainty. Working Paper

Becerra, J. S., & Sagner, A. (2020). Twitter-Based Economic Policy Uncertainty Index for Chile. Technical Report 883, Working Papers of the Central Bank of Chile 2020.

Bilgin, M. H., Demir, E., Gozgor, G., Karabulut, G., & Kaya, H. (2019). A novel index of macroeconomic uncertainty for Turkey based on Google-Trends. *Economics Letters*, *148*(C).

Bloom, N. (2014). Fluctuations in Uncertainty. *Journal of Economic Perspectives*, *28*, 153–167. https://doi.org/10.1257/jep.28.2.153

Caldarra, D. and Iacoviello. M. (2022). Measuring Geopolitical Risk. *American Economic Review* 2022, 112(4): 1194–1225

Castelnuovo, E., & Tran, T. D. (2017). Google It Up! A Google Trends-based Uncertainty index for the United States and Australia. *Economics Letters*, *161*, 149–153.

Donadelli, M., & Gerotto, L. (2019). Non-macro-based Google Searches, Uncertainty, and Real Economic Activity. *Research in International Business and Finance*, *48*, 111–142.

Hassett, K., & Metcalf, G. (1999). Investment with Uncertain Tax Policy: Does Random Tax Policy Discourage Investment? *Economic Journal*, *109*(457), 372–393.

Huang, Y., & Luk, P. (2020). Measuring Economic Policy Uncertainty in China. *China Economic Review*, *59*, 101367.

Jirasavetakul, L.-B. F., & Spilimbergo, A. (2018). Economic Policy Uncertainty in Turkey. WP/2018/272, International Monetary Fund

Knight, F. H. (1921). Risk, Uncertainty and Profit, Houghton Mifflin

Lee, K., Choi, E., & Kim, M. (2023). Twitter-based Chinese Economic Policy Uncertainty. *Finance Research Letters*, *53*(103627).

Liu, B. (2015). Sentiment analysis: Mining opinions, sentiments, and emotions. *Sentiment Analysis: Mining Opinions, Sentiments, and Emotions*, 1–367. https://doi.org/10.1017/CBO9781139084789

Pindyck, R. (1988). Irreversible Investment, Capacity Choice, and the Value of the Firm. *American Economic Review*, *78*(5), 969–985. https://EconPapers.repec.org/RePEc:aea:aecrev:v:78:y:1988:i:5:p:969-85

Rodrik, D. (1991). Policy Uncertainty and Private Investment in Developing Countries. *Journal of Development Economics*, *36*(2), 229–242.

UNDP (2023). The Increasing Role and Importance of Remittances in Lebanon, May.

Yeşiltaş, S., Şen, A., Arslan, B., & Altuğ, S. (2022). A Twitter-Based Economic Policy Uncertainty Index: Expert Opinion and Financial Market Dynamics in an Emerging Market Economy. *Frontiers in Physics*, *10*.

Zhang, L., Wang, S., & Liu, B. (2018). *Deep Learning for Sentiment Analysis: A Survey*. https://arxiv.org/pdf/1801.07883.pdf

APPENDIX

Table A.1. List of Economic Policy Uncertainty Related Keywords

Category	Words
Lebanon	lebanon, lebanese
Economic	ammonium nitrate, airport, assistance, aid, banks, bank, banking, bankers, businesses, business, bankruptcy, billions, billion, bonds, brexit, bse, collapse, crash, company, currency, crisis, crises, commercial, cash, capital, cost, costs, creditors, developing, debt, diesel, demand, dollars, dollar, deposit, economic, economy, economical, economically, economiccrisis, energy, electricity, export, exchange, economist, funding, fund, funds, financialcrisis, forecasts, fresh, fuel, fuels, financial, farmers, firms, fiscal, finance, gas, gdp, goods, hardship, hyperinflation, interest, interests, investing, investment, invest, infrastructure, investors, imf, inflation, imports, import, industrialists, income, incomes, industry, industrial, job, lira, loss, loans, liquidity, maritime arena, markets, market, million, monetary, manufacturing, macroeconomy, ngo, outcome, outcomes, opportunity, oil, planning, plan, prices, price, petrol, port, property, poverty, pound, production, profit, real estate, risks, risk, resources, sustainable, shares, solidere, salary, savings, supply, startup, stock, stocks, shortage, supplies, supplied, sanctions, subsidies, stability, stagnation, supplies, supplied, sanctions, subsidies, trader, trade, tons, thousands, usd, unemployment, violations, volatility, work
Policy	army, allies, amal, authorities, authority, ambassador, ambassadors, august 4th, august 4, 4 august, administration, administer, aoun, assassination, blast, blasts, beirutexplosion, beirutblast, budget, banned, bdl, boom, covid, candidates, curfew, corruption, corrupt, corona, coronavirus, central bank, cabinet, deal, demarcation, defenses, defense, diab, diplomatic, drone, elections, election, enforce, electoral, explosions, explosion, eurobond, forces, fpm, government, governments, gov, governed, governance, geagea, geopolitical, hezbollah, hizbollah, hariri, humanrights, israel, independents, invasion, joumblatt, lockdown, lebanonexplosion, lebanonblast, leaders, leader, leadership, law, legal, lebanonprotests, mikati, minister, ministers, military, missiles, middle class, macron, management, opposition, occupied territories, official, officials, polls, poll, protests, protest, protestors, protestor, political, politics, power, powers, protecting, president, party, parliament, parliamentary, psp, politicians, policy, pandemic, police, pm, premier, refugees, refugee, religions, religion, rockets, reconstruction, resignation, resigns, resign, revolution, restrictions, regime, saudi, shocks, shock, sectarianism, soldiers, security, sociopolitical, terror, tax, taxes, vote, votes, voter, war, wars, weapons
Uncertainty	uncertain, uncertainly, uncertainties, uncertainty, unpredictable, unpredictably, unclear, unclearly

Table A.2. Timeline of Events in Lebanon

Year	Date	Event
2011	12 January 2011	Opposition parties' resignations lead to the collapse of Hariri's unity government in Lebanon.
2012	February 2012	IMF warns of severe economic risks for Lebanon amid internal political uncertainty and the Syrian crisis.
2013	22 March 2013	Lebanese government collapses following the resignation of Prime Minister Najib Mikati.

2015	November 2015	Over 1.1 million Syrian refugees strain Lebanon's resources, creating a significant crisis.
2017	May 2017	Uncertainty from the third postponement of the general elections in Lebanon. Oil and gas tenders at risk due to ongoing election uncertainty.
	16 June 2017	Lebanese parliament extends its own term by 11 months. Under various pretexts, elections are postponed three times: 2013, 2014, and 2017.
	4 November 2017	Saad Al Hariri suddenly announces his resignation as Prime Minister from Saudi Arabia.
2018	6 May 2018	Lebanon's general elections are held.
	September 2018	Political uncertainty in Lebanon harms investor confidence, fueling warnings of a growing economic crisis from bankers and economists.
2019	17 October 2019	The beginning of Lebanon's October 2019 revolution.
2020	21 February 2020	Lebanon confirms first case of COVID-19: woman returning from Iran tests positive and is placed in quarantine at Beirut's Rafik Hariri Hospital.
	February 2020	Peak of the Syrian refugee crisis in Lebanon amidst current health and economic challenges.
	9 March 2020	Lebanon defaults on foreign debt for the first time, failing to repay USD 1.2 billion Eurobond and marking the first sovereign default in its history.
	4 August 2020	Beirut's port explosion: catastrophic blast damages large parts of Lebanon's capital, leaving more than 218 dead, 7,000 injured, and 300,000 displaced.
	10 August 2020	Lebanese prime minister Hassan Diab resigns following the Beirut port explosion tragedy.
2021	15 July 2021	Lebanese prime minister-designate Saad Al Hariri steps down after 8 months of failed attempts to form a unity government.
2022	15 May 2022	Lebanon's general elections result in independent candidates' breakthrough, creating uncertainty as no single party gains majority in parliament.

Source: Authors' elaboration.

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