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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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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 search for transmission mechanism that explain these drops. This study focus in 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 statistically significance prevent us from conclude the finding of a new mechanism.

Resumen

La incertidumbre sobre variables y polìticas econòmicas futuras se ha identificado como una causa de caídas de la actividad y la inversión en los últimos años. En particular, un grupo en la literatura busca mecanismos de transmisión que expliquen estas retracciones. Este estudio se centra 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 Cartera para Brasil, Chile, Colombia y Grecia, utilizando la metodología VAR Estructural con restricciones de corto plazo y controles macroeconómicos. 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.

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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. The scope of this work is not to deal with a general (and abstract) notion of uncertainty. Instead, the aim is on a specific dimension: economic policy uncertainty, the uncertainty about future government economic policies or actions.

2.1 A brief theoretical discussion

The idea that uncertainty can adversely affect economic activity dates back –at least- to Keynes (1936), who argued that changes in investment drive business cycles because it depends on views about the future, which is by definition uncertain. In addition, authors such as Friedman (1961) advocate for stable and predictable policies to foster economic growth, avoiding swings and errors. These arguments had been usually analyzed in theoretical models as shocks in the expected value on some variable, limiting the analysis to the first moment of the distribution of possible values. Afterward, the literature explored the effects of uncertainty as shocks in the variance of some stochastic variables.[2]

Following Knight's idea (1921), this notion can be considered an increase in measurable risks because the range of events does not change, only their probabilities. Knight contrasted it with the uncertainty related to non-measurable risks, incomplete information, and unknown factors. As mentioned previously, our focus is not on the abstract discussion or the definitions, but the Knight distinction illustrates the challenges associated with the concepts involved in the literature, both theoretical and empirical. For instance, Segal, Shaliastovich, and Yaron (2015) suggest that uncertainty can be related to uncertainty about the parameters, learning, robust control, and ambiguity.[3]

2.1.1 Uncertainty as a cause of changes in economic activity

The first way of thinking found in the 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. The seminal work of Bernanke (1983) describes a model in which uncertainty affects irreversible investment decisions and, therefore, the economy. As Bernanke remarks, if the investment dynamics depend on expectations and the available information, there would be an option value of waiting to invest. A central implication of his analysis is that willingness to invest will depend on the «bad news» (p. 91), regardless of the good ones. In other words, even if the investors are neutral to risk, a greater probability of future losses will increase the value of waiting and choosing with more information (delaying the investment).

[2]Some recent related work is Akerlof and Schiller (2011).
[3]A contemporaneous thinker with (in some sense) ideas related to Knightian uncertainty is Nassim Nicholas Taleb.

Nevertheless, as Bloom et al. (2007) remark, capital adjustment costs can generate «partial irreversibility» in investments without the need for total irreversibility. Therefore, according to their adjustment costs, different types of capital would have different degrees of irreversibility. The critical implication of the model is that firms would invest if the marginal productivity of capital is higher than a threshold, given by the cost of using capital (as in traditional models) and the option value of investing. Instead, firms would disinvest if marginal productivity is below a lower threshold, given by sale costs and the option value of disinvestment. Then, as the uncertainty (understood in the model as the variance of the productivity shocks) varies in time, its shocks affect the expected productivity and generate investment and disinvestment cycles. Hence, according to the model, significant fluctuations in output can be generated when firms with high adjustment costs adjust their capital stock.

In a similar vein, Stokey (2016) analyzes investment decisions when there is uncertainty about a one-time change in tax policy. In this context, the wait-and-see corporate strategy is the optimal decision, generating a temporary stop in investing. In her model, after the resolution of tax policy (the source of uncertainty), firms exploit the tabled projects in previous periods generating a temporary boom -inversely proportional to the tax rise. Stokey argues that this kind of investment delay applies to other types of policies, like tariffs or exchange rate devaluation.

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. As a result, this body of theory predicts that firms will be less responsive to government responses in a recession, like interest rate cuts or other policies.

The second group identified by Bloom (2014) highlights risk aversion's 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, so the interest rates must rise and, therefore, the cost of financing new projects. Second, the increase in precautionary savings can reduce consumption levels.

For instance, in the Basu and Blundick (2017) model, an uncertainty shock is understood as higher variance in a stochastic variable, and its macroeconomic effects are related to lower demand for durable goods. The central idea of the authors is that the response of the economic system will depend on the degree of price flexibility. If there are price adjustment costs and, consequently, prices are sticky, the production of durable goods will be lower to eliminate the excess supply. Moreover, if there were a lower activity level, the labor demand and the aggregate demand would also be lower. This would lower the expected marginal productivity of capital and the investment accordingly. Therefore, Basu and Blundick (2017) propose another mechanism for the propagation of uncertainty shocks which can also generate negative feedback, with disinvestment cycles, in the style of Bloom et al. (2007). A crucial feature of their model is the effective demand determining the activity level.

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. According to Bloom (2014), the intuition is that costs of bad scenarios have a lower bound because the firm can cancel the product losing only its sunk costs. In contrast, profits in good scenarios are not limited in their upside potential. Therefore, in this view, the expected profit rises with more uncertainty, understood as more dispersion in the distribution of possible results. For example, the model in Abel, Dixit, Eberly, and Pyndick (1996) emphasizes that if capital decisions can be reversed (i.e., the capital stock can be sold), the investment can be thought of as the acquisition of an option. Then, greater uncertainty will increase the value of the option.

Finally, Bloom (2014) suggests that there is a group of theories related to the Oi-Hartman-Abel effects. This effect highlights the possibility that a firm can be risk-loving if it can adjust the scale of production in response to economic conditions (Oi, 1961). In this context, a representative business is partly insured against unfavorable outcomes because it is able to reduce the scale and has the option to expand when it faces a good scenario. Thus, Bloom indicates that Oi–Hartman–Abel effects are not typically strong in the short-run because of adjustment costs, but they can be more powerful in the medium and long run.

Segal, Shaliastovich, and Yaron (2015) propose a possible asymmetry between positive and negative notions of uncertainty related to the volatility of variables. Their idea is related to the opposition between real and growth options, because they suggest that uncertainty about «how much» would the economy the enhanced by new technology can have asymmetrical effects than uncertainty about «how much» would the economy during a recession (pp. 369-370). Thus, it is possible to argue that both types of volatility will be related to different options.

2.1.2 Uncertainty as a consequence of changes in economic activity

The second strand of literature has also considered 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. Fajgelbaum et al. (2017) show that firms' expectations can generate uncertainty traps: long periods with high uncertainty and low economic activity. In particular, the authors consider that firms do not know with certainty the demand they will face in the future and form expectations in a Bayesian way. Therefore, an individual firm sees the investment decisions of other firms and makes an inference about the current level of economic activity and the future demand. This information externality is the potential mechanism that could generate negative feedback.

Then, when an uncertainty shock in the spirit of Bloom et al. (2007) has a large impact and generates disinvestment, the low levels of economic activity can be persistent with the mechanism indicated by Fajgelbaum et al. (2017). If uncertainty about future revenues is high because only a few firms are making investments, an individual firm can choose a low level of investment too, expecting low levels of future demand.

Moreover, as Pástor and Veronesi (2013) highlight, policy uncertainty can result from economic activity. According to their analysis, governments have more incentives and are more likely to act – correctly or incorrectly– when economies are in recessions. The authors also argue that economic policy uncertainty can increase the non-diversifiable risk and therefore have negative effects on asset prices.

In conclusion, empirical studies are needed to clarify the direction and the magnitude of the uncertainty shocks. As we have seen, the theory proposes complex interactions between the variables: uncertainty can lower economic activity, a recession can increase the uncertainty, and they can interact. Furthermore, the predicted duration of the effects is not clear either, given the general equilibrium considerations.

2.1.3 Some priors about capital flows

Regarding foreign investment, it is useful to remember some differences between the variables, according to the Balance of Payments methodology. Portfolio Investment includes the cross-border acquisition of financial assets, like stocks or bonds (IMF, 2013). Additionally, the sudden stops literature has always emphasized the importance of external factors in order to explain capital flows, especially in crises that apparently cannot be explained with vulnerabilities in local variables (for example, Calvo, 1998). A reason is precisely that portfolio equity and debt flows involve transactions that can, in principle, be executed very 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. It is true that all investments are exposed to political uncertainty, but as Julio and Yook (2016) point out, foreign investment is burdened with additional layers of rules and regulations, such as differential tax treatments. Moreover, as Rodrik (1991) suggests, uncertainty on the success or reversal of economic reforms and policies acts as a tax on the foreign investors who own capital in the local countries. Therefore, to the extent that investors incorporate it into their decisions, they could wait before investing in long-term projects.

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 in 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 benchmark to consider, and consequently, we start discussing this group. Afterward, we review some articles that use the EPU Index and finally, we examine literature devoted specifically to emerging economies and capital flows.

2.2.1 Evidence 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. An example is the article of Bloom (2009), who proposes a theoretical model and estimates it. By parameterizing it, the author argues that it can be used as a reference for empirical estimates with the autoregressive vector methodology. In particular, his estimates seem to be consistent with the prediction of real options theory: the product suffers a severe but transitory fall as there is a variance shock -used as a proxy for uncertainty- with rapid recovery (around six months). In addition, adjustment costs in the labor market are discarded as the only additional element to explain it, although the same does not happen with capital adjustment costs.

Another example is the work of Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramirez, and Uribe (2011). The authors estimate a stochastic model for interest rates and use it in a calibrated small-open economy dynamic stochastic general equilibrium (DSGE) model. The authors show that an increase in volatility in real interest rates triggers a fall in output, consumption, investment, and debt. In the model, volatility is understood as an increase in the variance of the process generating the interest rate.

In a similar but complementary way, Bloom et al. (2018) propose a DSGE model with heterogeneous firms to study uncertainty shocks on economic activity. They find that uncertainty shocks (understood as variance shocks) need to be complemented with level shocks to fit the US consumption data. Thus, they suggest that recessions are events associated microeconomically with negative shocks in levels (or expectations) and positive shocks in the variance of the variables. Furthermore, they show that the model implies that stabilization policies would lose three-quarters of their effectiveness in situations with high uncertainty. However, the simulation of Fajgelbaum et al. (2017) exhibits a discouragement of investments when the uncertainty is high and nonlinearities according to the size of shocks. Also, uncertainty acts as an amplifying and propagation mechanism in the simulated model.

Nevertheless, different strategies soon started to replace the focus on uncertainty as shocks in the variance of expected variables. Before the introduction of the widely used EPU indices (Baker, Bloom, and Davis, 2016), Bloom (2014) pointed out alternative strategies to estimate the effects of uncertainty, apart from the calibrated structural models. These approaches were based on the use of timing, taking advantage of events associated with spikes in uncertainty.

The bottom-line of Bloom's review is that evidence was suggestive but not conclusive about the short-term negative effects on economic activity, investment, hiring, consumption, and trade. Moreover, Bloom indicated that long-run effects seemed to be negative, but they were hard to show empirically in a credible way. Regarding the mechanisms, the author suggested that the delays were the dominant force in the short run and 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. They consider national elections in 48 countries held between 1980 and 2005 in which the outcome determined the national leader directly or indirectly. The authors find evidence supporting the hypothesis that political uncertainty leads firms to reduce investment expenditures until the electoral uncertainty is resolved. In particular, during election years, firms reduce investment expenditures relative to non-election years, controlling for country fixed effects, growth opportunities, and economic conditions. Furthermore, elections in which the outcome is "close" -as measured by voting results- lead to deeper investment cycles, and investment rates drop more when the incumbent national leader is classified as "market-friendly" by the World Bank.

These findings are consistent with a higher option value of delaying decisions. Moreover, Julio and Yook highlight that the firms' increase in cash holdings is similar in magnitude to the election-year decline in investment, suggesting that the funds that would have been used as an investment are temporarily held as cash until the election 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 to identify clearer causal relationships. Regarding the measurement, Jurado, Ludvigson and Ng (2015) support the notion that predictability is what matters in the analysis of uncertainty. So, they suggest that measuring the volatility or variance of data cannot be sufficient to capture the idea of uncertainty. Thus, they build economic and financial uncertainty indices based on the variance of the forecast errors of 132 economic variables and 147 financial ones. Furthermore, their Structural Vector Autoregressive analysis suggests that uncertainty shocks are as important as monetary policy shocks in their impact on economic activity. Although a short-run recursive order is used as an identification assumption, they impose two alternative orders -based on previous literature- and the results are similar.

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. Good uncertainty predicts an increase in future economic activity, such as consumption, output, and investment, and is positively related to valuation ratios, while bad uncertainty forecasts a decline in economic growth and depresses asset prices. Further, the market prices of risk and equity beta of good uncertainty are positive, while negative for bad uncertainty. Hence, both uncertainty risks contribute positively to risk premia and help to explain the cross-section of expected returns beyond cash flow risk.

The article by Ludvigson, Ma, and Ng (2021) is somewhat ambitious, as it seeks to determine whether uncertainty is a source or an endogenous response to fluctuations. To do this, they construct two indices to capture economic and financial uncertainty. Furthermore, they introduce a new identification strategy in structural VAR models, imposing inequality constraints for shocks based on the characteristics of the series. The authors 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 journalist 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, and she estimates that 27% of the drop observed after the Great Recession was due to this greater conflict. Additionally, she uses aggregated data for a preliminary analysis with VAR methodology and firm-level data for a panel data analysis, controlling for financial and macroeconomic variables. As the author suggests, one of the possible mechanisms for these negative effects may be the greater induced uncertainty.

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 testing 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 with other variables.

The EPU Index aims to serve as a proxy of 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 has a different number of local newspapers in its coverage.

In order to evaluate the dynamic of economic activity after an EPU shock, the authors estimate a panel data regression with firm-level observations and a structural VAR analysis with aggregate-level data. Both analyses 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 decisions´s delay, the increased financing cost and the reduction in credit.

An example of the focus on delays is Gulen and Ion (2016). The authors find a negative relationship between firm-level capital investment and the level of uncertainty implied by the EPU index. They claim the presence of precautionary delays related to investment irreversibility because they find stronger effects for firms with a higher degree of investment irreversibility and for firms that are more dependent on government spending. Regarding persistence, they find that policy uncertainty can affect investment levels up to eight quarters into the future.

Between the articles devoted to financing costs as mechanisms, we can mention the evidence of Pástor and Veronesi (2013), which is consistent with an increase in political risk premium in the stock market associated with greater uncertainty implied by the EPU index. In particular, both the volatility of individual stocks and the correlations between stocks increase during times of higher policy uncertainty. Also, they find that uncertainty tends to be higher during recession times. Xu (2020) identifies a cost-of-capital mechanism with negative effects on investment but oninnovation also. Interestingly, innovations of financially constrained firms and firms relying on external finance in a competitive environment are the most affected.

Furthermore, Drobetz, El Ghoul, Guedhami, and Janzen (2018) find that economic policy uncertainty depresses the investment levels and distorts the relation between investment and the cost of capital, with less sensibility to changes in the ex-ante cost of capital. Indeed, this effect is more pronounced for firms operating in countries with high state ownership and for firms operating in industries that depend strongly on government subsidies or government consumption. They use data of publicly listed firms of 21 countries to estimate a panel-data regression. As we have previously discussed, this is a prediction of the real options theory.

With regard to credit, Bordo, Duca, and Koch (2016) find that uncertainty slowed the growth of bank credit in the United States between 1961 and 2014. They use a panel data methodology, including macroeconomic and regulatory controls, and they find heterogeneity in the effects: large banks were more affected, while the more capitalized and more liquid banks (specifically, with higher money holdings) confronted milder effects.

In contrast, Barraza and Civelli (2020) report a contraction in bank credit, not deceleration as a mechanism. The authors use a structural VAR methodology and show that an exogenous increase in economic policy uncertainty is associated with a contraction in business loans by the banks. They find a restriction in the supply of spot funds and a reduction in the provision of liquidity insurance, reducing both current and future liquidity provision in consequence.

2.2.3 Emerging economies: capital flows and EPU

Finally, we can extract some interesting points about the empirical research devoted to effects of uncertainty on activity and investment in emerging economies and determinants of capital flows in emerging economies. For instance, the analysis of Carrière-Swallow and Céspedes (2013) shows evidence consistent with a different response of emerging economies to uncertainty shocks (compared with developed economies). They use the VXO index -an indicator of the volatility of the US stock market- as an exogenous variable in a Structural VAR model under the small open economy assumption for forty countries over a twenty-year period. For developed countries, they find an initial drop in investment with a quick return to the previous level. For developing countries, instead, they observe a large and more persistent drop. Despite the heterogeneity between countries, their analysis suggests that financial frictions are the most relevant mechanism to explain the different reactions. The results for Chile of Cerda, Silva, and Valente (2018) are similar, because they find a persistent effect.

Julio and Yook (2016) examine the effects of political uncertainty on cross-border capital flows using election timing as a source of fluctuations in political uncertainty. Using quarterly data of U.S. investors' direct investment to 43 countries between 1994 and 2010, they find that flows from US companies to foreign affiliates drop significantly during the period just before an election, conditional to institutional, macroeconomic, and financial variables. Interestingly, the decline is transitory; because FDI flows increase after the uncertainty is resolved. The evidence also suggests that the impact of political uncertainty on FDI flows is lower for countries with higher levels of institutional quality and higher when elections are more competitive. Crucially, the results imply a reduction almost three times greater than compared to domestic corporate investment as found in Julio and Yook (2012).

There are also a few studies that use the EPU Index to examine mechanisms of transmission of EPU to economic activity in emerging economies. Demir and Ersan (2017) examine the effect of country-specific EPU on cash holding decisions of firms in Brazil, Russia, India, and China. By using yearly firm-level data of the period of 2006–2015, they find that firms prefer to hold more cash when uncertainty increases, conditional on firm-level variables with industry and year fixed effects. These results hold both for country-specific and global EPU indices.

Krol (2014) found evidence that country-specific EPU increased exchange rate volatility for ten industrial and emerging economies since 1990, conditional on macroeconomic and financial variables. For the more integrated industrial economies, he finds that US EPU also increases the volatility of the currencies. Previous literature associates FX volatility with economic activity, so this is another potential mechanism.

The IMF (2013) suggests that increases in US and Europe levels of EPU temporarily reduce GDP growth and investment in other regions of the world. Balli, Uddin, Mudassar, and Yoon (2017) explore the determinants of these cross-country economic policy uncertainty (EPU) spillovers. They find that bilateral factors such as trade and common language play a highly significant role in explaining the magnitude of EPU spillovers. Furthermore, their analysis seems to indicate that the magnitude of EPU spillovers is higher for countries having higher vulnerability in terms of fiscal, trade, or financial liability imbalances.

Bernal, Gnabo, and Guilmin (2016) study spillovers associated with EPU shocks, focusing on sovereign spreads. The authors identify the determinants of risk spillovers by estimating a panel data model with macroeconomic variables and EPU indices of the four largest Eurozone countries (Germany, France, Italy, and Spain) and the United States. The model is estimated with quarterly data for ten countries. Their results support the idea that economic policy uncertainty in both core and periphery countries can transmit risk arising from individual countries' sovereign spreads to regional bond markets as a whole.

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.

Koepke (2019) reviews 34 empirical studies about the drivers of capital flows to emerging markets. His analysis suggests that determinants of FDI are different from portfolio flows. In particular, FDI seems to be least affected by global cyclical developments and closely tied to strategic decisions of multinational enterprises. Moreover, FDI's unique drivers seem to be long-term factors, such as the tax regime, trade protection, bilateral trade relations, exchange rate effects, and gravity effects. Instead, his evidence shows that financial variables are the most important drivers of portfolio flows, including asset returns, exchange rate volatility, and indicators of investor risk aversion.

Koepke makes a –traditional- distinction between "push" (external) and "push" (domestic) factors. His analysis concludes that push factors matter for portfolio flows, while pull factors are more relevant for banking flows. Regarding push factors, Koepke indicates there is evidence that increased global risk aversion and high interest rates in advanced economies have adverse effects on portfolio flows. In terms of mature economies output growth, Koepke points out there is –limited- support for the notion that external growth encourages EM portfolio flows. On the pull side, Koepke suggests that almost all studies find evidence that domestic economic performance is an important driver of portfolio flows, though the relationship is not always statistically robust (particularly for high-frequency data). Also, Koepke suggests there is evidence that local asset returns and country risk indicators serve as a pull factor, but the evidence is not robust for portfolio flows.

An interesting point of Koepke's review is the frequency in the used data because his analysis suggests different relative importance of capital flows drivers, according to its frequency. For instance, 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.

In the same vein as literature related to sudden stops, Forbes and Warnock (2012) study gross international capital flows and find that global factors are –on average- more important than local factors. Especially, their evidence points to the global risk affecting capital flows. Also, they find that contagion is important (via trade, banking and geography). Furthermore, Miranda-Agrippino and Rey (2020) suggest that US monetary policy shocks induce comovements in the international financial markets and affect asset prices worldwide. They find that monetary contractions lead to deleveraging, a decline in credit, and, therefore, retrenching international credit flows.

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.

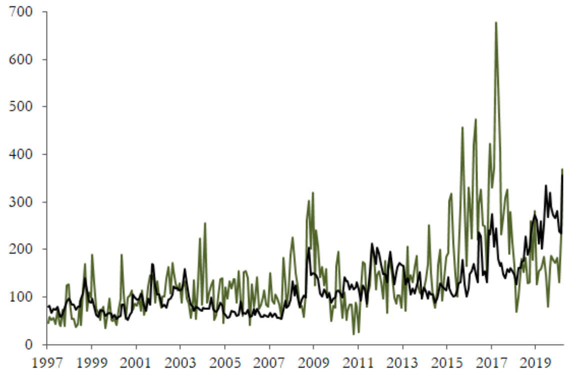
It is worth noting that the EPU index for the United States (the most used in empirical literature) consists of three components: a subindex based on newspaper content, a measure of the proportion of tax codes close to ending, and a subcomponent with the dispersion of economic forecasts. However, for 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).

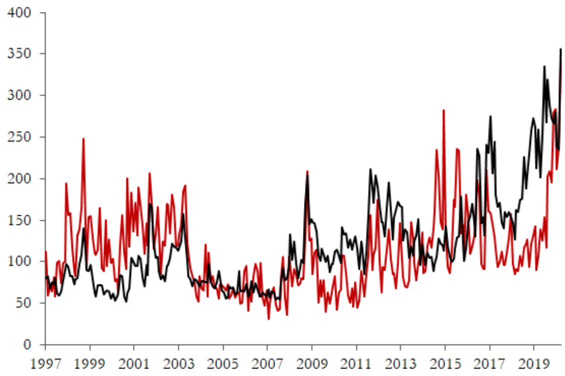
In Figure 1, the series of national EPU indices are shown, together with the Global EPU. As can be seen, there is some correlation between them, but idiosyncratic events drive the local indices. Moreover, for all the countries, the indices spike with identifiable events. The series with annotations related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

4.2 Other variables

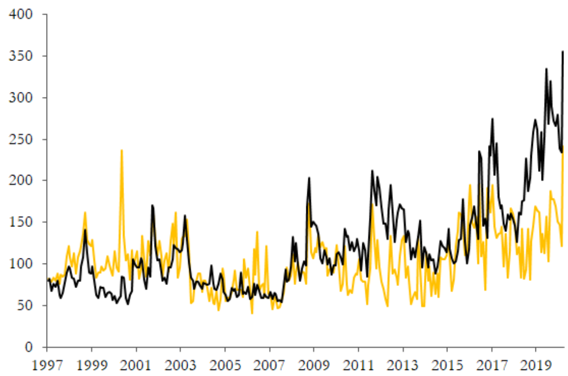
According to the sixth edition of the Balance of Payments Manual (IMF, 2013), Foreign Direct investment is a category of cross-border investment associated with residents in one economy having control or a significant degree of influence on the management of an enterprise that is resident in another 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



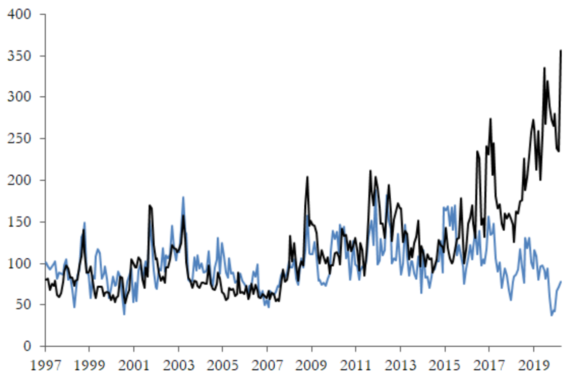
(a) Brazil (green) and Global EPU Index



(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). [4]

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

[4] 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.[5]

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

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.[6]

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.

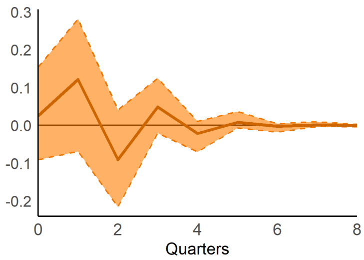
6.1 Foreign Direct Investment

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.

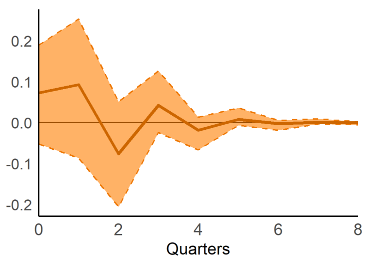
As positive values correspond to increased outflows, the IRFs are consistent with a reduction in Investment after a structural shock in EPU. The effects are stronger in the first two quarters and after a partial reversion is observed. As the models only include one lag, the effects are short-lived. These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

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

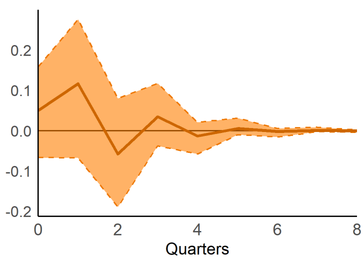
[6]Also, a «seed» for the random number generator is used: the simulations always give the same path, and in consequence, the graphs can be replicated in an exact way.



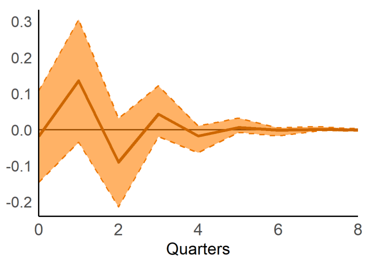
(a) Embi. VAR (1)



(b) Fedrate. VAR (1)



(c) GDP. VAR (1)

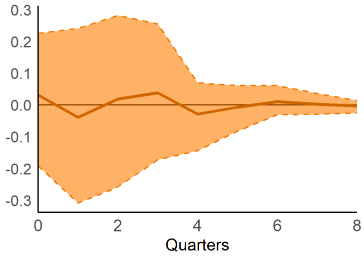


(d) Global EPU. VAR (1)

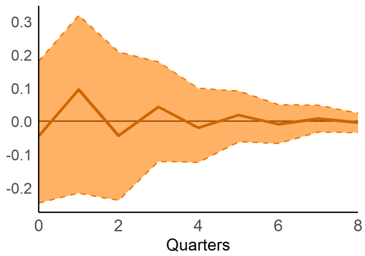
Figure 2: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Foreign Direct Investment in Brazil. First ordering (EPU first) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure 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.

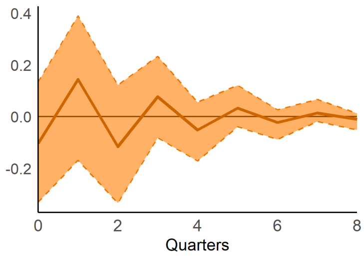
The IRFs resulting for Chile can be seen in Figure 3. Compared with the Brazil estimation, the results are more volatile and stronger in the first quarter after the shock.



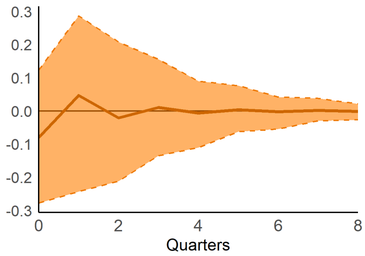
(a) Embi. VAR (2)



(b) Fedrate. VAR (1)



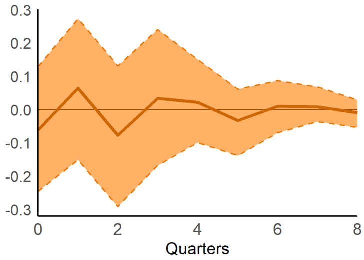
(c) GDP. VAR (1)



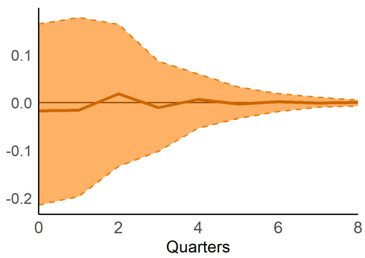
(d) Global EPU. VAR (1)

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.

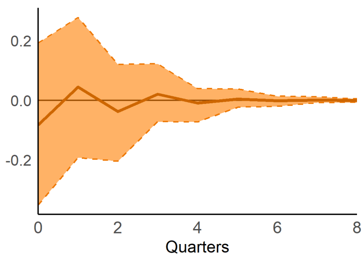
In Figure 4 there are the estimated IRFs for Colombia. The results are similar to the Colombia case, with small and not statistically significant effects. The IRFs resulting for Greece can be seen in Figure 5. The results are similar to the previous ones but with more volatility in the point estimates. 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.



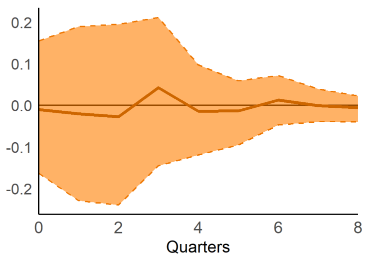
(a) Embi. VAR (2)



(b) Fedrate. VAR (1)

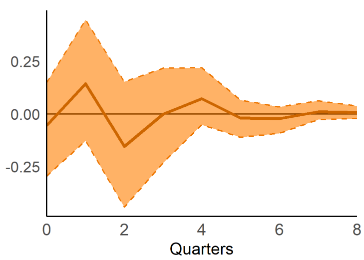


(c) GDP. VAR (1)

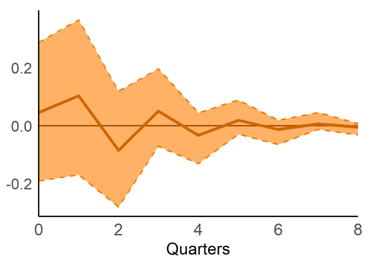


(d) Global EPU. VAR (2)

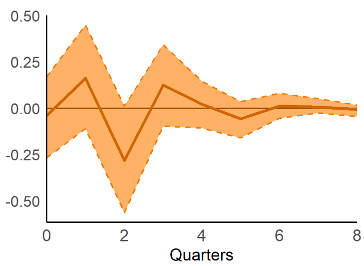
Figure 4: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Foreign Direct Investment in Colombia. First ordering (EPU first) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each 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.



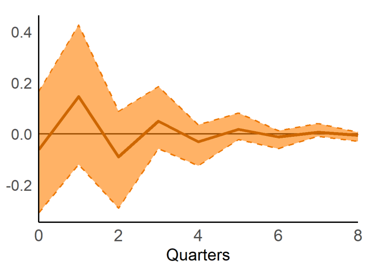
(a) Embi. VAR (2)



(b) Fedrate. VAR (1)



(c) GDP. VAR (2)

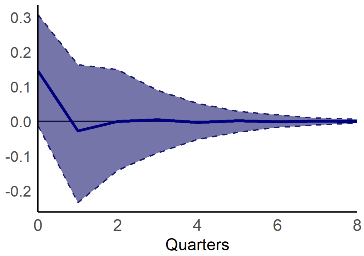


(d) Global EPU. VAR (1)

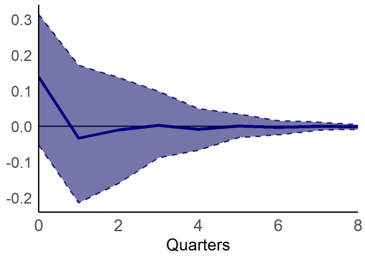
Figure 5: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Foreign Direct Investment in Greece. First ordering (EPU first) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure 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

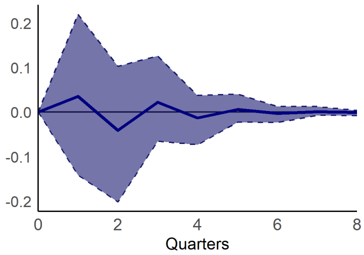
The Figures in this section show the estimated response of the first difference of Portfolio Investment to a one-standard deviation shock in the first difference of Local EPU. The logic of the Figures is the same as in the previous section. In Figure 6 we can see the IRFs resulting for Brazil.



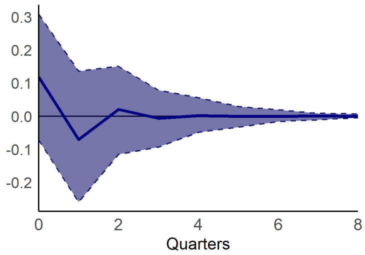
(a) Embi. VAR (1)



(b) Fedrate. VAR (1)



(c) GDP. VAR (1)

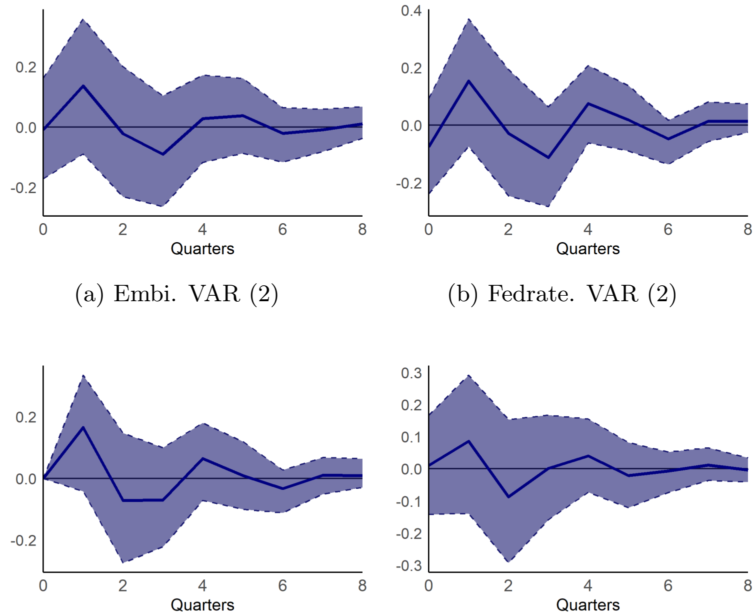


(d) Global EPU. VAR (1)

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)

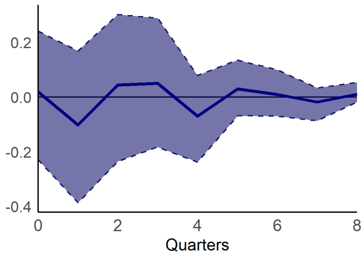
(c) GDP. VAR (2)

(d) Global EPU. VAR (2)

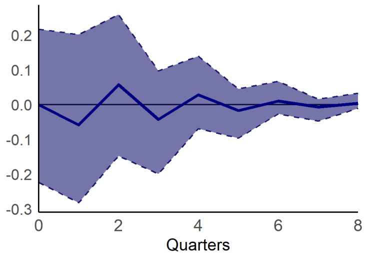
Figure 7: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Portfolio Investment in Chile. First ordering (EPU first) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure 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.

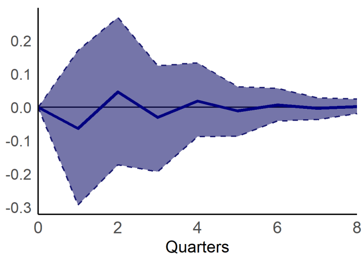
The same qualitative conclusions can be extracted with the estimations assuming the second ordering (as can be seen in Appendix D) or the third ordering for the GDP (see Appendix E). An interesting difference is that, in the Brazil case with the second ordering, all the responses are smaller in magnitude,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



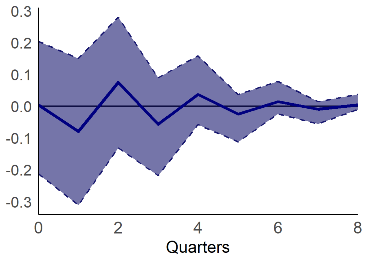
(a) Embi. VAR (2)



(b) Fedrate. VAR (1)

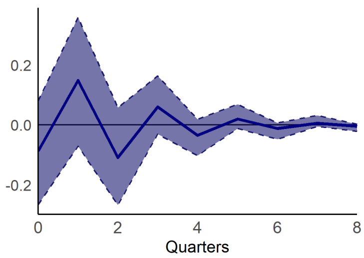


(c) GDP. VAR (1)

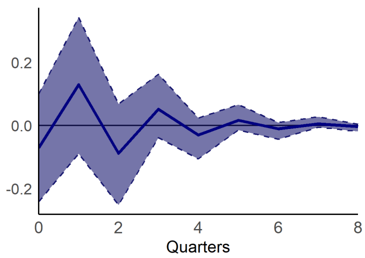


(d) Global EPU. VAR (1)

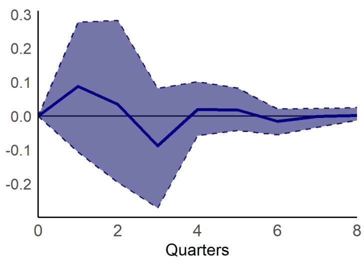
Figure 8: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Portfolio Investment in Colombia. First ordering (EPU first) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure 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.



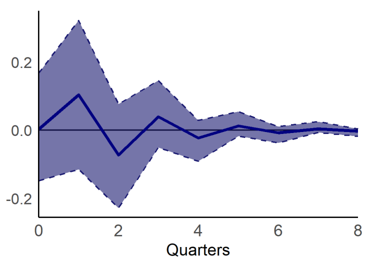
(a) Embi. VAR (1)



(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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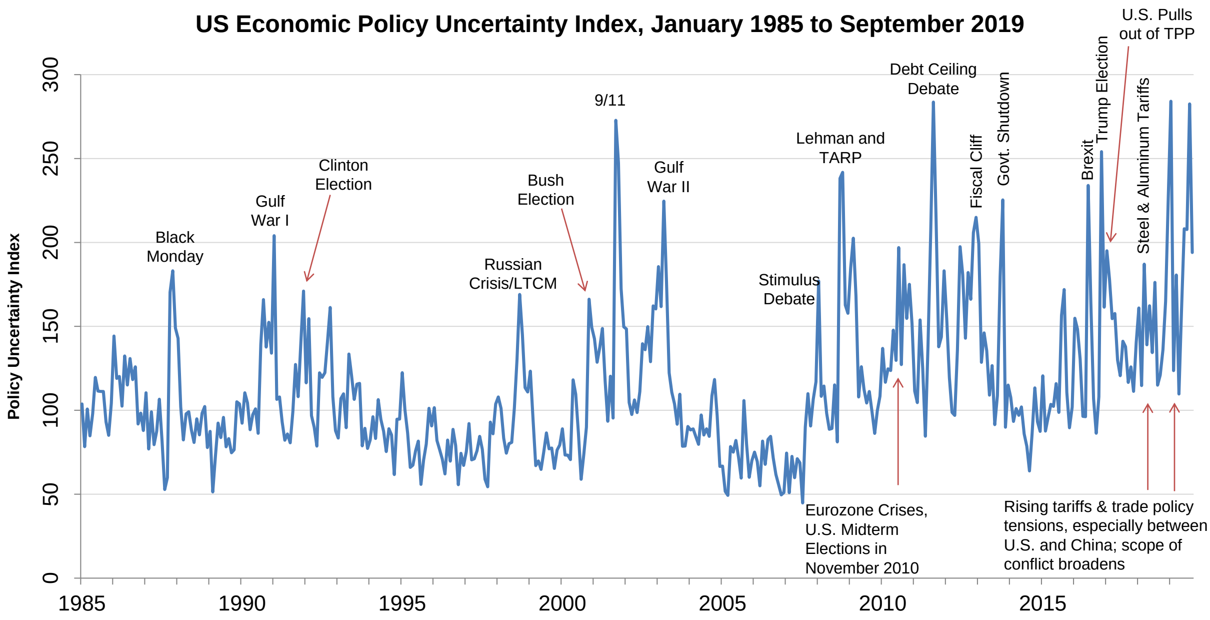
9 Appendix A: EPU series and events

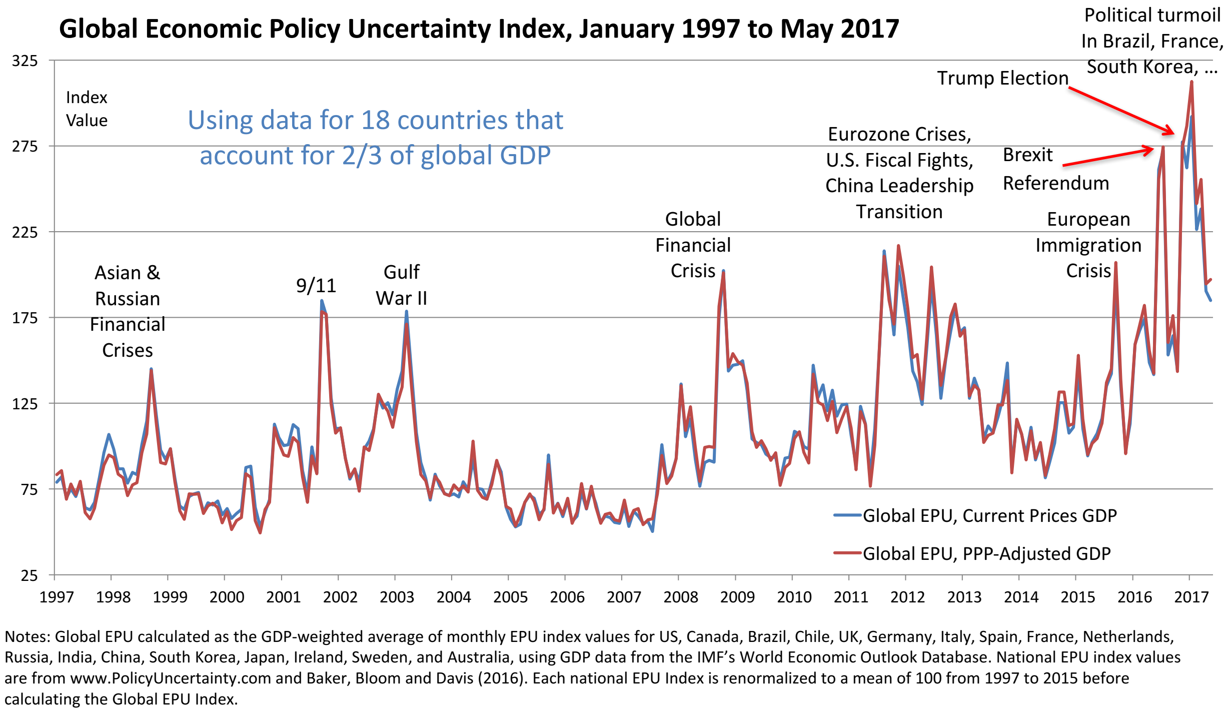
Figure 10: US EPU annotations



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.

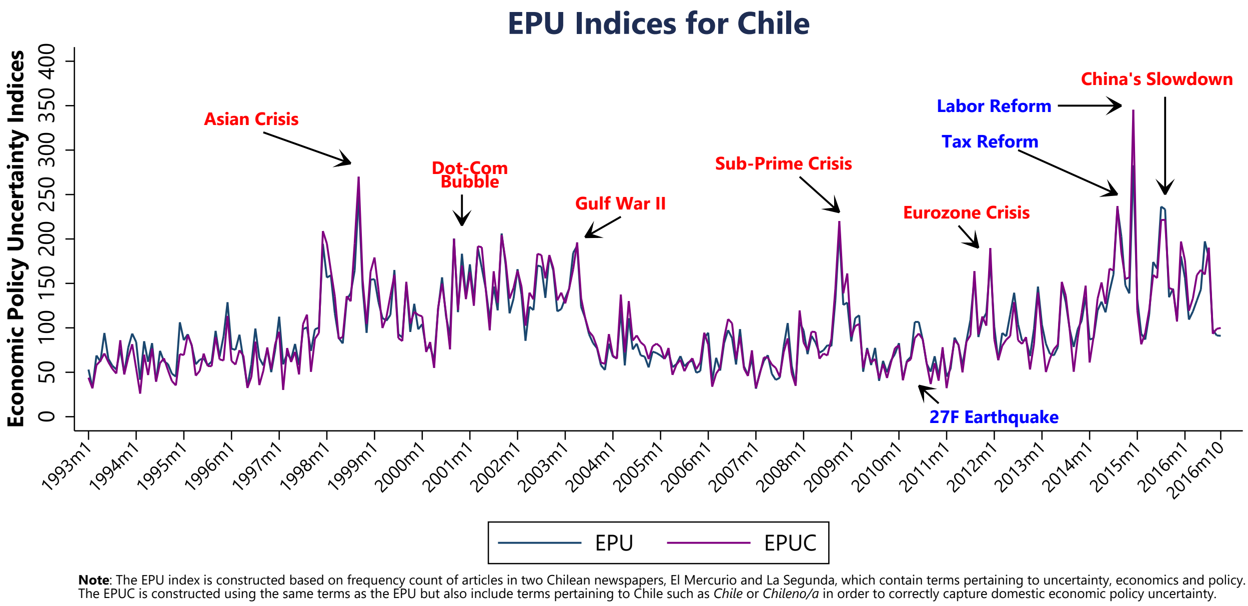
Source: policyuncertainty.com

Figure 11: Global EPU annotations



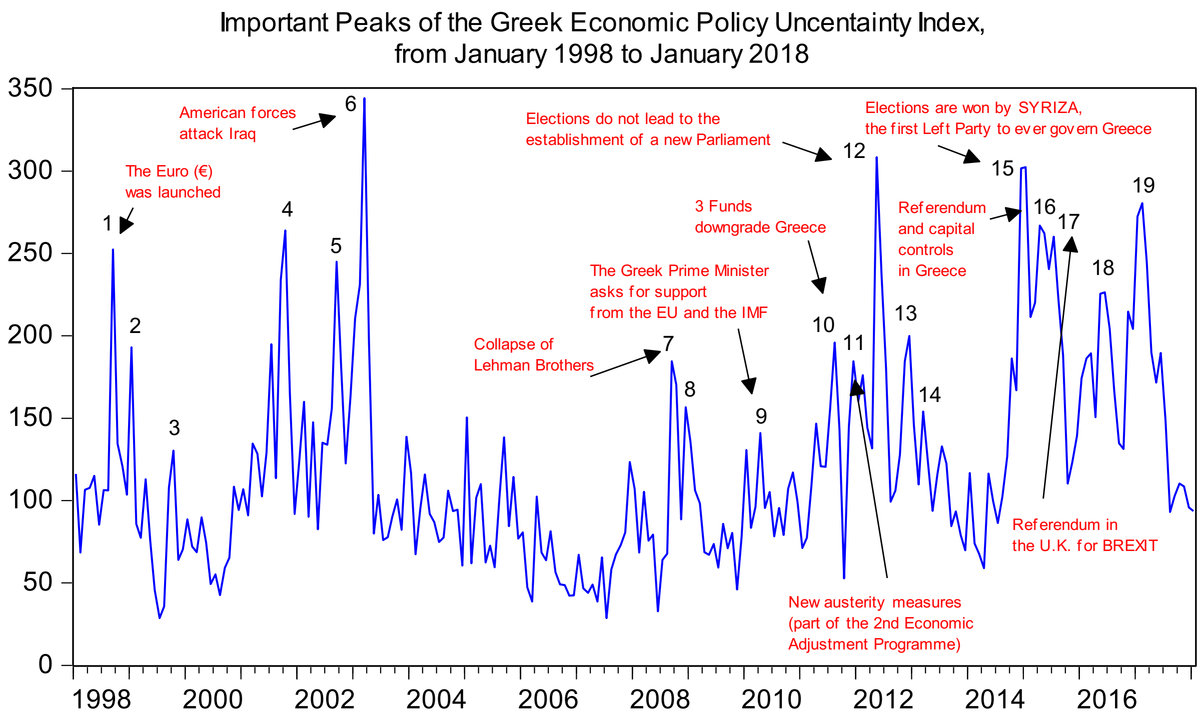
Source: policyuncertainty.com

Figure 12: Chile EPU annotations



Source: policyuncertainty.com

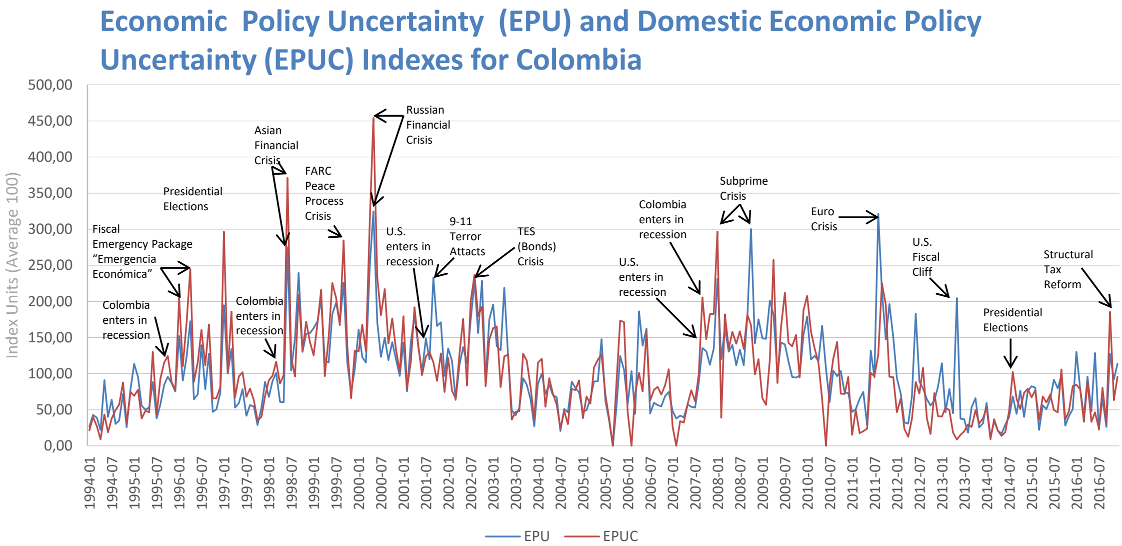
Figure 13: Greece EPU annotations



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

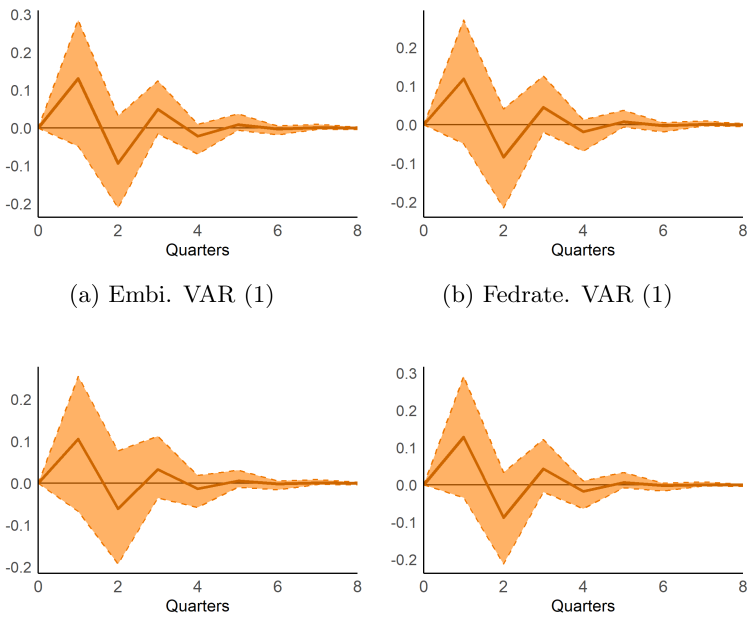
10 Appendix B: Lag selection

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)

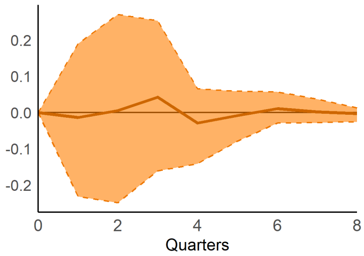
(b) Fedrate. VAR (1)

(c) GDP. VAR (1)

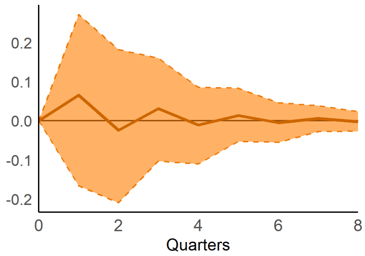
(d) Global EPU. VAR (1)

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.

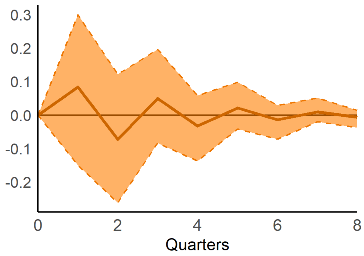
The IRFs resulting for Chile can be seen in the Figure 17.



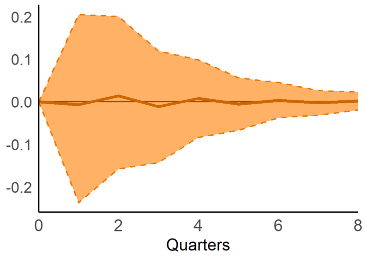
(a) Embi. VAR (2)



(b) Fedrate. VAR (1)



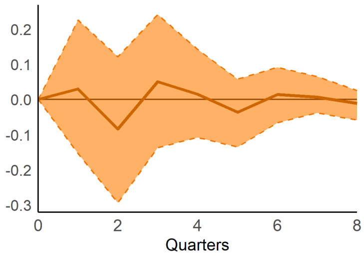
(c) GDP. VAR (1)



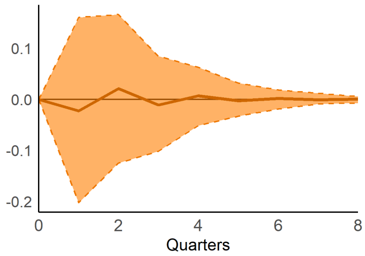
(d) Global EPU. VAR (1)

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.

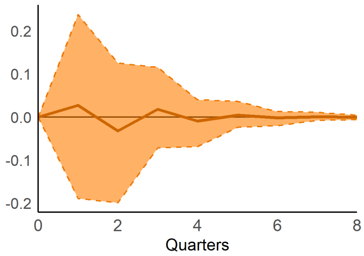
The IRFs resulting for Colombia can be seen in the Figure 18.



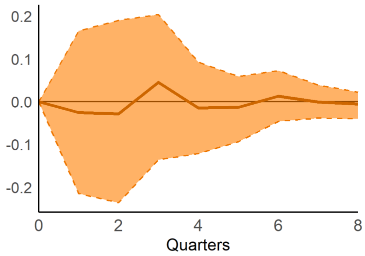
(a) Embi. VAR (2)



(b) Fedrate. VAR (1)



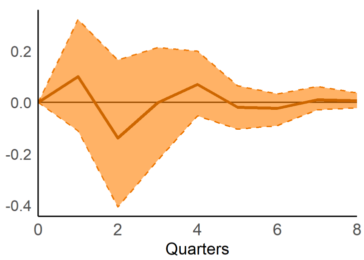
(c) GDP. VAR (1)



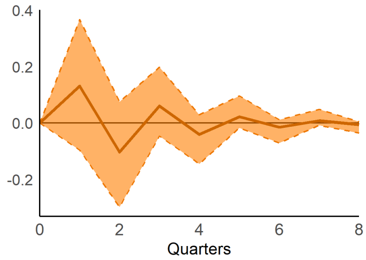
(d) Global EPU. VAR (2)

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.

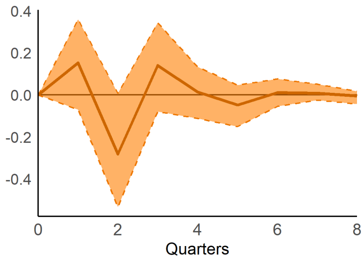
The IRFs resulting for Colombia can be seen in the Figure 19.



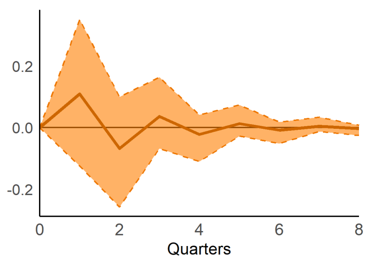
(a) Embi. VAR (2)



(b) Fedrate. VAR (1)



(c) GDP. VAR (2)

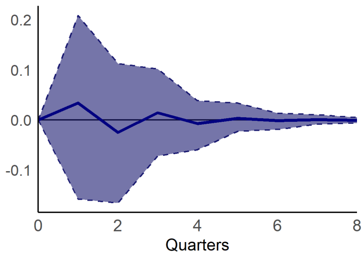


(d) Global EPU. VAR (1)

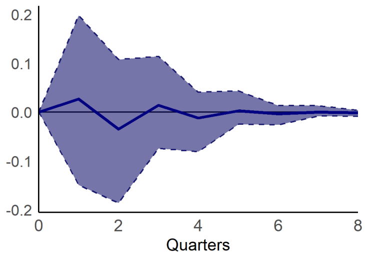
Figure 19: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Foreign Direct Investment in Greece. Second ordering (EPU last) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each 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

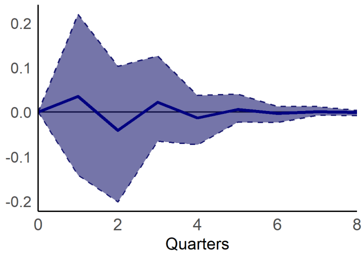
The IRFs resulting for Brazil can be seen in the Figure 20.



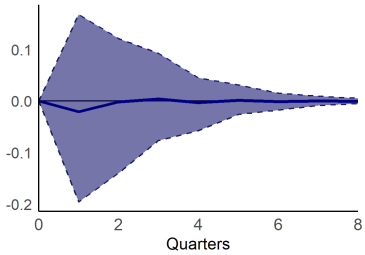
(a) Embi. VAR (1)



(b) Fedrate. VAR (1)



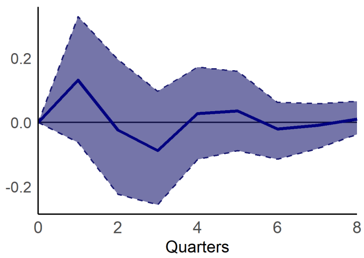
(c) GDP. VAR (1)



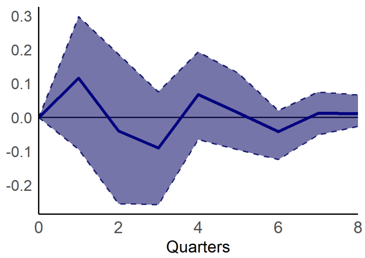
(d) Global EPU. VAR (1)

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.

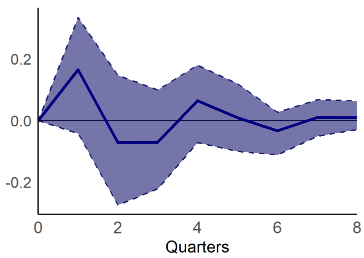
The IRFs resulting for Chile can be seen in the Figure 21.



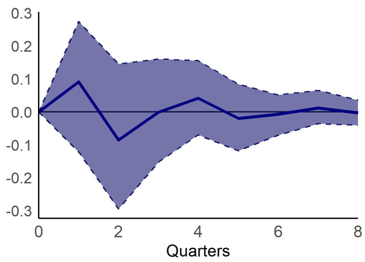
(a) Embi. VAR (2)



(b) Fedrate. VAR (2)



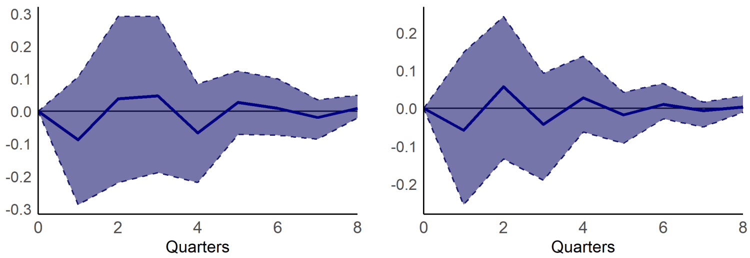
(c) GDP. VAR (2)



(d) Global EPU. VAR (2)

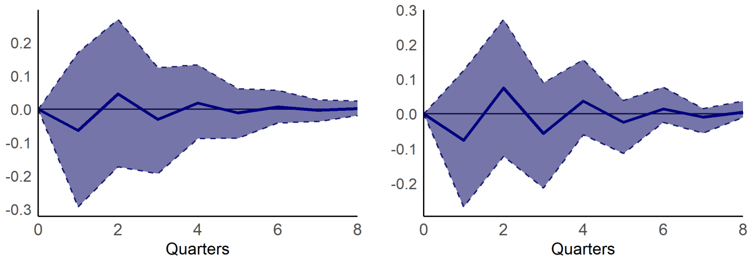
Figure 21: Orthogonalized Impulse Response Functions graphs for a one-standard-deviation shock in local EPU to Portfolio Investment in Chile. Second ordering (EPU last) is used as identification assumption. All variables are quarterly and standardized, with zero mean and unitary variance. Each subfigure 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)

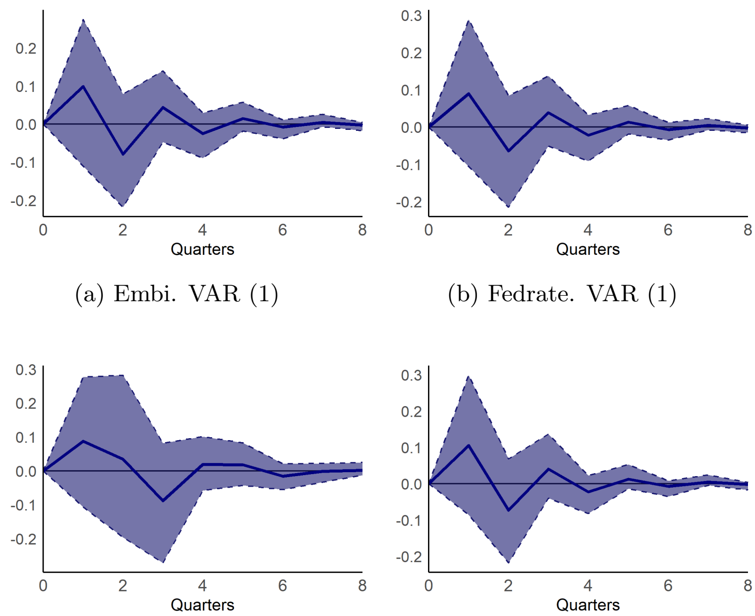


(c) GDP. VAR (1)

(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.



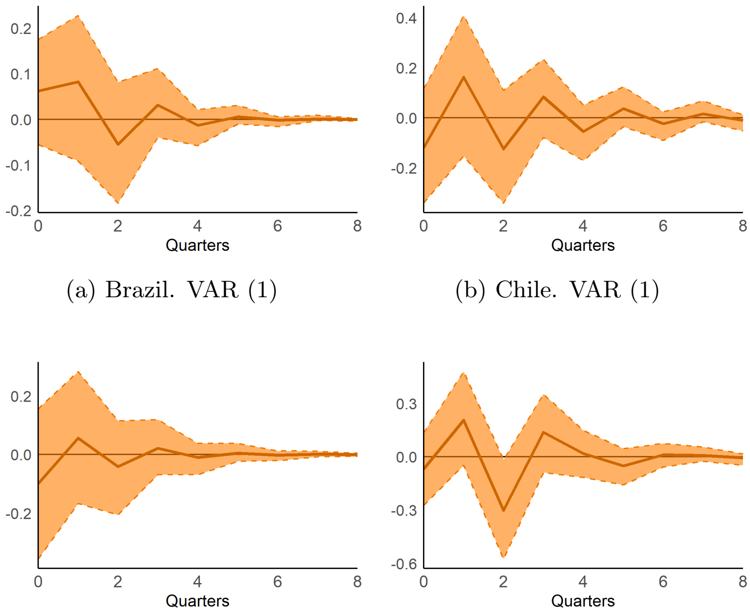
(a) Embi. VAR (1) (b) Fedrate. VAR (1)

(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)

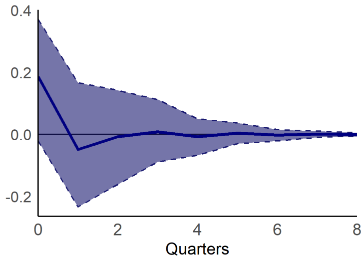
(b) Chile. VAR (1)

(c) Colombia. VAR (1)

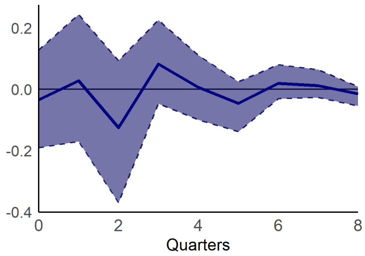
(d) Greece. VAR (2)

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.

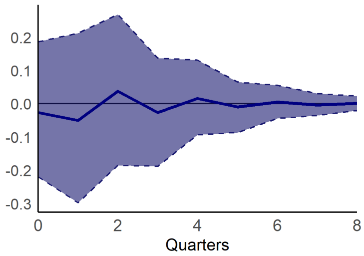
The IRFs resulting for PI can be seen in the Figure 25.



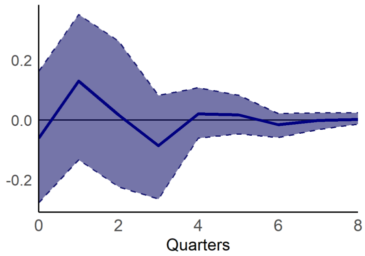
(a) Brazil. VAR (1)



(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.