Understanding Uncertainty Shocks in Uruguay through VAR modeling

Bibiana Lanzilotta
Gabriel Merlo
Gabriela Mordecki
Viviana Umpierrez

INSTITUTO DE ECONOMÍA
Serie Documentos de Trabajo

Octubre, 2020
DT 17/2020

ISSN: 1510-9305 (en papel)
ISSN: 1688-5090 (en línea)

Forma de citación sugerida para este documento: Lanzilotta, B., Merlo, G., Mordecki, G., Umpierrez, V. (2020) "Understanding Uncertainty Shocks in Uruguay through VAR modeling". Serie Documentos de Trabajo, DT 17/2020. Instituto de Economía, Facultad de Ciencias Económicas y Administración, Universidad de la República, Uruguay.

Understanding Uncertainty Shocks in Uruguay through VAR modeling

Bibiana Lanzilotta[1] Gabriel Merlo[2] Gabriela Mordecki[3] Viviana Umpierrez[4]

Resumen

Utilizando diferentes índices de incertidumbre cuantificamos para Uruguay el impacto de la incertidumbre económica en un conjunto de variables nominales y reales, para una economía pequeña y abierta. Nuestros índices de incertidumbre construidos para Uruguay se basan en dos metodologías diferentes: noticias de prensa e índices compuestos que cubren aproximadamente 15 años de información mensual. Los hallazgos principales sugieren que la incertidumbre económica tiene, hasta cierto punto, un impacto en el sector real de la economía, mientras que no encontramos evidencia en el sector financiero. Este resultado puede vincularse a la elevada estabilidad de la economía Uruguaya así como al pequeño tamaño del sector financiero.

Palabras clave: incertidumbre económica, índice EPU, VAR, volatilidad, Uruguay

Código JEL: D80, E32, E37, E44

Abstract

Using different measures of uncertainty indexes, we quantify how economic uncertainty impacts on a set of nominal and real variables in a small and open economy like Uruguay. Our measures of uncertainty are based on two different methods: newspaper-based and composite index-based, covering roughly 15 years of monthly data. The main findings suggest that economic uncertainty has, to a certain extent, an impact on the real economy, whereas we find no evidence over the financial sector. This result can be linked to the high stability of the Uruguayan economy and the small size of its financial sector.

Keywords: economic uncertainty, EPU index, VAR, volatility, Uruguay

JEL Classification: D80, E32, E37, E44

[1] IECON, Universidad de la República, Uruguay, correo electrónico: bibiana.lanzilotta@gmail.com
[2] IECON, Universidad de la República, Uruguay, correo electrónico: gabrielmerlomatto@gmail.com
[3] IECON, Universidad de la República, Uruguay, correo electrónico: gabriela@iecon.ccee.edu.uy
[4] IECON, Universidad de la República, Uruguay, correo electrónico: vumpierrez@iecon.ccee.edu.uy

1. Introduction

In recent years, there is a growing body of empirical literature studying the effects of uncertainty on the economy. However, most of the studies concentrate on developed economies, while the evidence for emerging countries is more incipient. Continuing with previous efforts for emerging economies, we aim to contribute to the empirical literature in this subject by analyzing the effects of economic uncertainty for the case of Uruguay.

Uruguayan economy presents certain particular characteristics. First, it is a small and open economy located in South America between two big countries, Argentina and Brazil. It is mainly a commodity exporter, taking prices from international markets and operates under a flexible exchange rate system. In addition, it is a bi-monetary economy, where the US dollar plays a major role as a reserve of value: real estate and durable goods transactions are traded in this currency.

As a small and open economy, the interrelations and interdependencies among Uruguay and its relevant trading partners can sometimes lead to a lack of autonomy or loss of effectiveness of certain local economic policies. At the same time, foreign policies from relevant partners can have a direct impact on the Uruguayan economy due to its exposure to external shocks. Hence, although Uruguay may have a relatively well-ordered economic and institutional policy, it can be significantly affected by global uncertainty.

With this in mind, the purpose of this paper is to explore the impact of economic uncertainty on key macroeconomic variables for Uruguay. We consider three different measures as proxies for economic uncertainty, namely, the Economic Policy Uncertainty index (EPU), the LDA economic uncertainty index (based on Latent Dirichlet Allocation modeling)[5], and the Uncertainty Composite Index (CPU). The first two are newspaper-based indexes following the methodology of Baker et al. (2016) and Azqueta-Gavaldón (2017), respectively. The third one is a composite index built following the methodology proposed by Lanzilotta et al. (2018). This methodology combines the external uncertainty captured by the EPU index of Brazil, Chile, and the Global index -with domestic uncertainty measured as the standard deviation of the 12-month exchange rate forecasts collected by the Central Bank of Uruguay (BCU).

The rest of the paper is organized as follows. Section 2 reviews in more detail the literature on economic uncertainty. Section 3 presents the uncertainty index for Uruguay. Section 4 introduces the data and the empirical approach used for the analysis. Section 5 presents the main results. Finally, section 6 concludes.

2. Background

2.1 Uncertainty measures

There is a wide consensus among researchers that uncertainty is important to understand economic performance. There is also agreement that there is no single

[5] Probabilistic modeling method used in natural language processing to discover abstract topics in a collection of documents. It is also known as Topic Modeling. See Blei et al. (2003) for more details.

measure that properly captures this phenomenon. Several proxy indicators of uncertainty have been defined in order to measure economic uncertainty and its impact on economic activity.

The seminal paper of Bloom (2009) is one of the most important contributions to this empirical literature. The author documents a strong relationship between stock market volatility and other measures of uncertainty related to real activity (e.g., standard deviation of firm profit growth or standard deviation of GDP forecasts). Using stock market volatility as a proxy of economic uncertainty, the author finds that an increase in uncertainty leads to a sudden fall and a subsequent overshooting in employment, output, and productivity growth. This evidence underlines the relevance of exogenous uncertainty shocks to the economy and how it can be affected by financial market volatility.

Measures of financial volatility are the most common and widely used indicators of uncertainty, but they are not the only ones. Other measures include discrepancies in survey-based forecasts made by experts (Ferderer, 1993) or managers (Bachmann et al., 2013; Bloom et al., 2017). The idea behind these types of measures is to capture the uncertainty of decision-makers, who play an important role in investment and innovation decisions.

More recently, the uncertainty measures developed by Baker et al. (2016) set a turning point in the study of the effects of uncertainty shocks on real activity. They introduced a novel indicator of economic uncertainty: the Economic Policy Uncertainty index (EPU), which is a uniform methodology for measuring uncertainty based on newspaper text searching. This indicator is currently being used in a wide range of countries, both in the developed and developing world. Moreover, the EPU index methodology is used as a basis for generating complementary measures. For example, Bontempi et al. (2016) estimate another uncertainty indicator using information from Internet queries, and Fundação Getulio Vargas (FGV) developed a composite index based on a weighted sum of EPUs for different countries (FGV, 2016). In addition, Ahir et al. (2019) constructed a World Uncertainty Index (WUI) for 143 countries using the Economist Intelligence Unit country report with quarterly frequency. This is a panel index of uncertainty for a large set of developed and emerging economies.

2.2 Transmission channels

There is a strand of literature that studies the effect of uncertainty transmissions channels based on its importance for economic activity. One major branch of this literature studies how uncertainty shocks drive fluctuations and explain the volatility in the business cycle through its negative impact on consumption and investment. In this sense, this research line seeks to find a linkage between the financial and monetary sectors with the real economy. For example, Leduc & Liu (2016) study how uncertainty shocks affect aggregate economic activity through the interaction from labor search frictions and an aggregate-demand channel associated with nominal rigidities. They found that uncertainty shocks conduct to a rise in unemployment, and declines in inflation and the nominal interest rate. Moreover, uncertainty can lead to an economic recession when adding search frictions.

On the other hand, Punzi (2020) investigates the international transmission of uncertainty between the financial and the real sector. In this case, the spillover effect arises through the banking channel where domestic banks suffer from decreasing demand from foreign households. Finally, Abid (2019), through an ARDL model, explores the effects of EPU on exchange markets, focusing on emerging economies for two main reasons. First, they usually experience strong currencies fluctuations, and second, trade structures are mainly based on commodities which prices are exposed to greater volatility in international markets. The countries included in the study are South Korea, India, Brazil, Mexico, and Chile. The main finding is that in the long-run, the uncertainty measured through EPU has a negative impact on exchange rate movements.

In order to investigate the relationship between uncertainty in output and investment, Ahir et al. (2019) estimate impulse response functions for one standard deviation increase of the WUI uncertainty index, finding that an increase in uncertainty can lead to a decline in both output and investment. According to these authors, the average effects mask important differences across countries depending on the level of institutional quality. Specifically, the effect of uncertainty is large and persistent in countries with a relatively lower institutional quality and is smaller and short-lived in countries with relatively high institutional quality.

Despite the increasing interest among economists in studying uncertainty shocks, most papers refer to developed economies, where financial markets are highly developed. In this sense, Carrière-Swallow & Céspedes (2013) made a significant contribution by comparing the uncertainty effects on economic activity between emerging and developed countries. Using an open-economy VAR approach, they estimate the response of investment and private consumption to global uncertainty shocks for a group of forty heterogeneous countries, consisting of twenty developed and twenty emerging economies. Their results point to the different reactions of emerging and developing countries to a global uncertainty shock. For emerging countries, they find an average fall in investment that is approximately four times as large as that found in developed countries. Moreover, developing economies experience a sharp drop in private consumption, while developed countries do not experience such an impact. They also noted that, on average, the recovery time from such a shock is much longer for emerging markets.

Delving specifically into the evidence for South American countries, we find the work of Barboza & Zilberman (2018) that studies the uncertainty effects on Brazilian economic activity or Cerda et al. (2017) that analyzes the Chilean case. For the Brazilian case, Barboza & Zilberman (2018) construct several proxies to capture the impact of domestic and external uncertainty (measured as the uncertainty of Brazil's main trading partners) and estimate structural vector autoregressions models following Baker et al. (2016). Using monthly data for the period from 2002 to 2016, they found that uncertainty has a significant effect on activity, and mainly on investment. Furthermore, their results show that the effects of domestic uncertainty outweigh the effects of external uncertainty. This evidence leads them to conclude that domestic uncertainty is an essential variable as a determinant of the Brazilian economic cycle.

Cerda et al. (2017) reach a similar result for the Chilean economy in the period 1992-2015. This case is of particular interest to Uruguay, because both Chile and Uruguay share similar characteristics in terms of being small and open economies, mainly exporters of commodities. Based on Baker et al. (2016), they construct an economic uncertainty index similar to the EPU index using the newspaper "El Mercurio." Through the estimation of VAR models, they find that an increase in economic uncertainty leads to a fall in GDP, investment, and employment with negative effects on the economy, even in the long-run.

So far, the results seem to convey a clear message. First, economic uncertainty plays a significant role in determining real activity, and second, the effects on emerging economies, compared to developed countries, seem to be significantly more profound. In particular, open and emerging economies are more vulnerable to global uncertainty and face more constraints than developed economies in finding an orderly way out. Moreover, interrelations and interdependencies among economies could facilitate not only to receive external uncertainty shocks but also amplified domestic uncertainty in developing economies. Our paper aims to contribute to the scarce empirical literature of economic uncertainty for small and open economies in the developing world. In the following section, we provide some insight into the available measures of uncertainty for Uruguay, which will be our input for analyzing uncertainty shocks on economic activity.

3. Uncertainty Indexes for Uruguay

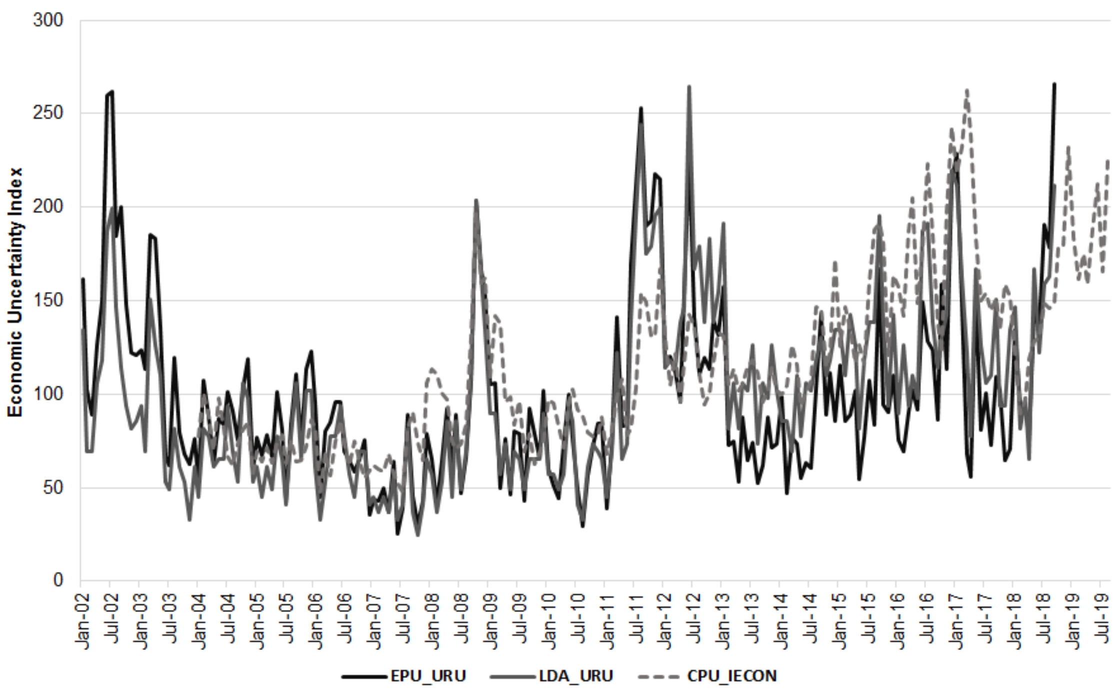
A set of uncertainty indexes have been recently developed for the Uruguayan economy. In this paper, we consider three alternative domestic uncertainty indexes with a monthly frequency. Two of them elaborated by Crocco et al. (2019) and a third one from Lanzilotta et al. (2018).

The first index, EPU Uruguay (Crocco et al., 2019), follows the methodology proposed by Baker et al. (2016) which consists of counting the relative monthly frequency of newspaper articles containing a trio of terms related to economy (E), politics (P), and uncertainty (U). In this case, we use the local newspaper "El Observador" as the source of news articles. Following the same methodology, Crocco et al. (2019) constructed another EPU index that combines the frequency of articles in three different local newspapers: "La Diaria," "Búsqueda," and "El Observador." For our analysis, we select the first index, based only on the news from "El Observador"-which is the only one available since 2002- given that the digital archives of the other two newspapers are not extensive enough to use for the purpose of our paper.

The second selected uncertainty index from Crocco et al. (2019), was constructed following Azqueta-Gavaldón (2017) and using a Latent Dirichlet Allocation (LDA) model. LDA-based models are a form of text data mining and statistical machine learning which consist in clustering words into "topics," clustering documents into "mixture of topics" and then applying a Bayesian inference model that associates each document with a probability distribution over topics, where topics are determined as the probability distribution over words. Specifically, LDA following Dirichlet distribution, initially assigns a probability p_(d,t) that document d belongs to topic t. Using an alternative procedure based on Jagarlamudi et al. (2012), Crocco et al. (2019) initialize LDA index through topical seeds, which take as reference the same categories used in the EPU index. The idea behind this method is to add probability to each word influenced not only by the Dirichlet distribution but also by the initial topics. Therefore, a new uncertainty indicator is obtained through a semi-supervised machine-learning algorithm named LDA index. As far as we know, this is the first index constructed by following this methodology for a developing country, which makes it a novel contribution that expands the methodologies for developing news-based uncertainty indexes. Table A1, in the Appendix, shows the final topics obtained after applying this approach.

Finally, Lanzilotta et al. (2018) constructed the third uncertainty index available for Uruguay, and it was constructed as a composite index, following the methodology proposed by Fundación Getulio Vargas (2016). Through the weights obtained by principal components analysis (PCA), it combines the EPUs of Brazil, Chile and the Global EPU with the standard deviation of the 12-month forecast of Uruguayan peso to US dollar exchange rate (calculated from the survey conducted by the BCU among economic analysts and experts). The idea behind this indicator is to capture the external uncertainty that relies on the evolution of the EPU indexes aforementioned and the domestic uncertainty, reflected in the deviation of exchange rate expectations. As stated previously, Uruguay is a price taker in international markets and operates under a flexible exchange rate system since 2002. Hence, a good approach to internal economic uncertainty is to consider deviations of exchange rate forecasts. Figure 1 shows the evolution of these three indices.

Figure 1 – Uncertainty indexes for Uruguay



Source: Author's calculations and Crocco et al. (2019).

As can be seen, the fluctuations in the three indicators of uncertainty estimated for Uruguay are very similar. All the series move very close together, with few exceptions. The relative co-movement of the indexes with the events that took place in the United States during this period is evident. For example, the bankruptcy of Lehman Brothers (Sept-2008), the fiscal stimulus package (Jan-2009), and the US debt downgrade (Aug-2011) are the most relevant. Other global episodes also impacted on these indexes: the global financial crisis (Oct-2008), the Panama papers scandal (Mar-2016), and the Brexit (Jun-2016). At a regional level, the Uruguayan uncertainty indexes spike at the time of Dilma Rousseff impeachment (Apr-2016). Finally, it is important to point out that the newspaper-based uncertainty indexes in Uruguay show a peak in June 2002, when one of the greatest crises in the country's history took place. This implies that Uruguayan indexes capture both domestic and global uncertainty. Figure A1 (in the Appendix) compares the evolution of the global uncertainty index with the Uruguayan uncertainty index.

4. Data and Empirical Strategy

4.1 Data

To study the impact of uncertainty on economic activity we consider a set of financial and nominal variables: devaluation and inflation rate, percentage of deposits in foreign currency over total deposits, as well as a set of real variables: industrial production index (IPI), imports of capital goods index, employment, total sales of new cars, and domestic VAT revenue.

Regarding financial variables, it is important to take into account that Uruguay does not have a developed financial market, and it is a highly dollarized economy (which explains, for example, the high share of foreign currency deposits in domestic banks). In relation to the selection of the variables on real activity, we seek to consider monthly proxies of GDP (industrial production and employment rate), capital investment (imports of capital goods), durable consumption (sales of new cars), and overall consumption (domestic VAT revenue), since production, investment and consumption measures in the National Accounts are only available on a quarterly basis.

Additionally, a set of global variables are introduced in order to account for the possible effect of exogenous shocks in global activity, prices and international uncertainty. This block of variables comprises a price index of Uruguayan exports, Global EPU index (GEPU), and the VIX volatility index[6].

In the first model, the series cover a period of about fifteen years: from February 2005 to September 2018. All series are recorded on a monthly basis. A brief description of the selected series and sources is given in Table A2. The series are seasonally adjusted and

[6] VIX is the ticker symbol and the popular name for the Chicago Board Options Exchange's CBOE Volatility Index.

considered in logarithms (if applicable), and those identified as non-stationary, in their first difference.

In a second model, trying to show the impact of the recent Covid-19 shock, as LDA and EPU are not available from September 2018 onward, and Chilean EPU was only updated up to February 2020, we built a new CPU (CPU3). This index only considers the global EPU, Brazilian EPU, and the standard deviation of the 12-month exchange rate forecasts collected by BCU, with weights also obtained by PCA. As we can see in Figure A2 (Appendix), both series have a similar trajectory, and they were considered from February 2015 to June 2020.

4.2 Empirical strategy

We estimate conventional reduced-form vector autoregression models (VAR) which can be specified as:

$$Y_t = A_0 + \sum_{n=1}^{12} A_n Y_{t-n} + u_t \qquad (1)$$

Where Y_t is a column vector kx1 of endogenous variables, n=12 is the VAR model order, or the number of lags of each variable in each equation, and u_t is a kx1 vector of innovations, i.e., processes without serial correlation, with $Var(u_t) = \sum_u$ constant. This methodology allows us to analyze the effects of shock simulations on the various random disturbances in the system by computing the impulse-response functions (IRF) and the variance decomposition.

Three alternate models are estimated for each uncertainty index and the selected nominal and activity indicators as endogenous variables. Figure A3 plots all endogenous variables for the full period of analysis. To analyze the impact of Covid-19 shock, we use the CPU3 index, through the same VAR methodology, calculating forecasts of selected variables for one and two steps.

5. Results

5.1 Main findings

Figure 2 shows the accumulated impulse response functions (IRFs) after an orthogonalized shock of one standard deviation in our three versions of the local uncertainty index. We started considering all variables proposed (see Table A2). However, mainly all financial and nominal variables were excluded from the models because the nominal variables did not provide significant information. In order to achieve a more parsimonious model, they were not considered for the following analysis of results. All responses are shown for a 12-month horizon and are accompanied by one and two standard deviation confidence intervals. Standard deviations have been estimated using a parametric bootstrapping procedure with 200 simulations. The order of the variables (from most exogenous to most endogenous) in all models is the same: uncertainty index, IPI, imports of capital goods index, and total sales of new cars.

First of all, it is interesting to see that the IRFs considering the three different uncertainty measures show a different impact on the variables, analyzing the path of propagation of the initial uncertainty shocks. One common result is that the signs of the answers to the shocks are all negative, in line with what the theory tells us.

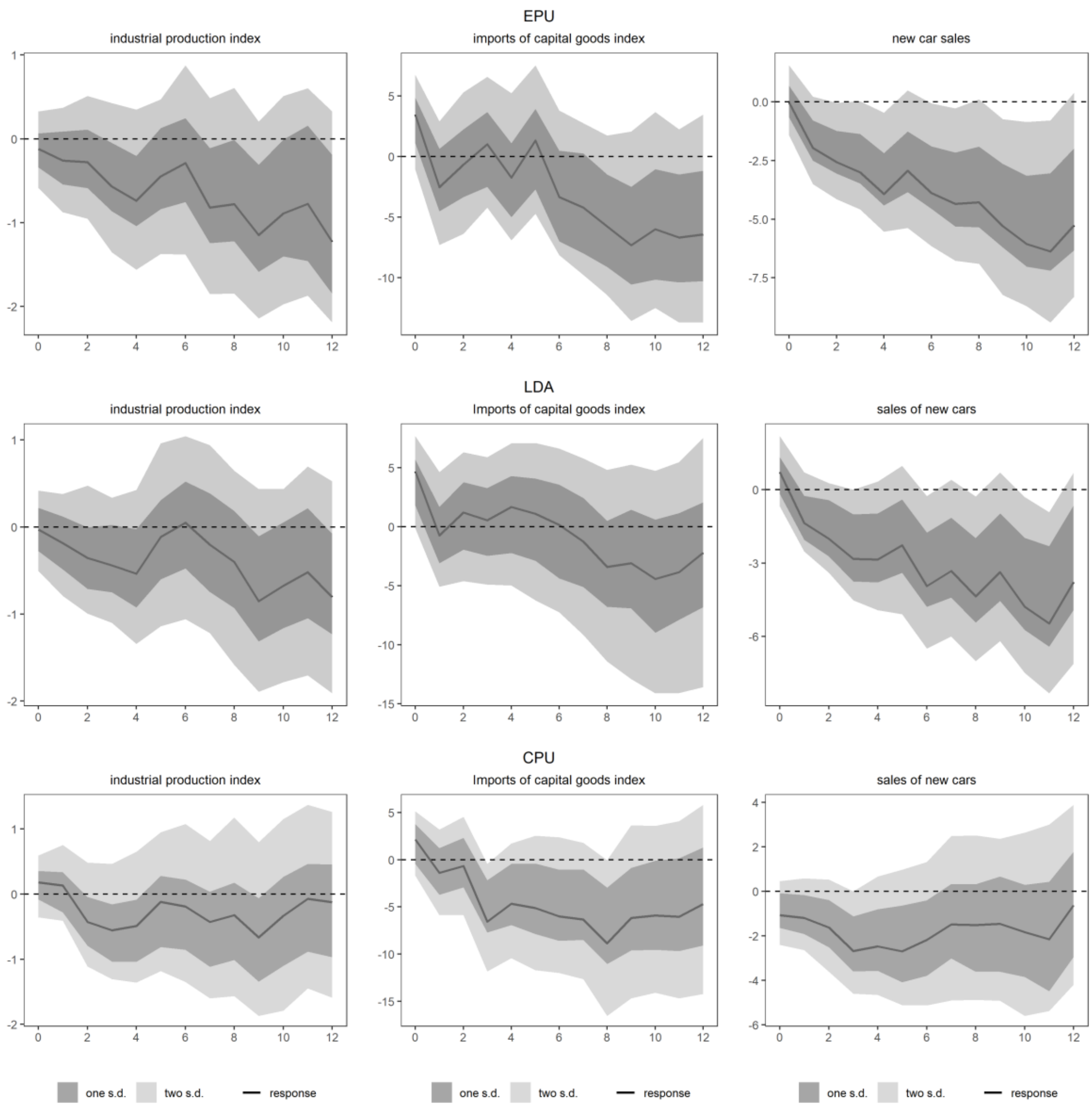
Considering the EPU shock, taking into consideration the interval of one standard deviation (the dark grey shaded area) the impact is different from zero mainly after six months, and the new car sales is the variable that shows the more significant impact of the shock.

Analyzing the results of an uncertainty shock considering the LDA index, impacts appear to be less important than the ones shown by the EPU index. In particular, the response of imports of capital goods to an LDA shock does not appear to be different from zero, considering one standard deviation interval.

Regarding the responses of the different variables to a CPU shock, they appear somewhat different from the LDA. In this last case, new car sales seems to lose impact as more months are considered, and on the contrary, imports of capital goods show a bigger impact than in the other cases.

In short, the important thing that comes out of this analysis is that there is an impact of uncertainty, regardless of which measure is chosen, on relevant real variables in the economy. As noted above, we discarded the financial and nominal variables because they did not provide relevant information to the model. This may be due to the particularity of the Uruguayan economy, which is small and has underdeveloped financial markets. Therefore, the impact of uncertainty is mostly verified in the real variables.

Figure 2 – Accumulated response to an orthogonalized local uncertainty shock

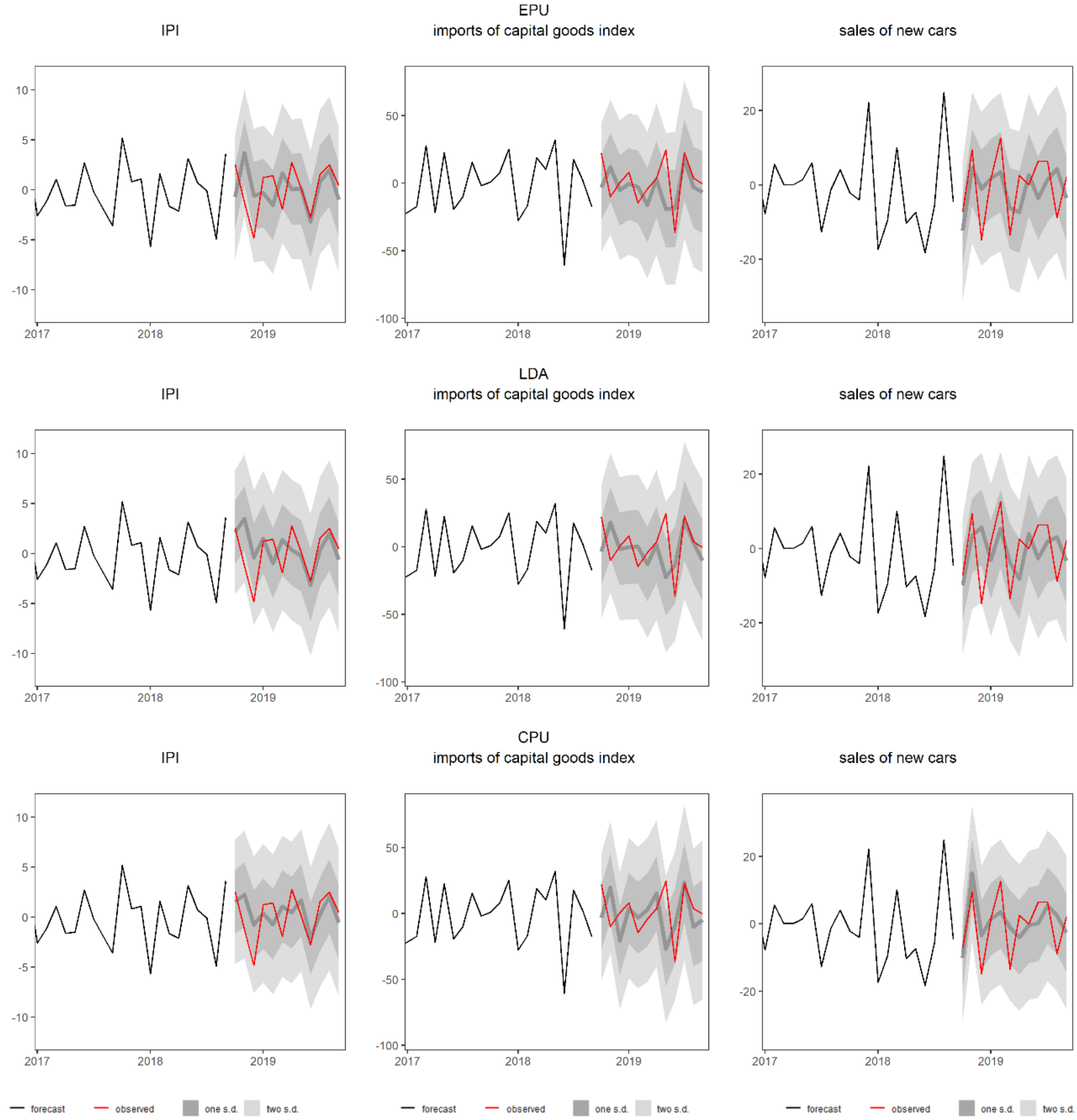


Source: Author's calculations

5.2 Forecasting performance

To analyze the predictive power of the models, we forecast the model from November 2018 onward, and then compared the results of the projections (in grey) with the values of the series (in red), for the three indexes. In the three cases, the most accurate forecast seems to be the imports of capital goods, but all three show a similar trajectory to the actual value of the series.

Figure 3 – 12 steps ahead forecast for each uncertainty index VAR model



Source: Author's calculations

5.3 Covid-19 shock

Regarding the impact of COVID-19 there is a growing literature that is analyzing the impact of the novel Coronavirus in uncertainty and the economy.

Leduc & Liu (2020) analyzes its effects on uncertainty at the U.S. economy and find evidence that by raising uncertainty, the coronavirus affects the economy in a way similar to a decline in aggregate demand. Nevertheless, through the uncertainty channel, the pandemic is likely to weigh on the economy persistently beyond the short-term, also affecting the supply-side effects such as supply chain disruptions and labor shortages.

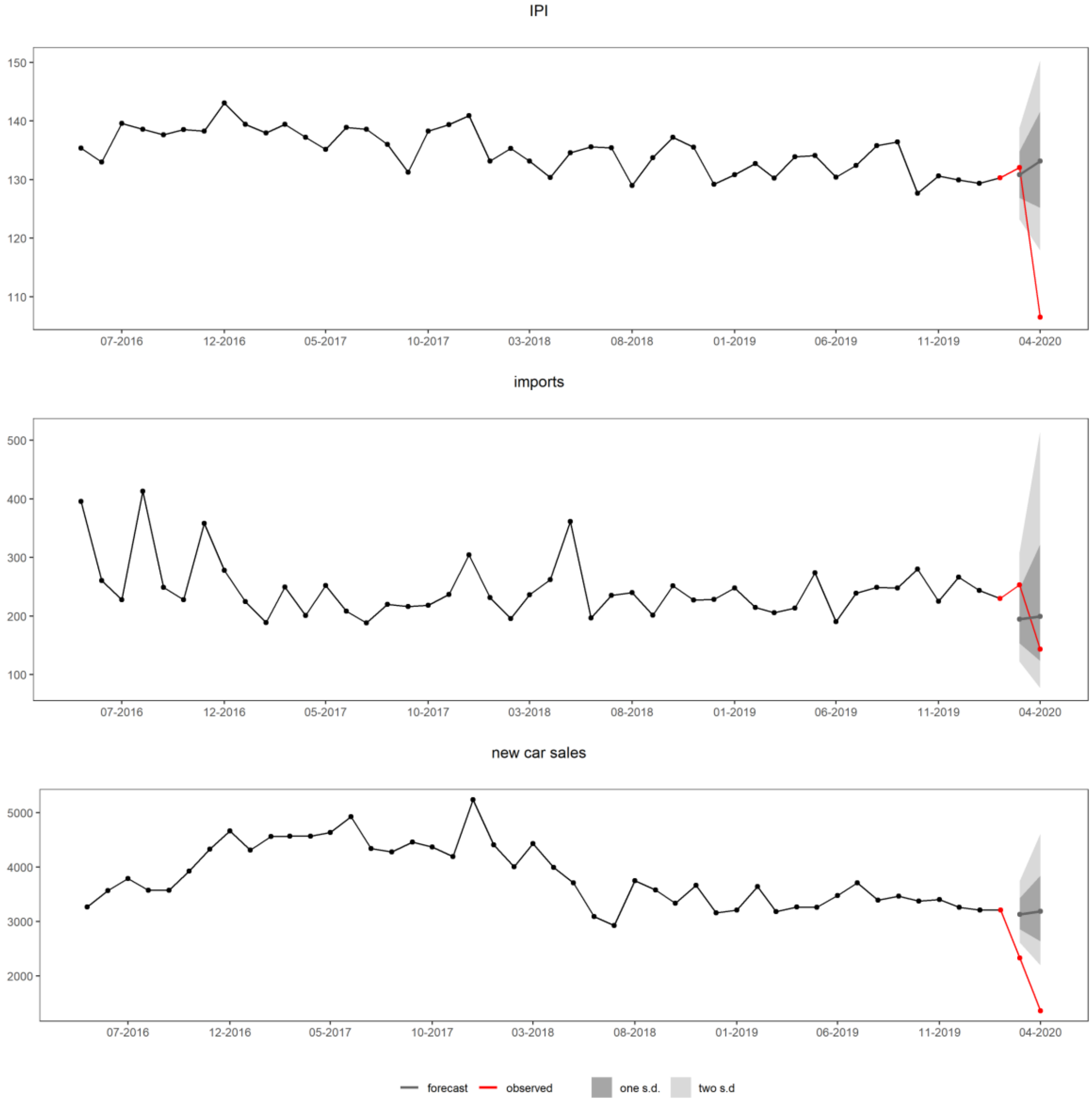
On the other hand, Baker et al. (2020) point out that effects of COVID-19 developments and policy responses on the U.S. stock market are without historical precedent. Finally, Altig et al. (2020) consider several economic uncertainty indicators for the U.S. and U.K (stock market volatility, newspaper-based policy uncertainty and forecaster disagreement about future GDP growth), before and during COVID-19 pandemic. They find a huge uncertainty jumps in reaction to the pandemic and its economic fallout and most indicators reach their highest values on record. They also highlight that COVID-19 pandemic and its economic fallout lack close historic parallels because the suddenness and huge of the massive job losses and due to the severity of the economic contraction relative to the size of the mortality shock. They fit vector autoregressive models (VARs) to estimate the relationship of output and employment to uncertainty in U.S. data and find that COVID-size innovation represent a 19% fall in industrial production. This magnitude is about four times as large as the drop implied by 2008/09-size uncertainty shock. They point out that ongoing high levels of uncertainty do not bode well for a full and rapid economy recovery because elevated uncertainty generally leads to consumers and enterprises to be more cautious, retarding investment, hiring and expenditures on consumer durables.

Trying to show the impact of the recent Covid-19 shock, we built a second model considering a new index. As LDA and EPU are not available from September 2018 onward, and Chilean EPU was only updated up to February 2020, we built a new CPU (CPU3). This index only considers the global EPU, Brazilian EPU, and the standard deviation of the 12-month exchange rate forecasts collected by BCU, with weights also obtained by PCA.

In figure 4, we show the result of the forecast of the model, comparing it with the results of the variables from March 2020, when the impact of the pandemic in Uruguay was verified. As can be seen, both in the case of industrial production and for the sale of new cars, the series values fall outside the margins of one and two standard deviations of the original model's forecast. In this sense, albeit in different magnitude, it is possible state that the negative effects of the coronavirus in terms of industrial production and durable goods (accounted by the new car sales) are similar to those found in the recent international literature.

But we cannot say this for capital goods imports, whose trajectory falls within the limits of the confidence interval. This last result can be portraying the low impact that uncertainty shocks appear to have in this variable, as discussed when analyzing the IRFs.

Figure 4 – Two steps ahead median forecast for CPU VAR model



Source: Author's calculations

6. Final Remarks

The objective of this paper is to contribute to the scarce literature on economic uncertainty for small and open economies in the developing world. In this sense, we explore the impact of economic uncertainty on key macroeconomic variables for Uruguay. We consider three different measures as proxies for Uruguayan economic uncertainty computed through different techniques.

It is important to note that Uruguayan economy, as a small and open economy, is considerably exposed to international shocks, but, at the same time, it possesses strong institutions that may help mitigate external shocks (e.g., they could provide trust to investors maintaining policy rules through time). In addition, it is a bi-monetary economy, in which the US dollar plays a major role as a reserve of value, especially under volatile and uncertain periods.

Our results show the impact of economic uncertainty shocks represented by the economic uncertainty index on real variables, as nominal variables were excluded from the models in order to obtain more parsimonious representations. This result is similar to those found in Abid (2019) but slightly differs from those found in Carrière-Swallow & Céspedes (2013) for emerging countries.

Impulse-response functions show an important impact of uncertainty represented by the three different indexes, with the greatest impact on industrial production and new car sales, while the impact on capital goods imports appears to be less relevant. This result may be a consequence of the decision making related to the import of capital goods, which in Uruguay is a good proxy for investments in capital goods, since Uruguay does not have a national industry of this type of goods. In general, these are longer-term decisions and surely are not as affected as other decisions, such as the purchase of new cars, due to the uncertainty shocks in the economy.

The comparison between the series' forecasts with the actual series also shows the relationship between the uncertainty captured by any of the measures used in the evolution of the different economic series analyzed here.

This illustrates the usefulness of these novel measures of domestic uncertainty in order to anticipate and minimize the effects of adverse shocks. A greater effort is needed to completely understand the channels of transmission of uncertainty in the case of Uruguay.

To complement this analysis, we developed a fourth indicator, CPU3, which includes the uncertainty up to June 2020, when the COVID-19 shock effects could be captured by the uncertainty measures. Based on this new model, we also made a comparison between the series values and the model projections from February, when the index had not yet registered the shock of the outbreak of the pandemic in Uruguay. Here again, we find that the greatest impact is on industrial production and especially on the sale of new cars, while the impact on imports of capital goods is lower. In this sense, albeit in different magnitude, it is possible state that the negative effects of the coronavirus in terms of industrial production and durable goods (accounted by the new car sales) are similar to those found in the recent international literature (Altig et al., 2020; Baker et al., 2020, Leduc & Liu, 2020).

References

Abid, A. (2019). *"Economic Policy Uncertainty and Exchange Rates in Emerging Markets: Short and Long Runs Evidence"*. Finance Research Letters.

https://doi.org/10.1016/j.frl.2019.101378

Ahir, H., Bloom, N. & Furceri, D. (2019). *"The World Uncertainty Index"*, Stanford mimeo.

Altig, D., Baker, S., Barrero, J.M., Bloom, N., Bunn, P., Chen, C., Davis, S.J. (2020). *"Economic Uncertainty Before and During the COVID-19 Pandemic"*. Journal of Public Economics 191. https://doi.org/10.1016/j.jpubeco.2020.104274

Azqueta-Gavaldón, A. (2017). *"Developing news-based Economic Policy Uncertainty Index with unsupervised machine learning"*. Economic Letters 158 pp. 47-50.

Bachmann, B. R., Elstner, S., & Sims, E. R. (2013). *"Uncertainty and Economic Activity: Evidence from Business Survey Data"*. American Economic Association 5(2), 217–249.

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

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). *"The Unprecedented Stock Market Reaction to COVID-19"*. White Paper June 2020. Becker Friedman Institute.

Barboza, R. D. M., & Zilberman, E. (2018). *"Os efeitos da incerteza sobre a atividade econômica no Brasil"*. Revista Brasileira de Economia, 72(2), 144-160.

Blei, D. & Lafferty, J. (2009). *"Topic Models"*.

http://www.cs.columbia.edu/~blei/papers/BleiLafferty2009.pdf

Bloom, N. (2009). "The Impact of Uncertainty Shocks". Econometrica, 77(3), pp. 623-685.

Bloom, N., Davis, S. J., Foster, L., Lucking, B., Ohlmacher, S., & Saporta Eksten, I. (2017). *"Business-level expectations and uncertainty"*. Available at SSRN 3085377.

Bontempi, M.E., Golinelli, R. & Squadrani, M. (2016). *"A New Index of Uncertainty Based on Internet Searches: A Friend or Foe of Other Indicators?"* https://doi.org/10.13140/RG.2.1.5179.3048

Caldara, D., Fuentes-Albero, C., Gilchrist, S. & Zakrajsek, E. (2016). *"The Macroeconomic Impact of Financial and Uncertainty Shocks"*. NBER Working Paper 22058. http://www.nber.org/papers/w22058

Carrière-Swallow, Y. & Céspedes, L.F. (2013) *"The Impact of Uncertainty Shocks in Emerging Economies"*. Journal of International Economics 90 (2013) pp. 316-325.

Cerda, R., Silva, A. & Valente, J. (2017). *"Impact of Economic Uncertainty in a Small Open Economy: the case of Chile"*. Applied Economics, 50:26, pp. 2894-2908, DOI: https://www.tandfonline.com/doi/full/10.1080/00036846.2017.1412076

Crocco, S., Dizioli, G., Herrera & S. (2019). *"Construcción de un indicador de incertidumbre económica en base a las noticias de prensa"*. Tesis de Grado. Biblioteca Central de la Facultad de Ingeniería, Universidad de la República, Uruguay.

Ferderer, P. J. (1993). *"Does Uncertainty Affect Investment Spending?"* Journal of Post Keynesian Economics, 16(1), 19–35.

Fundaçao Getulio Vargas - Instituto Brasileiro de Economia. (2016). *"Metodologia para o cálculo do indicador de incerteza da economia Brasil"* (IIE-Br), 3.

Jagarlamudi, J., Daume, I., & Raghavendra, U. (2012). *"Incorporating Lexical Priors into Topic Models"*. Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics, pp. 204-2013.

Lanzilotta, B., Mordecki, G. & Umpierrez, V. (2018). *"Political Economic Uncertainty in a Small and Open Economy: the Case of Uruguay"*. IECON, UDELAR, DT 05/2018. ISSN/ISBN: 1688-5090.

Leduc, S. & Liu, Z. (2016). *"Uncertainty shocks are aggregate demand shocks"*. Journal of Monetary Economics, 82, pp. 20-35.

Leduc, S. & Liu, Z. (2020). *"The Uncertainty Channel of the Coronavirus"*. Economic Letter. Federal Reserve Bank of San Francisco.

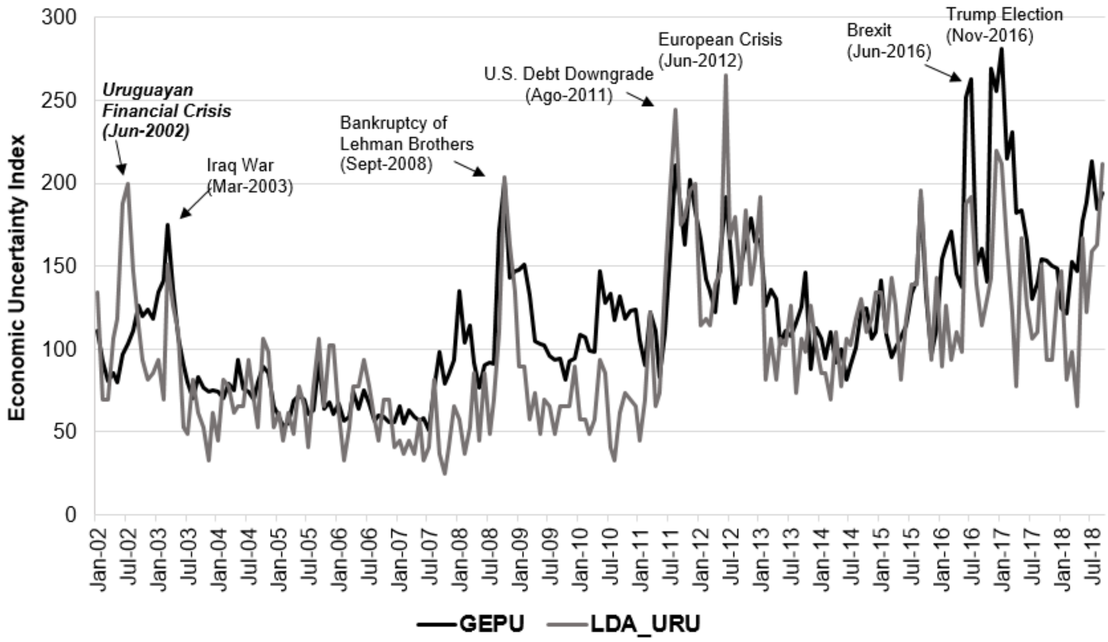
Punzi, M.T. (2020). *"The impact of uncertainty on the macro-financial linkage with international financial exposure"*. Journal of Economic and Business.

https://doi.org/10.1016/j.jeconbus.2020.105894

Appendix

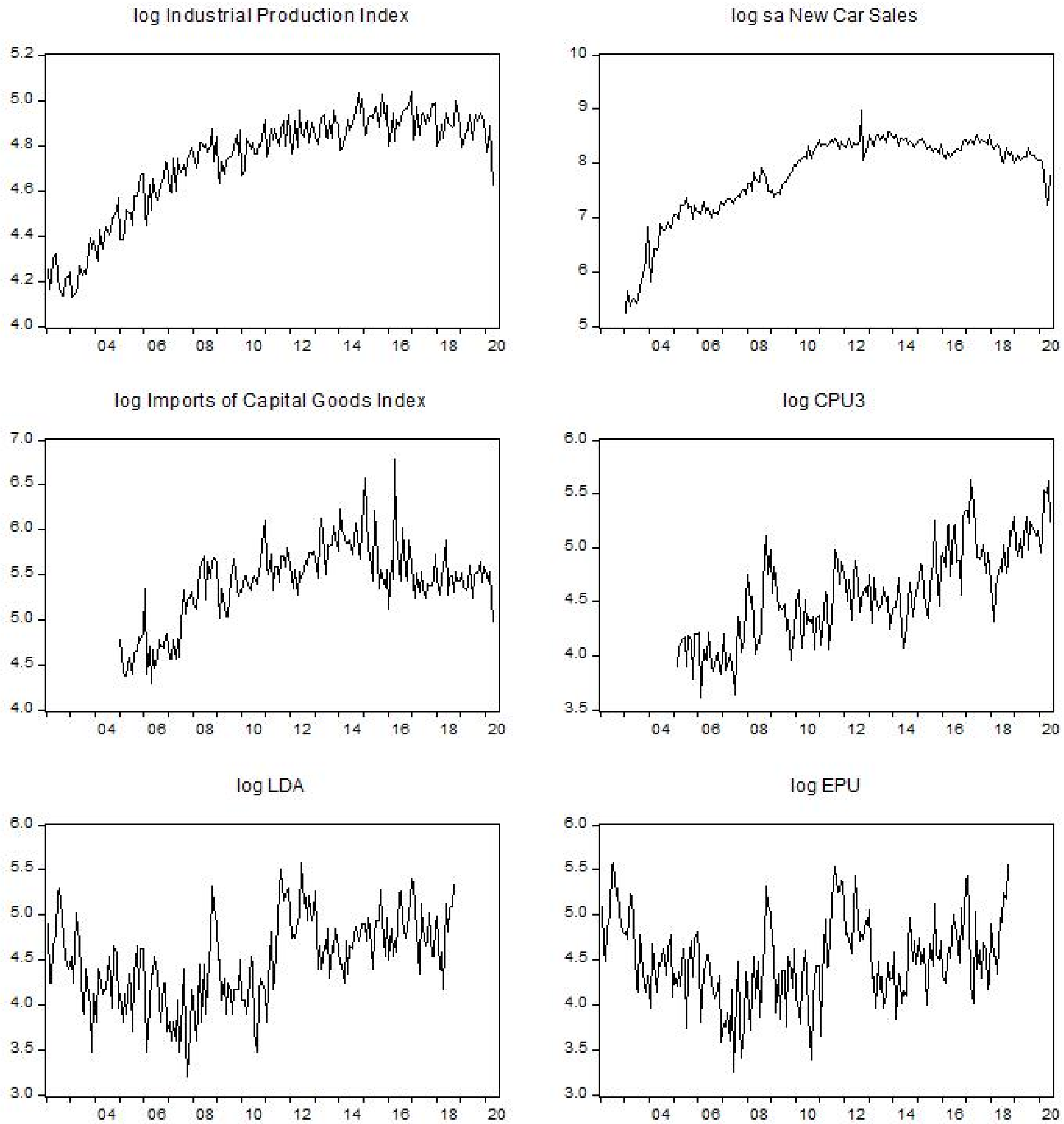
Appendix A Figures

Figure A1 – Evolution of global EPU vs. LDA URU uncertainty index



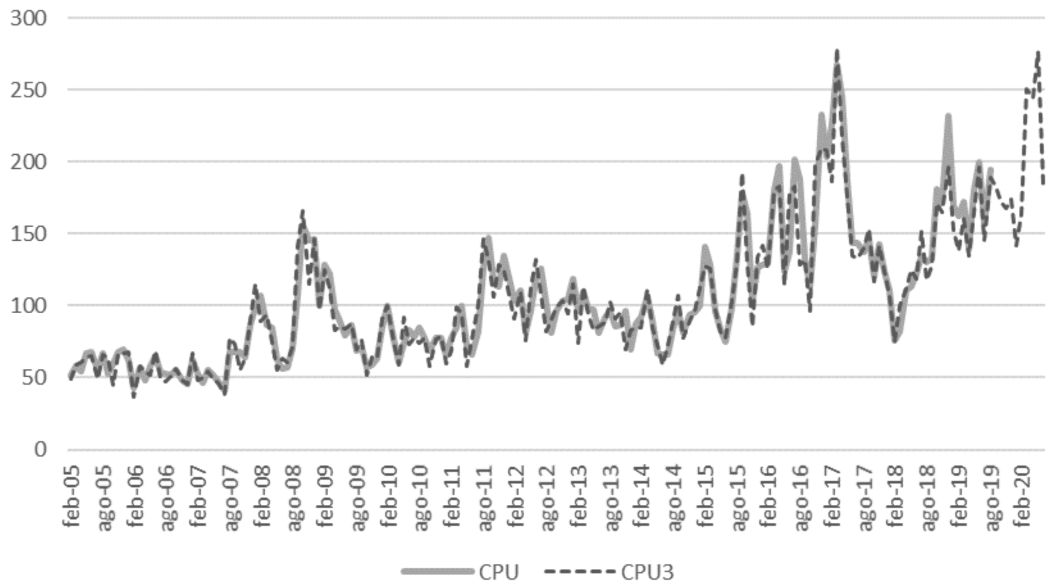
Source: https://www.policyuncertainty.com/ and Crocco et al. (2019)

Figure A2 – Endogenous variables – log transformation



Source: Author's calculations from official websites

Figure A3 – Evolution of CPU and CPU3 uncertainty indexes



Source: Author's calculations

Table A1 – LDA uncertainty index: topics

Topic	Words
1	mundi, unic, crecimiento, europ, edifi, choqu, impuest, eur, unidos, interes, riesg, ubic.
2	presupuest, ejerc, franci, volunt, eleccion, canast, variacion, ministeri, optim, deud, gir
3	financieros, garantiz, publica, paises, deten, uruguaya, defend, ministeri, ajust, interpret, cediti, impos, flotacion, Duhalde
4	soberan, calm, mundial
5	uruguaya, expertos, productividad, apuntal, produj, productivo, impid, bordaberry, costos, carl, comport, individual, ven, empez, socied
6	tarif, dobl street, bols, reisg, uruguaya, docent, interven, deten, intendent, inest, monedas, central, opon, calm, tir, mont, bloque, comport, pobr, linea, Batlle, coyuntur, gestión, Bordaberry, calcul, favorec
7	crecimiento, inest, interpret, productivo, cae, creciendo, trimestr, especializ, registr, tarif, calm, consumidores, region, incorpor, expertos, deflacion, apuntal.
8	empez, legisl, proyecto, negr, nasdaq, gobierno, interpret, efecto

Table A2 – Description of the Series

Type	Variable Name	Definition	Source
Local Uncertainty	epu	economic policy uncertainty index calculated using "El Observador" newspaper	Crocco et al. (2019)
	lda	epu index using unsupervised lda technique using "El Observador" newspaper	Crocco et al. (2019)
	cpu	composite policy uncertainty index	Lazilotta et al. (2018)
	sd_next12m	standard deviation of exchange rate expectations (experts survey)	BCU
Global Uncertainty	gepu	global economic policy uncertainty index (GDP weights)	Economic Policy Uncertainty
	gepu_ppp	global economic policy uncertainty index (PPP adjusted GDP weights)	Economic Policy Uncertainty
Real Economy Variables	ipi	industrial production index without oil refinery (2006 = 100)	INE
	empl	employment rate (urban areas)	INE
	unempl	unemployment rate (urban areas)	INE
	imp_k	imports of capital goods index (2017 = 100)	BCU
	car_sales	new car sales	ASCOMA
	vat	value added tax revenue (millions of constant UY$) (cpi Dec-2006 = 100)	DGI
Nominal Variables	ex_rate	interbank buying and selling avg. of UY$/US$ nominal exchange rate	BCU
	cpi	Consumer price index	INE
	dep	ratio of deposits in foreing currency over total deposits	BCU
Exogenous Variables	fed	effective federal funds rate	FRED
	oil	brent crude oil price (US$ per barrel)	IMF
	food	commodity food price index (2005 = 100)	IMF
	meat	price in US$ per kilogram	USDA

Table A.3 – Unit root test for selected series

Serie	ADF Specification		Null Hypotesis	Lags (AIC)	Test Statistic	Value t-test	Comments
D_L_EPU	None	$y_t=\phi y_{t-1}+e_t$	$\phi=0$	0	τ	**-6.599**	Rejected at 1%
D_L_EPU	Drift	$y_t=\alpha+\phi y_{t-1}+e_t$	$\varphi=0$ $\alpha=\varphi=0$	3	τ	**-10.226**	Rejected at 1%
D_L_EPU	Trend	$y_t=\alpha+\beta t+\phi y_{t-1}+e_t$	$\varphi=0$ $\alpha=\beta=\phi=0$ $\beta=\phi=0$	3	τ	**-10.235**	Rejected at 1%
D_L_EX_RATE	None	$y_t=\phi y_{t-1}+e_t$	$\phi=0$	0	τ	**-8.67**	Rejected at 1%
D_L_EX_RATE	Drift	$y_t=\alpha+\phi y_{t-1}+e_t$	$\varphi=0$ $\alpha=\varphi=0$	0	τ	**-8.65**	Rejected at 1%
D_L_EX_RATE	Trend	$y_t=\alpha+\beta t+\phi y_{t-1}+e_t$	$\varphi=0$ $\alpha=\beta=\phi=0$ $\beta=\phi=0$	0	τ	**-8.56**	Rejected at 1%
D_SA_DEP	None	$y_t=\phi y_{t-1}+e_t$	$\phi=0$	4	τ	**-4.87**	Rejected at 1%
D_SA_DEP	Drift	$y_t=\alpha+\phi y_{t-1}+e_t$	$\varphi=0$ $\alpha=\varphi=0$	0	τ	**-12.87**	Rejected at 1%
D_SA_DEP	Trend	$y_t=\alpha+\beta t+\phi y_{t-1}+e_t$	$\varphi=0$ $\alpha=\beta=\phi=0$ $\beta=\phi=0$	4	τ	**-4.81**	Rejected at 1%
D_L_IPI	None	$y_t=\phi y_{t-1}+e_t$	$\phi=0$	12	τ	**-3.81**	Rejected at 1%
D_L_IPI	Drift	$y_t=\alpha+\phi y_{t-1}+e_t$	$\varphi=0$ $\alpha=\varphi=0$	12	τ	**-5.72**	Rejected at 1%
D_L_IPI	Trend	$y_t=\alpha+\beta t+\phi y_{t-1}+e_t$	$\varphi=0$ $\alpha=\beta=\phi=0$ $\beta=\phi=0$	12	τ	**-3.37**	Rejected at 1%
D_L_IMP_K	None	$y_t=\phi y_{t-1}+e_t$	$\phi=0$	3	τ	**-10.01**	Rejected at 1%
D_L_IMP_K	Drift	$y_t=\alpha+\phi y_{t-1}+e_t$	$\varphi=0$ $\alpha=\varphi=0$	3	τ	**-10.13**	Rejected at 1%
D_L_IMP_K	Trend	$y_t=\alpha+\beta t+\phi y_{t-1}+e_t$	$\varphi=0$ $\alpha=\beta=\phi=0$ $\beta=\phi=0$	3	τ	**-10.01**	Rejected at 1%
D_L_SA_CAR_SALES	None	$y_t=\phi y_{t-1}+e_t$	$\phi=0$	1	τ	**-15.19**	Rejected at 1%
D_L_SA_CAR_SALES	Drift	$y_t=\alpha+\phi y_{t-1}+e_t$	$\varphi=0$ $\alpha=\varphi=0$	1	τ	**-16.12**	Rejected at 1%
D_L_SA_CAR_SALES	Trend	$y_t=\alpha+\beta t+\phi y_{t-1}+e_t$	$\varphi=0$ $\alpha=\beta=\phi=0$ $\beta=\phi=0$	1	τ	**-15.03**	Rejected at 1%