A Twitter-based Economic Policy Uncertainty Index for Turkey*

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October, 2021

Abstract

In this paper, we develop a Twitter-based measure of public sentiment that is useful for measuring the economic policy uncertainty that impacts individual decisions for Turkey. We extract a Twitter-based Economic Policy Uncertainty (TEPU) Index based on a selected set of Twitter user accounts whose tweets are considered to reflect expert opinion on the topic by the general public. We track the behavior of the constructed index in relation to economic and political events that are thought to create uncertainty in Turkey, a key emerging market economy, and examine its relationship with salient financial variables since 2013.

Keywords: Twitter-based data, public sentiment, economic policy uncertainty, Turkey

JEL Codes: E58, E62, G12, G17

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1 Introduction

The role of uncertainty in affecting the behavior of economic decision-makers has been widely studied. A relatively new and growing field of literature examines methods of economic uncertainty measurement by using text search methods. A recent study by study by Baker, Bloom and Davis (2016) develops Economic Policy Uncertainty (EPU) Index for the US economy based on the frequency of a selected list of words in 10 leading US newspapers since 1985. Using the Dow Jones' Factiva global news database, Jirasavetakul and Spilimbergo (2018) follow Baker et al. (2016) to construct a EPU Index for Turkey. Recent studies have also examined data sets derived from popular social media platforms such as Twitter, Facebook, blogs etc. Baker, Bloom, Davis, and Renault (2021) generate an EPU Index using Twitter data from 2011 onward based on counts of tweets about the "economy" and "uncertainty". Likewise, Becerra and Sagner (2020) constitute an EPU Index for Chile based on Twitter data closely following Baker et al. (2016).

The application of sentiment analysis based on social media interactions has increased rapidly in recent years. O'Connor, Balasubramanyan, Routledge and Smith (2010) compare measures of public sentiment created through traditional presidential election/approval polls versus text analysis of tweets during 2008-2009. Using three measures of influence including in-degree, retweets and mentions, Cha, Haddadi, Benevenuto and Gummadi (2010) investigate the dynamics of user influence across topics and time based on these notions and among other findings, show that influence is typically gained through concerted effort such as limiting tweets to a single topic. Verweij (2012) studies the interactions between a group of Dutch journalists and politicians and show that contacts on Twitter are driven by the need for finding and spreading news, as opposed to religious or ideological identity of parties and media.

In this paper, we extract Twitter data of expert accounts selected based on a bootstrapping method. In this way, we are able to better capture the interactions among Twitter users who are thought to be experts in Turkey in the sphere of economic policy. Our paper differs from existing studies that are typically based on the usage of bulk Twitter data. Our bootstrapping approach based on selected expert accounts allows us to remove tweets with only a weak impact on public opinion and also to eliminate the need for scaling noisy data.

Using a selected set of user accounts whose tweets are considered to reflect expert opinion on economic policy issues, we construct a Twitter-based EPU Index for Turkey for the period 2013-2021. We find that the TEPU captures the uncertainty created by salient political and economic events and correlates well with a variety of financial indicators for the Turkish economy over this period. Implementing this approach in the context of an emerging market economy such as Turkey is important for tracking the evolution of uncertainty induced by a number of significant economic and political events as well as the recent Covid-19 shock in the past decade.

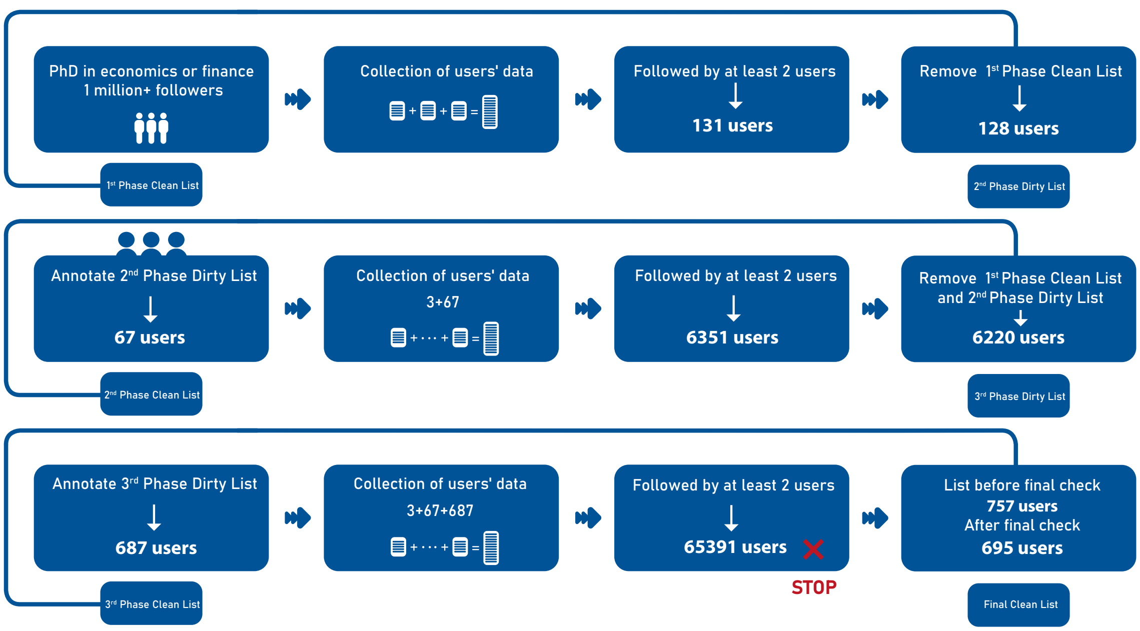
2 Data and Methodology

The data used in this study are obtained via Twitter Application Programming Interface (API) and web scraping methods. We use the sample period 2013-2021 because this period coincides with the onset of many events associated with political and economic uncertainty in Turkey.

2.1 A bootstrapping approach to collecting Twitter data

Analyzing the entire bulk of tweets can be thought of as using the archives of all local and national newspapers, including cartoons, cars, puzzles, advertisements and magazine attachments in any analysis. However, given the fact that the tweets posted by certain user accounts interact with more people in society, one should consider the number of followers and interaction of such user accounts and make use of their Twitter data in the analysis (Cha et al. (2010)). The usage of tweets of user accounts which have expertise in certain areas will increase the accuracy of the relevant analysis. Hence, one can think of using the Twitter data of these selected user accounts as if one is analyzing the articles of leading newspapers. Any potential selection bias may then be corrected based on a bootstrapping approach. Figure 1 illustrates our approach.

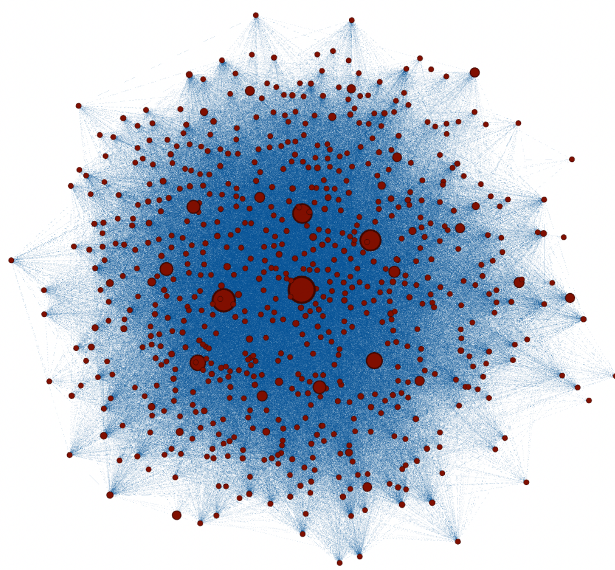
Figure 1: Bootstrapping Phases



In the first phase, we identify a list of user accounts with expertise in a certain area to serve as a nucleus for the analysis. This is termed the bootstrapping approach (Greene, Reid, Sheridan and Cunningham (2011)). In this phase, we identify three user accounts in Turkey according to the following criteria: 1) to hold a PhD degree in economics or finance, 2) to possess the highest number of followers (1 million +). We name the resulting sample of user accounts as the 1^{st} Phase Clean list in Figure 1. Second, we obtain the lists of user accounts followed by at least two of these users. In this way we obtain a list of 131 users from which we remove the first three users that we name as the 1^{st} Phase Dirty List. Following the annotation process suggested by Giachanou and Crestani (2016), we then retain the user accounts which belong to experts in the field of economics and finance. We also remove user accounts that are not open to the public, that have been closed during the course of our study or that are used only for personal tweets. We thus end up with a list of 67 user accounts (2^{nd} Phase Clean List).

Figure 1 shows how the second phase is derived. This is accomplished by obtaining the user accounts followed by the 67-user list and combining them with the original list of 3 user accounts from the first phase. We obtain a list of 6,351 users followed by at least two of the 70 users above. From this list, we remove the users from the 1^{st} Phase Clean List and 2^{nd} Phase Dirty List, yielding us the 3^{rd} Phase Dirty List of 6220 user accounts. After the annotation process, we obtain a list of 687 user accounts, namely, the 3^{rd} Phase Clean List. Combining the resulting clean list of users with the clean lists created in the previous phases, we end up with the list of 757 user accounts. We then obtain a list of 65,391 user accounts followed by at least two of these 757 user accounts. After randomly examining the information in the resulting list of 65,391 user accounts, we observe that these accounts are not representative of the population of experts that we are interested in. As a consequence, we end the algorithm at this point. After removing the user accounts that were closed or turned into private accounts during the course of our study, we obtain the final list of 695 user accounts that we use to construct our TEPU Index.

Figure 2: Network of Selected Twitter Users



Notes: Nodes indicate the selected user accounts in Twitter. The size of the nodes reflects the number of their followers.

Starting with the three Twitter user accounts who are the most-followed experts in the field of economics and finance in Turkey, we obtain a network of user accounts that that not only capture the influence of these people on public opinion but their interaction with other user accounts that they follow. The connections in Figure 2 illustrate the following-follower status of the selected user accounts and the size of the nodes showing their relative influence. The final list of 695 user accounts is comprised of academics, company executives, politicians, consultants, journalists, portfolio managers and bureaucrats. In this list, the 10 user accounts with the largest node in Figure 2 are comprised of two from the original set of three user accounts but also include seven other influential user accounts whose interactions occur mainly in the economic policy sphere.

Finally, we check the robustness of the final list of user accounts used in our study by implementing the bootstrapping approach with alternative nuclei. In this exercise, we repeat the bootstrapping first, with lists of user accounts followed by 16 user accounts who have more than 500,000 followers, and then with lists of user accounts followed by 7 randomly selected user accounts out of the 16 user accounts who have more than 500,000 followers. Doing this yields final lists of user accounts that are identical to the final list of 695 user accounts used in the construction of the TEPU Index.

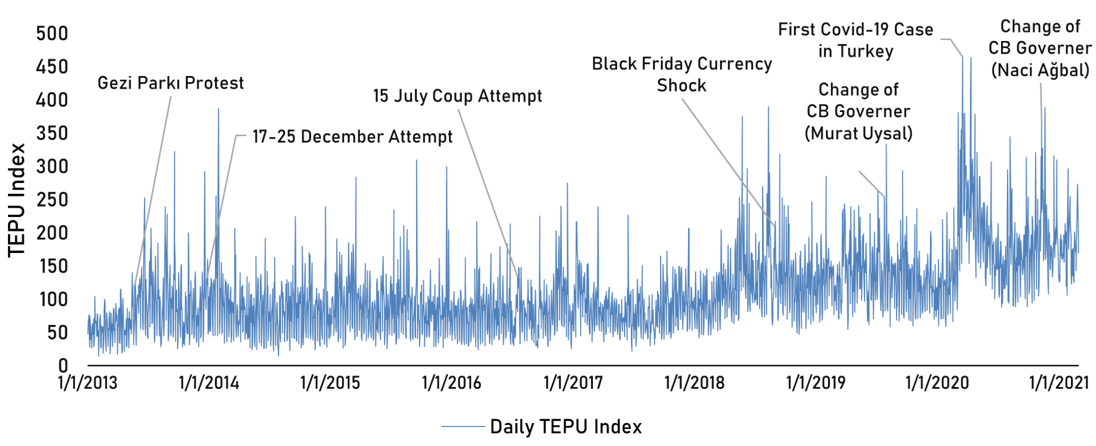
2.2 The calculation of the TEPU Index

In earlier work, Baker et al. (2016) and Baker et al. (2021) construct economic policy uncertainty indices according to the frequency of a list of policy-related words found in newspaper articles and Twitter posts, respectively. Following these papers, we create the Twitter-based EPU Index by collecting all tweets posted by the selected user accounts in the above-mentioned final list from January 1, 2013 to February 28, 2021. In our paper, we track the Turkish version of the 58 words considered by Baker et al. (2016) in each tweet and record the word count data. We treat Twitter-data based series as if they are extracted from a single newspaper and apply the standardization methodology developed in Baker et al. (2016) to these series.

3 Discussion

Figure 3 plots the daily TEPU Index from January 1, 2013 to February 28, 2021 and tracks the evolution of uncertainty for Turkey. The observable spikes in the TEPU Index correspond to important economic and political events that have resulted in increases in uncertainty in Turkey.

Figure 3: The Daily TEPU Index



Note: The TEPU index for Turkey is renormalized to a mean of 100 from January 1, 2013 to February 28, 2021.

Specifically, such events reflect the occurrence of the 2013 Gezi Protests, which erupted due to a disagreement regarding the usage of a municipal park and turned into nation-wide protests against the government, the revelation of corruption allegations against various members of the government during December 17-25, 2013 as well as the unsuccessful coup attempt of July 15, 2016. There is a large jump in the TEPU Index associated with the devaluation of the Turkish Lira from 4 TRY per US Dollar in mid-March 2018 to nearly 7 TRY to US Dollar in August 2018, an event known as the Black Friday currency shock. The unexpected change in successive governors of the Central Bank of the Republic of Turkey on July 5, 2019 and again on November 7, 2020 also registers among the largest increases in the TEPU Index. However, by far the largest increase in the TEPU Index is associated with the first official Covid-19 case on March 14, 2020 in Turkey.

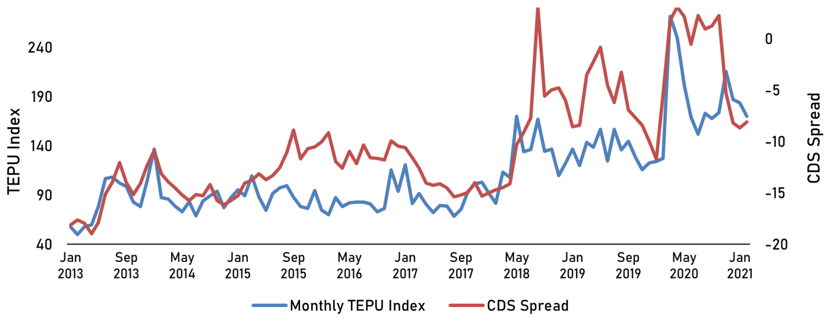
Next, Figure 4 examines the relationship between the TEPU Index and selected financial indicators. First, there has been a secular increase in the TEPU Index over the sample period. Second, financial indicators such as the CDS spread for Turkey and the volatility index of Chicago Board Options Exchange (VIX) move almost one-for-one with the TEPU Index. On the other hand, changes in the Borsa Istanbul Stock Exchange (BIST) Index and in the TRY-USD exchange rate lag the movements in the TEPU Index.

The VIX Index captures changes in the risk perceptions of foreign investors due to exogenous shocks, external monetary and financial conditions, and developments specific to emerging market economies including the Turkish economy. In this regard, the strong correlation between the VIX Index and the TEPU Index partially reflects the fact that the Turkish economy is vulnerable to episodes of divergence between its policy actions relative those of the US, as argued by Kalemli-Özcan (2019). This is due to its dependence on international capital flows for financing its current account deficit. Further, Turkey's CDS spread tends to capture a systematic assessment of the uncertainty and risk associated with long-term prospects for the Turkish economy. This is evidenced by its sharp rise around the August 2018 currency shock as well as the Covid-19 shock and its tendency to remain higher thereafter. On the other hand, uncertainty about policy decisions reflected in the TEPU Index appears to lead observed changes in the behavior of the BIST-100 index and the TRY-USD exchange rate.

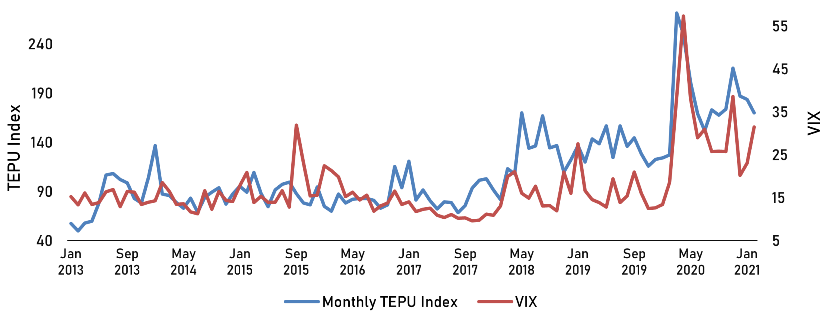
4 Conclusion

In this paper, we have constructed a Twitter-based economic policy uncertainty index that tracks many political and economic events thought to create uncertainty in Turkey. Our analysis provides a novel measure of economic policy uncertainty reflected through public sentiment. Such a measure may be used in future work to assess more precisely the channels through which uncertainty propagates, especially in emerging economy contexts.

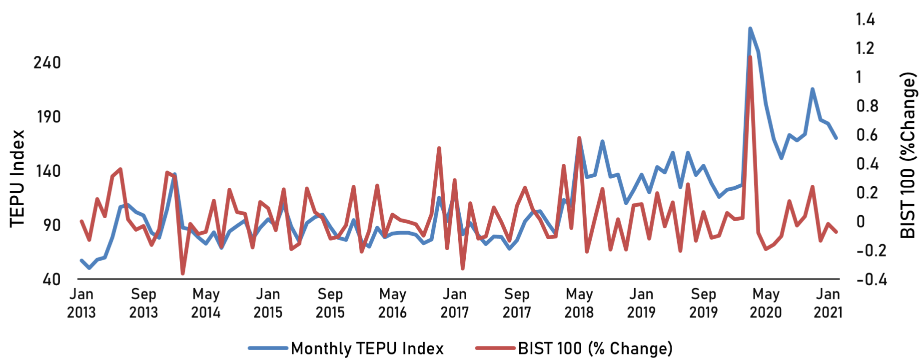
Figure 4: The Comparison of the TEPU Index with Financial Indicators



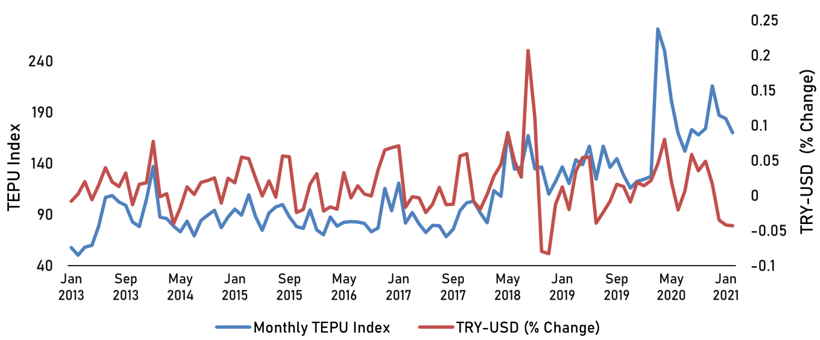
(a) TEPU vs CDS spread, correlation: 0.82



(b) TEPU vs VIX, Correlation: 0.69



(c) TEPU vs BIST-100 (%), Correlation: 0.33



(d) TEPU vs TRY-USD (%), Correlation: 0.27

Note: The series on the VIX Index, the BIST-100 Index, the TRY-US Dollar exchange rate, and the CDS Spread are taken from Yahoo Finance, the Central Bank of the Republic of Turkey, and the Investing.com, respectively.

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