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Twitter-Based Economic Policy Uncertainty Index for Chile

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Abstract

In this paper, we develop a daily-frequency measure of economic uncertainty for Chile employing information that was obtained from Twitter accounts using web scraping techniques and following closely the methodology proposed by Baker et al. (2016). Our proposed measures, called DEPU and DEPUC, aim to capture the level of generaldisagreement —a proxy for economic uncertainty— in topics such as the economy, economic policies, uncertainty about particular events, and the current economic situation in Chile. Both indices, available from 2012 onwards, show significant hikes that coincide with several local and international episodes that provoked extraordin ary levels of economic uncertainty in Chile, especially after the events around the civil protests in mid-October 2019 and the COVID-19 pandemic in mid-March 2020. An empirical exercise reveals that the proposed measures are significant determinants of the nominal exchange rate dynamics, especially when the magnitude of this variable is high and a week after the shock occurs. When the exchange rate is low, on the contrary, 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.

Resumen

En este artículo, desarrollamos una medida de incertidumbre económica en frecuencia diaria para Chile utilizando información obtenida desde cuentas de Twitter mediante técnicas de web scraping, y siguiendo de cerca la metodología propuesta por Baker et al. (2016). Las medidas propuestas, denominadas DEPU y DEPUC, apuntan a capturar el nivel de desacuerdo general en los contenidos de tweets –una proxy de incertidumbre económica– en tópicos relacionados con la economía, políticas económicas, incertidumbre acerca de eventos particulares, y la contingencia económica en Chile. Ambas medidas, disponibles desde 2012, muestran aumentos significativos que coinciden con varios episodios locales e internacionales que provocaron niveles extraordinarios de incertidumbre económica en Chile, especialmente luego de los eventos en torno a las protestas civiles de mediados

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de Octubre 2019 y la pandemia del COVID-19 a mediados de Marzo 2020. Los resultados de un ejercicio empírico revelan que la medida propuesta es un determinante significativo de la dinámica del tipo de cambio nominal, especialmente cuando la magnitud de esta variable es elevada y luego de una semana de ocurrido un shock de incertidumbre. Por el contrario, cuando el tipo de cambio se encuentra en niveles bajos, los impactos de la incertidumbre sobre esta variable son cuantitativamente menores para cualquier horizonte de proyección. Estas características, y otras discutidas en el artículo, destacan la utilidad de la métrica propuesta como un indicador adicional que los encargados de formular políticas pueden incorporar en su set de herramientas de monitoreo.

1   Introduction

Recently, economic 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, for emerging economies, VIX captures global uncertainty 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].

Yet 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.* (2016) 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 measures the DEPU and DEPUC indices. To the best of our knowledge, this is the first news-based uncertainty metric at daily frequency available for the Chilean economy. Following our work, Chile will become the third country —out of a total of 21— that disposes of an EPU-based measure at daily frequency[3].

Our results show that the proposed metrics depict significant hikes that coincide with several local and international events that triggered substantial economic uncertainty in Chile. More precisely, both DEPU and DEPUC scaled well above one standard deviation after

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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.

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

the episodes around the social protests in October 2019 and the coronavirus pandemic in March 2020. Overall, the indices have a medium-to-low correlation with other daily-frequency measures of uncertainty, such as the VIX and the volatility of local stock returns. Still, they share a common trend with monthly measures 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 one, on average, a week after this shock occurs. Lastly, when the nominal exchange rate is low, the impacts of economic uncertainty 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. In Section 3.1, we discuss its in-sample properties to evaluate its consistency with known local episodes and its similarities with other uncertainty measures. In Section 3.2, we provide 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.

2 Methodology

In this section, we describe the methodology behind our measure of economic uncertainty. The first part is devoted to all the details involved in the elaboration of 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 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 vibrant, 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 next subsection.

We focus our attention on the official Twitter accounts of 15 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 newscasts accounts (@CHVNoticias, @T13, @CNNChile, @24HorasTVN, @Puntonoticias_), seven newspapers accounts (@Emol, @DFinanciero,

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

`@EYN_ELMERCURIO`, `@elmostrador`, `@pulso_tw`, `@Estrategiacl`, `@latercera`), and three radio accounts (`@biobio`, `@adnradiochile`, `@cooperativa`). With this sample of Twitter accounts, we hope to cover the news spectrum and trends in Chile from a broad perspective.

To collect the necessary information, i.e., the content of all tweets posted by the 15 selected accounts, we had to perform two procedures. In the first one, we construct a daily, multi-dimensional panel of all tweets by account, covering the period from January 2012 to December 2019. We consider the year 2012 as the starting point of our database because, at that moment in time, all accounts in our sample had already joined Twitter and had at least one year of tweeting records[5]. This first step is costly in terms of processing time because it requires downloading a webpage (*fetching*) and then extracting its content. Although this process can be automated —a technique known as *web scraping*— it has to be performed for every Twitter account, every day. In our sample, this process amounts to almost 1.4 million searches in total. After January 2020, the procedure is significantly simplified 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[6].

Table 2 depicts the main characteristics of the resulting database. From it, we note that, in general, there is an average of 476 tweets per day, where there is a slightly higher posting activity by newspaper accounts, followed by newscast and radio accounts (199, 149 and 127 tweets per day on average, respectively). Moreover, in periods of low activity, the selected Twitter accounts drop the number of tweets per day by 23%, where this decrease is concentrated mainly in newscasts and radio accounts. Analogously, in periods of high posting activity, the number of tweets per day increases roughly 34%, being the newscast and radio accounts that raise the most.

Figure 1 extends the previous findings and shows the evolution of tweets per day by type of Twitter account. We note that, before mid-2018, the overall tweet activity was below 500 tweets per day, with overriding participation of newspaper accounts (around 44% of total daily tweets). After this period, the posting activity increased well above this number, notably after the COVID-19 was officially declared a pandemic. The number of tweets jumped to almost 1,500 per day, with more or less equal participation of all types of Twitter accounts.

2.2 Economic Uncertainty Measures

Once having constructed the database from Twitter accounts, the second step in the computation of our measure of economic uncertainty is the processing of 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 previous categories (U); or the general economic situation in Chile (C); according to the dictionary of keywords described in Table 3. For instance, we classify a tweet into the category E if the post contains any word or term in Spanish beginning with *econ*, both in lowercase or capital characters, or a combination of the two. Similarly, tweets that contain words beginning with *incer* or *incier*

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[5]Most of the accounts in our sample joined Twitter between 2008 and 2010. The only exception is the newscast account `@Puntonoticias_`, which joined Twitter in September 2014.

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

—the Spanish equivalent of *uncer* in both cases— belong to the 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 $k = \{\text{Newscast}, \text{Newspaper}, \text{Radio}\}$, 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 3. In this paper, we consider two versions of the set Y, namely $Y_1 = E \cup P \cup U$ and $Y_2 = E \cup P \cup U \cup C$. In other words, Y_1 contains all keywords of the categories economy (E), policies (P) and uncertainty (U), whereas Y_2 also includes the keywords of the category general economic situation in Chile (C). Thereby, we name DEPU and DEPUC to our daily-frequency measure of economic uncertainty for Chile based on the sets Y_1 and Y_2, respectively. Note that these sets are similar to the ones defined in Cerda *et al.* (2016). However, our category C contains some keywords related to the civil protests of mid-October 2018 and the COVID-19 pandemic. The latter in the spirit of the World Pandemics Uncertainty Index developed by Ahir *et al.* (2018)[7]. All in all, our classification rule can be summarized by the following expression:

$$
t_{ijkt}(x) = \begin{cases} 1 & \text{if} \quad x \supset y, \quad y \subset Y_1 \text{ or } y \subset Y_2 \\ 0 & \text{otherwise} \end{cases} \tag{1}
$$

for all i, j, k and t.

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 Table 2 and Figure 1, we scale the frequency by the total number of tweets by type of account, $k = \{\text{Newscast}, \text{Newspaper}, \text{Radio}\}$. Therefore, if N_{kt} gives 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

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

for $y \subset Y_1$ or $y \subset Y_2$, 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

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

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[7]The World Pandemics Uncertainty Index (WPUI) is a sub-index of the World Uncertainty Index. In a nutshell, the WPUI is the number of times that the word *uncertainty* is mentioned near a word related to pandemics or epidemics in the Economist Intelligence Unit country reports.

respectively, and where $T = 2,916$ is the total number of daily observations in this period. Hence, the standardized series are computed as $\tilde{\bar{t}}_{kt}(y) = \left(\bar{t}_{kt}(y) - \bar{\bar{t}}_k(y)\right)/\sigma_k(y)$, for $y \subset Y_1$ or $y \subset Y_2$ and $k = \{\text{Newscast}, \text{Newspaper}, \text{Radio}\}$. Our measures of economic uncertainty DEPU and DEPUC are the average among the categories of Twitter accounts of the standardized scaled frequencies:

$$DEPU_t = \frac{1}{3} \sum_k \tilde{\bar{t}}_{kt}(y), \qquad y \subset Y_1 \tag{3}$$

and

$$DEPUC_t = \frac{1}{3} \sum_k \tilde{\bar{t}}_{kt}(y), \qquad y \subset Y_2 \tag{4}$$

Note that in the previous expressions, we consider a simple average 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 economy, policies, uncertainty, and economic situation embodied in their tweets. In contrast, a weighted average, as could be one using the number of retweets, could be interpreted as the intensive margin of uncertainty. 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, of uncertainty. As a robustness check exercise, we computed both DEPU and DEPUC under the intensive margin. The global results do not change significantly, thus are not reported.

3 Results

Figure 2 shows the DEPU and DEPUC measures for the Chilean economy from 2012 onwards, computed using expressions (3) and (4), where both series are expressed using a 7-days moving average to avoid excessive daily variability. Several aspects are worth highlighting from this figure. First, both measures tend to move together over time, except at the end of the sample when they diverge. Indeed, the full-sample correlation between DEPU and DEPUC is 0.64, but it increases to 0.77 if we discard the period during which the COVID-19 pandemic flared up (after February 2020). Intuitively, the economic uncertainty captured by the DEPUC measure during this period spiked to over two standard deviations because there is not much consensus about the duration of the pandemic, and the most effective mechanisms to prevent mass contagion, among others. Hence, a large number of tweets are discussing these aspects. On the contrary, during the same period, the DEPU measure remained around an average of 0.25 standard deviations because of the coronavirus's adverse effects on the overall economy and international trade and the subsequent policy response by several governments worldwide are mostly well understood. Therefore, a limited number of tweets talk over these topics.

Second, our measures exhibit sizable peaks, i.e., increases above one standard deviation, that coincide with various episodes of significant global and local economic uncertainty: (i) the credit downgrade on the European Financial Stability Facility —the eurozone's bailout fund to help indebted European countries— following the downgrade of France and Austria by mid-January 2012; (ii) the tax reform bill announcement in April 2012 under the first administration of President Sebastian Piñera that includes higher taxes to companies and on

alcoholic beverages, and benefits for investments in education; (iii) 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 of that year with former President Michelle Bachelet elected again; (iv) the approval of the tax reform bill in mid-May 2014 under the second administration of President Michelle Bachelet that introduced a number of significant changes to the Chilean tax system[8]; and the explosive attack in September 2014 in a shopping center close to a subway station that left 14 wounded, among many other episodes.

Finally, but perhaps more importantly, our economic uncertainty measures captured several events during the civil protests of 2019 and the COVID-19 pandemic at the beginning of 2020, causing significant volatility in the local stock market and the exchange rate. In the first case, both DEPU and DEPUC jumped above one standard deviation after the clash between protesters and the police on October 18, and the subsequent state of emergency and curfew announcement. Moreover, both metrics identify the signature of an agreement by most of the Chilean political parties supporting a referendum and the impeachment process against the President, which was later defeated. In the case of the coronavirus epidemic, our measures reached almost 1.5 standard deviations by the end of January 2020, when the central government of Chine imposed a lockdown in Wuhan and other cities in the Hubei province. Then, the DEPUC measure reached the highest levels recorded since the start of our sample, reaching values over two standard deviations. These magnitudes are related to events like the official recognition of the disease as a pandemic, the declaration of a state of catastrophe at the national level, the closure of all land borders and both 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.

3.1 Statistical Properties

Table 4 depicts the descriptive statistics of both measures. In general, we note that the two series are quite volatile relative to their corresponding sample means. In this sense, the standard deviation of DEPU is about 65 times larger than its mean, and in the case of DEPUC, this relation is around 13 times. Regarding extreme values, the statistics for the full sample indicate that DEPU has more significant kurtosis than DEPUC. However, if one considers the scaled kurtosis, i.e., $\tilde{K} = K/(1 + S^2)$ where K is the kurtosis and S is the skewness, then both measures show similar values (2.52 versus 2.44, respectively)[9]. This result implies that both metrics identify roughly the same number of extreme events where economic uncertainty is unusually high.

Table 4 also shows that after the civil protests and riots of 2019, uncertainty increased substantially. Before October 2019, both measures had a sample average close to -0.02 standard deviations. Nonetheless, after this date, both DEPU and DEPUC spiked to an average of 0.44 and 1.15 standard deviations, correspondingly. Further, during this last period, our measures of uncertainty are between 1.1 and 1.5 times more volatile than the

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[8]Most changes include provisions that, broadly speaking, revise the corporate and dividend taxation integration rules, make changes to the thin capitalization rules, modify the expense deduction rules, impose limits on the deductibility of *tax goodwill*, enact controlled foreign corporation rules, and provide for a general anti-avoidance rule.

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

pre-October period. Moreover, both metrics depict higher persistence, especially in the case of DEPUC, where the autocorrelation coefficient tripled.

Figure 3, on its part, presents the periodogram of DEPU and DEPUC. The power spectra were obtained using the Bartlett (1963) window with a bandwidth $h = 2\sqrt{T} = 110$ periods. This figure confirms the observation originally stated by Granger (1966), in the sense that the spectral shape of our economic uncertainty measures concentrates most of their spectral mass at low frequencies, declining as frequency increases. In this avenue, we note that roughly 50% of the total power spectrum of both metrics is concentrated in the frequency band $[0, 3\pi/10]$. Furthermore, the periodogram of DEPU, and to a lesser extent that of DEPUC, reveals an important seasonal component. In particular, the spectrum contains secondary peaks at frequencies corresponding to a period of 7 days and its first harmonic (3.5 days). Thus, if these daily series are considered in time series models, we recommend to control for, or filter, this seasonality.

Figure 4 compares the dynamics of DEPUC with two other measures of uncertainty that are available at daily frequency, namely VIX and the volatility of 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 is mainly representative of the Chilean economy. However, the remarkable jump of both measures after the coronavirus was officially declared a pandemic indicates that the effects of this event were global and hit both local and international markets equally. All in all, the correlation between these series is about 0.37 within the full 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, while the scope of DEPUC is broader. The correlation, in this case, is about 0.44, driven mainly by the peaks observed in the two measures after the civil protests in October 2019 and the coronavirus epidemic in March 2020.

Lastly, Figure 5 compares the monthly evolution of our measures with the economic uncertainty metrics EPU and EPUC proposed by Cerda *et al.* (2016), available until February of the present year. The monthly version of DEPU and DEPUC correspond to averages of daily observations within each month. In general, these series share a common trend, that reverted its increasing drift in mid-2014, and increased again steadily after October 2019. Yet, the short-run movements show some differences, especially during the period 2015 - 2017, which implies that the full-sample correlation between DEPU and EPU, and DEPUC and EPUC are close to 0.35 and 0.46, respectively.

3.2   Empirical Application

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

To that end, and considering the events that occurred in Chile recently, 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:

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

where $s_t = \{L, H\}$ is a discrete, unobserved random variable that describes the regime or state of nature, with transition probabilities $P[s_t = j | s_{t-1} = i] = p_{ij}$, $i, j = \{L, H\}$; h is the forecasting horizon; α_{s_t} and β_{s_t} 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) in the sense that 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[10]. 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 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; the logarithm of EMBI Global, as a way to capture sovereign risk spread of emerging economies; the logarithm of commodity prices relevant for the Chilean economy such as copper and oil price; the inflation rate in Chile and the US, as a way to account for the Purchasing Power Parity hypothesis; he difference between the 1-year swap interest rate in Chile and the US, as a way to account for the Interest Rate Parity hypothesis; the logarithm of VIX or the volatility of the daily returns of the IPSA index to characterize the uncertainty of stock markets; and the DEPUC measure, to include the uncertainty of the overall economy, respectively. We obtained most variables from Bloomberg.

Figure 6 shows the daily evolution of the nominal exchange rate and all variables described previously from 2012 onwards. From it, we note that the Chilean peso depreciated against the US dollar roughly 61% over our entire sample. Most of this depreciation was seen after the social protests, when the exchange rate increased from levels around \$715 in mid-October to levels over \$800 per US dollar by the end of November 2019, and at the beginning of the COVID-19 epidemic, where e_t scaled above \$850 per US dollar in April 2020. A similar trend can be seen in the case of the Broad index, which climbed almost 34% over our entire sample. The rest of the variables depict sharp dynamics after the coronavirus 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 was officially declared a pandemic. In contrast, commodity prices declined 10%, on average, during the same period.

Table 5 shows the estimation results of the two-regimes Markov-switching model (5) 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

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

rate regime and transit to the same state in the next period is about 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, and 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 8 depicts the effects of economic uncertainty on the nominal exchange rate under the two regimes, h days ahead, given by the econometric model (5). We compute these coefficients under specification (3) shown in Table 5, based on the Schwartz-Bayesian information criterion. Our results suggest that, in the high exchange rate regime, the effects become quantitatively meaningful after a week of an economic uncertainty variation. More precisely, a sudden increase in DEPUC of 2.64 standard deviations would depreciate the Chilean peso, all other things equal, and on average, in about $25 to $35 per US dollar one week later. Note that 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. In the low exchange rate state, meanwhile, the effects of economic uncertainty on e_t are quite stable across forecasting horizons, implying 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 in approximately 30% of the cases, especially in forecasting horizons between 16 and 30 days, these effects are statistically not significant.

4   Conclusions

In this paper, we develop a daily-frequency measure of economic uncertainty for Chile using information that was obtained from Twitter accounts using web scraping techniques. In the process, we construct a novel and exclusive database covering the period from 2012 onwards and 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 current economic situation in Chile. We name these measures DEPU and DEPUC.

Our results show that the proposed measures depict significant spikes that coincide with several episodes of substantial economic uncertainty of both local and international origin. In particular, DEPU and DEPUC scale well above their historical average after the events around the civil protests in October 2019 and the COVID-19 pandemic in March 2020. The empirical application reveals that the proposed measures are significant determinants of the

nominal exchange rate dynamics, especially when the magnitude of this variable is high. Further, the effects of economic uncertainty on the exchange rate are more prominent a week after the shock occurs. When the exchange rate is low, the impacts are quantitatively smaller for any forecasting horizon.

These features highlight the usefulness of the proposed metric as an additional indicator that policymakers can incorporate into their monitoring toolkit.

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Figure 1: Tweets by Type of Account
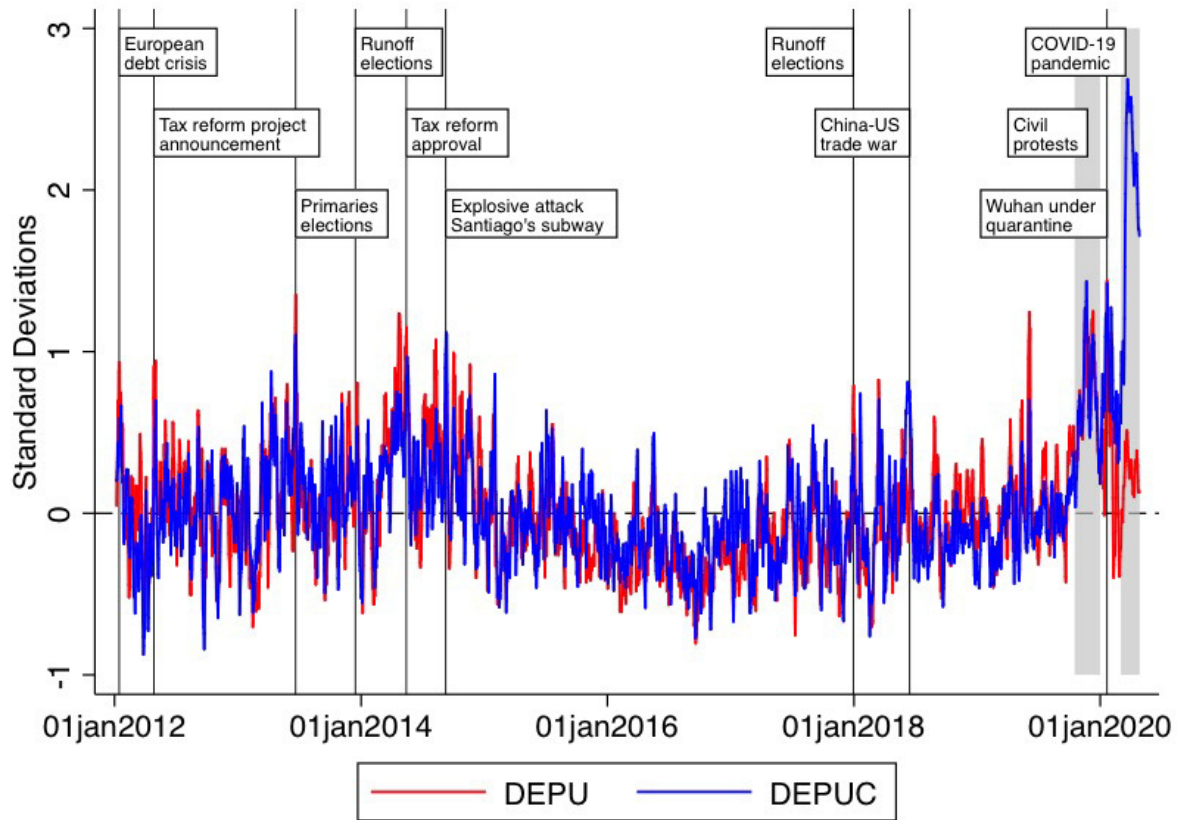
(a) Tweets per Day
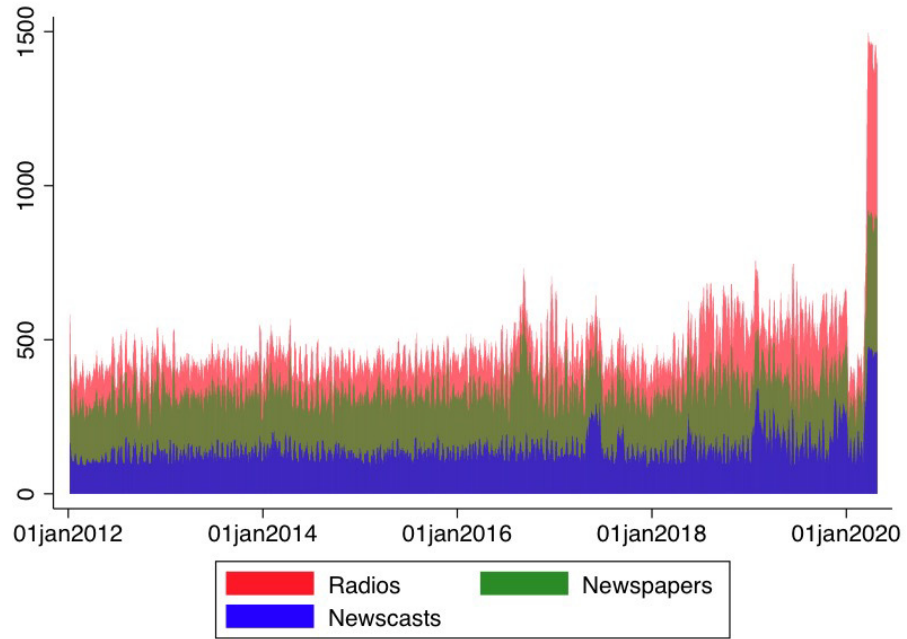
(b) Proportion of Total Tweets per Day
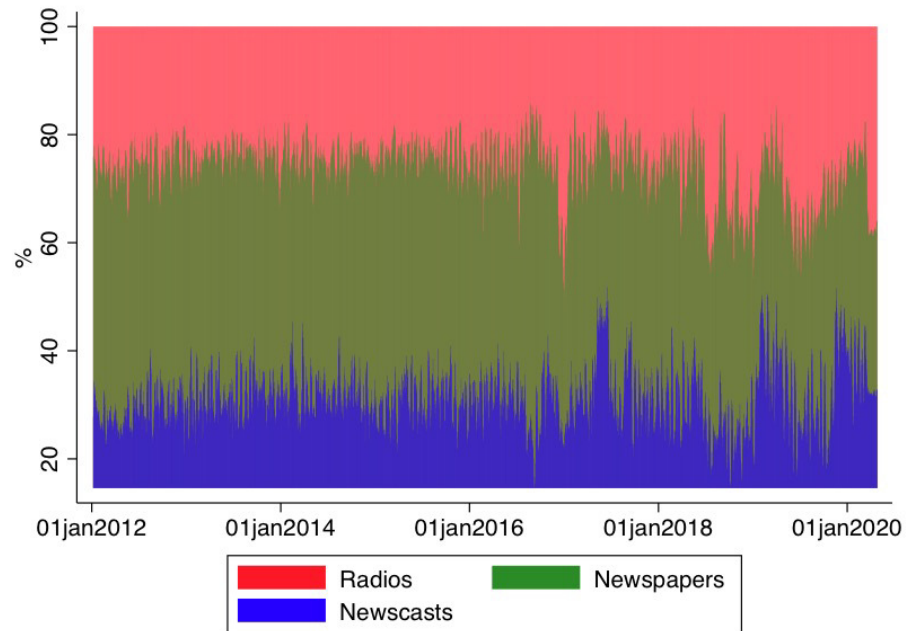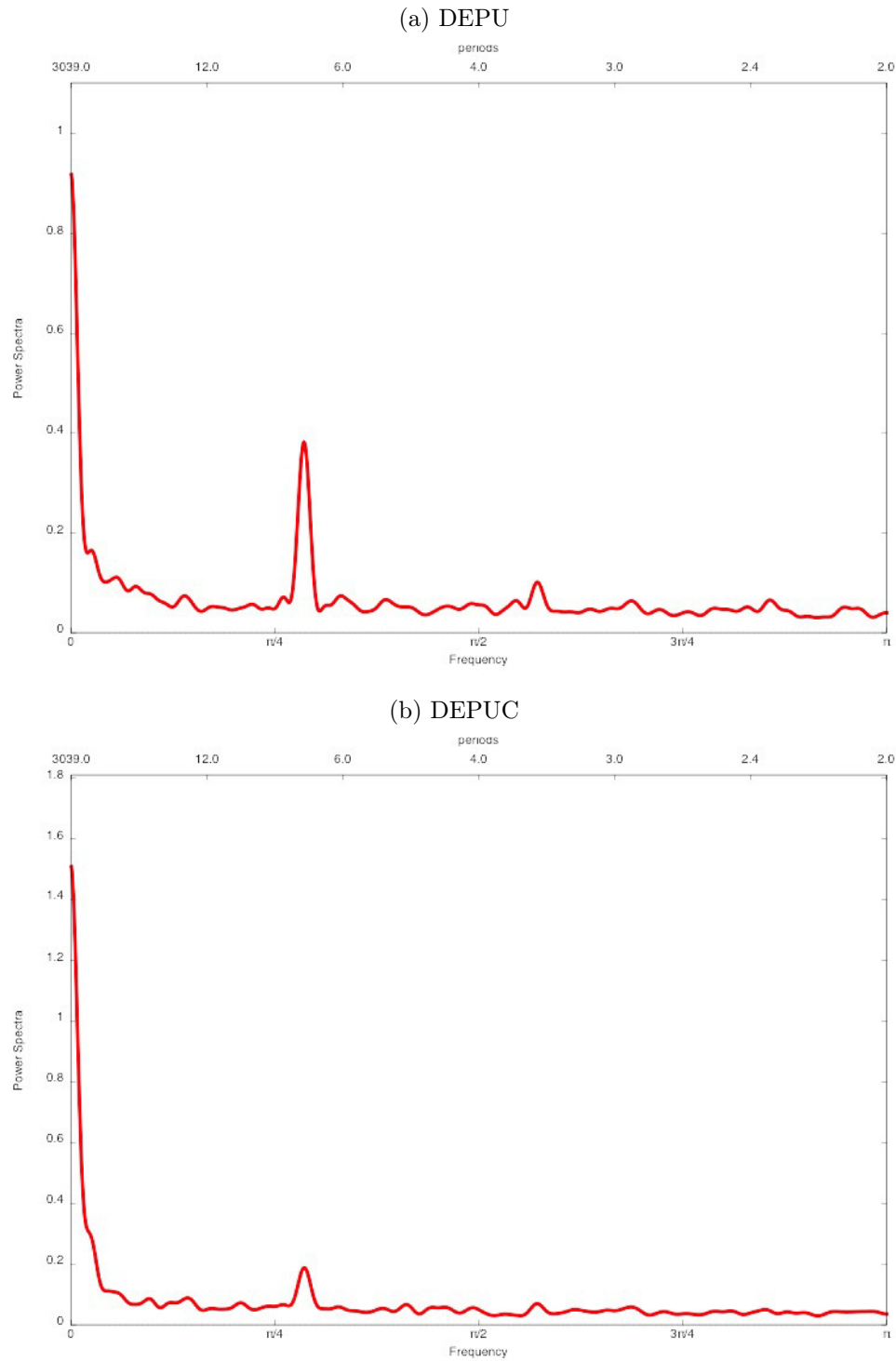

Source: Authors' elaboration.

Figure 2: Daily Economic Policy Uncertainty Measures

Both series were filtered using a 7-days moving average to avoid excessive daily variability. Vertical lines mark events of substantial economic uncertainty, whereas shaded areas mark various events related to the civil protests and riots of October 2019 and the COVID-19 pandemic starting mid-March 2020 onwards.
Source: Authors' elaboration.

Figure 3: Periodogram of Daily Economic Policy Uncertainty Measures

(a) DEPU

(b) DEPUC

Both periodograms were calculated using a Bartlett window with a bandwidth of 110 periods, which is equal to twice the square root of the sample size.
Source: Authors' elaboration.

Figure 4: Comparison with other Daily Uncertainty Measures

(a) DEPUC and VIX
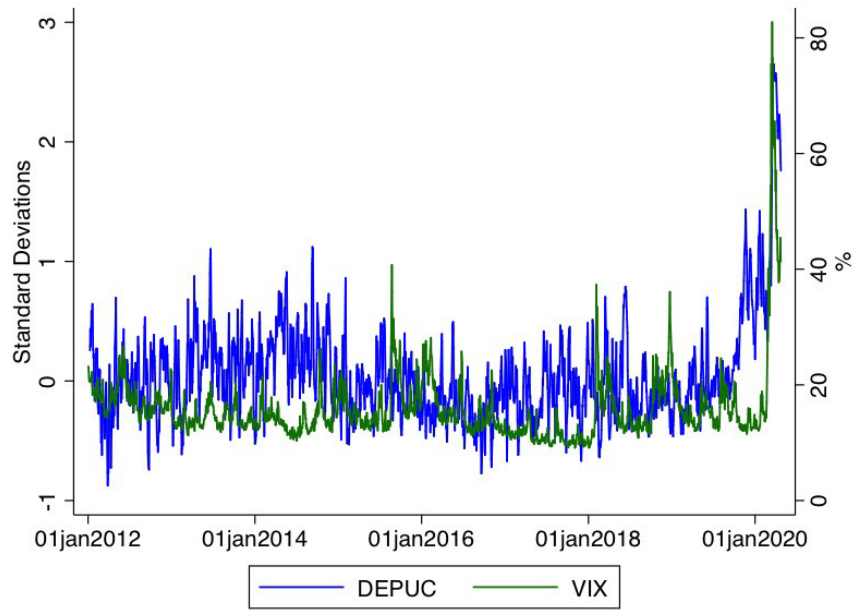
(b) DEPUC and Volatility of IPSA
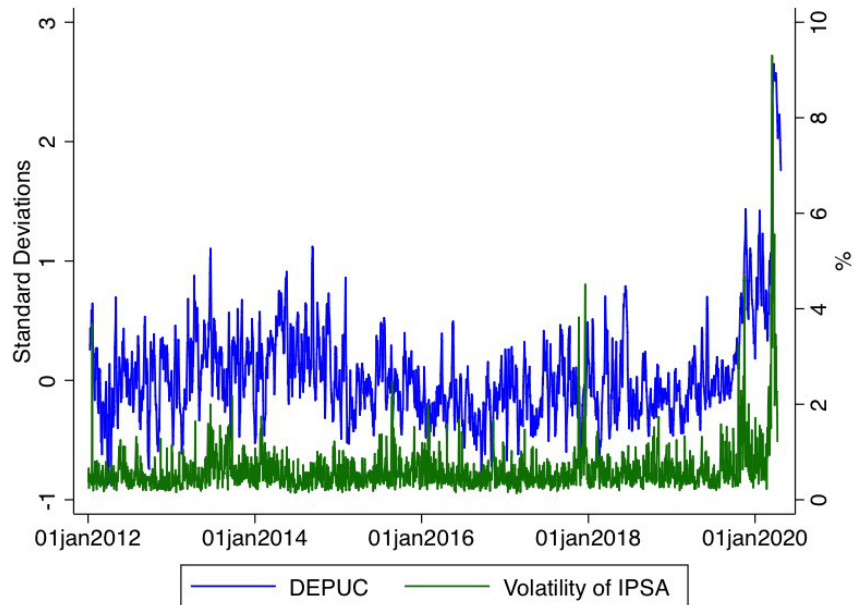
DEPUC was filtered using a 7-days moving average to avoid excessive daily variability. The volatility of IPSA corresponds to the range-based estimator of volatility proposed by Parkinson (1980), which considers high and low prices during a trading day.
Source: Bloomberg and authors' elaboration.

Figure 5: Comparison with other Monthly Uncertainty Measures

(a) DEPU and EPU
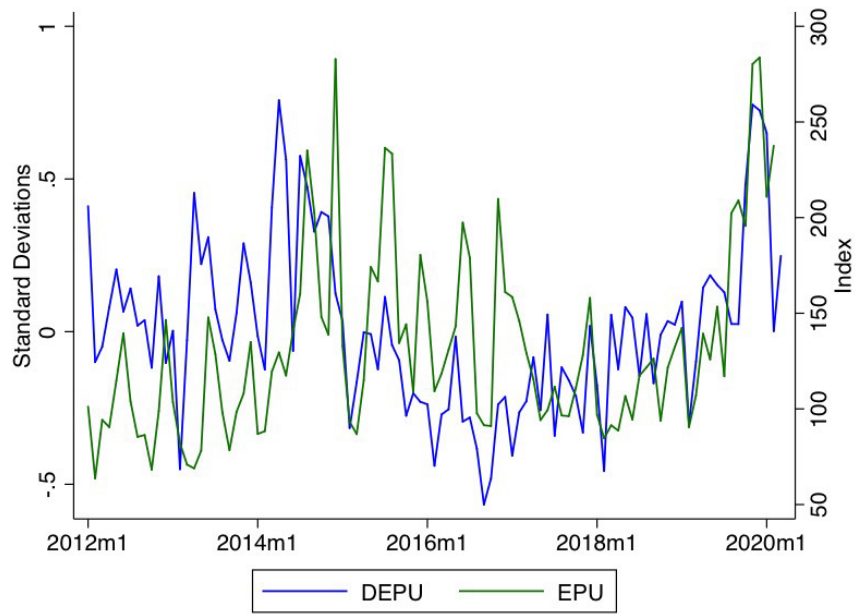
(b) DEPUC and EPUC
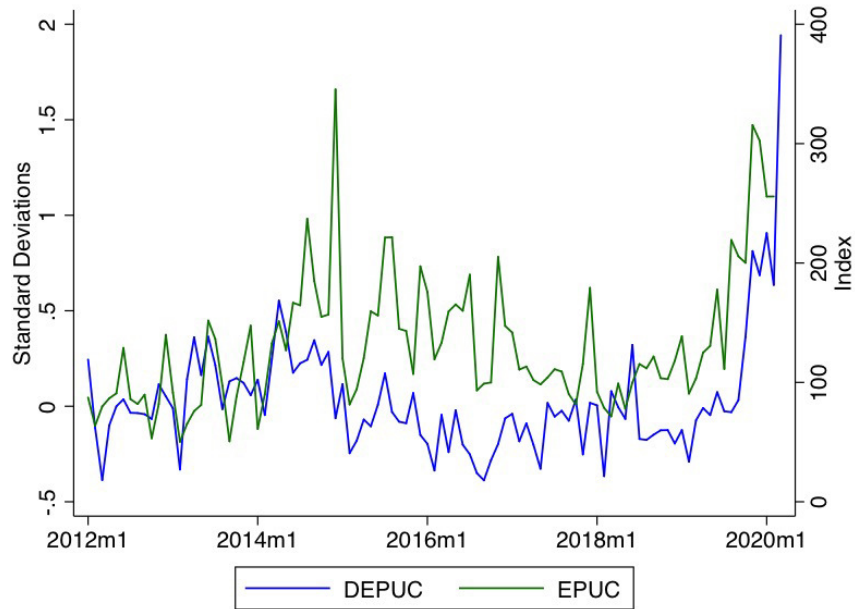
Monthly series of DEPU and DEPUC correspond to averages of daily observations within each month. EPU and EPUC are the news-based economic uncertainty measures proposed by Cerda *et al.* (2016) that are available at monthly frequency until February 2020. Source: Cerda *et al.* (2016) and authors' elaboration.
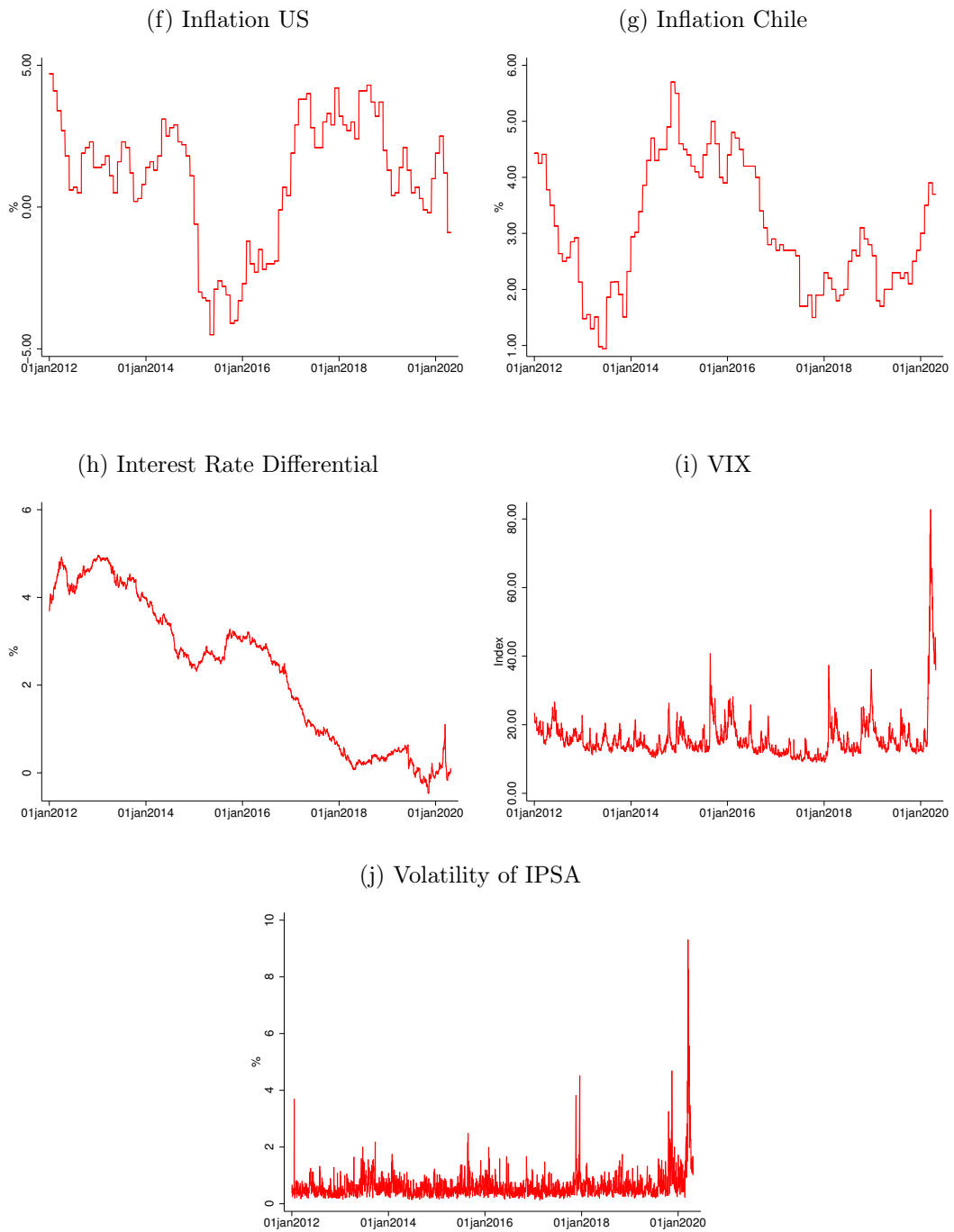
Figure 6: Variables for the Estimation

(a) Exchange Rate

(b) Broad Index

(c) EMBI Global

(d) Oil Price
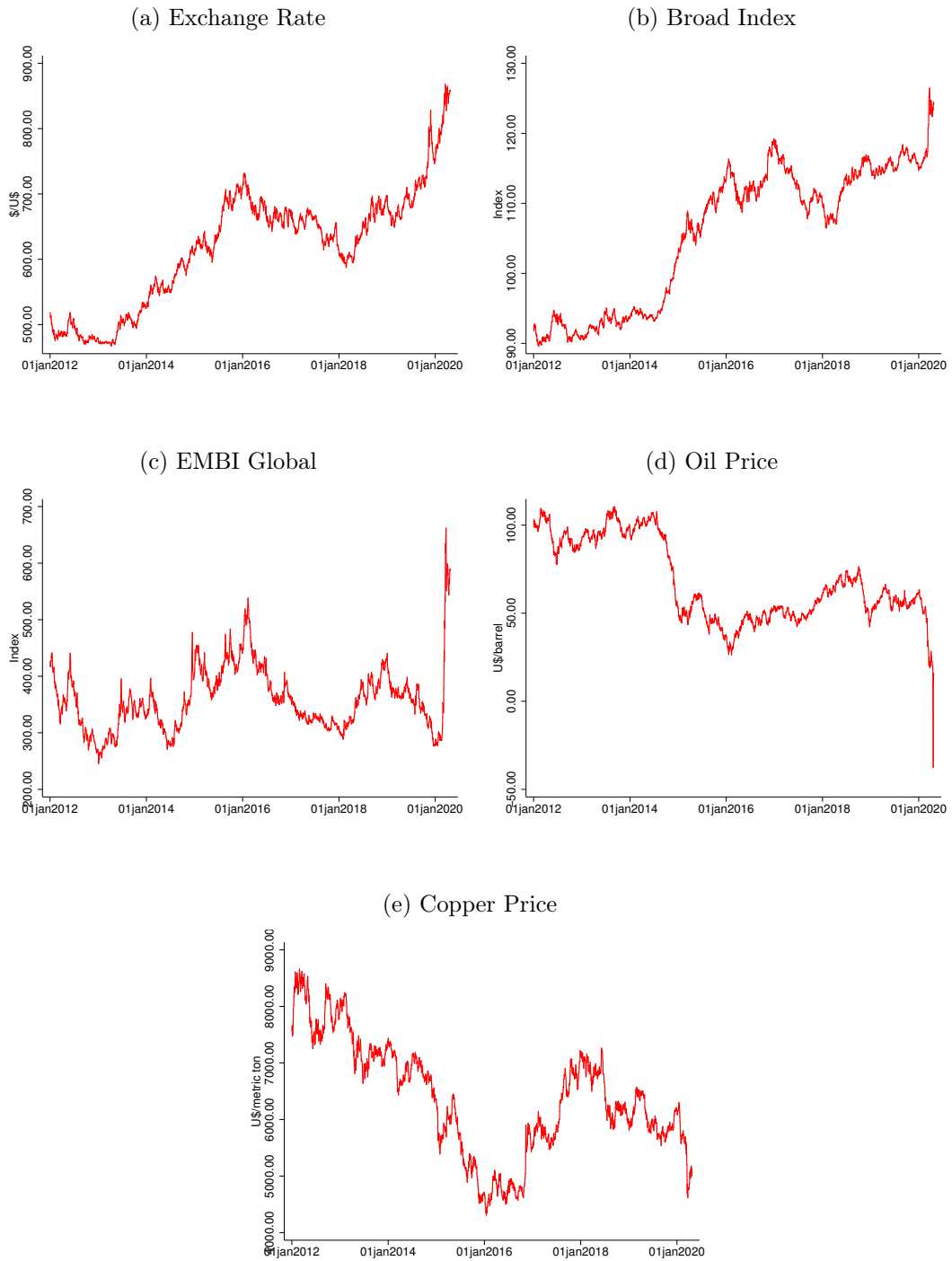
(e) Copper Price

Broad Index is a weighted average of the foreign exchange value of the US dollar against 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 6: (continued)

(f) Inflation US

(g) Inflation Chile

(h) Interest Rate Differential

(i) VIX

(j) Volatility of IPSA

Inflation US and Chile 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.

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Figure 8: Effects of DEPU on Exchange Rate
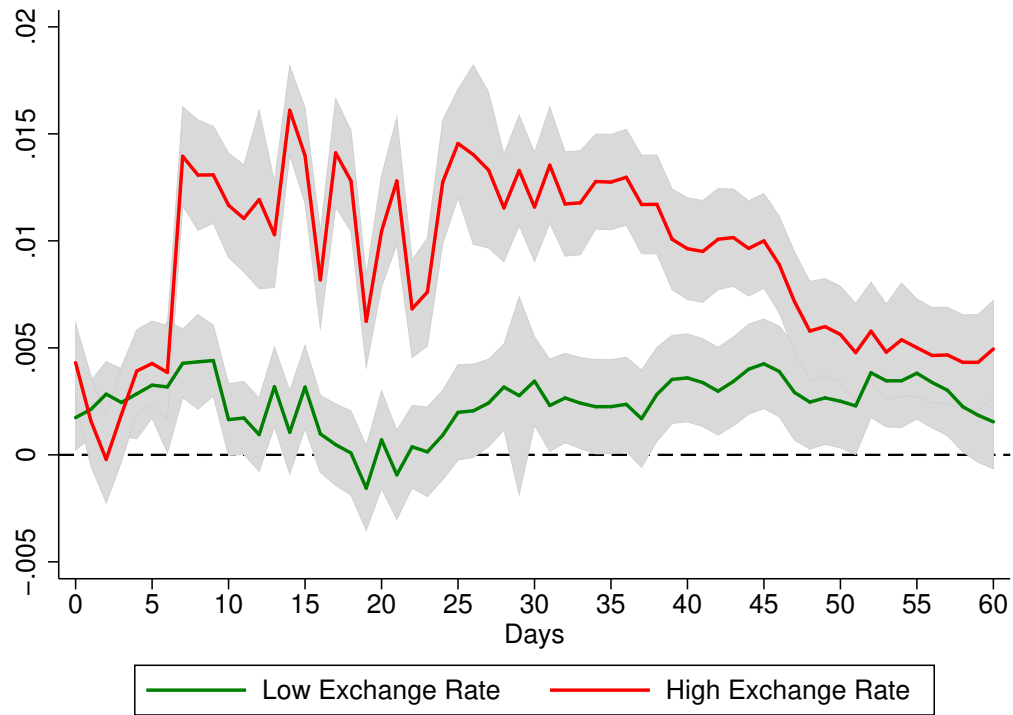
This figure shows the coefficients associated with DEPUC under specification (3) of the two-regimes Markov-switching model (5). Shaded areas represent the 95% confidence intervals, for each value of the forecasting horizon h, of the corresponding coefficients. Source: Authors' elaboration.

Table 1: Twitter Accounts Considered

Category	Official Twitter Account
Newscasts	@CHVNoticias, @T13, @CNNChile, @24HorasTVN, @Puntonoticias_
Newspapers	@Emol, @DFinanciero, @EYN_ELMERCURIO, @elmostrador, @pulso_tw, @Estrategiacl, @latercera
Radios	@biobio, @adnradiochile, @cooperativa

Source: Authors' elaboration.

Table 2: Descriptive Statistics of the Database

Daily tweets	Newscasts	Newspapers	Radios	Total
Mean	149	199	127	476
Std. Dev.	53	48	62	135
Minimum	86	114	84	305
P5	100	143	86	366
P95	242	278	227	636
Maximum	478	480	579	1497

P5 and P95 stand for the 5th and 95th percentile, respectively.
Source: Authors' elaboration.

Table 3: Dictionary of Keywords

Category	Subcategory	Words / Terms
Economy (E)		Any word / term beginning with "econ"
Policy (P)	Fiscal policy	"politica fical", "impuesto", "gasto publico", "deficit fiscal", "presupuesto", "tributaria", "deuda publica", "gasto fiscal", "presupuesto fiscal", "Ministerio de Hacienda", "Hacienda"
	Monetary policy	"Banco Central", "politica monetaria", "Reserva Federal", "FED", "tipo de cambio", "BCCh", "dolar"
	Trade policy	"arancel", "tratado de libre comercio", "TLC", "comercio internacional"
Uncertainty (U)		Any word / term beginning with "incer" and "incier"
Economic situation Chile (C)		"pais", "estallido social", "crisis", "crisis social", "nomasafp", "AFP", "colusion", "pensiones", "nueva constitucion", "constitucion", "asamblea constituyente", "asamblea", "constituyente", "COVID", "coronavirus", "pandemia"

Source: Authors' elaboration.

Table 4: Descriptive Statistics of Economic Uncertainty Measures

	Before Oct. 2019	After Oct. 2019	Full Sample
Panel A. DEPU			
Mean	-0.016	0.438	0.010
Std. Dev.	0.643	0.697	0.655
Skewness	1.068	0.730	1.037
Kurtosis	5.493	3.436	5.228
Autocorr.	0.262	0.394	0.290
Panel B. DEPUC			
Mean	-0.017	1.152	0.051
Std. Dev.	0.597	0.865	0.674
Skewness	0.631	0.105	0.925
Kurtosis	3.924	2.206	4.533
Autocorr.	0.216	0.667	0.389

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.

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