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Economic Policy Uncertainty and Foreign Investment in Emerging Economies. An empirical study for Brazil, Chile, Colombia, and Greece

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"Incertidumbre de política económica e inversión extranjera en economías emergentes. Un estudio empírico para Brasil, Chile, Colombia y Grecia"

Resumen

La incertidumbre sobre las políticas y los resultados económicos futuros se ha identificado como una causa de reducción de la actividad económica y de la inversión en los últimos años. En particular, un grupo de literatura busca mecanismos de transmisión que expliquen estas caídas. Este estudio se enfoca en los efectos de los shocks *en el Índice de Incertidumbre de Política Económica desarrollado por Baker, Bloom y Davis (2016) sobre la Inversión Extranjera Directa y la Inversión de Portafolio en Brasil, Chile, Colombia y Grecia, usando la metodología VAR Estructural con restricciones de corto plazo y variables de control macroeconómicas. Los efectos estimados son negativos para ambas medidas de inversión extranjera (en línea con investigaciones previas). Sin embargo, la falta de significatividad estadística nos impide concluir el hallazgo de un nuevo mecanismo.*

Palabras clave: incertidumbre de política económica, índice EPU, inversión, economías emergentes, inversión extranjera directa, inversión de cartera, VAR estructural, restricciones de corto plazo

"Economic Policy Uncertainty and Foreign Investment in Emerging Economies. An empirical study for Brazil, Chile, Colombia, and Greece"

Abstract

Uncertainty about future economic outcomes and policies has been identified as a cause of decrease in activity and investment in recent years. In particular, a group of literature searches for transmission mechanisms that explain these drops. This study focuses on the effects of shocks in the Economic Policy Uncertainty Index developed by Baker, Bloom, and Davis (2016) on Foreign Direct Investment and Portfolio Investment for Brazil, Chile, *Colombia, and Greece, using the Structural VAR methodology with short-run restrictions and macroeconomic controls. The estimated effects are negative for both measures of foreign investment (in line with previous research). However, the lack of statistical significance prevents us from concluding the finding of a new mechanism.*

Keywords: economic policy uncertainty, EPU index, investment, emerging economies, foreign direct investment, portfolio investment, structural VAR, short-run restrictions

Códigos JEL: D80, F20, F32, E66, G18, H30.

Contents

1 Introduction

The future is, by definition, uncertain. Since economic theory suggests that expectations about future outcomes determine present decisions, it is straightforward to ask: what are the effects of more uncertainty? An increased interest in the relationship between uncertainty and the economy has emerged in recent years; in particular, it has been an important topic of discussion in the public sphere after the Great Recession. Also, recent social unrest and political changes are bringing back related debates in Latin America, with government policies as protagonists.[1]

Nevertheless, uncertainty is not an easy concept or idea to define and measure, as Bloom (2014) and Knight (1921) have suggested. Even if it could be measured correctly, there is no theoretical consensus on the nature of the relationship between uncertainty and economic activity or investment. In terms of Bernanke (1983), uncertainty can be an impulse or a propagation mechanism. If we think in terms of impulses, uncertainty would come as an exogenous shock and affect the other variables. Instead, if it works as a propagation mechanism, uncertainty would generate as a response to other shocks. Therefore, it is necessary to study these dynamic relationships empirically.

Although a considerable body of research has focused on this topic, less attention has been paid to investigating the role of uncertainty in emerging countries, even when it is known that most of them have high economic volatility. Explanations of this volatility include the financial sector (Carrière-Swallow and Céspedes, 2013) and political risks (Rodrik, 1991). Furthermore, there are few studies about the relationship between policy uncertainty and foreign investment (like Azzimonti [2019] for the United States).

Therefore, this study sought to explore the link between a specific dimension of uncertainty: the economic policy uncertainty (EPU) and the foreign investment in emerging economies. Our guiding question is: does a shock in the EPU affect Foreign Direct Investment (FDI) and Portfolio Investment (PI) in Brazil, Chile, Colombia, and Greece? Tax, expenditure, subsidy, tariffs, industrial and monetary policies -among others- impact on decisions of economic agents. Thus, it is easy to argue that private sector economic decisions are based on current and expected government decisions.

The empirical analysis of this article relies on the methodology of Structural Vector Autoregressions, and it uses the widely exploited EPU Index of Baker, Bloom, and Davis (2016). As it is extensively used in this literature, the identification strategy relies on short-run recursive restrictions to estimate the Structural Impulse Response functions. We employ quarterly macroeconomic data from the International Monetary Fund (IMF) and the Federal Reserve Economic Data (FRED) databases. The results obtained for Brazil, Chile, Colombia, and Greece indicate that shocks in EPU are associated with a retrenchment in Foreign Direct Investment and Portfolio Investment, but the estimates are not statistically significant. However, the confidence bands implied by the bootstrap inference are wide, with few available observations in some variables.

[1] As an illustrative example, "Spanish business freeze investment in Chile until they see how Boric acts" (December 20, 2021) in https://www.lapoliticaonline.com/espana/las-empresas-espanolas-congelan-inversiones-en-chile-hasta-ver-como-actua-boric/.

2 Previous and related literature

The literature about future uncertainty and its effects on the economy is vast. On the one hand, arguments about the negative effects of economic or policy uncertainty have been presented for a long time (Akerlof and Schiller, 2011; Keynes, 1936; Friedman, 1961). On the other, there are different notions and empirical definitions in the literature, as uncertainty is a challenging concept, as the classical Knight (1921) distinction between risk and uncertainty illustrates. In this review, we focus on recent literature and the articles most connected with our topic, the uncertainty about future government economic policies and actions. We also discuss previous research which is relevant as another benchmark and precedent for our work. In addition, we also review research about determinants of capital flows, as we study the effect on foreign investment in emerging economies.[2]

2.1 A brief theoretical discussion

2.1.1 Uncertainty and economic activity: cause or consequence?

The first way of thinking found in the theoretical literature is to consider the uncertainty as an exogenous shock. In other words, in these theories, uncertainty is an impulse, and the focus is on the effects that greater uncertainty creates. Bloom (2014) classifies the theory about the effects of uncertainty on activity and investment in four groups related to real options, risk aversion's role, growth options, and Oi-Hartman-Abel effects.

A common characteristic in the real options arguments is some form of irreversibility in investments, generating a real option value (Dixit and Pindyck, 1994). Namely, following a «wait and see» strategy can be an optimum response, delaying decisions to get more information (Bernanke, 1983; Bloom et al., 2007). Interestingly, Bloom (2014) observes that the real option argument not only predicts a reduction in levels of investment, hiring, and consumption due to greater uncertainty. It also predicts that uncertainty reduces the sensibility of economic actors to change in business conditions, and to government responses in a recession. In a similar vein, Stokey (2016) finds that the wait-and-see corporate strategy regarding investments is the optimal decision when there is uncertainty about a one-time change in relevant economic policies.

The second group identified by Bloom (2014) highlights the risk aversion role in predicting the adverse effects of uncertainty. As Bloom summarizes, the argument is twofold: first, more significant uncertainty is associated with higher risk for the investors, which translates into higher interest rates and the cost of financing new projects. Second, the increase in precautionary savings can reduce consumption levels. For instance, in Basu and Blundick (2017), the higher uncertainty causes lower demand for durable goods, in a context of low price flexibility and there is a negative feedback between uncertainty and activity.

Nevertheless, there are arguments for positive effects on investment too. Indeed, the argument in the third group is about the "growth options" and is based on the insight that uncertainty can encourage investment if it increases the firms' potential benefits (see for example Abel, Dixit, Eberly, and Pindyck [1996], and Segal, Shaliastovich, and Yaron [2015]). Finally, the group of theories related to the Oi-Hartman-Abel effects highlights the possibility that a firm can be risk-loving if it can adjust the scale of production in response to economic

[2] A previous, longer version of this literature review is available in https://github.com/franco-nunez/EPU_Emerging

conditions (Oi, 1961).

In contrast, a second strand of literature considers uncertainty as a propagation mechanism of other economic shocks or developments. A particular form is the emergency of uncertainty endogenously in response to macroeconomic conditions, as Fajgelbaum, Schaal, and Taschereau-Dumouchel (2017) suggest. Moreover, as Pástor and Veronesi (2013) highlight, policy uncertainty may emerge from economic activity, because of government actions in recessions.

In conclusion, empirical studies are needed to clarify the direction and the magnitude of the uncertainty shocks. As we have seen, the available theory proposes complex interactions between the variables: uncertainty may lower economic activity, a recession may increase the uncertainty, and feedback is possible. Furthermore, the expected duration of effects is also unclear, given the general equilibrium considerations.

2.1.2 Some priors on capital flows

Regarding foreign investment, it is convenient to remember some differences between the variables of interest, according to the Balance of Payments methodology. Portfolio Investment includes the cross-border acquisition of financial assets, like stocks or bonds (IMF, 2013). Furthermore, the sudden stops literature has always emphasized the importance of external factors to explain capital flows, especially in crises that apparently cannot be explained by vulnerabilities in local variables (for example, Calvo, 1998). One reason is precisely that equity and portfolio debt flows involve transactions that, in principle, can be executed quickly, as Koepke (2019) indicates. Thus, the investors may adjust the composition of their portfolios in response to economic news and short-term fluctuations in global financial markets.

In contrast, Foreign Direct Investment (FDI) includes the cross-border investments that provide control or a significant degree of influence on the management of an enterprise (IMF, 2013). Thus, FDI tends to be long-term, costly to reverse, and exposed to additional risks. Whereas all investments are exposed to political uncertainty, foreign investment is burdened with additional layers of rules and regulations, as Julio and Yook (2016) point out. Moreover, as Rodrik (1991) suggests, foreign investments are particularly exposed to uncertainty on the success or reversal of economic reforms. Therefore, theory suggests a more intense response from Portfolio Investment to uncertainty shocks, while it is not clear if FDI should react.

2.2 Empirical evidence

As we mentioned, empirical studies are needed to test the different predictions of theories about uncertainty and its impact on economic variables. It is possible to classify the relevant literature regarding uncertainty into two groups, according to whether they use the EPU Index (Baker, Bloom, and Davis, 2016) or not. While the articles that use the index are the most relevant for our study, the others are also related to the topic and are another relevant benchmark to consider, and consequently, we start discussing this group. Afterward, we review some articles that use the EPU Index, and finally, we examine research specifically devoted to emerging economies and capital flows.

2.2.1 Evidence about effects of uncertainty not based on EPU Index

The calibration of structural models was the first way to quantify the relative importance and duration of effects indicated by theory. Models of Bloom (2009), Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramirez, and Uribe (2011) find adverse effects of shocks in uncertainty, understood as shocks in the variance of some variable, consistent with the real options theory. Calibrated models of Bloom *et al.* (2018) and Fajgelbaum *et al.* (2017) also exhibit lower investment levels but with non-linear dynamics. Moreover, Bloom *et al.* (2018) show that the model implies that stabilization policies would lose their effectiveness in situations with high uncertainty. Interestingly, in the simulation of Fajgelbaum *et al.* (2017) uncertainty acts as an amplifying and propagation mechanism in the simulated model.

In addition, Bloom (2014) points out alternative strategies to estimate the effects of uncertainty, based on timing, taking advantage of events associated with spikes in uncertainty. Whereas the findings of these articles are consistent with a higher option value of delaying decisions, Bloom (2014) suggests that the delays were the dominant force in the short run, but the growth options effects were in the long run. For instance, Julio and Yook (2012) study cycles in corporate investment corresponding with the timing of national elections and find evidence supporting the hypothesis that political uncertainty leads firms to reduce investment expenditures until the electoral uncertainty is resolved.

On top of this evidence, the literature continued to search for new measures of uncertainty with the objectives of defining more specific notions of uncertainty and sometimes identifying more clear causal relationships. Regarding the measurement, Jurado, Ludvigson, and Ng (2015) support the notion that predictability is what matters in the analysis of uncertainty. Segal, Shaliastovich, and Yaron (2015) decompose aggregate uncertainty into 'good' and 'bad' volatility components, associated with positive and negative innovations to macroeconomic growth. They document that these two uncertainties have opposite impacts on aggregate economic growth and asset prices. Ludvigson, Ma, and Ng (2021) find that financial uncertainty seems a likely source of recessions, while uncertainty about macroeconomic and political variables appears to be an endogenous response, with persistent effects.

Another related measure is the Partisan Conflict Index from Azzimonti (2018). She develops an index based on newspaper coverage of disagreements among legislators over policies (not only economic policy or regulations). This index is related to the EPU notion because polarized politics implies more difficulty in forecasting what policies will be implemented –and when. Her results suggest that the conflict persistently discourages private investment.

2.2.2 EPU Index: effects and transmission mechanisms

The introduction of the Economic Policy Uncertainty (EPU) Index by Baker, Bloom, and Davis (2016) has allowed the estimation of the effects of a clearly defined type of uncertainty. Also, it has allowed the testing of the predictions of the theory with several identification strategies, such as panel data regressions or Structural Vector Autoregressive (VAR) models. Identification of effects is challenging in this macroeconomic context, because there are several confounding factors and because the EPU Index is a proxy of the underlying uncertainty (Baker, Bloom, and Davis, 2016; Xu, 2020). Consequently, the validity is conditional on the identification assumption and is not definitive, even controlling for other variables.

The EPU Index aims to serve as a proxy for uncertainty about «what» and «when» economic policy actions will be undertaken, and the «economic effects of policy actions (or inaction)» (Baker, Bloom, and Davis, 2016, p. 1598). Also, the measure pretends to capture both short and long-term concerns. It is based on the frequency of articles containing terms associated with uncertainty, economy, and policy, relative to the total number of articles in a month and newspaper. Each country index has a different set of words associated with each category, to capture idiosyncratic characteristics and covers a different number of local newspapers.

The results of Baker, Bloom, and Davis (2016) suggest that an EPU shock is associated with more volatility in the stock prices, a drop in investment, and lower economic activity. As Barraza and Civelli (2020) indicate, considerable research using the EPU Index also seems to indicate that heightened EPU leads to a fall in economic activity, with negative consequences for employment, industrial production, and business investment. The literature has examined different transmission mechanisms to explain those negative impacts. Among them we can mention the decision delay (Gulen and Ion, 2016), the increased financing cost (Pástor and Veronesi, 2013; Xu, 2020), and the reduction in credit (Bordo, Duca, and Koch, 2016; Barraza and Civelli, 2020). Furthermore, Drobetz, El Ghoul, Guedhami, and Janzen (2018) find that economic policy uncertainty distorts the relation between investment and cost of capital, as real options theory predicts.

Finally, we can extract some interesting points about the empirical research devoted specifically to the effects of uncertainty on activity and investment specifically in emerging economies. In particular, it seems that uncertainty has an even more negative effect on these economies. For instance, the analysis of Carrière-Swallow and Céspedes (2013) shows evidence consistent with a more persistent and large response of emerging economies to uncertainty shocks, compared with developed economies. The results for Chile in Cerda, Silva, and Valente (2018) are similar, as they find a persistent effect.

We can also highlight some studies that use the EPU Index to examine the transmission mechanisms of EPU to economic activity in emerging economies. Demir and Ersan (2017) find that firms in Brazil, Russia, India, and China prefer to hold more cash when uncertainty increases (both country-specific and global EPU indices), thus reducing investment. Krol (2014) finds evidence that country-specific EPU increases exchange rate volatility. The IMF (2013) suggests that increases in US and Europe levels of EPU temporarily reduce GDP growth and investment in other world regions. Balli, Uddin, Mudassar, and Yoon (2017) explore the determinants of these cross-country EPU spillovers and highlight the role of bilateral factors and prior macroeconomic vulnerabilities. Also, Bernal, Gnabo, and Guilmin (2016) highlight the role of risk transmission via sovereign bond spreads.

To summarize, empirical literature indicates adverse effects of economic and policy uncertainty shocks on activity, which are even harsher for emerging economies. Among the transmission mechanisms, the literature has focused on investment decisions, credit, and international spillovers. However, despite the importance of foreign investment for emerging economies, very few studies have investigated the effects of uncertainty shocks on these flows.

2.2.3 Emerging economies: capital flows and EPU

Finally, we can extract some interesting points about the empirical research devoted to determinants of capital flows in emerging economies. An interesting antecedent regarding Foreign Direct Investment is the contrast between the results in Azzimonti (2019) and Azzimonti (2018). In Azzimonti (2019), the EPU index is not statistically significant in her panel data regressions to explain the FDI, while her measure of political polarization over trade is. Nevertheless, in Azzimonti (2018), both the EPU and partisan conflict index have predictive power over corporate investment, conditional on standard controls. These differences indicate a lower sensibility of FDI to surges in EPU, at least in the short run. However, Julio and Yook (2016) examine the effects of political uncertainty on cross-border capital flows and find a reduction in US flow to foreign affiliates almost three times greater than compared to domestic corporate investment reduction, as found in Julio and Yook (2012).

Koepke (2019) points out that determinants of FDI are different from portfolio flows. In particular, FDI seems to be least affected by global cyclical developments and is closely tied to the strategic decisions of multinational enterprises. Moreover, FDI's unique drivers seem to be long-term factors. Instead, his evidence shows that financial variables are the most important drivers of portfolio flows, such as increased global risk aversion and high interest rates in advanced economies, in line with Forbes and Warnock (2012) and Miranda-Agrippino and Rey (2020). An interesting point of Koepke's review is the frequency in the data: he finds that external factors are the dominant drivers of short-run movements in portfolio flows, but pull factors (as macroeconomic conditions) matter more for long-term trends. Therefore, prior evidence suggests that we should include international financial variables to control for other factors affecting investment decisions. Additionally, we should expect a more significant impact on Portfolio Investment than on FDI.

3 Identification strategy

We estimate the effect of economic policy uncertainty with a Structural Vector Autoregressive (SVAR) analysis. The vector autoregressive (VAR) model is a standard approach for multivariate time series analysis, and it consists of a system of regression equations. VAR models exploit the time-series variation in the data and are estimated by regressing each model variable on lags of its own as well as lags of the other model variables up to some prespecified maximum lag order (P). In a VAR model, every variable is endogenous because it depends on its own lags as well as the lags of every other model variable (Kilian and Lütkepohl, 2017).

If we define y_t as the vector of variables of interest in the period t, Π as the vector of constants, Φ_p as the matrix of coefficients on $t-p$ (for $p = 1, 2, ..., P$) and e_t as the vector of errors, we can write the VAR model as is shown in the equation (1).

$$y_t = \Pi + \sum_p \Phi_p * y_{t-p} + e_t \tag{1}$$

Nevertheless, the estimation of the equation (1) cannot provide a consistent estimation of the effects of any variable. Since the matrix $Var(e_t) = \Sigma$ is not diagonal, it contains news about the three variables, and we cannot isolate causal effects. It can be thought as the equivalent of having omitted variables in every regression equation to be estimated. As Kilian and Lütkepohl (2017) highlight, an econometric model is structural if each equation's errors or stochastic shocks are mutually uncorrelated. When specified in a structural form, the model allows considering situations in which one structural shock moves while leaving all other shocks unchanged. Then, we need to impose identification assumptions. As Kilian and Lütkepohl (2017) suggest, a possible way to view the identification problem is to consider a new set of shocks μt, created by linear combinations of the original errors, e_t. This is shown in the equation (2), where Q is a rotation matrix.

This is shown in the equation (2), where Q is a rotation matrix.

$$\mu_t = Q * e_t \tag{2}$$

This new set of shocks is orthogonal because we are imposing contemporaneous relationships between the variables in the system. In some sense, it is equivalent to assume a certain data structure, and because of this, the new shocks are called structural shocks and the model becomes a Structural VAR. Regarding Q, infinite combinations of elements make the matrix achieve orthogonalization. As we are interested only in the identification of shocks in EPU, we only need to impose partial identification, in the sense that we are not interested in a consistent definition or estimation of all coefficients in the system.

As Kilian and Lütkepohl (2017) analysis shows, a standard VAR model is a reduced-form model, but a structural VAR model allows thinking in terms of variation in the data, driven by cumulative effects of economically interpretable shocks. Consequently, Baker, Bloom, and Davis (2016) postulate that drawing causal inferences from VARs is «extremely challenging », but they are useful for characterizing dynamic relationships (p. 1628). Even when the identification assumptions are clearly stronger than those used in microeconomic causal studies, the lack (or difficulty in the finding) of natural experiments in macroeconomics has made them a standard tool (Christiano, Eichenbaum and Evans, 1999).

The usual restrictions consist of short and long-term restrictions in the relationship between the variables, but there are more alternatives, such as signs or moment-based (Kilian and Lütkepohl, 2017). The election of the restrictions depends on previous theory and stylized facts in the topic of interest. Consequently, as usual in the literature of policy uncertainty, we impose short-run recursive restrictions in our study. The identification assumption is a contemporaneous causal order between the variables. This ordering implies that the first shock is uncorrelated with others, the second is correlated only with the first, the third with the first and second, and so on. Naturally, with longer periods, this will be more difficult to maintain.

3.1 First ordering: EPU first

In particular, with global or «exogenous» variables, we can impose the order of equation (3) as a first alternative.

$$\begin{bmatrix} global_t \\ epu_t \\ investment_t \end{bmatrix} = y_t \tag{3}$$

What does it imply? This order is equivalent to assuming that in the period t, the shock of the global variable is uncorrelated with the others. In some sense, it works like an exogenous variable. After, the economic policy uncertainty (EPU) can be affected for the global variable but not from the investment variable in the period t.

Finally, the investment can respond to the others. Naturally, all variables can respond to the lagged values of the others.

If the local GDP is included, the order will be as in equation (4). It is equivalent to imposing that the shocks in uncertainty are uncorrelated with the contemporaneous shocks in GDP and investments variables.

$$\begin{bmatrix} epu_t \\ gdp_t \\ investment_t \end{bmatrix} = y_t \tag{4}$$

3.2 Second ordering: EPU last

As a second alternative, we can think that EPU is an endogenous response to the investment conditions. As mentioned in the literature review, some models imply feedback process or uncertainty being a response to worsening economic conditions. Thus, including an alternative order is a robustness check. This ordering is equivalent to assuming that in the period t, the investment variable can be affected for the global variable but not from the economic policy uncertainty (EPU). After, the EPU responds to the two other variables. This can be seen in the equation (5).

$$\begin{bmatrix} global_t \\ investment_t \\ epu_t \end{bmatrix} = y_t \tag{5}$$

If we include the local GDP, the order is shown in equation (6). It implies that GDP shocks are contemporaneously uncorrelated with the others. Meanwhile, the investment variable can respond to these activities shocks, and the other two shocks affect the uncertainty.

$$\begin{bmatrix} gdp_t \\ investment_t \\ epu_t \end{bmatrix} = y_t \tag{6}$$

3.3 Third ordering: EPU in the middle for GDP model

Finally, we can consider the EPU as an intermediate response between investment and GDP as an additional robustness check. This ordering is equivalent to situations with investment responding to GDP and EPU shocks contemporaneously, while the EPU only reacts to GDP shocks. The GDP shocks would be uncorrelated to other contemporaneous shocks, as in the second ordering. This third ordering is shown in the equation (7).

$$\begin{bmatrix} gdp_t \\ epu_t \\ investment_t \end{bmatrix} = y_t \tag{7}$$

4 Data

Below we describe details about the included variables. A relevant point is that we make two procedures to the raw data. All the variables are normalized for a better comparison, with zero mean and unitary variance. Moreover, the variables are included in their first difference because stationarity is needed to estimate the models.

4.1 Economic Policy Uncertainty Index

The Economic Policy Uncertainty index is available on a monthly basis in policyuncertainty.com and is developed following the methodology of Baker, Bloom, and Davis (2016). While they built the index for Brazil, other authors developed indices for other countries, following the same methodology. For Chile, the reference is Cerda, Silva, and Valente (2018); for Colombia, Gil and Silva (2018) and Perico-Ortiz (2018); for Greece, Fountas, Karatasi, and Tzika (2018) and Hardouvelis, Karalas, Karanastasis, and Samartzis (2018).

The EPU index is based on the frequency of articles containing terms associated with uncertainty, economy and policy, relative to the total number of articles in a month and newspaper. Each country has a different set of words associated with each category, to capture idiosyncratic characteristics and has a different number of local newspapers in its coverage.

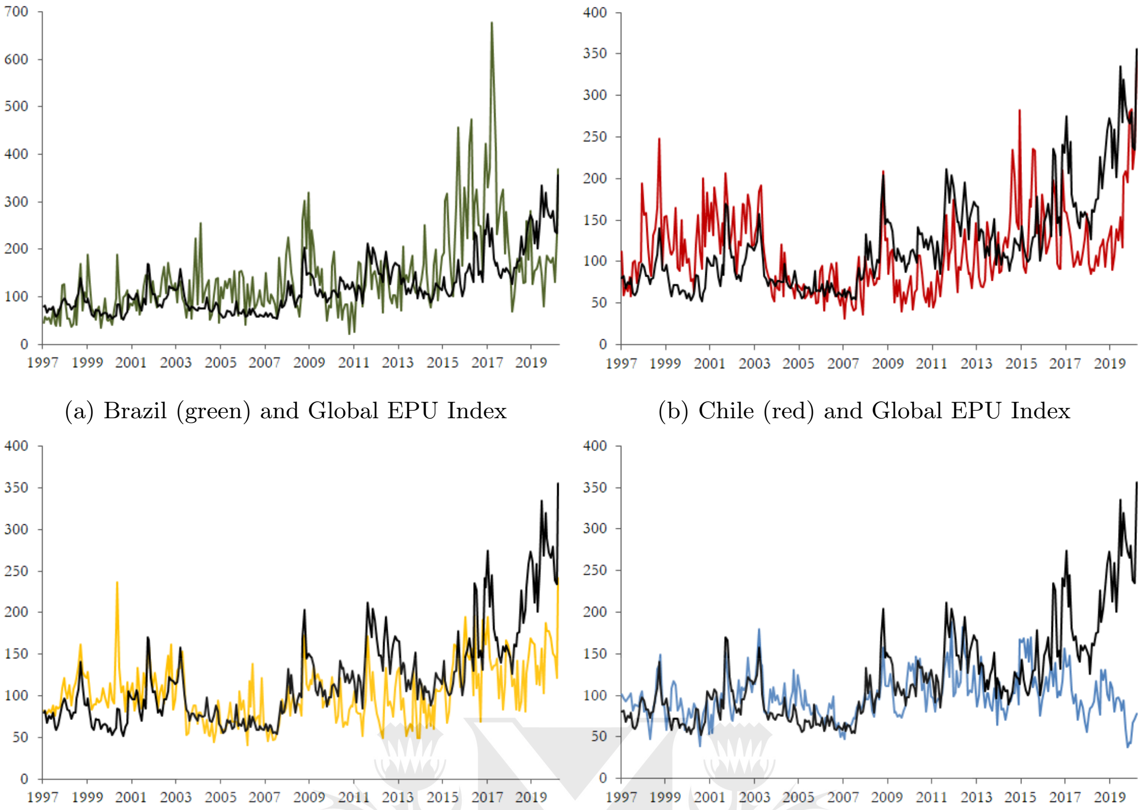
It is worth noting that the EPU index for the United States (the most used in empirical literature) consists of three components: a subindex based on newspaper content, a measure of the proportion of tax codes close to ending, and a subcomponent with the dispersion of economic forecasts. However, for the other countries, the EPU index only includes the component based on the news. This is not a considerable loss because it is the subindex with more weight in the US EPU, and it is more comparable between countries.

For Brazil, Chile, Colombia, and Peru, the index is available starting in the first quarter of 1997, and we limit the analysis to the period 1997Q1-2020Q1 in order to exclude the observations during the pandemic. The Global EPU variable is constructed, weighting the values from 21 national EPU indexes according to their GDP (PPP adjusted).

In Figure 1, the series of national EPU indices are shown, together with the Global EPU. As can be seen, there is some correlation between them, but idiosyncratic events drive the local indices. Moreover, for all the countries, the indices spike with identifiable events. The series with annotations related to major events that drive the indices from the authors can be found in Appendix A.

4.2 Other variables

According to the sixth edition of the Balance of Payments Manual (IMF, 2013), Foreign Direct investment is a category of cross-border investment associated with residents in one economy having control or a significant degree of influence on the management of an enterprise that is resident in another economy. This category includes equity acquisition that gives substantial control, investments associated with relationships with enterprises, investments in fellow enterprises, some kinds of debt, and reverse investment. The Foreign Direct Investment



(a) Brazil (green) and Global EPU Index

(b) Chile (red) and Global EPU Index

(c) Colombia (yellow) and Global EPU Index

(d) Greece (blue) and Global EPU Index

Figure 1: Country and global EPU Indices, January 1997 to March 2020.
Notes: (1) All indices are normalized, but the moment equal to 100 is different between countries (2) In all cases the black line is the Global EPU Index. Source: policyuncertainty.com, based on Baker, Bloom and Davis (2016).

(FDI) is called «Direct Investment» in the IMF's Balance of Payments methodology, and it is available on a quarterly basis in current dollars in the International Financial Statistics (IFS) database. Hence, we convert it to constant prices using the US CPI.

Like FDI, Portfolio Investment (PI) flows are available on a quarterly basis in current dollars in the IFS database. We also convert it to constant dollars using the US CPI. The IMF (2013) definition for PI includes cross-border transactions involving debt or equity securities, other than those included in FDI or reserve assets. Both the net FDI and PI flows are defined as the difference between net asset acquisition and net liabilities acquisitions. Therefore, positive values are associated with net «capital outflows» and negative with «capital inflows». We access both measures with the R package «IMFData» (Lee, 2016), which retrieves the data from the International Financial Statistics database, from the IMF.

Regarding the control variables, as a proxy of a global or free-risk interest rate, we use the effective Fed Funds rate. Available at St Louis Fred database on a monthly basis, we convert it to quarterly, taking the three-month average. For a proxy of the global mean of the «emerging country risks», we take the EMBI+ index, elaborated by JP Morgan. This measures the difference between the implied yield of the dollar-denominated bonds of emerging countries and those issued by the US Treasury. It is available in the World Bank dataset on a monthly basis since 1998Q1, and it is converted to quarterly by taking the three-month average.

For the country's GDP, our source is the IMF System of National Accounts, reported in the International Financial Statistics database on a quarterly basis. We use the constant prices and seasonally adjusted series. We do not use the GDP expressed in dollars in order to avoid the decline in the measure after exchange rate depreciation, even if the activity in real terms does not change.

As we mentioned, we use the US CPI to deflate some variables. The dollar inflation is calculated as the quarter-over-quarter percentage change of the all-items Index of Consumer Prices. The source is again the FRED database.

5 Estimation

As we mentioned before, all the models are estimated with quarterly observations and with three normalized variables: the direct or portfolio investment, the EPU, and a control variable (different in each model). The models with the Fed interest rate and the Global EPU as controls are estimated with the full sample, with observations during the period 1997Q1-2020Q1. As the Embi index is available since 1998, the model which includes it uses the period 1998Q1-2020Q1 as the sample. Finally, the models with local GDP are estimated with the full sample, except for Colombia; in this case the data availability limits the estimation to the 2005Q1-2020Q1 period.

We use the Cholesky decomposition to diagonalize the matrix of variance of the errors. The VAR and SVAR estimations are made with the library «Vars» (Pfaff, 2008, version 1.5.3) of the statistical software R (version 4.0.3). Regarding estimation methods, this package estimates VAR models with OLS (equation by equation) and SVAR models with numerical methods for Maximum Likelihood estimation. We estimate 64 models: we are interested in 2 variables (FDI and PI) for four countries, using four different controls, and using two different orderings (4x4x2x2). [3]

As Kilian and Lütkepohl (2017) suggest, the main interest is not the identification of structural shocks. They are only an intermediate step to estimate the response of each element of the vector of variables y to a one-time impulse due to a structural shock. Finally, the objective is to make a time-series plot with the responses of each variable to each structural shock over time. This is called a structural Impulse Response Function and is show in the equation (8), where μ_t is the vector of structural shocks and Θ_t is the vector of IRFs for the time horizon. Since there are K variables and K structural shocks, the outputs of each model are K^2 impulse response functions, each of length H + 1, where H is the maximum propagation horizon of the shocks

$$\frac{\partial y_{t+h}}{\partial \mu_t} = \Theta_h, \qquad h = 1, 2, ..., H \tag{8}$$

As we are interested in only one IRF and due to space considerations, we only report the IRF functions from EPU shocks to investment variables, but the full set of graphs can be found in the Online Appendix. In the equation (9) we can see the version of (8), but corresponding to a one element, the shock k, in this case it will

[3] Codes and data are available in https://github.com/franco-nunez/EPU_Emerging.

be the shock to EPU and its effect on $y_{j,t+h}$, the investment variable in the system.[4]

$$\frac{\partial y_{j,t+h}}{\partial \mu_{kt}} = \theta_{jk,h}, \qquad h = 1, 2, ..., H \tag{9}$$

Interestingly, the optimal number of lags, determined by the Hannan-Quinn Information Criteria, is set equal to only 1 in 42 models and equal to 2 in the other 22 (details in Appendix B). This is a natural result if we consider that 94 quarters (in the more complete samples) are a low number of observations relative to the parameters estimated. As Kilian and Lütkepohl (2017) highlight, in a VAR model, the number of parameters escalates in a non-linear way with the number and variables: including three variables and one lag, there are 18; with three variables and two lags, there are 27. Then, the degrees of freedom are low in our data, and we are limited to include more variables in the VAR system, a natural extension.

Finally, the inference of each impulse response function –a non-linear function of parameters- is made with a bootstrap estimation. As Kilian and Lütkepohl (2017) show, it is a non-parametric technique and is based on drawing residuals at random with replacement. The procedure gives K matrix data with the estimated errors from the original estimation and then estimates the IRF for the new re-sampling. The underlying idea is that having several IRFs serve as a proxy for the unknown data generating process, as Kilian and Lütkepohl indicate.

In all cases, 1000 bootstrap replications of the model are estimated with the Vars package (Pfaff, 2008) in order to generate the 95% confidence bands. As Kilian and Lütkepohl (2017), the percentile for the confidence level is approximated with the empirical distribution of the estimated IRF generated with the bootstrap.[5]

6 Results

This section shows the main results: the IRFs corresponding to a shock in the Local EPU and its effects on the investment variables. As can be seen below, in no case do the effects appear to be statistically significant at the proposed level.

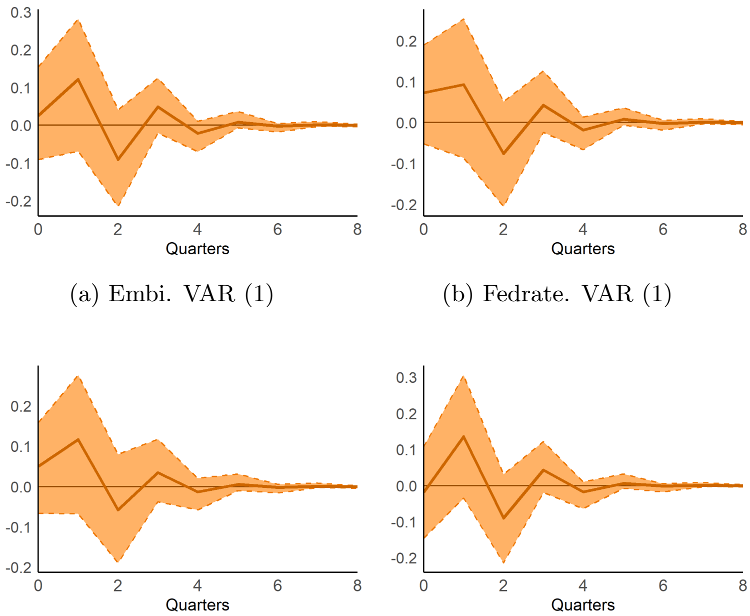
6.1 Foreign Direct Investment

The Figures in this section show the estimated response of the first difference of Foreign Direct Investment to a one-standard-deviation shock in the first difference of Local EPU. In each panel, there are the results of the four models estimated for each country, corresponding to the subpanels. For example, in Figure 2, we can see the IRFs for Brazil, corresponding the subfigure a) to the model with the Embi index as a control variable. The main line corresponds to the point estimation, and the colored area to the confidence bands implied by the bootstrap estimation for a 95% confidence level.

As positive values correspond to increased outflows, the IRFs are consistent with a reduction in Investment after a structural shock in EPU. The effects are stronger in the first two quarters and after a partial reversion is observed. As the models only include one lag, the effects are short-lived. These results are consistent with

[4]The Online Appendix is available in https://github.com/franco-nunez/EPU_Emerging.

[5]Also, a «seed» for the random number generator is used: the simulations always give the same path, and in consequence, the graphs can be replicated in an exact way.



(a) Embi. VAR (1)

(b) Fedrate. VAR (1)

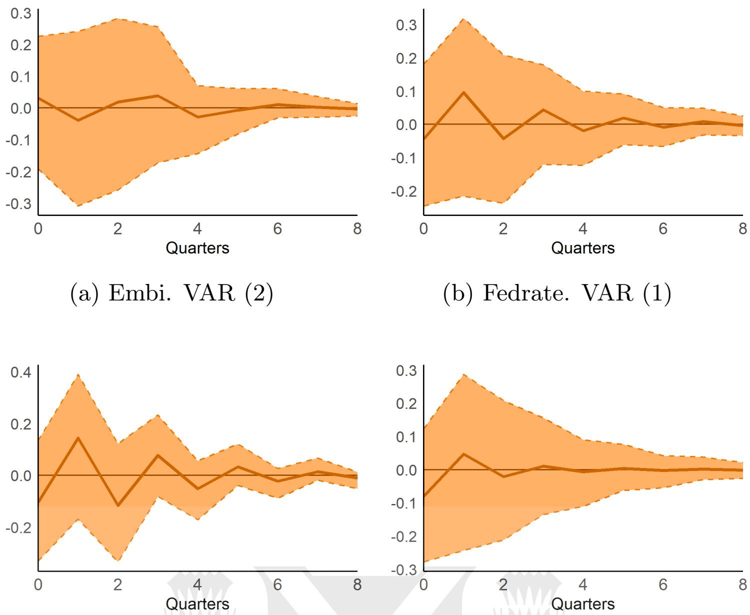
(c) GDP. VAR (1)

(d) Global EPU. VAR (1)

Figure 2: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Foreign Direct Investment in Brazil. First ordering (EPU first) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

the literature previously discussed about real options theory, but in all cases, the estimated response is not statistically significant at the specified level.

The IRFs resulting for Chile can be seen in Figure 3. Compared with the Brazil estimation, the results are more volatile and stronger in the first quarter after the shock.

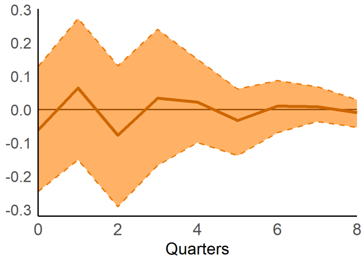


(a) Embi. VAR (2) (b) Fedrate. VAR (1)

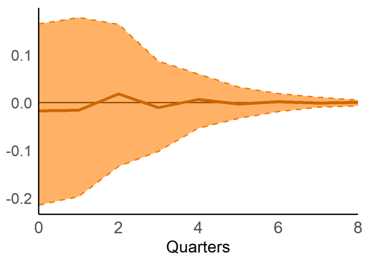
(c) GDP. VAR (1) (d) Global EPU. VAR (1)

Figure 3: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Foreign Direct Investment in Chile. First ordering (EPU first) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

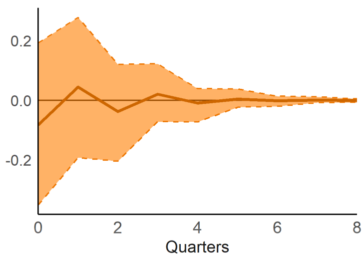
In Figure 4 there are the estimated IRFs for Colombia. The results are similar to the Colombia case, with small and not statistically significant effects. The IRFs resulting for Greece can be seen in Figure 5. The results are similar to the previous ones but with more volatility in the point estimates. The same qualitative conclusions can be extracted with the estimations assuming the second ordering (as can be seen in Appendix C) or the third ordering for the GDP (see Appendix E) with some quantitative differences. However, as the results are not statistically significant, it does not affect the implications.



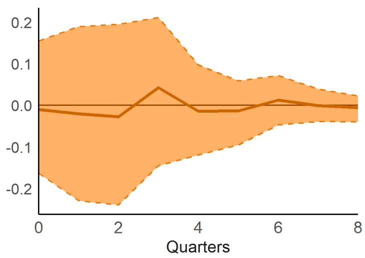
(a) Embi. VAR (2)



(b) Fedrate. VAR (1)

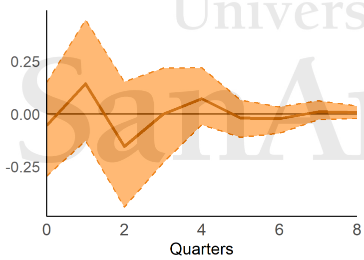


(c) GDP. VAR (1)

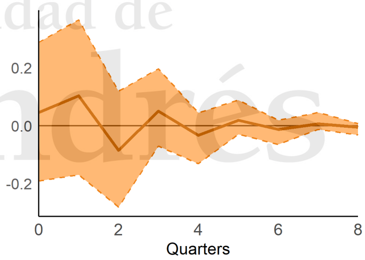


(d) Global EPU. VAR (2)

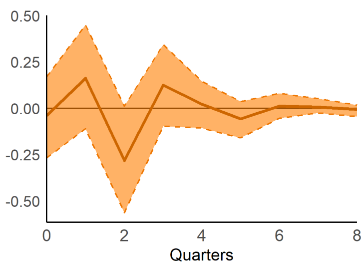
Figure 4: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Foreign Direct Investment in Colombia. First ordering (EPU first) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.



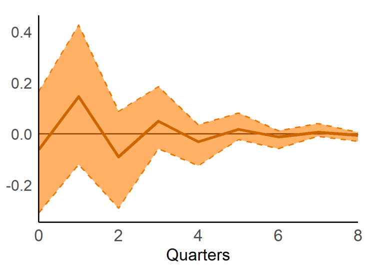
(a) Embi. VAR (2)



(b) Fedrate. VAR (1)



(c) GDP. VAR (2)

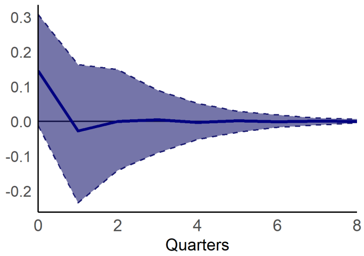


(d) Global EPU. VAR (1)

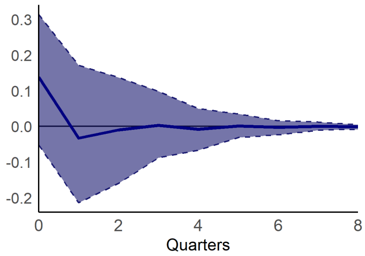
Figure 5: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Foreign Direct Investment in Greece. First ordering (EPU first) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

6.2 Portfolio Investment

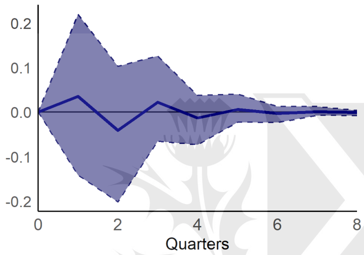
The Figures in this section show the estimated response of the first difference of Portfolio Investment to a one-standard deviation shock in the first difference of Local EPU. The logic of the Figures is the same as in the previous section. In Figure 6 we can see the IRFs resulting for Brazil.



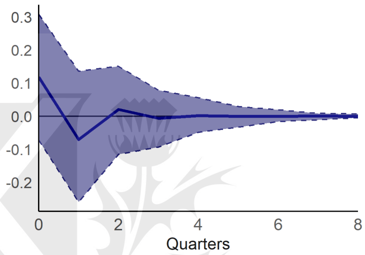
(a) Embi. VAR (1)



(b) Fedrate. VAR (1)



(c) GDP. VAR (1)

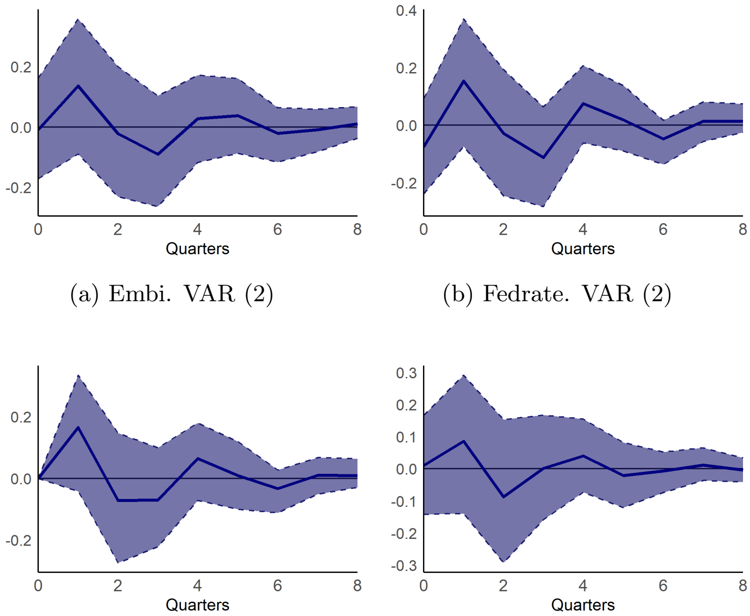


(d) Global EPU. VAR (1)

Figure 6: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Portfolio Investment in Brazil. First ordering (EPU first) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

The results imply a rapid response in the period when the shock is produced, except in the model with GDP. In particular, the Portfolio Investment reduces after an EPU shock but with almost no effect after the second quarter. These results are consistent with the stylized fact of fast portfolio adjustments, as discussed in previous sections. However –again- in all cases, the estimated responses are not statistically significant at the specified level.

The IRFs resulting for Chile can be seen in Figure 7. Interestingly, the IRFs are consistent with more persistent effects than in Brazil, especially in the model with GDP as control. However, the magnitude is smaller, and again the effects are not statistically significant.



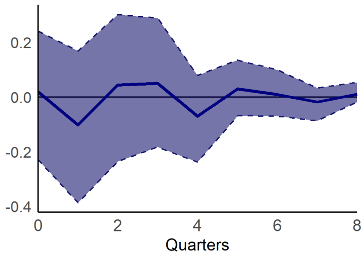
(a) Embi. VAR (2)　(b) Fedrate. VAR (2)

(c) GDP. VAR (2)　(d) Global EPU. VAR (2)

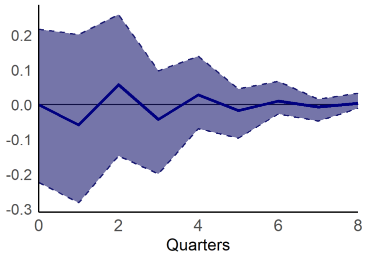
Figure 7: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Portfolio Investment in Chile. First ordering (EPU first) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

The IRFs resulting for Colombia can be seen in Figure 4. Differently from the other cases, the results imply a short-lived increase in Portfolio Investment after an EPU shock, compensated with declines in the second quarter. The IRFs resulting for Greece can be seen in Figure 9. The results are similar to the Chile case, with persistent effects and the estimates are not statistically significant at the reported level.

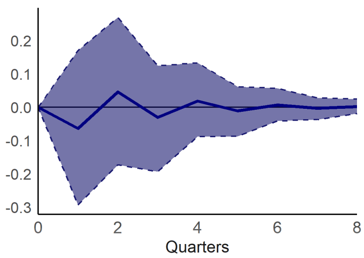
The same qualitative conclusions can be extracted with the estimations assuming the second ordering (as can be seen in Appendix D) or the third ordering for the GDP (see Appendix E). An interesting difference is that, in the Brazil case with the second ordering, all the responses are smaller in magnitude, close to zero. For all cases, the results are not statistically significant at the proposed level of 95



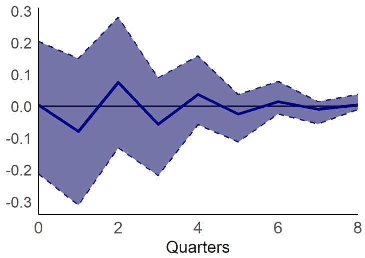
(a) Embi. VAR (2)



(b) Fedrate. VAR (1)

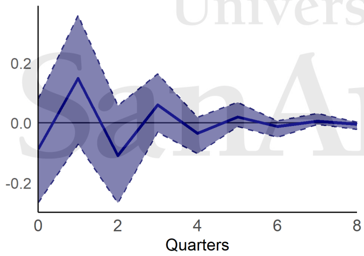


(c) GDP. VAR (1)

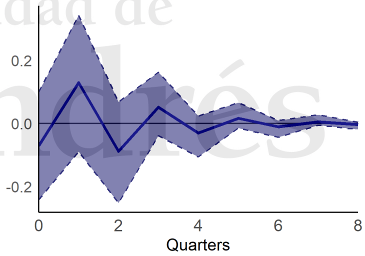


(d) Global EPU. VAR (1)

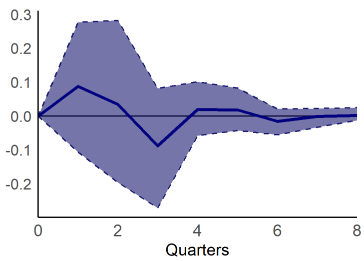
Figure 8: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Portfolio Investment in Colombia. First ordering (EPU first) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.



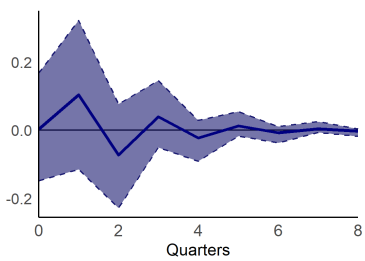
(a) Embi. VAR (1)



(b) Fedrate. VAR (1)



(c) GDP. VAR (2)



(d) Global EPU. VAR (1)

Figure 9: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Portfolio Investment in Greece. First ordering (EPU first) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

7 Final comments

As we have discussed, the effects of economic policy uncertainty have been widely studied with the use of the EPU Index of Baker, Bloom, and Davis (2016). The bottom line of the literature review is that negative effects on activity, investment and employment are identified; with the decisions' delay, augmented cost of capital, and reduced bank credits as the transmission mechanisms. This study has aimed to contribute to examining an alternative mechanism relevant for Emerging Economies: foreign investment.

With the Structural VAR methodology, we estimate the effects of a structural shock of EPU to Foreign Direct Investment and to Portfolio Investment, with different control variables (EMBI Index, Fed Funds rate, local GDP, and Global EPU) and different orderings. The results indicate a decline in these investments, but the confidence bands reveal the estimates as not statistically significant. While there is a possibility that there are no effects, the lack of statistical significance could also be explained by the few degrees of freedom implied by the number of observations or the specification.

A natural limitation of the analysis is the use of only three variables in the VAR system, but the data availability limits the inclusion of more. With more observations, the estimation could be enriched with more controls. Naturally, as the literature does not definitively underpin the identification problem, the results can be interpreted as one study more with partial evidence, being the accumulation and contrast of articles the key for a consensus.

For future research, the analysis can be expanded to include other countries if the EPU Index is available for them in the future. Another possibility is the inclusion of an «filtered» index, understood as the residual of a regression with macroeconomic variables as controls, as Xu (2020).

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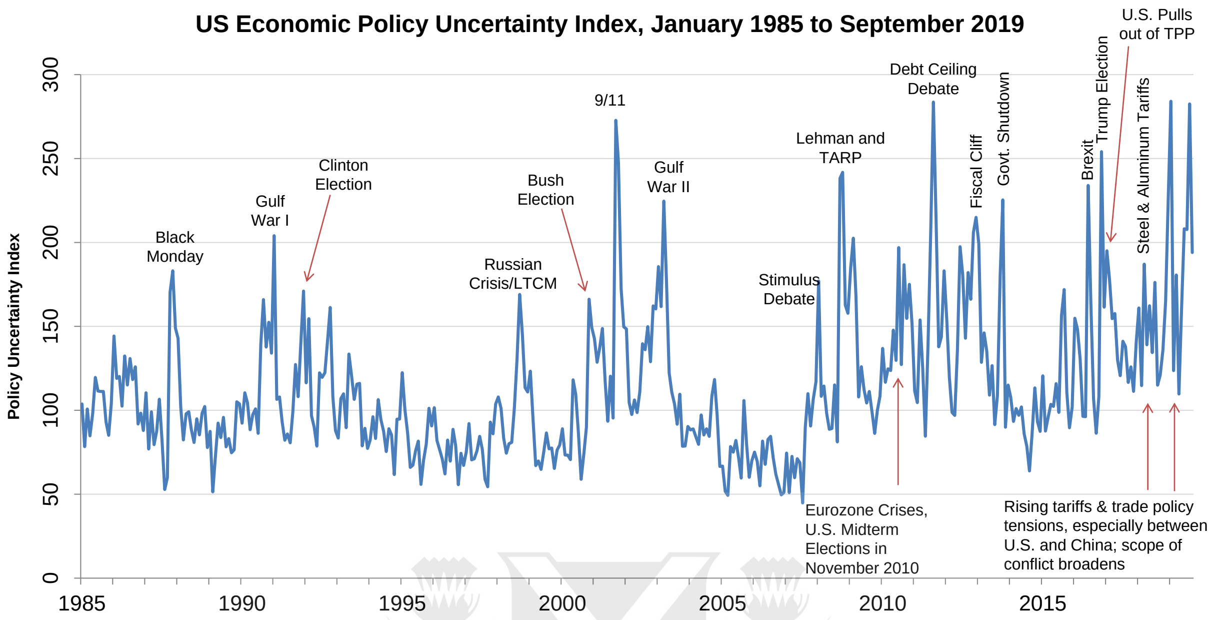
9 Appendix A: EPU series and events

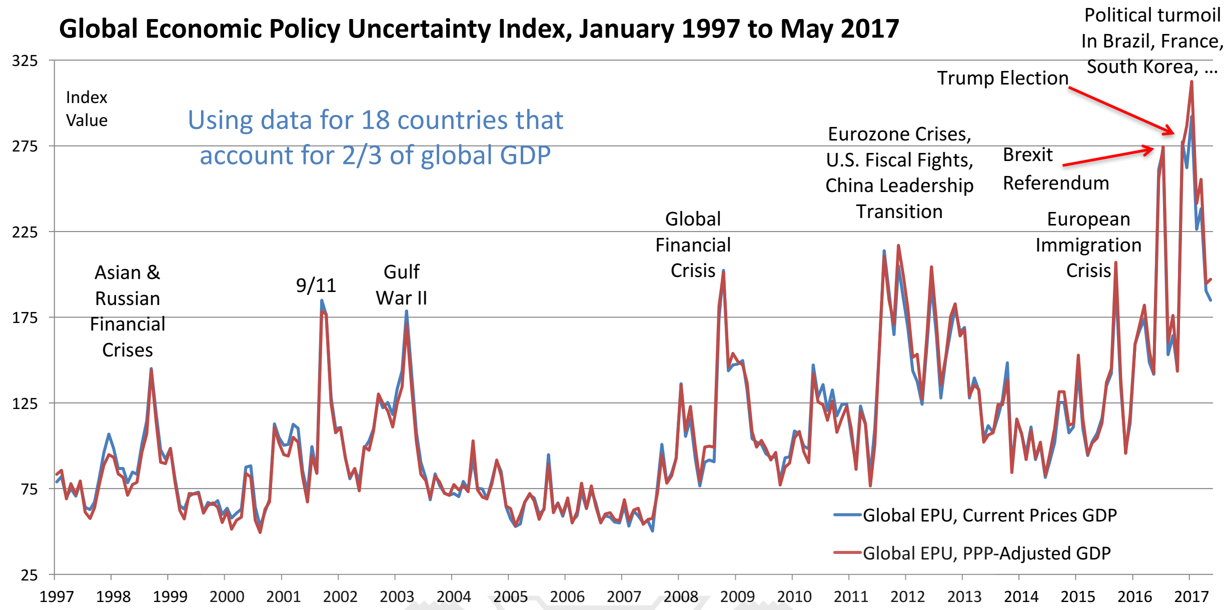
Figure 10: US EPU annotations



Source: "Measuring Economic Policy Uncertainty" by Scott R. Baker, Nicholas Bloom and Steven J. Davis, as updated at www.policyuncertainty.com. Monthly data normalized to 100 prior to 2010.

Source: policyuncertainty.com

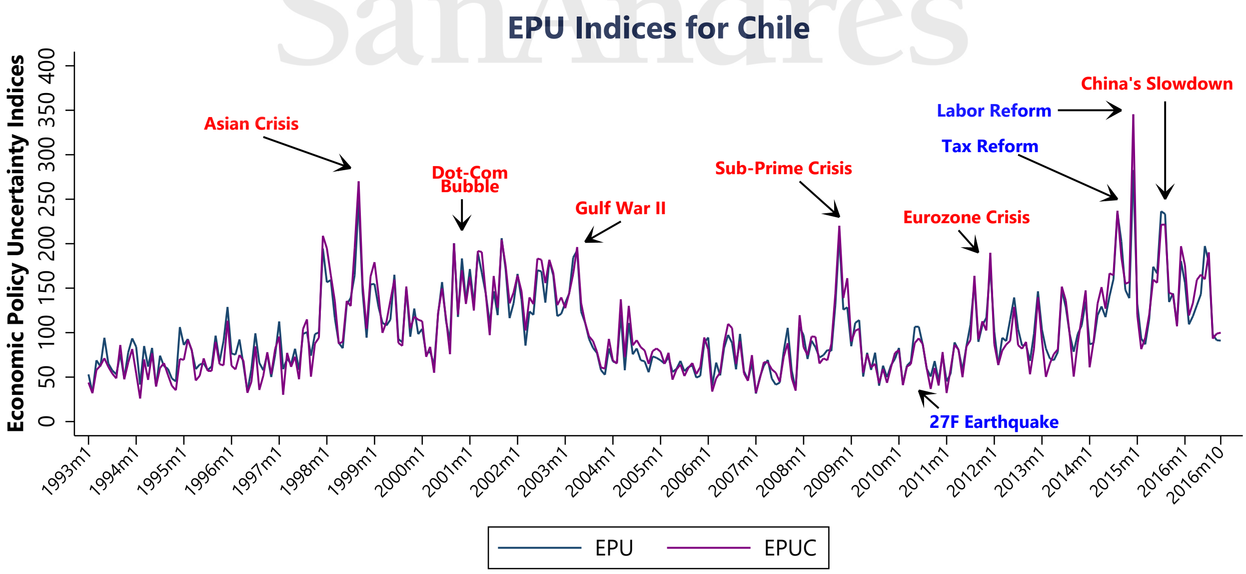
Figure 11: Global EPU annotations



Notes: Global EPU calculated as the GDP-weighted average of monthly EPU index values for US, Canada, Brazil, Chile, UK, Germany, Italy, Spain, France, Netherlands, Russia, India, China, South Korea, Japan, Ireland, Sweden, and Australia, using GDP data from the IMF's World Economic Outlook Database. National EPU index values are from www.PolicyUncertainty.com and Baker, Bloom and Davis (2016). Each national EPU Index is renormalized to a mean of 100 from 1997 to 2015 before calculating the Global EPU Index.

Source: policyuncertainty.com

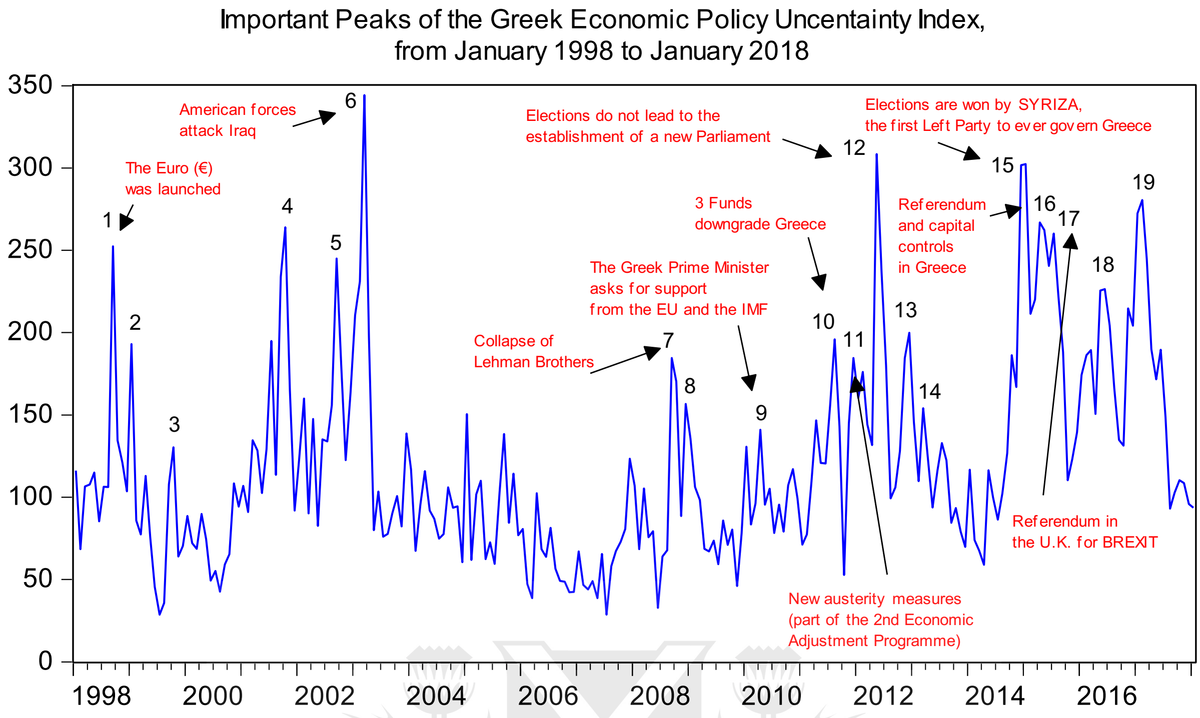
Figure 12: Chile EPU annotations



Note: The EPU index is constructed based on frequency count of articles in two Chilean newspapers, El Mercurio and La Segunda, which contain terms pertaining to uncertainty, economics and policy. The EPUC is constructed using the same terms as the EPU but also include terms pertaining to Chile such as *Chile* or *Chileno/a* in order to correctly capture domestic economic policy uncertainty.

Source: policyuncertainty.com

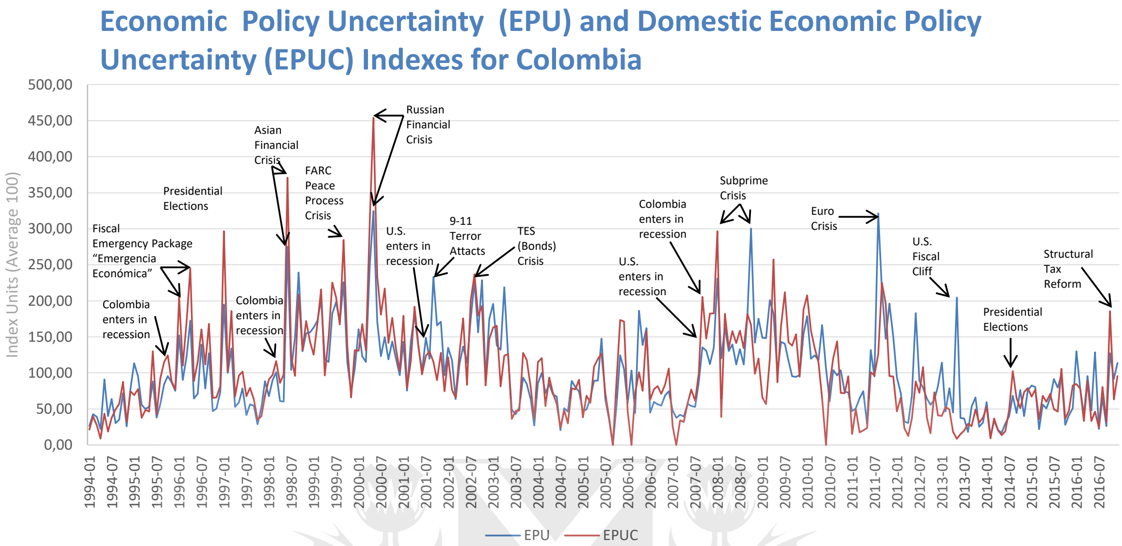
Figure 13: Greece EPU annotations



Graph 1

Source: policyuncertainty.com

Figure 14: Colombia EPU annotations



Note: Indexes reflect the scaled and normalized montly counts of articles from the national newspaper *El Tiempo* for the period between January 1994 and December 2016 containing specific keywords grouped into the categories "Economic", "Policy", "Uncertainty" for the EPU index and the additional category "Colombia" for the EPUC index.

Source: policyuncertainty.com

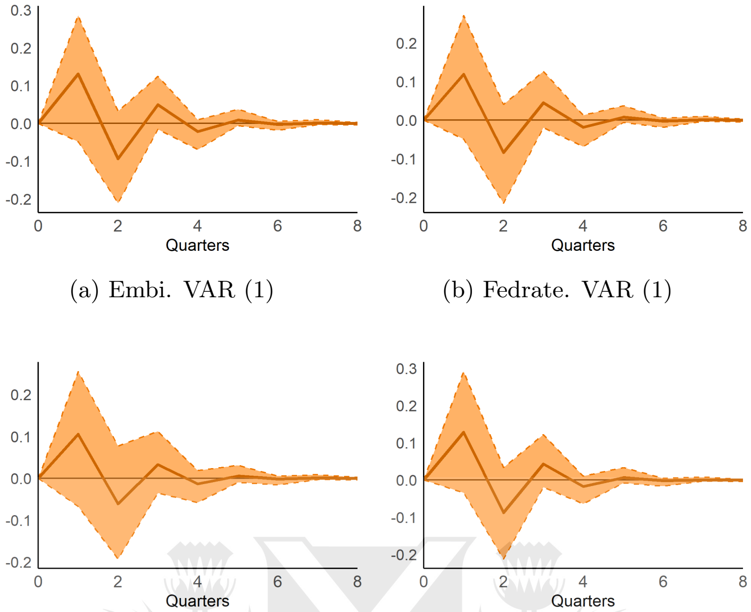
10 Appendix B: Lag selection

Figure 15: Number of lags selected by the Hannan-Quinn selection in each model

		Brazil		**Chile**		**Colombia**		**Greece**	
Model	Variable	1st ordering	2nd ord.	1st ord.	2nd ord.	1st ord.	2nd ord.	1st ord.	2nd ord.
EMBI	FDI	1	1	2	2	2	2	2	2
	PI	1	1	2	2	2	2	1	1
Fed Rate	FDI	1	1	1	1	1	1	1	1
	PI	1	1	2	2	1	1	1	1
Global EPU	FDI	1	1	1	1	2	2	1	1
	PI	1	1	2	2	1	1	1	1
GDP	FDI	1	1	1	1	1	1	2	2
	PI	1	1	2	2	1	1	2	2

11 Appendix C: IRFs in the second ordering: FDI

The IRFs resulting for Brazil can be seen in the Figure 16.



(a) Embi. VAR (1)

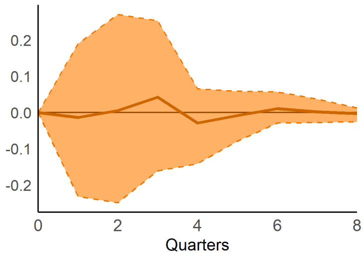
(b) Fedrate. VAR (1)

(c) GDP. VAR (1)

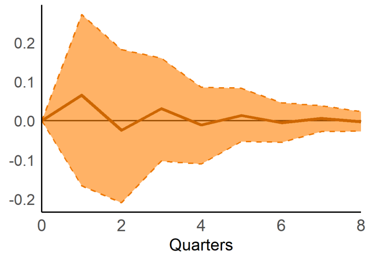
(d) Global EPU. VAR (1)

Figure 16: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Foreign Direct Investment in Brazil. Second ordering (EPU last) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

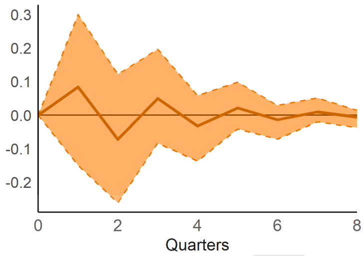
The IRFs resulting for Chile can be seen in the Figure 17.



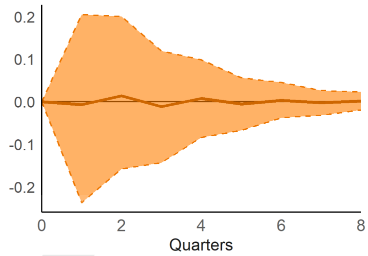
(a) Embi. VAR (2)



(b) Fedrate. VAR (1)



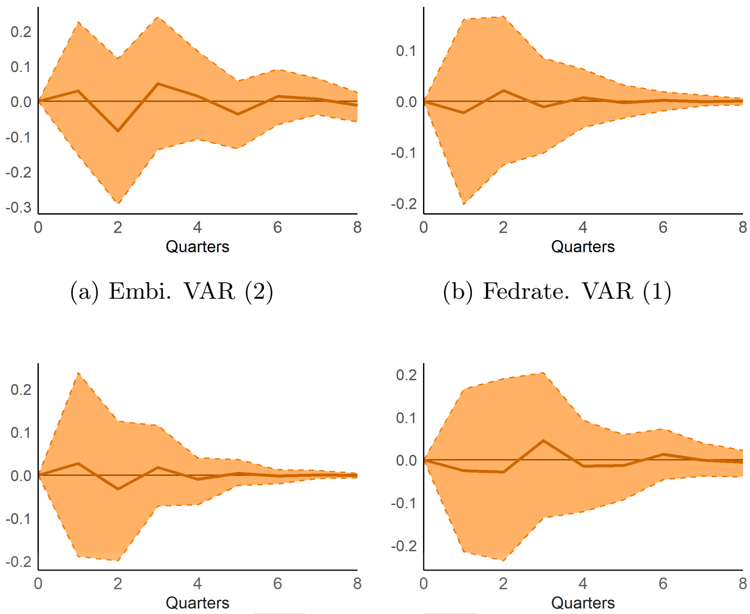
(c) GDP. VAR (1)



(d) Global EPU. VAR (1)

Figure 17: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Foreign Direct Investment in Chile. Second ordering (EPU last) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

The IRFs resulting for Colombia can be seen in the Figure 18.



(a) Embi. VAR (2)

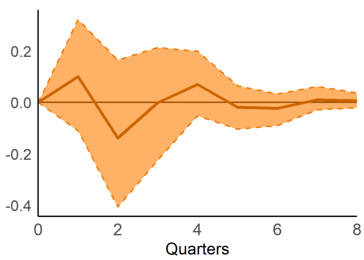
(b) Fedrate. VAR (1)

(c) GDP. VAR (1)

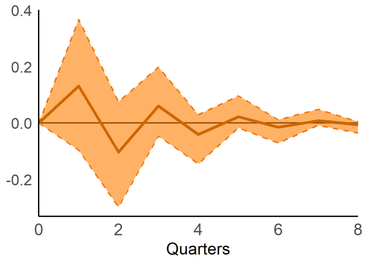
(d) Global EPU. VAR (2)

Figure 18: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Foreign Direct Investment in Colombia. Second ordering (EPU last) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

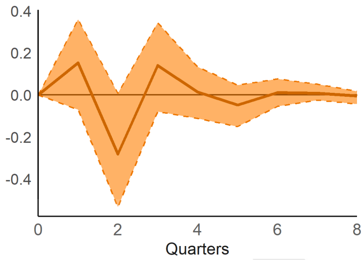
The IRFs resulting for Colombia can be seen in the Figure 19.



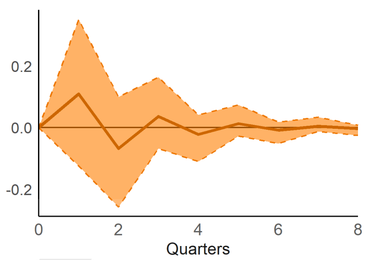
(a) Embi. VAR (2)



(b) Fedrate. VAR (1)



(c) GDP. VAR (2)

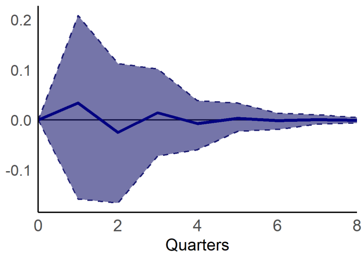


(d) Global EPU. VAR (1)

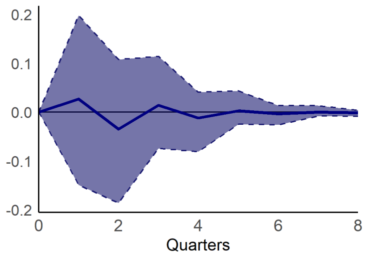
Figure 19: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Foreign Direct Investment in Greece. Second ordering (EPU last) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

12 Appendix D: IRFs in the second ordering: PI

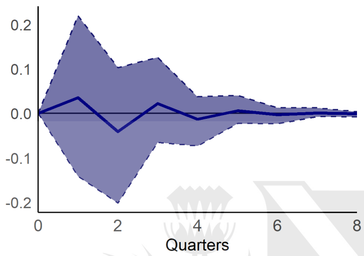
The IRFs resulting for Brazil can be seen in the Figure 20.



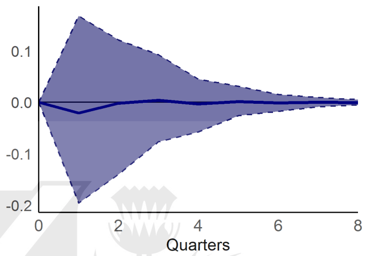
(a) Embi. VAR (1)



(b) Fedrate. VAR (1)



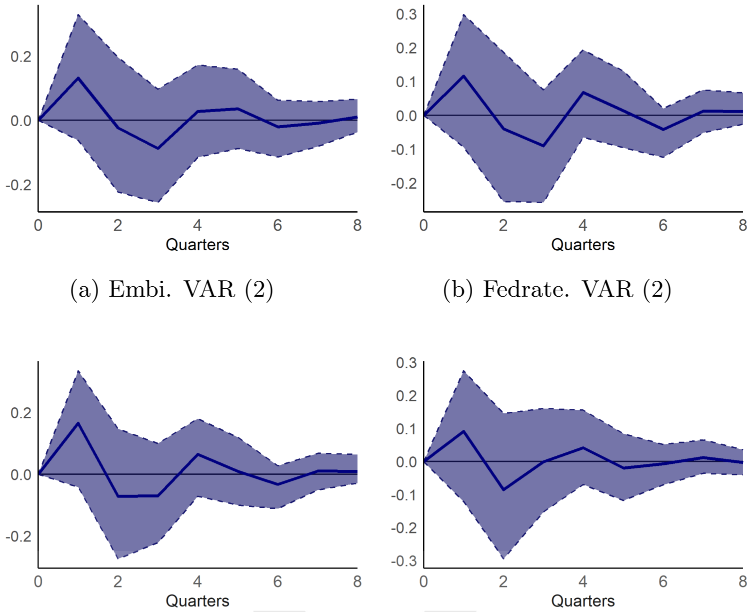
(c) GDP. VAR (1)



(d) Global EPU. VAR (1)

Figure 20: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Portfolio Investment in Brazil. Second ordering (EPU last) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

The IRFs resulting for Chile can be seen in the Figure 21.



(a) Embi. VAR (2)

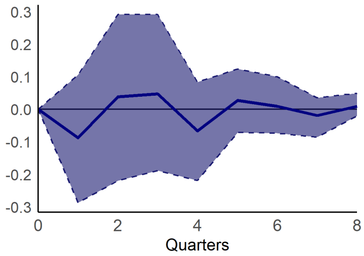
(b) Fedrate. VAR (2)

(c) GDP. VAR (2)

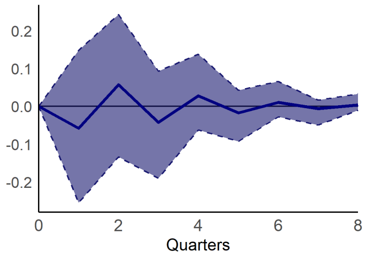
(d) Global EPU. VAR (2)

Figure 21: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Portfolio Investment in Chile. Second ordering (EPU last) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

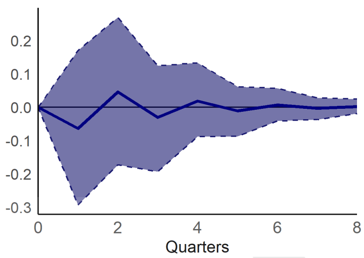
The IRFs resulting for Colombia can be seen in the Figure 22.



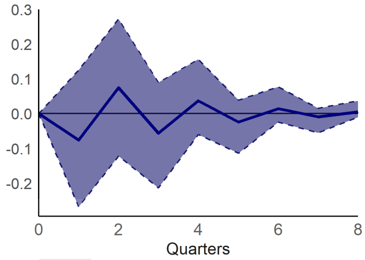
(a) Embi. VAR (2)



(b) Fedrate. VAR (1)



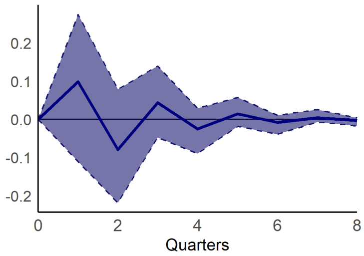
(c) GDP. VAR (1)



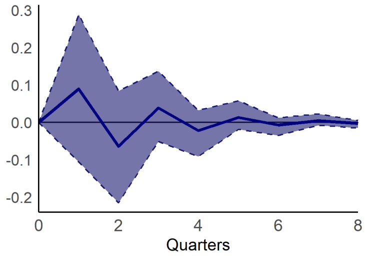
(d) Global EPU. VAR (1)

Figure 22: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Portfolio Investment in Colombia. Second ordering (EPU last) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

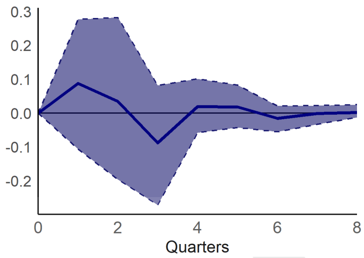
The IRFs resulting for Greece can be seen in the Figure 23.



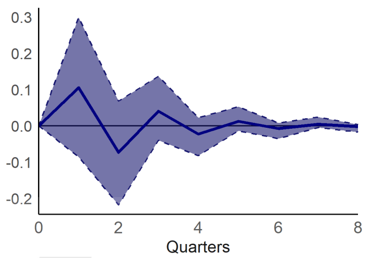
(a) Embi. VAR (1)



(b) Fedrate. VAR (1)



(c) GDP. VAR (2)

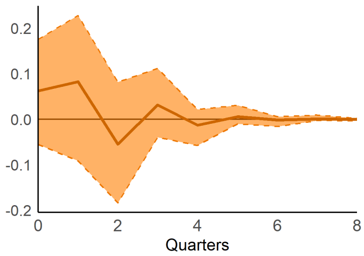


(d) Global EPU. VAR (1)

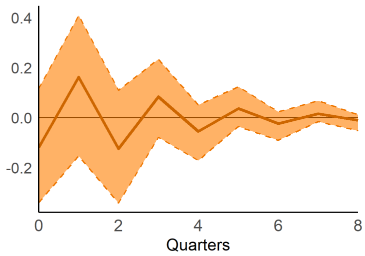
Figure 23: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Portfolio Investment in Greece. Second ordering (EPU last) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with the variable in its subtitle as the control. Sample: 1997Q1-2020Q1, except for the Embi model, which is 1998Q1-202Q1. VAR(p) refers to the lag specification of the model.

13 Appendix E: IRFs in the third ordering with GDP as control

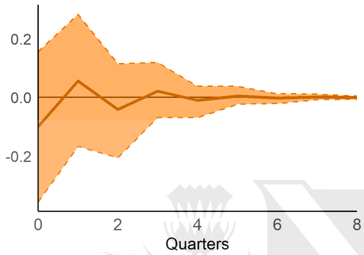
The IRFs resulting for FDI can be seen in the Figure 24.



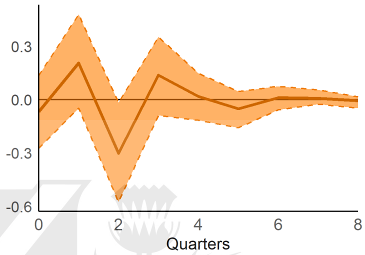
(a) Brazil. VAR (1)



(b) Chile. VAR (1)



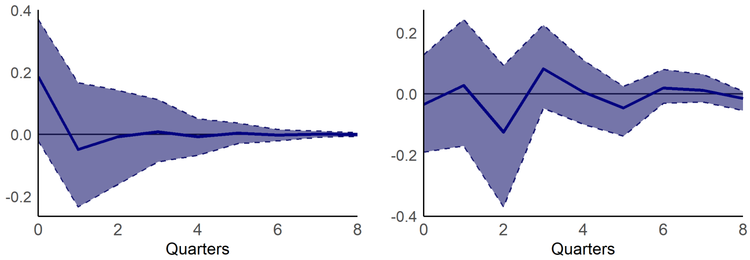
(c) Colombia. VAR (1)



(d) Greece. VAR (2)

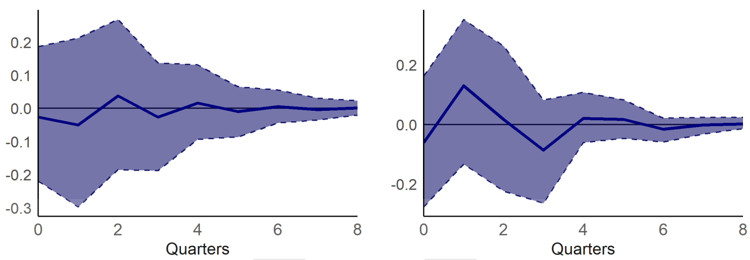
Figure 24: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Foreign Direct Investment in the four countries. Third ordering (GDP, EPU, FDI) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with GDP as the control for the specified country. Sample: 1997Q1-2020Q1, except for Colombia model, which is 2005Q1-2020Q1. VAR(p) refers to the lag specification of the model.

The IRFs resulting for PI can be seen in the Figure 25.



(a) Brazil. VAR (1)

(b) Chile. VAR (2)



(c) Colombia. VAR (1)

(d) Greece. VAR (2)

Figure 25: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Portfolio Investment in the four countries. Third ordering (GDP, EPU, PI) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure correspond to a model with GDP as the control for the specified country. Sample: 1997Q1-2020Q1, except for Colombia model, which is 2005Q1-2020Q1. VAR(p) refers to the lag specification of the model.