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TWITTER-BASED ECONOMIC POLICY UNCERTAINTY INDEX FOR CHILE*

INDICE DE INCERTIDUMBRE ECONOMICA Y POLITICA PARA CHILE BASADO EN TWITTER

JUAN SEBASTIAN BECERRA**
Central Bank of Chile

ANDRES SAGNER***
Central Bank of Chile

Abstract

In this paper, we develop a daily-frequency measure of economic and policy uncertainty for Chile, employing information obtained from Twitter accounts using web scraping techniques and following closely the methodology proposed by Baker et al. (2016). Our proposed measure, called DEPUC, aims to capture the level of general disagreement –a proxy for economic and policy uncertainty– in topics such as the economy, economic policies, uncertainty about particular events, and Chile's conjuncture situation. The index, available from 2012 onwards, shows significant hikes that coincide with several local and international episodes that provoked extraordinary levels of uncertainty in Chile, especially after the events around the civil protests in mid-October 2019 and the start of the COVID-19 pandemic in mid-March 2020. An empirical exercise reveals that the proposed measure is a significant determinant of the nominal exchange rate dynamics, especially

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** Financial Stability Area, Prospective Risk Analysis Department. Agustinas 1180, 2nd floor. Email: jbecerra@bcentral.cl

*** Financial Stability Area, Financial Analysis Department. Agustinas 1180, 2nd floor. Email: asagner@bcentral.cl

when this variable's magnitude is high and a week after the shock occurs. On the contrary, when the exchange rate is low, the impact of uncertainty on this variable is quantitatively smaller for any forecasting horizon. These features, and others discussed in the paper, highlight the usefulness of the proposed metric as an additional indicator that policymakers can incorporate into their monitoring toolkit.

Keywords: *Economic uncertainty, financial stability, monitoring tools, web scraping.*

JEL Classification: *C13, D80, E30, E66, G18.*

Resumen

En este artículo proponemos una medida de incertidumbre económica y política para Chile en frecuencia diaria empleando información obtenida de cuentas oficiales de Twitter mediante técnicas para extraer información desde sitios web y siguiendo de cerca la metodología propuesta por Baker et al. (2016). Nuestra medida propuesta, denominada DEPUC, tiene como principal objetivo capturar el nivel de desacuerdo general en estos medios –una aproximación de la incertidumbre económica y política– en temas como la economía, las políticas económicas, la incertidumbre acerca de varios eventos particulares, y la coyuntura en Chile. El índice, disponible desde el año 2012, muestra alzas significativas que coinciden con varios episodios locales e internacionales que provocaron aumentos extraordinarios de la incertidumbre en Chile, especialmente luego de los hechos ocurridos en torno a las protestas civiles de mediados de octubre de 2019 y el inicio de la pandemia del Covid-19 a mediados de marzo de 2020. Un ejercicio empírico revela que la medida propuesta es un determinante significativo de la dinámica del tipo de cambio nominal especialmente cuando la magnitud de esta variable es alta y luego de una semana de ocurrido el shock *de incertidumbre. Por el contrario, cuando el tipo de cambio es bajo, el impacto de la incertidumbre acerca de esta variable es cuantitativamente menor en cualquier horizonte de proyección. Estos hallazgos, y otros discutidos en el documento, resaltan la utilidad de la métrica propuesta como un indicador adicional que los encargados de política pueden incorporar a sus herramientas de monitoreo.*

Palabras clave: *Incertidumbre económica, estabilidad financiera, herramientas de monitoreo,* web scraping.

Clasificación JEL: *C13, D80, E30, E66, G18.*

I. INTRODUCTION

Recently, economic and policy uncertainty is a variable that has become especially relevant for policymakers in Chile. From a local perspective, the start of the civil protests and riots in mid-October 2019 and, from a rather global perspective, the pandemic –triggered by the worldwide-scale spread of the COVID-19 virus– declared in mid-March 2020, has implied an unusual level of volatility observed not only in several financial asset prices but also in a broad range of short- and medium-term economic activity forecasts. Further, there is still no clear consensus about which policy action to take to mitigate the effects of these events on the stability of the local financial system.

The speed at which these events evolve in Chile is quite fast. Thus, it is imperative to have high-frequency measures to support monitoring tasks related to large swings of uncertainty and its consequent impacts on other local financial variables. In this sense, a popular metric corresponds to VIX, which measures the 30-day expected volatility of the S&P 500 index[1]. However, VIX captures global uncertainty for emerging economies since its computation does not incorporate explicit information about idiosyncratic expected fluctuations. Other alternatives correspond to the conditional volatility of the local stock market index IPSA or the cross-sectional dispersion of macroeconomic forecasts and firms' excess returns, as proposed by Jurado *et al.* (2015) and Gilchrist *et al.* (2014), respectively. Nevertheless, these measures represent just one part of the overall economy, and their dynamics may not be closely related to the theoretical, unobserved economic uncertainty[2].

Another alternative corresponds to the Economic Policy Uncertainty (EPU) index proposed by Baker *et al.* (2016). EPU is a news-based metric that considers the coverage frequency of US newspaper articles containing words related to the economy, policy actions, and related uncertainties. Cerda *et al.* (2016a, 2016b) extended this methodology to Chile's case, but the index is only available at a monthly frequency.

In this paper, we develop an uncertainty measure at daily frequency using the informational content of tweets posted by several Chilean news, newspapers, and radio Twitter accounts. The computation of our index is similar to that of the EPU, in the sense that we count all tweets using web scraping techniques, containing words or terms in the categories economy, policy, uncertainty, and an additional category related to the current economic situation, especially the civil protests and the COVID-19 virus in Chile. We call our measure the DEPUC index. To the best of our knowledge, this is the first news-based uncertainty metric at daily frequency available for the Chilean

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[1] For more details on the construction of the VIX, see CBOE (2019).

[2] For example, changes in leverage and risk aversion may affect the volatility of asset prices. Heterogeneity in the sensitivity of each firm's excess returns to the systemic risk factor or in the information set that economic agents dispose of when computing forecasts may induce fluctuations in the corresponding cross-section volatilities without any change in uncertainty.

economy. Following our work, Chile will become the third country –out of 21– that disposes of an EPU-based measure at daily frequency[3].

Our results show that the proposed metric depicts significant hikes that coincide with several local and international events that triggered substantial economic uncertainty in Chile. More precisely, DEPUC scaled well above one standard deviation after the episodes around the social protests in October 2019 and the coronavirus pandemic in March 2020. Overall, the index has a medium-to-low correlation with other daily-frequency measures of uncertainty, such as the VIX and the volatility of local stock returns. Still, it shares a common trend with monthly measures such as EPU and EPUC. In an empirical application related to the factors that influence the dynamics of the Chilean peso-US dollar exchange rate, we find that economic uncertainty, captured by our DEPUC measure, has meaningful effects on the exchange rate, especially when the level of this variable is high. In particular, a sudden increase in DEPUC of 2.64 standard deviations –such as the hike seen in mid-March 2020– would depreciate the Chilean peso in about \$25 to \$35 per US dollar, on average a week after this shock occurs. Lastly, when the nominal exchange rate is low, economic uncertainty impacts on this variable are quantitatively smaller for any forecasting horizon.

The rest of the paper is organized as follows. Section 2 describes in detail the methodology employed to compute our DEPU index. In particular, Section 2.1 portrays the steps involved in the database construction, whereas Section 2.2 explains the data treatment we implemented to, ultimately, get the DEPU index. Section 3, on its part, presents our DEPU measure for the Chilean economy that was computed using data starting from 2012 onwards. Section 3.1 discusses its in-sample properties to evaluate its consistency with known local episodes and its similarities with other uncertainty measures. Section 3.2 provides an empirical application related to the Chilean peso-US dollar exchange rate to illustrate the usefulness of the proposed uncertainty measure in monitoring tasks. Lastly, Section 4 concludes.

II. METHODOLOGY

In this section, we describe the methodology behind our measure of economic uncertainty. The first part of this section is devoted to all details involved in elaborating the database, whereas the second part delves into the construction of the proposed metric.

2.1. Database Construction

The first step in the computation of our measure of economic uncertainty is the making of the database. To this end, we construct a novel and exclusive database with

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[3] The other two countries are the UK and the US.

information extracted from the microblogging service Twitter. This service, created in March 2006, is one of the most popular social networks nowadays, with over 330 million monthly active users worldwide posting and interacting with 140-characters-long messages covering a broad spectrum of topics known as tweets[4]. Thus, tweets are a rich, readily available source of information about users' perceptions concerning economic subjects, especially where the degree of coincidence or disagreement of these perceptions can be exploited as a proxy for economic uncertainty, as we will explain in detail in the following subsection.

We focus our attention on the official Twitter accounts of 17 Chilean mass media specialized in or with segments/programs devoted to economics. In particular, and as can be seen from Table 1, we consider five newscast accounts (@CHVNoticias, @T13, @CNNChile, @24HorasTVN, @PuntoOnoticias_), nine newspaper accounts (@Emol, @DFinanciero, @EYN_ELMERCURIO, @ElMercurio_cl, @elmostrador, @pulso_tw, @Estrategiacl, @latercera, @EM_Inversiones), and three radio accounts (@biobio, @adnradiochile, @cooperativa). Our sample is small, considering the universe of TV, cable and radio stations, and daily circulation/electronic national newspapers in Chile[5]. However, our sample of Twitter accounts is very influential. To get an idea of this, until March 13 of 2022, the number of followers of newscast, newspaper, and radio accounts amounted to roughly 12.7, 6.7, and 9.2 million, respectively. Moreover, this sample has posted over 7.2 million tweets since the accounts joined Twitter, implying an average of about 97 tweets per day. Radio accounts are the most active in this sense, posting 182 tweets per day, followed by newscasts (94 tweets per day) and newspapers (66 tweets per day). We hope to cover Chile's news spectrum and trends from a broad perspective with this sample of Twitter accounts.

We had to perform two procedures to collect the necessary information, i.e., the content of all tweets posted by the 17 selected accounts. In the first one, we construct a daily, multi-dimensional panel of all tweets by account, covering January 2012 to December 2019. We consider the year 2012 as the starting point of our database because, at that moment in time, most accounts in our sample had already joined Twitter and had at least one year of tweeting records[6]. This first step is costly in processing time because it requires downloading a webpage (*fetching*) and extracting its content. Although this process can be automated –a technique known as *web scraping*– it has to be performed every day for every Twitter account. This process

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4 Starting in November 2017, tweets are allowed to contain up to 280 characters for all non-Asian languages.

5 According to the Chilean Undersecretary of Telecommunications (Subtel), there are currently seven local TV stations, 15 local cable channels operating in the country, and 37 FM radio stations broadcasting from the Metropolitan Area of Santiago. In the same line, Chile has seven newspapers of national circulation and 13 national electronic newspapers.

6 Most of the accounts in our sample joined Twitter between 2008 and 2010 (see Table 1). The only exceptions are the newspaper accounts @EM_Inversiones and @ElMercurio_cl, and the newscast account @Puntonoticias_, which joined Twitter in February 2013, April 2013, and September 2014.

TABLE 1

TWITTER ACCOUNTS CONSIDERED
(THOUSANDS)

Category	Official Twitter Account	Joined	Followers	Tweets since start
Newscasts	@CHVNoticias	Jun-09	1.453,6	128,7
	@T13	Mar-09	3.640,4	648,0
	@CNNChile	Dec-08	3.676,7	424,9
	@24HorasTVN	Nov-09	3.969,5	824,3
	@Puntonoticias_	Sep-14	4,0	1,6
Newspapers	@Emol	May-10	2.071,7	556,5
	@DFinanciero	Aug-09	247,0	233,3
	@EYN_ELMERCURIO	Sep-09	65,2	86,5
	@ElMercurio_cl	Apr-13	181,9	121,9
	@elmostrador	Jan-08	1.888,1	290,9
	@pulso_tw	Nov-11	117,1	155,9
	@Estrategiacl	Jul-10	77,5	77,8
	@latercera	Apr-07	2.057,9	1.000,0
	@EM_Inversiones	Feb-13	26,2	43,9
Radios	@biobio	May-08	3.616,2	892,7
	@adnradiochile	Oct-10	2.401,1	467,1
	@Cooperativa	Jul-07	3.208,1	1.300,0

All statistics as of March 13, 2022.
Source: Twitter.

amounts to roughly 7.5 million searches in total in our sample. After January 2020, the procedure significantly simplifies thanks to the software R since Twitter provides an API (Application Programming Interface) that facilitates the communication between the two platforms through packages specially designed for such purposes[7].

Figure 1 depicts the main characteristics of the resulting database. From Panel (a), we note that, in general, the tweets posted by the selected official Twitter accounts contain around 15 words on average, and this extension is very homogenous across account categories. In this sense, we can deduce that the informational content of each post in our database is pretty concise. Panel (b) of this figure reveals that overall posting activity between 2013 and 2018 was above 2,000 tweets per day, with a notorious peak in 2015 and 2016, where daily posts reached 2,850. Newspapers accounts have an overriding contribution to tweeting activity, amounting to roughly 42% of total daily posts in the sample, followed by radio accounts (30%) and newscasts accounts (28%). However, this contribution across account categories has tended to equate in recent years.

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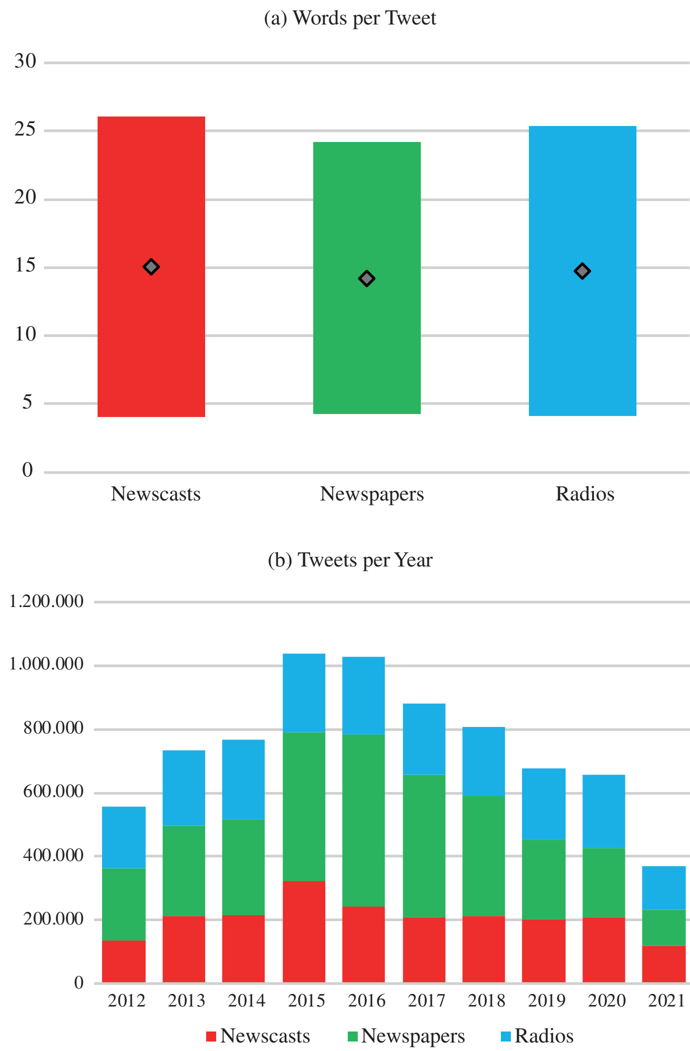
[7] We use the R package rtweet. For further details, refer to https://rtweet.info/.

FIGURE 1

TWEETS BY TYPE OF ACCOUNT



The range of columns in panel (a) represents the 95% confidence interval for the corresponding sample mean.
Source: Author's elaboration.

2.2. Economic Uncertainty Measures

Once having constructed the database from Twitter accounts, the second step in computing our measure of economic uncertainty is processing this database. To this end, we closely follow the methodology initially proposed by Baker *et al.* (2016). In particular, for each day, we count all tweets containing words related to the Chilean economy (E); fiscal, monetary, and trade policy in Chile (P); uncertainty about the categories as mentioned earlier (U); or the general conjuncture situation in Chile (C) related or not to the COVID-19 pandemic; according to the dictionary of keywords described in Table 2. For instance, we classify a tweet into category E if the post contains any word or term in Spanish beginning with *econ*, both in lowercase or capital characters or combining the two. Similarly, tweets that contain words beginning with *incer* or *incier* –the Spanish equivalent of *uncer* in both cases– belong to category U. It is essential to highlight that, due to our database's flexibility, it is possible to add or remove some keywords in these categories that may be of particular interest within a given time frame.

To formalize the classification rule sketched above, let $t_{ijkt}(x)$ be the i-th tweet by Twitter account j in the category $k = \{Newscast, Newspaper, Radio\}$ during day t that has a post x. The variable x is just a chain of characters with $0 < dim(x) \leq 140$ until October 2017. After this date, the maximum length of x doubled to 280. Further, let $y \subset Y$ be a chain of characters belonging to the dictionary of keywords defined in Table 2. The set Y is defined as $Y = E \cup P \cup U \cup C$, i.e., it contains all keywords of categories economy (E), policy (P), uncertainty (U), and general conjuncture situation in Chile (C). Thus, we name DEPUC to our daily-frequency measure of economic and policy uncertainty for Chile based on the set Y. Note that this set is similar to the one defined in Cerda *et al.* (2016a, 2016b), especially when looking at categories E and U. However, our category P contains additional keywords related to monetary and trade policies. Also, the keywords in category C are closely related to the civil protests of mid-October 2019 and the COVID-19 pandemic[8], in contrast to Cerda *et al.* (2016a, 2016b), where the only conjuncture keyword is *Chile*. All in all, our classification rule can be summarized by the following expression:

$$t_{ijkt}(x) = \begin{cases} 1 & if \;\; x \supset y,\; y \subset Y \\ \\ 0 & \;\;\;\; otherwise \end{cases} \tag{1}$$

for all i, j, k and t.

8 Our choice for the keywords in category C related to the COVID-19 pandemic is in the spirit of the World Pandemics Uncertainty Index (WPUI) developed by Ahir *et al.* (2018). In a nutshell, the WPUI is a sub-index of the World Uncertainty Index and corresponds to the number of times the word *uncertainty* is mentioned near a word related to *pandemics* or *epidemics* in the Economist Intelligence Unit country reports.

TABLE 2

DICTIONARY OF KEYWORDS

Category	Subcategory	Words/Terms
Economy (*E*)		Any word / term beginning with “econ”
Policy (*P*)	Fiscal policy	“politica”, “impuesto”, “regulacion”, “recaudacion”, “reforma”, “congreso”, “senado”, “diputado”, “gasto publico”, “deficil fiscal”, “presupuesto”, “tributaria”, “deuda publica”, “presupuesto fiscal”, “gasto fiscal”, “ministerio de hacienda”, “hacienda”, “reforma”, “congreso”, “regulacion”, “decreto”, “corte suprema”, “tribunal”, “gobierno”, “presidente”
	Monetary Policy	“banco central”, “bcch”, “ente rector”, “ente regulador”, “reserva federal”, “fed”, “tipo de cambio”, “dolar”
	Trade Policy	“arancel”, “tratado libre comercio”, “tlc”, “comercio internacional”
Uncertainty (*U*)		Any word / term beginning with “incer” and “incier”
Conjuncture situation (*C*)	No COVID	“estallido”, “crisis”, “crisis social”, “estallido social”, “nomasafp”, “afp”, “colusion”, “pensiones”, “nueva constitucion”, “constitucion”, “asamblea”, “constituyente”, “isapres”, “convencion”, “convencion constitucional” “elecciones”, “rusia”, “ucrania”, “chile”
	COVID	“coronavirus”, “corona”, “covid”, “covid19”, “covid-19”, “pandemia”, “cuarentena”, “omicron”

For further details on the English meaning of each keyword, please refer to the webpage https://sebabecerra.github.io/depu/.
Source: Authors’ elaboration.

Note that, at this point, our procedure differs slightly from that proposed by Baker *et al.* (2016). In particular, we consider any tweet containing words in at least one category described above, whereas the original methodology would only consider tweets containing keywords in all categories. The reason to proceed this way is that the tweets in our sample have an average length of 5 to 25 words (Figure 1.a). Thus, the likelihood that a given tweet contains keywords in all categories simultaneously is low, as opposed to news articles that are, on average, ten to twenty times longer (Carr, 2002) and, therefore, the chances that they contain keywords in all categories are ample. However, the inclusion of 17 official Twitter accounts into our analysis ensures that, for any given day, all categories of keywords are more or less present. Hence, the interpretation of the resulting index is similar to that of Baker *et al.* (2016).

Then, for each day t, we compute the frequency of tweets meeting the requirement $t_{ijkt}(x) = 1$. Given that the number of tweets per day can vary over time, as revisited in Figure 1.b, we scale the frequency by the total number of tweets by type of account, $k = \{Newscast, Newspaper, Radio\}$. Therefore, if N_{kt} represents the total number of tweets posted by the k-th category of Twitter accounts, then the scaled frequency $\bar{t}_{kt}(y)$ is computed as

$$\bar{t}_{kt}(x) = \frac{1}{N_{kt}} \sum_{i} \sum_{t} t_{ijkt}(x \supset y) \tag{2}$$

for $y \subset Y$, and all k and t.

Finally, we standardize each of the series obtained by expression (2). To that end, we consider the sample mean and standard deviation from 2012 to 2019, i.e.,

$$\bar{\bar{t}}_{k}(y) = \frac{1}{T} \sum_{t=1jan2012}^{31dec2019} \bar{t}_{kt}(y)$$

and

$$\sigma_k(y) = \sqrt{\frac{1}{T} \sum_{t=1jan2012}^{31dec2019} \left(\bar{t}_{kt}(y) - \bar{\bar{t}}_{k}(y)\right)^2}$$

respectively, and where $T = 2{,}916$ is the total number of daily observations in this period. Hence, the standardized series are computed as $\tilde{t}_{kt}(y) = \left(\bar{t}_{kt}(y) - \bar{\bar{t}}_{kt}(y)\right) / \sigma_k(y)$, for $y \subset Y$ and $k = \{Newscast, Newspaper, Radio\}$. This procedure avoids that series with large fluctuations or with a sizeable number of posts, such as newspaper accounts (see Figure 1.b), drive the overall dynamics of the proposed index. That said, our measure of economic and policy uncertainty DEPUC is the average among the categories of Twitter accounts of the standardized scaled frequencies:

$$DEPUC_t = \frac{1}{3} \sum_{k} \tilde{t}_{kt}(y), \qquad y \subset Y \tag{3}$$

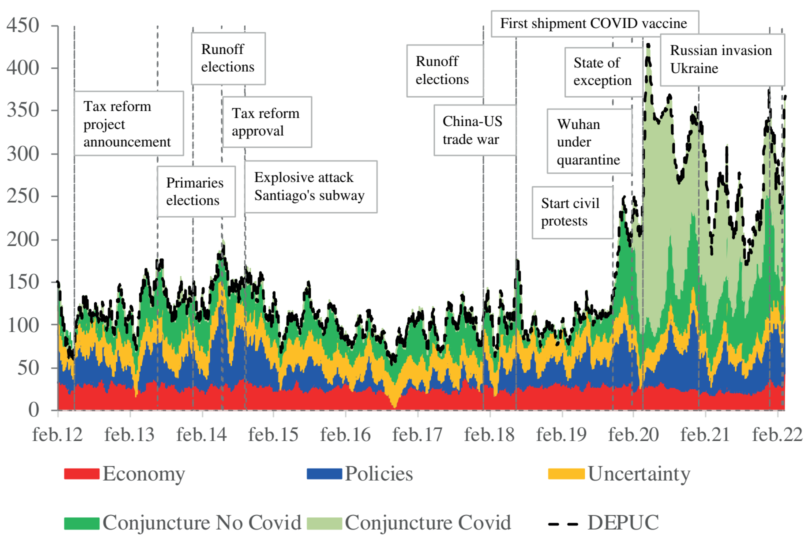
Note that we consider a simple average in the previous expression instead of a weighted one, in line with the original methodology of Baker *et al.* (2016). In our context, a simple average could be interpreted as the extensive margin of overall uncertainty, captured by the degree of disagreement of people's perceptions about the economy, policies, uncertainty, and conjuncture situation embodied in their tweets. In contrast, a weighted average could be interpreted as the intensive margin of uncertainty as one using the number of retweets. The argument here is that the number of times a given tweet is shared or reposted by other persons signals its importance in the overall level of disagreement and, thus, uncertainty. As a robustness check exercise, we computed DEPUC under the intensive margin, and the global results do not change significantly and thus are not reported.

III. RESULTS

Figure 2 shows the evolution of our measure of economic and policy uncertainty for Chile from 2012 onwards. We depict this variable and the contribution of each keyword category –computed using expressions (1) to (3)– where we further normalize the series to make it comparable with other international economic and policy uncertainty measures[9]. Also, we use a 30-days moving average on the measure to avoid excessive daily variability. Several aspects are worth highlighting in this figure.

FIGURE 2

DAILY ECONOMIC POLICY UNCERTAINTY MEASURE FOR CHILE
(INDEX, 01/01/2012 = 100)



The measure was filtered using a 30-days moving average to avoid excessive daily variability. Vertical dashed lines mark events of substantial economic uncertainty as detailed in the corresponding boxes.
Source: Authors' elaboration.

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9 In particular, we set the observation of January 1, 2012, equal to 100.

First, our measure exhibits sizable peaks that coincide with various episodes of substantial local and global uncertainty driven by sources of different nature:

1. The announcement of the tax reform bill in April 2012 under the first administration of President Sebastian Piñera included, among other elements, higher taxes on companies and on alcoholic beverages and benefits for investment in education, which increased uncertainty related to fiscal policies and the overall economy.
2. The presidential primaries elections by the end of June 2013 of the two major Chilean political coalitions, and the presidential runoff elections in mid-December 2013 with former President Michelle Bachelet elected again, where the uncertainty spike was driven by the conjuncture dimension mainly.
3. The approval of the tax reform bill in mid-May 2014 under the second administration of President Michelle Bachelet introduced several significant changes to the Chilean tax system and boosted uncertainty related to fiscal policies[10].
4. The release of an initial tariff list (25% on more than 1,000 products) and the announcement of a second tariff list within the US-China trade war in mid-June 2018 scaled conjuncture- and trade policies-related uncertainty, among many other episodes.

Second, our economic and policy uncertainty measure captured several critical events during the civil protests of 2019. In this context, DEPUC jumped to values close to 250, i.e., 2.5 times larger than those observed at the beginning of 2012, and occurred after the clash between protesters and the police on October 18 and the subsequent state of emergency and curfew announcement, causing significant volatility in the local stock market and exchange rate. Most of this initial trend was driven by the conjuncture component of uncertainty. However, other aspects of this variable, such as the economy, policies, or uncertainty, played a crucial role in further related episodes. For instance, most Chilean political parties' signature of an agreement supporting a referendum and the impeachment process against the president in November 2019, which was later considered not presented, implied an expansion of the policy- and uncertainty-related components. Moreover, the elections held on 15 and 16 May 2021 –after being postponed twice– to elect the delegates for the Constitutional Convention derived in a transitory increment of uncertainty driven by the policy component.

Third, at the beginning of the coronavirus pandemic, our measure reached a magnitude of almost 210 by the end of January 2020, when the central government of China imposed a lockdown in Wuhan and other cities in the Hubei province.

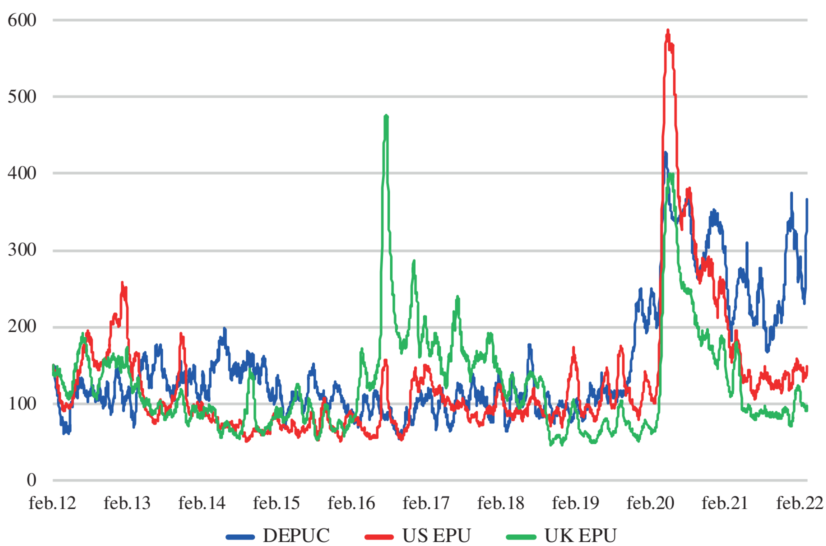
[10] Most changes included provisions that revised the corporate and dividend taxation integration rules and changed the thin capitalization rules. Moreover, the tax reform bill modified the expense deduction rules, imposed limits on the deductibility of tax goodwill, enacted controlled foreign corporation rules, and provided a general anti-avoidance rule.

Then, in mid-April of that year, DEPUC reached the highest level recorded since the start of our sample, reaching values of about 430 and propelled by the Covid-related dimension of our measure. These magnitudes are related to events such as the official recognition of the disease as a pandemic; the declaration of a state of catastrophe at the national level and the consequent closure of all land borders, ports, and airports; the establishment of a curfew; and the release of latest economic data signaling the first adverse effects on local financial markets and the overall economy.

Lastly, DEPUC is also capable of capturing the effects of geopolitical events on local uncertainty. For instance, the proposed measure jumped to values close to 170 in mid-June 2018, when the US imposed a 25% tariff on US$ 50 billion of Chinese exports. Chinese authorities interpreted this decision as launching a trade war between the two countries and retaliated by threatening with similar actions. As a result, the copper price dropped 4.4% during the next two trading days, reaching values of around US$ 3.09 per pound. More recently, our measure spiked to values around 370, driven by the conjuncture dimension of DEPUC, after the Russian invasion of Ukraine by the end of February 2022. This event implied a significant price shock worldwide, affecting energy and food prices, financial prices such as Libor and Euribor spreads, and world uncertainty.

FIGURE 3

ECONOMIC POLICY UNCERTAINTY FOR SEVERAL COUNTRIES
(INDEX, 01/01/2012 = 100)



All measures were filtered using a 30-days moving average to avoid excessive daily variability.
Source: Authors’ elaboration and www.policyuncertainty.com.

Figure 3 compares the dynamics of our proposed measure, DEPUC, with other measures of uncertainty for the US and UK available at a daily frequency on the Economic Policy Uncertainty webpage. We note that, in general, uncertainty was more or less contained before the Covid-19 pandemic, showing fluctuations around 100. The most notably idiosyncratic exceptions are:

1. In the US, the increase of uncertainty in January 2013 to values around 250 related to the signature into law of the American Taxpayer Relief Act to avoid a fiscal cliff of automatic tax increases and cuts in federal expenditures and the inauguration of former President Barack Obama for a second term by the end of that month.
2. In the UK, the dramatic spike of uncertainty after the referendum by the end of June 2016, when almost 52% voted in favor of leaving the European Union, thus marking the start of Brexit.
3. In Chile, the rise of uncertainty after the civil protests of October 2018 and the sustained high uncertainty environment from 2021 onwards related to the structural break observed in the local capital market due to the several pension funds withdrawals that occurred in the context of the Covid-19 pandemic (CBCh, 2021) and the development of the constituent process.

3.1. Statistical Properties

Table 3 depicts descriptive statistics of our measure and each keyword category. From panel A of this table, we note that DEPUC has limited volatility relative to its full-sample mean, i.e., the standard deviation is about 0.7 times its mean. However, the categories related to policies and conjuncture depict substantial variability, wherein in both cases, the standard deviation is roughly 1.4 times the mean. Regarding extreme values, the statistics for the entire sample indicate that the uncertainty category is the one that has the largest kurtosis. However, considering the scaled kurtosis, i.e., $\tilde{K} = K / \left(1 + S^2\right)$, where K is the kurtosis and S is the skewness, both the policy and economy dimensions show about the same number of extreme events where uncertainty within these categories is unusually high[11]. Moreover, the proposed metric depicts high persistence due to the conjuncture dimension. On the contrary, the economy- and uncertainty-related dimensions are close to uncorrelated processes.

Panels B and C of Table 3 also show that after the civil protests and riots of 2019 and the Covid pandemic, uncertainty increased substantially and is more persistent. In particular, the average magnitude of DEPUC before October 2019 was close to 111, and it increased to around 275 afterward. Further, the autocorrelation of the proposed metric more than tripled, scaling from 0.20 to 0.67. In contrast, the volatility of our

[11] For more information about the scaled kurtosis statistic, see Rohatgi and Szekely (1989).

TABLE 3

DESCRIPTIVE STATISTICS OF DEPUC

	Mean	Std. Dev.	Skewness	Kurtosis	Autocorr.
	Panel A. Full Sample				
DEPUC	150.71	103.81	0.65	3.07	0.64
Economy	29.26	16.99	3.66	34.02	0.08
Policy	33.52	47.45	1.03	5.76	0.32
Uncertainty	28.65	3.82	7.56	101.96	0.06
Conjuncture	59.29	82.74	1.01	3.83	0.67
	Panel B. Before Oct-19				
DEPUC	110.95	74.65	0.64	3.90	0.20
Economy	28.40	17.92	3.39	27.63	0.07
Policy	27.11	48.15	1.30	6.74	0.24
Uncertainty	28.43	3.89	8.02	111.62	0.03
Conjuncture	27.01	56.66	1.29	5.33	0.18
	Panel C. After Oct-19				
DEPUC	275.77	80.82	0.10	4.07	0.67
Economy	31.93	13.33	6.04	90.13	0.09
Policy	53.70	38.80	0.68	4.46	0.44
Uncertainty	29.34	3.50	6.22	67.25	0.14
Conjuncture	160.80	68.54	0.71	5.03	0.75

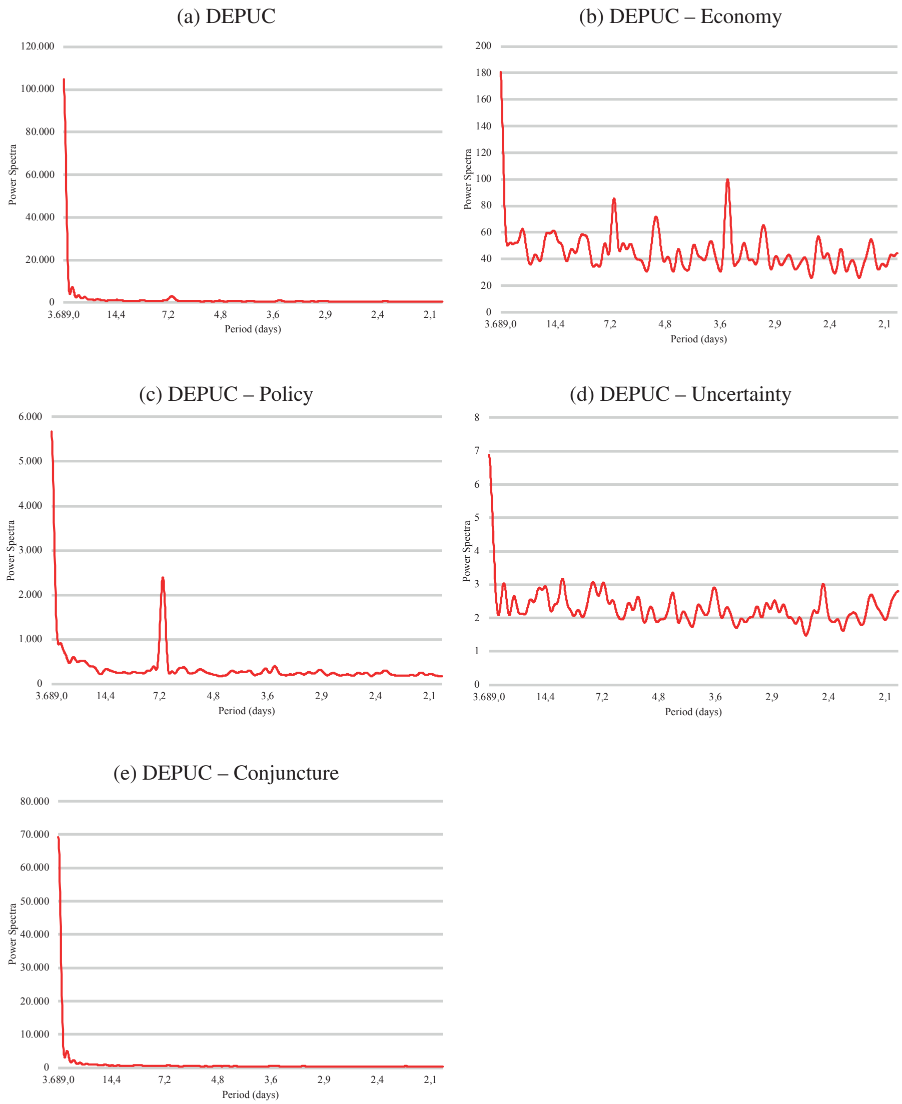
Source: Authors' elaboration.

measure remained almost invariant within these two periods, and most of it was driven by the policy and conjuncture dimensions. Lastly, after October 2019, the occurrence of specific events that carried high uncertainty was somewhat higher. In this sense, the scaled kurtosis raised from 2.8 to around 4.0. Most of this increase was propelled by the conjuncture and policy dimensions of DEPUC, whereas before October 2019, the key categories were policy and economy.

Panels (a) through (e) from Figure 4 present the periodogram of DEPUC and its subcategories. The power spectrum was obtained using the Bartlett (1963) window with a bandwidth of $h = 2\sqrt{T} = 121$ periods. This figure confirms the observation originally stated by Granger (1966), in the sense that the spectral shape of our economic and policy uncertainty measure concentrates most of its spectral mass at low frequencies (high period), declining as frequency increases (period decreases). In this avenue, roughly 50% of the total power spectrum is concentrated in periods between three months and ten years. Furthermore, the periodogram of DEPUC reveals a weak seasonal component inherited from the policy- and economy-related categories. In particular, the spectrum of the policy dimension contains a remarkable secondary peak at a period of 7 days, whereas the economy dimension contributes with a secondary peak at the

FIGURE 4

PERIODOGRAM OF UNCERTAINTY MEASURE

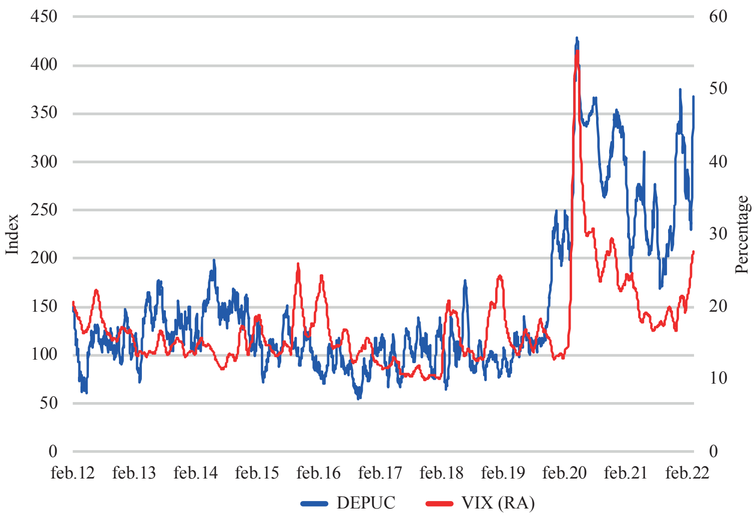


All periodograms were calculated using a Bartlett window with a bandwidth of 121 periods, equal to twice the square root of the sample size.
Source: Authors' elaboration.

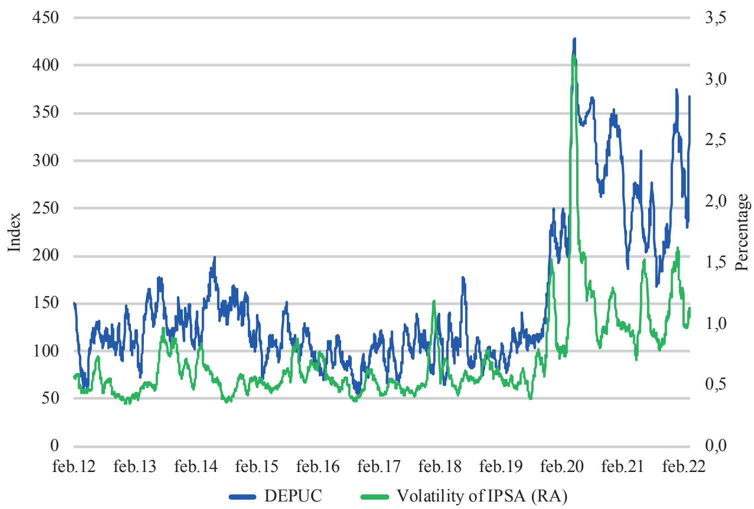
FIGURE 5

DEPUC AND OTHER VOLATILITY MEASURES

(a) DEPUC and VIX



(b) DEPUC and Volatility of IPSA



All variables were filtered using a 30-days moving average to avoid excessive daily variability. The volatility of IPSA corresponds to the range-based estimator of volatility proposed by Parkinson (1980), which considers high and low prices during a trading day.
Source: Bloomberg and authors’ elaboration.

first harmonic period (i.e., 3.5 days). Uncertainty and conjuncture categories, on their part, show that long-run movements drive most dynamics of these series. Moreover, the uncertainty dimension has a low contribution to the total power spectrum and depicts high noise due to small peaks at lower periods. The conjuncture dimension, on the contrary, has a significant contribution to the total power spectrum, and most of its variability is concentrated at low frequencies.

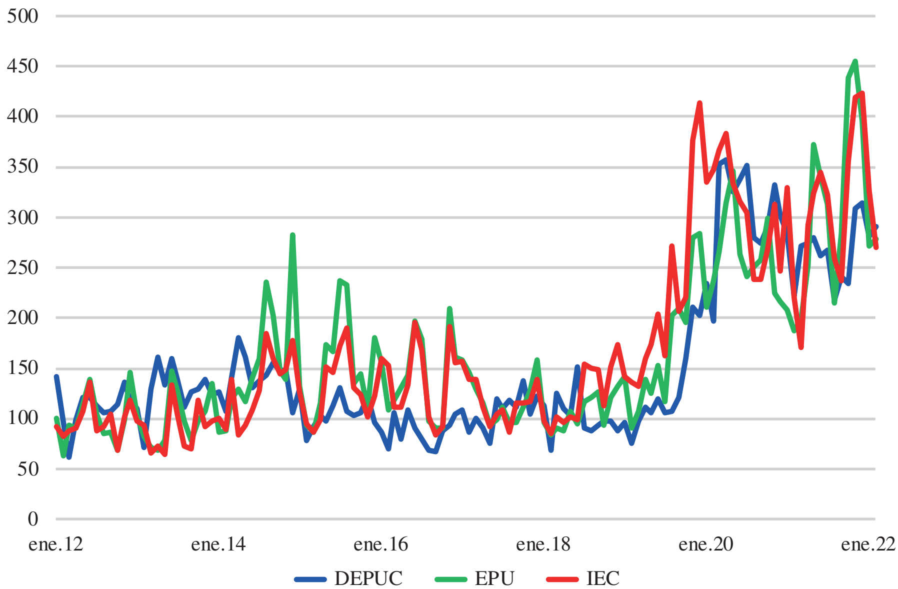
Figure 5 compares the dynamics of DEPUC with other global and local volatility measures available at daily frequency, namely VIX and the volatility of the local stock market index (IPSA). First, we note that the evolution of DEPUC and VIX before the COVID-19 pandemic share few things in common. Intuitively, this result is because the VIX captures uncertainty in the US financial markets within a short-term horizon. In contrast, DEPUC is, by construction, not restricted to any particular time horizon and mainly represents the Chilean economy. However, the remarkable jump in both measures after the Covid was officially declared a pandemic, and to a lesser extent after the Russian invasion of Ukraine, indicates that the effects of these events were global and hit both local and international markets equally. All in all, the correlation between these series is about 0.67 within the entire sample. Second, when comparing the dynamics of DEPUC and the volatility of IPSA, we obtain similar results to the previous case. The argument is somewhat akin in the sense that the volatility of IPSA characterizes the uncertainty of daily asset returns in the Chilean stock market, whereas the scope of DEPUC is broad. The correlation, in this case, is about 0.79, driven mainly by the peaks observed in the two measures after the civil protests in October 2019, the Covid-19 pandemic, and the presidential elections in 2021.

Lastly, Figure 6 compares the monthly evolution of our proposed measure with the news-based economic uncertainty metrics EPU and IEC proposed by Cerda *et al.* (2016a, 2016b), available at a monthly frequency[12]. The monthly version of DEPUC corresponds to averages of daily observations within each month. From this figure, we note that, in general, these series share a common trend that reverted its increasing drift in mid-2014 and increased again steadily after October 2019. Nevertheless, the short-run movements show some differences, especially during the period 2015-2017 and 2021 when the presidential general and run-off presidential elections took place. Despite these discrepancies, all series have roughly the same coefficient of variation (between 0.50 and 0.55), and the full-sample correlation between DEPUC and EPU and DEPUC and IEC is 0.77 and 0.81, respectively.

[12] EPU corresponds to an economic policy uncertainty measure, whereas IEC corresponds to an economic uncertainty measure.

FIGURE 6

COMPARISON WITH OTHER MONTHLY UNCERTAINTY MEASURES



Monthly series of DEPUC correspond to averages of daily observations within each month. EPU and IEC are the news-based economic uncertainty measures proposed by Cerda *et al.* (2016a, 2016b), available at monthly frequency.
Source: Cerda *et al.* (2016a, 2016b) and authors' elaboration.

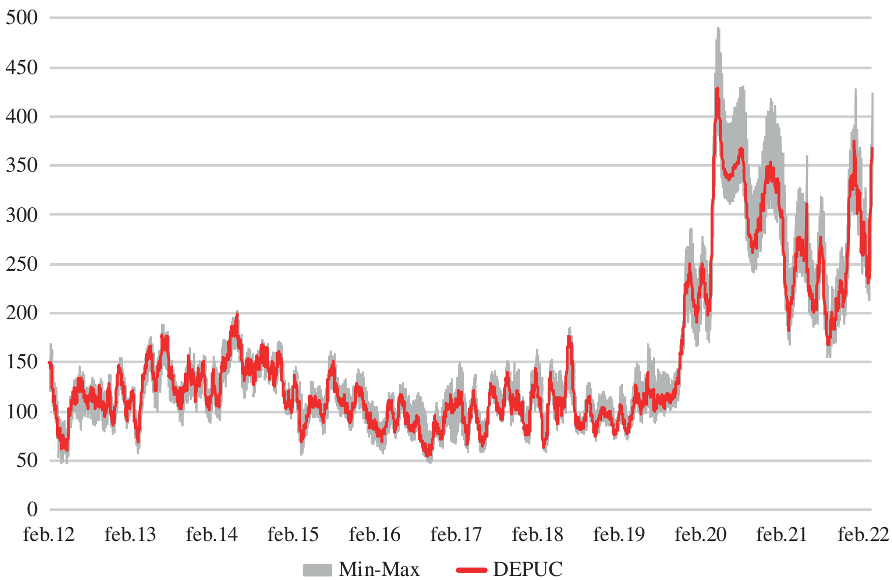
3.2. Robustness Check

One concern related to these types of measures is whether one or few Twitter accounts detailed in Table 1 drive the overall dynamics of the series. If that is the case, the remaining accounts are uninformative about the underlying uncertainty. As a consequence, the representativeness of DEPUC could be seriously affected.

Thus, to shed light on this issue, in this subsection, we perform a robustness check exercise in which we measure the relative importance of each Twitter account in the overall dynamics of DEPUC. In particular, we compute our measure excluding one Twitter account, and then we compare its dynamics with the original DEPUC. If the evolution of both series is similar, the excluded account is not significant in determining the short- and long-run movements of our measure. On the contrary, if the Twitter account is relevant in determining the overall dynamics, then the evolution of both series should depict important discrepancies.

FIGURE 7

DYNAMICS OF DEPUC AND DEPUC EXCLUDING ONE TWITTER ACCOUNT



Grey shaded area corresponds to the range of values (minimum and maximum) that DEPUC adopts when one Twitter account is excluded.
Source: Authors' elaboration.

TABLE 4

RELATIVE IMPORTANCE OF ACCOUNTS IN OVERALL DYNAMICS OF DEPUC

Category	Official Twitter Account	Statistic	
		Correlation	$1–R^2$
Newscasts	@CHVNoticias	0.9930 [0.9925;0.9934]	0.033
	@T13	0.9901 [0.9895;0.9907]	0.044
	@CNNChile	0.9453 [0.9418;0.9486]	0.220
	@24HorasTVN	0.9827 [0.9816;0.9838]	0.070
	@Puntonoticias_	0.9714 [0.9695;0.9731]	0.096

Category	Official Twitter Account	Statistic	
		Correlation	1–R^2
Newspapers	@Emol	0.9942 [0.9938;0.9946]	0.027
	@DFinanciero	0.9935 [0.9931;0.9939]	0.033
	@EYN_ELMERCURIO	0.9964 [0.9962;0.9966]	0.018
	@ElMercurio_cl	0.9921 [0.9916;0.9926]	0.035
	@elmostrador	0.9923 [0.9918;0.9928]	0.035
	@pulso_tw	0.9855 [0.9846;0.9864]	0.073
	@Estrategiacl	0.9924 [0.9919;0.9929]	0.033
	@latercera	0.9848 [0.9838;0.9857]	0.064
	@EM_Inversiones	0.9972 [0.9970;0.9974]	0.014
Radios	@biobio	0.9626 [0.9602;0.9649]	0.192
	@adnradiochile	0.9280 [0.9234;0.9323]	0.338
	@Cooperativa	0.9995 [0.9994;0.9996]	0.002

95% confidence interval of the correlation between DEPUC and the measure excluding the corresponding Twitter account in square brackets. R^2 is the coefficient of determination of a linear regression between the first difference of DEPUC and the first difference of the measure, excluding the corresponding Twitter account.
Source: Authors' elaboration.

We consider two alternative statistics to evaluate the relative importance of each Twitter account in determining the fluctuations of DEPUC. Let $DEPUC_t^{-j}$ be our measure computed excluding the Twitter account *j*. The first statistic corresponds to the correlation between $DEPUC_t$ and $DEPUC_t^{-j}$. Thus, if $CORR\left[DEPUC_t, DEPUC_t^{-j}\right]$ is close to 1, then the *j*-th Twitter account is not relevant in determining our measure's dynamics by itself. The second statistic is based on the coefficient of determination R^2 of the following linear regression:

$$\Delta DEPUC_t = \mu + \beta \Delta DEPUC_t^{-j} + \varepsilon_t \qquad (4)$$

where ε_t is an error term. Hence, if the *j*-th Twitter account is not relevant by itself in the overall dynamics of DEPUC, then $1 - R^2$ is close to zero because the first difference of our measure $\left(\Delta DEPUC_t\right)$ and that excluding one account $\left(\Delta DEPUC_t^{-j}\right)$ are alike.

Figure 7 contrasts the evolution of DEPUC and the range of values that the measure adopts in each period when one Twitter account is excluded from the sample. This figure shows that the overall dynamics of the proposed measure do not change dramatically when one account is excluded, suggesting that none of them has the sufficient weight to drive the overall dynamics of DEPUC. In addition, Table 4 shows the correlation between $DEPUC_t$ and $DEPUC_t^{-j}$ and $1 - R^2$ related to the estimation of the linear regression given by expression (4). The average correlation between the two series is high and around 0.982, and it tends to be somewhat lower for radio and newscasts accounts (0.963 and 0.977, respectively). When the accounts @adnradiochile and @CNNChile are excluded from the sample, the correlation coefficient drops to 0.928 and 0.945. This last result could explain the broader range of values adopted by DEPUC –without these series– during the Covid-19 pandemic, as shown in Figure 7. We obtain similar conclusions when analyzing the statistic $1 - R^2$. In particular, the average value of this metric is 0.08, increasing to 0.18 and 0.09 for radio and newscasts accounts, and more intensely when we exclude from the sample the Twitter accounts mentioned before.

Therefore, to sum up, the results suggest that none of the 17 accounts considered in our sample significantly drive the overall dynamics of our proposed measure, which contributes to the representativeness of our sample of Twitter accounts to proxy the economic and policy uncertainty in Chile.

3.3. Empirical Application

This section provides an empirical application to illustrate the usefulness of our economic uncertainty measure as an additional tool to support research projects or monitoring tasks. In particular, we examine the Chilean peso-US dollar nominal exchange rate dynamics in response to its traditional determinants plus our metric DEPUC.

To that end, and considering the recent events in Chile and the world, we model the logarithm of the daily exchange rate e_t as a two-regimes Markov-switching phenomenon, i.e., the magnitude of this variable can be low (*L*) or high (*H*) depending on the state of nature. Moreover, because we are interested in the dynamic response over regimes of the nominal exchange rate to variations of its determinants, especially economic uncertainty characterized by DEPUC, we evaluate the Markov-switching model within a forecasting context. Thus, the econometric model that we estimate is the following:

$$e_{t+h} = \alpha_{s_t}^h + \beta_{s_t}^h X_t + u_{t+h}, \qquad h = 0,1,2,\dots \tag{5}$$

where $s_t = \{L,H\}$ is a discrete, unobserved random variable that describes the regime or state of nature, with transition probabilities $P[s_t = j \mid s_{t-1} = i] = p_{ij},\ i,\ j = \{L,H\}$;

h is the forecasting horizon; $\alpha_{s_t}^h$ and $\beta_{s_t}^h$ are state-dependent coefficients; and u_{t+h} is an error term with mean 0 and variance σ^2.

Note that expression (5) is similar to a local projection model (see Jorda, 2005, for instance) because it consists of sequential regressions of the nominal exchange rate shifted h periods ahead. However, we do not consider lags of e_t on the right-hand side of (5) because this variable is likely to be non-stationary[13]. We further assume that the Markov process's transition probabilities are the same for all forecasting horizon h and that the variance of the error term is state-independent.

Regarding the regressors X_t, we include (i) the logarithm of the Broad index, which is a weighted average of the foreign exchange value of the US dollar against currencies of a broad group of major US trading partners; (ii) the logarithm of EMBI Global, as a way to capture sovereign risk spread of emerging economies; (iii) the logarithm of commodity prices relevant for the Chilean economy such as copper and oil price; (iv) the inflation rate in Chile and the US, as a way to account for the Purchasing Power Parity hypothesis; (v) the difference between the 1-year swap interest rate in Chile and the US, as a way to account for the Interest Rate Parity hypothesis; (vi) the logarithm of VIX or the volatility of the daily returns of the IPSA index to characterize the uncertainty of stock markets; and (vii) our DEPUC measure, to include the uncertainty of the overall economy, respectively. We obtained most variables from Bloomberg.

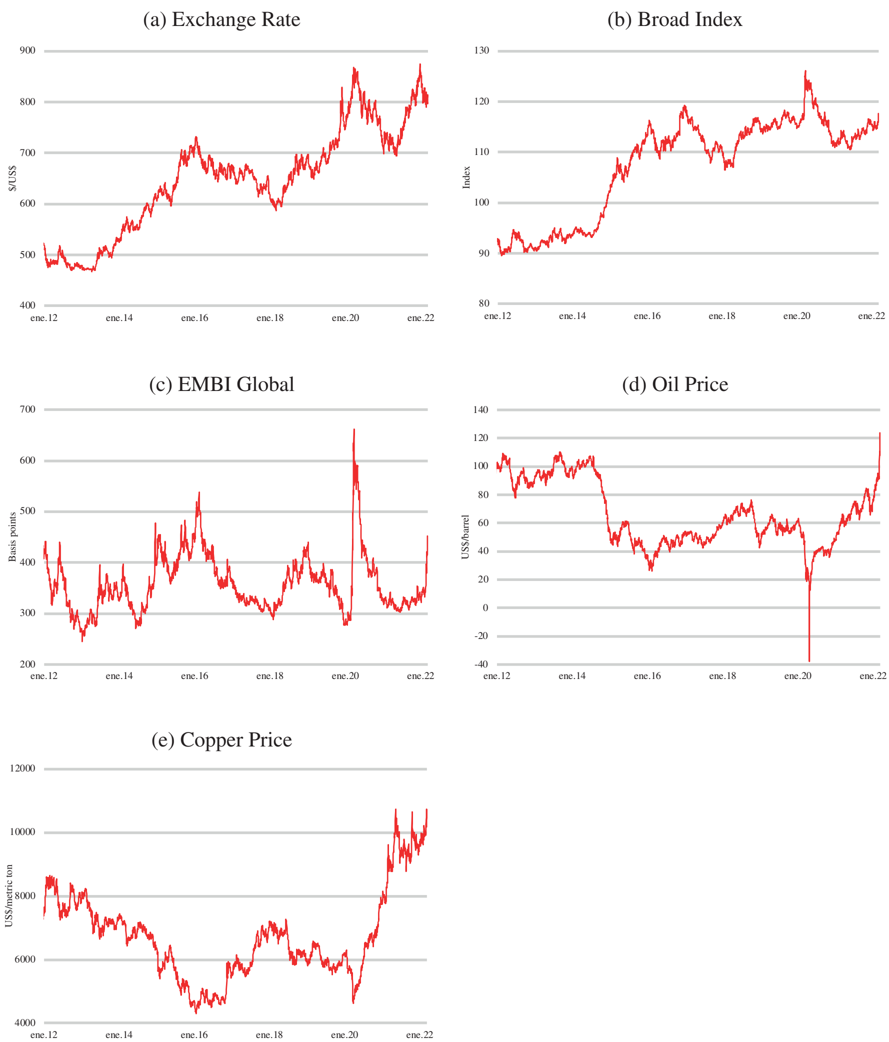
Figure 8 shows the daily evolution of the nominal exchange rate e_t and all variables described previously from 2012 onwards. From it, we note that the Chilean peso depreciated against the US dollar by roughly 56% over our entire sample. Most of this depreciation was seen after the social protests, when the exchange rate increased from around \$715 in mid-October to over \$800 per US dollar by November 2019. Further, at the beginning of the COVID-19 epidemic, e_t scaled above \$850 per US dollar in April 2020 and reached its maximum monthly value of \$875 by December 2021. A similar trend can be seen in the case of the Broad index, which climbed almost 28% over our entire sample. The rest of the variables depict sharp dynamics after the Covid-19 outbreak in mid-March 2020. For instance, VIX, EMBI Global, and the volatility of IPSA returns increased by 29 percentage points, 99 basis points, and 7.8 percentage points, respectively, a week after the COVID-19 has officially declared a pandemic. In contrast, on average, commodity prices declined 10% during the same period. Lastly, inflation in the US and Chile and the interest rate differential show a significant increasing trend after the second quarter of 2021, reaching values above 7%.

Table 5 shows the estimation results of the two-regimes Markov-switching model (4) in the case of $h = 0$. Several aspects are worth highlighting from it. First, both exchange rate regimes are very persistent. In particular, the probability of being in the high (low) exchange rate regime and transit to the same state in the next period is about

[13] In our sample, the Augmented Dickey-Fuller and Phillips-Perron tests do not reject the null hypothesis of a unit root.

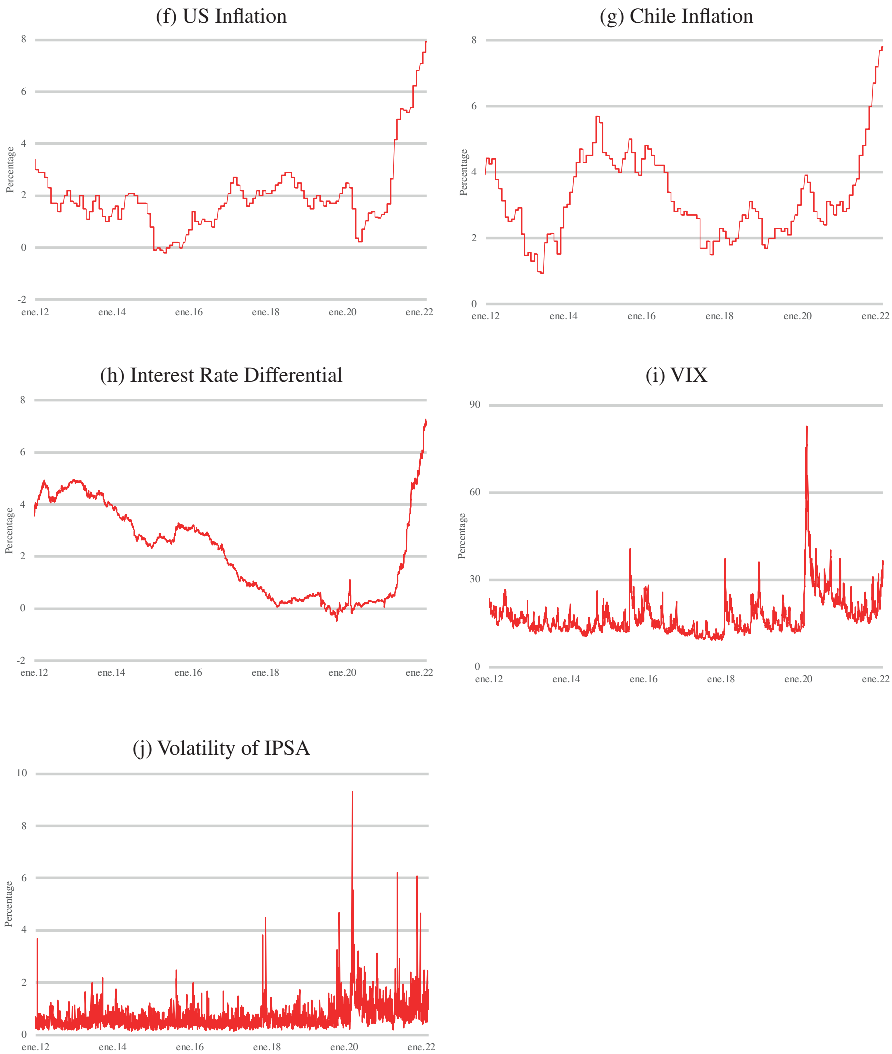
FIGURE 8

VARIABLES FOR THE ESTIMATION



Broad Index is a weighted average of the foreign exchange value of the US dollar against the currencies of a broad group of major US trading partners. Oil price is the West Texas Intermediate (WTI) crude oil price. Copper price is the London Metal Exchange (LME) copper price.
Source: Bloomberg and authors' elaboration.

FIGURE 8 (CONTINUED)



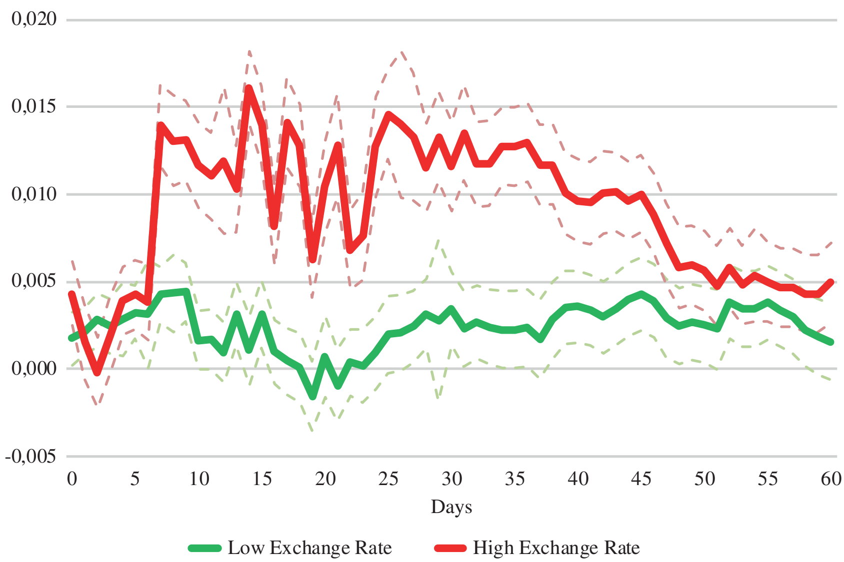
US and Chile inflation is the annual variation of the Producer Price Index (PPI) and the Consumer Price Index (CPI), respectively, based on monthly data. The interest rate differential is the difference between the 1-year swap rates in Chile and the US. The volatility of IPSA corresponds to the range-based estimator of volatility proposed by Parkinson (1980), which considers high and low prices during a trading day.
Source: Bloomberg and authors' elaboration.

0.995 (0.990). These results imply that, in our sample, the unconditional probability of the regime where e_t is high is 68.8%. Second, the economic uncertainty captured by our DEPUC measure has significant contemporaneous effects on the exchange rate, notably when the magnitude of the latter variable is high. For instance, an abrupt increment in DEPUC of 2.64 standard deviations –such as the increase seen in mid-March 2020– would imply an average depreciation of the Chilean peso of \$4.8 to \$6.4 per US dollar during the same day. The effects under the low exchange rate regime are roughly half of those in the high regime but statistically not significant. Lastly, the contemporaneous effects of the other regressors considered in our estimations are, in general, meaningful. Their absolute magnitude tends to increase under the high exchange rate regime, especially in the case of the EMBI Global, oil price, and US inflation rate. In all other cases, the magnitude of the effect on e_t remains approximately equal.

Figure 9 depicts the effects of economic and policy uncertainty on the nominal exchange rate under the two regimes, *h* days ahead, given by the econometric model (5). We compute these coefficients under the third specification shown in Table 5, based

FIGURE 9

EFFECTS OF DEPUC ON EXCHANGE RATE



This figure shows the coefficients associated with DEPUC under specification (5) of the two-regimes Markov-switching model (5). Dashed lines represent the corresponding coefficients' 95% confidence intervals for each value of the forecasting horizon h (in days).
Source: Authors' elaboration.

TABLE 5

ESTIMATION RESULTS

	(1)		(2)		(3)	
	Low	High	Low	High	Low	High
Broad Index	0.844	0.684	0.760	0.660	0.834	0.691
	(0.022)	(0.019)	(0.040)	(0.023)	(0.038)	(0.021)
EMBI Global	0.020	0.052	-0.003	0.065	0.018	0.047
	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)	(0.005)
Oil Price	0.013	-0.022	0.020	-0.013	0.012	-0.021
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Copper Price	-0.197	-0.199	-0.191	-0.205	-0.203	-0.200
	(0.010)	(0.008)	(0.013)	(0.008)	(0.014)	(0.008)
Inflation US	-0.001	-0.002	-0.004	-0.003	0.000	-0.003
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Inflation Chile	0.013	0.013	0.013	0.013	0.013	0.013
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Interest Rate Diff.	-0.046	-0.030	-0.051	-0.031	-0.045	-0.029
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
DEPUC	0.002	0.003	0.001	0.002	0.002	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
VIX			0.015	0.016		
			(0.004)	(0.003)		
IPSA Volatility					0.005	0.010
					(0.001)	(0.001)
Constant	4.156	4.770	4.568	4.860	4.261	4.763
	(0.129)	(0.140)	(0.276)	(0.162)	(0.252)	(0.157)
p_{HH}	0.995		0.995		0.995	
	(0.002)		(0.002)		(0.002)	
p_{LH}	0.011		0.009		0.011	
	(0.004)		(0.004)		(0.004)	
Observations	2,170		2,170		2,170	
Log Likelihood	5,697.6		5,722.0		5,738.9	
SBIC	-5.177		-5.192		-5.208	

Standard errors in brackets. SBIC stands for Schwarz-Bayesian information criterion.
Source: Authors' elaboration.

on the Schwartz-Bayesian information criterion. Our results suggest that the effects become quantitatively meaningful in the high exchange rate regime after a week of an economic and policy uncertainty variation. More precisely, a sudden increase in DEPUC of 2.64 standard deviations would depreciate the Chilean peso, all other things equal, by about \$25 to \$35 per US dollar one week later, on average. This effect is 4 to 7 times larger than when $h = 0$, but it tends to diminish as the forecasting horizon grows. Indeed, after one and a half months, the impact of economic uncertainty on the nominal exchange rate under both regimes is indistinguishable. Meanwhile, in the low exchange rate state, the effects of economic uncertainty on e_t are pretty stable across forecasting horizons. The previous finding implies that, on average, the exchange rate would hike up to $5 per US dollar as a result of an increase in the economic uncertainty, $h = 0,1,2,\ldots$ days ago, of 1.5 standard deviations (a magnitude like that seen by the end of January 2020). However, note that these effects are statistically not significant in approximately 30% of the cases, especially in forecasting horizons between 16 and 30 days.

IV. CONCLUSIONS

This paper develops a daily-frequency measure of economic and policy uncertainty for Chile using information obtained from Twitter accounts using web scraping techniques. In the process, we construct a novel and exclusive database covering the period from 2012 onwards. Then, based on the methodology proposed by Baker *et al.* (2016), we compute the frequency of tweets containing words or terms related to the economy, economic policies, uncertainty, and conjuncture situation in Chile. We name this measure DEPUC.

Our results show that the proposed measure depicts significant spikes that coincide with several substantial economic and policy uncertainty episodes of both local and international origin. In particular, DEPUC scales well above its historical average after the events around the civil protests in October 2019, the COVID-19 pandemic in March 2020, and the Russian invasion of Ukraine by the end of February 2022. The empirical application reveals that the proposed measure is a significant determinant of the nominal exchange rate dynamics, especially when the magnitude of this variable is high. Further, the effects of economic and policy uncertainty on the exchange rate are more prominent a week after the shock occurs. The impacts are more negligible for any forecasting horizon when the exchange rate is low.

The construction characteristics of the proposed measure show great flexibility to incorporate new words or terms in the dictionary of keywords to keep track and update recent elements that can affect the overall uncertainty, such as the escalation of geopolitical risks and current economic and political developments in Chile, among others. Moreover, the in-sample properties of DEPUC highlight its usefulness as an additional indicator that policymakers can incorporate into their monitoring and modeling toolkit.

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