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Spillovers to Emerging Market Economies

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Spillovers to Emerging Market Economies

by

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Abstract

This dissertation consists of three essays investigating the impact of macroeconomic shocks in emerging markets. The first chapter explores for spillovers from monetary policy in the United States to a number of emerging market economies. The chapter starts with estimating a bivariate structural GARCH-in-Mean VAR in the U.S. monetary policy rate and the policy rate of each of six emerging economies that target the inflation rate — Brazil, Chile, Mexico, Romania, Serbia, and South Africa. We also estimate the same model in the U.S. monetary policy rate and the exchange rate (against the U.S. dollar) of each of six emerging economies that target the exchange rate — Bosnia and Herzegovina, Bulgaria, Comoros, Croatia, the Former Yugoslav Republic of Macedonia, and Montenegro. The primary conclusion of this chapter is that positive (negative) U.S. monetary policy shocks tend to appreciate (depreciate) the currencies of the exchange rate targeting emerging economies, but have an ambiguous effect on the policy rates of the inflation-targeting emerging economies.

The second chapter presents a comprehensive examination of the effects of oil price shocks on real economic activity in the EM7 economies in the context of two classes of empirical models. The chapter provides evidence that, in general, oil price uncertainty has statistically significant effects on the real output of the EM7 economies and that the relationship between oil prices and economic activity is in general symmetric. The chapter also finds that oil price uncertainty has in general a negative effect on world crude oil production.

The final chapter investigates for spillovers from monetary policy uncertainty in the United States to the policy rates of seven inflation targeting emerging economies — Brazil, Chile, Colombia, Indonesia, Mexico, Poland, and South Africa. The chapter uses monthly data, with the start of the sample period being dictated by the start of the inflation targeting regime, and a multivariate GARCH-in-Mean vector autoregression (VAR), controlling for the traditional Taylor rule type variables. The chapter also employs a multivariate structural VAR and a different measure of U.S. monetary policy uncertainty, achieving identification by a combination of short-run and long-run restrictions. The chapter concludes that U.S. monetary policy uncertainty, irrespective of how it is measured, has negative effects on the macroeconomic and financial fundamentals of emerging economies.

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Dedication

To my parents, brother, sister and wife

Table of Contents

Abstract ii

Acknowledgements iii

Dedication iv

Table of Contents vi

List of Figures viii

List of Tables ix

1 Monetary Policy Spillovers in Emerging Economies 1
- 1.1 Introduction . . . 1
- 1.2 Nominal Targets for Monetary Policy . . . 3
  - 1.2.1 Exchange Rate Targeting . . . 3
  - 1.2.2 Inflation Targeting . . . 5
- 1.3 The Data . . . 6
  - 1.3.1 Inflation Rate Targeters . . . 7
  - 1.3.2 Exchange Rate Targeters . . . 8
  - 1.3.3 Unit Root Tests . . . 10
- 1.4 The Structural GARCH-in-Mean VAR . . . 12
- 1.5 Empirical Evidence . . . 13
  - 1.5.1 Inflation Targeters . . . 40
  - 1.5.2 Exchange Rate Targeters . . . 41
- 1.6 Conclusion . . . 42

2 Oil Price Shocks in Major Emerging Economies 44
- 2.1 Introduction . . . 44
- 2.2 The Multivariate GARCH-in-Mean VAR . . . 46
- 2.3 The Data . . . 48
- 2.4 Empirical Evidence . . . 56
- 2.5 On the (A)symmetric Relationship . . . 57
- 2.6 Conclusion . . . 60

3 Spillovers of U.S. Monetary Policy Uncertainty on Inflation Targeting Emerging Economies 62
- 3.1 Introduction . . . 62
- 3.2 The Multivariate GARCH-in-Mean VAR . . . 64
  - 3.2.1 The Data . . . 66
  - 3.2.2 Empirical Evidence . . . 68
  - 3.2.3 Robustness . . . 70
- 3.3 The Bjørnland and Leitemo (2009) VAR . . . 73
  - 3.3.1 Empirical Evidence . . . 76

3.3.2 Robustness 84
3.4 Conclusion 100

Bibliography **102**

A Appendix of Tables and Figures - Chapter 2 **108**

B Appendix of Tables and Figures - Chapter 3 **112**

List of Figures

1.1 Impulse Response Functions for Brazil 28
1.2 Impulse Response Functions for Chile 29
1.3 Impulse Response Functions for Mexico 30
1.4 Impulse Response Functions for Romania 31
1.5 Impulse Response Functions for Serbia 32
1.6 Impulse Response Functions for South Africa 33
1.7 Impulse Response Functions for Bosnia and Herzegovina 34
1.8 Impulse Response Functions for Bulgaria 35
1.9 Impulse Response Functions for Comoros 36
1.10 Impulse Response Functions for Croatia 37
1.11 Impulse Response Functions for Former Yugoslav Republic of Macedonia 38
1.12 Impulse Response Functions for Montenegro 39

2.1 Real output and its growth rate for the EM7 countries 50
2.2 Brent crude oil price and its growth rate for the EM7 countries 51
2.3 World crude oil production and its growth rate 52
2.4 World economic activity 53

3.1 Responses of domestic variables in Brazil to a U.S. monetary policy uncertainty shock 78
3.2 Responses of domestic variables in Chile to a U.S. monetary policy uncertainty shock 79
3.3 Responses of domestic variables in Colombia to a U.S. monetary policy uncertainty shock . . 80
3.4 Responses of domestic variables in Indonesia to a U.S. monetary policy uncertainty shock . . 81
3.5 Responses of domestic variables in Mexico to a U.S. monetary policy uncertainty shock . . . 82
3.6 Responses of domestic variables in Poland to a U.S. monetary policy uncertainty shock 83
3.7 Responses of domestic variables in South Africa to a U.S. monetary policy uncertainty shock 84
3.8 Responses of domestic variables in Brazil to a U.S. monetary policy uncertainty shock after reordering of variables 86
3.9 Responses of domestic variables in Chile to a U.S. monetary policy uncertainty shock after reordering of variables 87
3.10 Responses of domestic variables in Colombia to a U.S. monetary policy uncertainty shock after reordering of variables 88
3.11 Responses of domestic variables in Indonesia to a U.S. monetary policy uncertainty shock after reordering of variables 89
3.12 Responses of domestic variables in Mexico to a U.S. monetary policy uncertainty shock after reordering of variables 90
3.13 Responses of domestic variables in Poland to a U.S. monetary policy uncertainty shock after reordering of variables 91
3.14 Responses of domestic variables in South Africa to a U.S. monetary policy uncertainty shock after reordering of variables 92
3.15 Responses of domestic variables in Brazil to a U.S. economic policy uncertainty shock 93
3.16 Responses of domestic variables in Chile to a U.S. economic policy uncertainty shock 94
3.17 Responses of domestic variables in Colombia to a U.S. economic policy uncertainty shock . . 95
3.18 Responses of domestic variables in Indonesia to a U.S. economic policy uncertainty shock . . 96

3.19 Responses of domestic variables in Mexico to a U.S. economic policy uncertainty shock 97
3.20 Responses of domestic variables in Poland to a U.S. economic policy uncertainty shock 98
3.21 Responses of domestic variables in South Africa to a U.S. economic policy uncertainty shock 99

List of Tables

1.1 Inflation targeting and exchange rate targeting economies . . . 7
1.2 Unit root tests in first differences of policy rates and exchange rates . . . 11
1.3 Estimates of the GARCH-in-Mean VAR for Brazil . . . 15
1.4 Estimates of the GARCH-in-Mean VAR for Chile . . . 16
1.5 Estimates of the GARCH-in-Mean VAR for Mexico . . . 17
1.6 Estimates of the GARCH-in-Mean VAR for Romania . . . 18
1.7 Estimates of the GARCH-in-Mean VAR for Serbia . . . 19
1.8 Estimates of the GARCH-in-Mean VAR for South Africa . . . 20
1.9 Estimates of the GARCH-in-Mean VAR for Bosnia and Herzegovina . . . 21
1.10 Estimates of the GARCH-in-Mean VAR for Bulgaria . . . 22
1.11 Estimates of the GARCH-in-Mean VAR for Comoros . . . 23
1.12 Estimates of the GARCH-in-Mean VAR for Croatia . . . 24
1.13 Estimates of the GARCH-in-Mean VAR for Former Yugoslav Republic of Macedonia . . . 25
1.14 Estimates of the GARCH-in-Mean VAR for Montenegro . . . 26
1.15 λ coefficient estimates from the GARCH-in-Mean VARs . . . 27

2.1 Unit root and stationarity tests on the logged difference series . . . 54
2.2 SIC values for the standard VAR and the multivariate GARCH-in-Mean VAR . . . 55
2.3 Coefficients of interest, λ_{41} and λ_{43}, from the multivariate GARCH-in-Mean model . . . 55
2.4 p-values for statistical test of the null hypothesis of symmetric impulse responses to positive and negative oil price shocks . . . 59

3.1 Countries, central banks and sample period . . . 68
3.2 λ_{43} coefficient estimates from the multivariate GARCH-in-Mean VAR . . . 69
3.3 λ_{41} coefficient estimates from the multivariate GARCH-in-Mean VAR with US shadow rates ordered first . . . 70
3.4 λ_{43} coefficient estimates from the multivariate GARCH-in-Mean VAR with BIS policy rates . 72

A.1 Data sources . . . 108
A.2 Data description . . . 111

B.1 Data sources . . . 112
B.2 Data transformations . . . 114
B.3 Unit root and stationarity tests . . . 115
B.4 SIC values for standard and multivariate GARCH-in-Mean VARs . . . 116
B.5 SIC values for standard and multivariate GARCH-in-Mean VARs with US shadow rates ordered first . . . 117
B.6 SIC values for the standard and multivariate GARCH-in-Mean VARs with BIS policy rates . 118

Chapter 1

Monetary Policy Spillovers in Emerging Economies[1]

Nahiyan Faisal Azad and Apostolos Serletis

1.1 Introduction

Monetary policy in the United States, and the role of the U.S. dollar as an international currency, play an important role in determining global financial conditions. As Edwards (2018) put it, "even under flexible exchange rates, there is significant policy interconnectedness across countries. In a highly globalized setting, even when there are no obvious traditional reasons for raising interest rates, some central banks will follow the Fed. This phenomenon may be called 'policy spillover,' and could be the result of a number of factors, including the desire by central banks to protect domestic currencies from 'excessive' volatility. If this is indeed the case, then even under flexible exchange rates there is no such a thing as true 'monetary independence.' " Motivated by these considerations, in this paper we explore for spillovers from monetary policy in the United States to a number of emerging market countries. These economies are becoming extremely relevant for global economic growth, as they account for about 70 percent of global growth in output and consumption, and as Serletis and Azad (2020) recently put it in the Conclusion, "the growth prospects of emerging market economies are becoming extremely relevant for global economic growth."

We estimate the Elder and Serletis (2010) bivariate structural GARCH-in-Mean VAR in the U.S. monetary policy rate and the policy rate of each of six emerging economies that target the inflation rate —

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Brazil, Chile, Mexico, Romania, Serbia, and South Africa. We also estimate the same model in the U.S. monetary policy rate and the exchange rate (against the U.S. dollar) of each of six emerging economies that target the exchange rate — Bosnia and Herzegovina, Bulgaria, Comoros, Croatia, the Former Yugoslav Republic of Macedonia, and Montenegro. We associate the U.S. monetary policy rate VAR residual with exogenous U.S. monetary policy shocks, use the conditional standard deviation of the forecast error for the change in the U.S. monetary policy rate as a measure of monetary policy uncertainty in the United States, and investigate the relationship between the U.S. monetary policy rate and the policy stance in each of the emerging economies.

We estimate the structural (identified) GARCH-in-Mean VAR using full information maximum likelihood, avoiding Pagan (1984) generated regressor problems associated with estimating the variance equation separately from the conditional mean equation. We use monthly data and two new data sets, recently compiled by the Bank for International Settlements (BIS) — one on monetary policy rates (for 38 countries) and one on exchange rates (for 190 countries). We investigate the effects of positive and negative U.S. monetary policy shocks, and also whether monetary policy uncertainty in the United States has had statistically significant spillover effects on each of the emerging economies. Our evidence suggests that positive (negative) U.S. monetary policy shocks tend to appreciate (depreciate) the currencies of the exchange rate targeting emerging economies, but have an ambiguous effect on the policy rates of the inflation-targeting emerging economies, and that monetary policy uncertainty in the United States leads to an increase in policy rates in those emerging economies that target the inflation rate and leads to depreciation of the currencies of those emerging economies that target the exchange rate.

The paper contributes in two ways to the existing literature. First, the paper uses two novel data sets, recently made available by the Bank for International Settlements, to investigate for monetary policy spillovers from U.S. monetary policy to inflation targeting and exchange rate targeting emerging economies. The second contribution to the existing empirical literature is that the paper provides an empirical investigation of the Dornbusch (1976) overshooting hypothesis in the context of emerging economies. In this regard, most of the existing studies investigate the overshooting hypothesis in the context of advanced economies, as in Eichenbaum and Evans (1995), and very few studies have been conducted in the context of emerging economies. Our paper investigates the overshooting hypothesis in the context of the United States economy, where the response of the U.S. dollar against the currencies of six exchange rate targeting emerging economies is investigated due to a monetary policy shock in the United States.

The outline of the paper is as follows. Section 2 discusses monetary policy strategies for emerging market economies, in particular, exchange rate targeting and inflation targeting. Section 3 presents the data and discusses their time series properties using unit root and stationarity tests. In Section 4, we briefly explain the Elder and Serletis (2010) empirical model while in Section 5 we present and discuss the empirical results. The last section briefly concludes the paper.

1.2 Nominal Targets for Monetary Policy

What economic variable should serve as the nominal anchor? There are several monetary policy strategies that could be used to promote price stability, including the money supply, the exchange rate, the inflation rate, the price level, and nominal GDP. In what follows we briefly discuss exchange rate targeting and inflation targeting. In this regard, after the abandonment of monetarism in the early 1980s by the Federal Reserve in the United States and other industrialized countries around the world, because of unstable money demand functions (due to velocity shocks), between the mid-1980s and mid-1990s, the dominant approach for many developing countries to lower inflation rates was the use of the exchange rate as the monetary policy target. In recent years, however, a large number of emerging and developing economies started targeting the inflation rate and have given their central banks greater independence, following the success of inflation targeting in advance economies, such as New Zealand, Canada, and the United Kingdom.

1.2.1 Exchange Rate Targeting

As already noted, a monetary policy strategy that could be used to promote price stability is exchange rate targeting (also refered to as an exchange rate peg). It involves fixing the value of the domestic currency to that of a large, low-inflation country (the anchor country). It requires an easing of monetary policy when there is a tendency for the domestic currency to appreciate and a tightening of monetary policy when there is a tendency for the domestic currency to depreciate. It has the advantage of increasing international trade and investment by reducing transaction costs and exchange risk and by preventing speculative bubbles. Moreover, if the nominal anchor of an exchange rate target is credible (i.e., expected to be adhered to), it helps mitigate the time inconsistency problem associated with rule type monetary policy making.

Exchange rate targeting, however, requires giving up an independent monetary policy. For example, the central bank of the targeting country cannot use monetary easing (increase the money supply, reduce interest rates, or devalue its currency), in response to domestic bad shocks. Also, under exchange rate targeting, shocks to the anchor country are directly transmitted to the pegging country, and so changes in interest rates and the inflation rate in the anchor country lead to corresponding changes in interest rates and the inflation rate in the targeting country. Another problem with exchange rate targeting is that it leaves the targeting country open to speculative attacks on its currency. For example, if the anchor country is practicing tight monetary policy, the pegging country is subjected to a negative demand shock that leads to a decline in economic activity. If speculators reason that the pegging country will not tolerate the decline in economic activity and start to question its commitment to the exchange rate peg, there could be speculative attacks on the pegging country that can lead to full-scale financial crises (examples are the speculative attacks to the European ERM countries in September 1992, Mexico in 1994, East Asia in 1997, and Argentina in 2002).

Over the years, exchange rate targeting has been effective in controlling inflation in both industrialized countries as well as in emerging market economies. However, the emerging market currency crises that started in the early 1990s and ended in the early 2000s, all involved the abandonment of exchange rate targeting. In many countries (including Mexico and Argentina), this happened because of speculative attacks that led to gradual but sustained losses of international reserves, and so forced the abandonment of exchange rate anchors. Other countries such as, for example, Chile and Colombia, preemptively switched to floating exchange rates. Also, some smaller countries responded by moving to institutionally locked-in arrangements, such as currency boards or full dollarization.

In a currency board arrangement, the domestic currency is backed 100% by a foreign (reserve) currency (such as the U.S. dollar) and the exchange rate between the two currencies is fixed. A currency board is thus a variant of a fixed exchange-rate regime with an even stronger commitment mechanism, since domestic money can be issued only if it is fully backed by foreign reserves. In fact, a currency board arrangement is the modern day equivalent of a fully backed gold standard with foreign reserves taking the place of gold reserves. Currency boards have been adopted by Hong Kong (in 1983), Argentina (in 1991), and Lithuania (in 1994) with the U.S. dollar, and Estonia (in 1992), Bulgaria (in 1997), and Bosnia and Herzegovina (in 1999) with the euro.

Another possible exchange rate arrangement is 'dollarization' — one country's use of another country's money (which may not be the U.S. dollar). Dollarization is another variant of a fixed exchange-rate regime, with an even better commitment device than a currency board. In particular, dollarization avoids the possibility of a speculative attack on the domestic currency and also eliminates the inflation-bias problem of discretionary policy (arising from attempts to stimulate the economy and incentives to monetize the public debt). However, dollarization is subject to the usual disadvantages of a fixed exchange-rate regime — it implies the loss of an independent monetary policy, the inability of the central bank to act as a lender of last resort, and the loss of seigniorage (the revenue that the government receives by issuing money). Recently, Ecuador (in 2000) and El Salvador (in 2001) adopted full dollarization.

Currency boards and dollarization, however, are strong measures that tend to be applied in extreme circumstances. They have been advocated as monetary policy strategies for emerging market countries, especially in parts of Latin America that have had a long history of monetary instability. In sum, as Frankel (2010) put it, "from the longer-term perspective of the four decades since 1971, the general trend has been in favor of floating exchange rates."

1.2.2 Inflation Targeting

In recent years, a large number of emerging and developing economies switched from exchange rate targeting to inflation targeting, following the success of inflation targeting in advanced economies. Brazil, Chile, Colombia and Mexico switched from exchange rate pegs to inflation targeting in 1999, as well as Armenia, Hungary, Poland, and the Czech Republic, while they were making the transition from centrally planned to market economies. Israel, Korea, South Africa, and Thailand also switched from exchange rate targets to inflation targeting about the same time. Then Mexico followed in 2001, Indonesia and Romania in 2005, and Turkey in 2006. Currently there are 66 advanced, emerging, and developing economies around the world that target the inflation rate, and many other countries are moving toward this monetary policy framework.

As already noted, inflation targeting has been very successful in industrialized countries. In emerging market and developing economies, however, inflation targeting can be vulnerable to temporary supply (price) shocks, which tend to be larger than for advanced countries, because it builds unnecessary procyclicality into the automatic monetary mechanism. In the case, for example, of a temporary negative supply shock, short-run inflation stabilization requires a significant autonomous tightening of monetary policy, and leads to a larger deviation in aggregate output from potential, relative to a no policy response, with the entire fall in nominal GDP being borne by real GDP.

In this regard, it should be kept in mind that inflation-targeting central banks typically target headline (based on total CPI) inflation, mainly for transparency and communication reasons (i.e., the public is more likely to understand what the central bank is doing). Inflation-targeting central banks also use core (or underlying) inflation (the rate of inflation based on core CPI that excludes food, energy, and the effects of changes in indirect taxes) to "look through" temporary changes in total CPI and focus on the underlying trend of inflation. However, it has been argued that targeting headline inflation (sticky price inflation) leads to distortions in relative prices and less-than-full output stabilization whereas targeting core inflation without sticky prices (of food and energy) is always optimal. In this regard, Pourroy et al. (2016) argue that the optimal monetary policy depends on a country's income level. In particular, headline inflation targeting is optimal in low- and medium-income countries (which have a high share of food and energy goods in the consumption basket). In high-income countries, the optimal choice is core inflation.

Also, if the supply shocks are terms of trade shocks (shocks to the price of imports relative to exports, both expressed in domestic currency), then CPI inflation targeting can be destabilizing, because it requires monetary tightening (and thereby currency appreciation) when the price of imports increases, but not when the price of exports increases on world markets, exactly the opposite of the desired pattern of response. That is, the headline CPI inflation rate they target does not exclude terms of trade shocks. For this reason, a nominal anchor that accommodates, rather than exacerbating, the macroeconomic effects of movements in the terms of trade will be a better choice in the case of small countries with exportable and importable goods.

1.3 The Data

We use monthly data on monetary policy rates and exchange rates for a large number of emerging market countries and the United States — see IMF (2016) for a classification of exchange rate arrangements and monetary policy frameworks. The United States is used as an indicator of the global economy, because as Kose et al. (2017) put it, "developments in the U.S. economy, because of its size and international linkages, are bound to have substantial implications for the global economy. The United States is the world's single largest economy (at market exchange rates), accounting for almost 22 percent of global output and over a third of stock market capitalization. It is prominent in virtually every global market, accounting for about one-tenth of global trade flows, one-fifth of global FDI stock, close to one-fifth of remittances, and one-fifth of global energy demand."

We use the newly constructed monetary policy rate series by the Bank for International Settlements (BIS), made publicly available for research on September 2017 — see BIS (2018). Although the data set consists of monetary policy rates for 38 countries, we use the data for six inflation-targeting emerging market countries — Brazil, Chile, Mexico, Romania, Serbia, and South Africa. It is to be noted that the information on monetary policy rates is provided by the national central banks to the Bank for International Settlements, which in turn reports the specific interest rate that each national central banks considers as the monetary policy rate. We restrict our analysis to the period after the adoption of inflation targeting in the respective emerging economies (see column 1 in panel A of Table 1).

We also use exchange rate data for six exchange-rate targeting emerging market countries — Bosnia and Herzegovina, Bulgaria, Comoros, Croatia, the Former Yugoslav Republic of Macedonia, and Montenegro. We obtain the monthly exchange rate series (against the United States dollar) also from the Bank for International Settlements — see BIS (2017). Like the database on policy rates, this newly constructed BIS database contains nominal exchange rate data for 190 countries. Again, we restrict our analysis to the period after the adoption of exchange rate targeting (see column 1 in panel B of Table 1.1).

Table 1.1: Inflation targeting and exchange rate targeting economies

A. Inflation rate targeters

Country	Adoption year	Target inflation rate (percent)
Brazil	1999	4.5 ± 1
Chile	1999	3 ± 1
Mexico	2001	3 ± 1
Romania	2005	3 ± 1
Serbia	2006	$4 - 8$
South Africa	2000	$3 - 6$

B. Exchange rate targeters

Country	Adoption year	Regime
Bosnia and Herzegovina	1997	Currency Board
Bulgaria	1997	Currency Board
Comoros	1994	Conventional peg
Croatia	1993	Crawl-like arrangement
Former Yugoslav Republic of Macedonia	1995	Stabilized arrangement
Montenegro	1999	Unilateral use of Euro

1.3.1 Inflation Rate Targeters

In panel A of Table 1.1 we list the six emerging market countries that target the inflation rate, together with the year when inflation targeting was adopted (in column 1) and the inflation target range (in column 2). In this regard, after experiencing double-digit inflation, Chile was the first among the emerging economies in the world to adopt inflation targeting as the primary monetary strategy in the early 1990s. In September 1999, the central authority officially adopted full inflation targeting with a floating exchange rate. The objective is to keep the inflation rate based on the Consumer Price Index (CPI) at 3% with ±1 percentage point tolerance level — see the central bank of Chile's website (at http://www.bcentral.cl). Around the same time (in mid-1999), Banco do Brasil, the central bank of Brazil, adopted a full inflation targeting monetary policy strategy after adopting a floating exchange rate earlier in the year. Banco do Brasil targets an annual target of 4.5%, with a tolerance range of ±1.5% — see the Banco do Brasil's website (at https://www.bcb.gov.br). After the balance of payments crisis in 1994-1995, known as the Tequila crisis, Banco de Mexico (Mexico's central bank), switched to a free-floating exchange rate regime. In 2001, Banco de Mexico formally adopted an inflation targeting framework. The target inflation rate is 3% with a tolerance range of 1%. A free-floating exchange rate and an inflation target has facilitated to bring the inflation rate down from double digits (an inflation rate of around 50% in late 1995 and early 1996) to less than 5% today — see the Banco de Mexico's website (at http://www.banxico.org.mx/).

Banca Nationala a Romaniei, the central bank of Romania, adopted inflation targeting in August 2005. Their primary aim was to bring the annual inflation rate down to single-digit levels. Currently, the central bank of that country targets the annual inflation rate at 3% with the tolerance range being ±1% — see the Banca Nationala a Romaniei's website (at http://www.bnr.ro). Also, the National Bank of Serbia manages money and interest rates to keep the medium-term inflation rate within the target tolerance band of 3% (±1%) and formally adopted direct inflation rate targeting in 2006. The targeted inflation rate, is calculated as an annual percentage change in the CPI. The domestic economy aims to meet nominal, real and structural convergence to the European Union countries through its inflation targeting strategy — see the National Bank of Serbia's website (at https://www.nbs.rs). Finally, the South African Reserve Bank adopted a flexible inflation-targeting framework in February 2000 with the inflation target set at a range of 3%-6% annual increase in the headline CPI on a continuous basis. When the inflation targeting framework was first adopted, the target was CPIX and not CPI. CPIX is a variation of CPI and consisted of CPI for urban and metropolitan areas and excluded interest rates on mortgage bonds from the calculation. However, over time due to changes in the treatment of housing, interest rates on mortgage bonds were included in the computation — see the South African Reserve Bank's website (at https://www.resbank.co.za).

1.3.2 Exchange Rate Targeters

We list the six emerging economies that target the exchange rate, together with the year when exchange rate targeting was adopted and the exchange rate regime in panel B of Table 1.1. The Central Bank of Bosnia and

Herzegovina adopted a fixed exchange rate regime with the motivation to provide monetary, institutional, and political stability in the country in the post-war period. After starting its operation in August 1997, the domestic currency was pegged to the German Deutsche mark, but after the introduction of the euro in January 1999, the currency was pegged to the euro at the same rate as for the Deutsche mark (1.95583 per euro) — see the Central Bank of Bosnia and Herzegovina website (at https://www.cbbh.ba) and Kovačević (2003) for more details.

After the hyperinflation episode in late 1996 and early 1997, the Bulgarian National Bank adopted a currency board on July 1, 1997 and managed to bring inflation to single digit levels by mid-1997. At first the Bulgarian lev was pegged to the Deutsche mark and then the euro after its introduction in 1999. The Bulgarian National Bank maintains an exchange rate regime which allows the central note-issuing authority to issue its own currency, the Bulgarian lev. The Bulgarian lev is fully backed by euro reserves by the Bulgarian National Bank — see the Bulgarian National Bank's website (http://www.bnb.bg/). With the help of the fixed exchange rate regime, the country has been able to maintain macroeconomic stability despite adverse external shocks such as the Russian financial crisis in 1998, the global financial crisis in 2007-2009, and the Kosovo conflict.

Since Comoros gained independence, the country has issued its own franc. First, Institut d' Emission des Comores issued domestic franc during the period from 1976 to 1984, then the Banque Centrale des Comores from 1984 to the present. In 1994, the Comoros franc was fixed against the French franc, but after the introduction and subsequent adoption of the euro by France, the Comoros franc was pegged to the euro in 1999 — see the Banque Centrale des Comores's website (at http://www.banque-comores.km) and Lamine et al. (2006) for more details.

After Croatia declared independence from Yugoslavia in 1991, the economy became heavily euroised. The domestic currency, kuna, was first pegged to the Deutsche mark during the period from October 1994 to January 1999 and then the euro, after its introduction. The domestic currency can fluctuate within a low tolerance range about the target currency. The exchange rate anchor has allowed the country to tackle hyperinflation and provide macroeconomic stability after the war — see the Croatian National Bank's website (at https://www.hnb.hr) and Crespo-Cuaresma et al. (2005) for more details. The National Bank of the Republic of Macedonia adopted a strategy of targeting the nominal exchange rate of the Denar against the Deutsche mark in October 1995 to meet the primary objective of price stability. In January 2002, the peg was switched against the Euro. For a small open emerging economy like the Republic of Macedonia, maintaining Denar exchange rate stability helps to increase transparency and maintain credibility. Prior to the adoption of the fixed exchange rate regime, the National Bank of the Republic of Macedonia had targeted the money supply (M1) as their primary medium run monetary policy — see the National Bank of the Republic of Macedonia's website (at http://www.nbrm.mk).

Finally, at the beginning of 1999, the government of Montenegro adopted a fixed exchange rate regime with the Deutsche mark. The country established a parallel currency system where the Deutsche mark was the legal tender and was allowed to float freely alongside the Dinar, the other legal tender in the country. Until November 1999, the country was under unofficial dollarization. Montenegro underwent full dollarization against the euro in 2002 — see the Central Bank of Montenegro's website (at http://www.cb-cg.org) and Fabris et al. (2004) for more details.

1.3.3 Unit Root Tests

We start by conducting a battery of unit root and stationary tests in the levels of the policy rates of the countries that have adopted inflation targeting and the logarithms of the exchange rates of the countries that have adopted exchange rate targeting. The sample periods are different across countries and start when inflation rate targeting was adopted in the case of the inflation-targeting countries (see column 1 of panel A of Table 1.1) and when exchange rate targeting was adopted in the case of the exchange-targeting countries (see column 1 of panel B of Table 1.1).

In particular, we use the Augmented Dickey-Fuller (ADF) test [see Dickey and Fuller (1981)] assuming both a constant and trend, to test the null hypothesis of a unit root. The optimal lag length is selected using the Schwarz information criterion (SIC). We also conduct Phillips-Perron (PP) unit root tests [see Phillips and Perron (1988)]. For both the ADF and PP unit root tests, the null hypothesis of the presence of a unit root in each of the series cannot be rejected at conventional significance levels. This leads us to the conclusion that all the series representing the levels of the policy rates and the logarithms of the exchange rates of the emerging economies are non-stationary. We also conduct the KPSS test [see Kwiatkowski et al. (1992)] on the levels of the policy rates and the logarithms of the exchange rates of the emerging economies to test the null hypothesis of stationarity against the alternative of a unit root, assuming both a constant and a linear trend. Consistent with our findings with the ADF and PP tests, we reject the hypothesis that the time series are stationary at conventional significance levels. These results are not reported but are available upon request.

In Table 1.2, we report ADF, PP, and KPSS tests using the first level differences of the policy rates of the countries that have adopted inflation targeting (see panel A of Table 1.2) and the logarithmic first differences of the exchange rates of the countries that have adopted exchange rate targeting (see panel B of Table 1.2). As can be seen, the null hypothesis of the presence of unit root is rejected at conventional significance levels by both the ADF and PP test statistics in all 13 time series. Results from the KPSS tests on the first differences of the policy rates of inflation-targeting economies and the logged first differences of the exchange rates of exchange-rate targeting emerging market economies show that the null hypothesis of stationarity cannot be rejected at 1% significance level for all 13 series.

Thus, all first level differences of the policy rates of the countries that have adopted inflation targeting (Brazil, Chile, Mexico, Romania, Serbia, and South Africa) and the United States are stationary, and all logarithmic first differences of the exchange rates of the countries that have adopted exchange rate targeting (Bosnia and Herzegovina, Bulgaria, Comoros, Croatia, the Former Yugoslav Republic of Macedonia, and Montenegro) are also stationary. In what follows, we use the stationary series.

Table 1.2: Unit root tests in first differences of policy rates and exchange rates

Country	ADF	PP	KPSS
A. Inflation rate targeters			
Brazil	−5.004	−8.753	0.042
Chile	−13.052	−13.052	0.033
Mexico	−4.872	−12.546	0.099
Romania	−9.165	−9.360	0.095
Serbia	−10.278	−10.242	0.042
South Africa	−4.310	−14.207	0.043
United States	−4.771	−14.072	0.069
B. Exchange rate targeters			
Bosnia & Herzegovina	−11.461	−11.258	0.108
Bulgaria	−11.067	−11.096	0.097
Comoros	−12.507	−12.448	0.072
Croatia	−12.553	−12.506	0.086
Former Yugoslav Republic of Macedonia	−11.039	−11.039	0.101
Montenegro	−11.161	−11.191	0.098

Notes: The 1% asymptotic critical value for both the ADF and PP tests is -4.022 for the series in panel A and -3.994 for the series in panel B. The 1% asymptotic critical value for the KPSS test is 0.216 for all the series.

1.4 The Structural GARCH-in-Mean VAR

We use a bivariate structural VAR model with GARCH-in-Mean errors. More specifically, we measure the uncertainty about U.S. monetary policy as the standard deviation of the one-step-ahead forecast error, conditional on the contemporaneous information set. The standard deviation of the one-step-ahead forecast error is a measure of the dispersion in the forecast and hence is a proxy for uncertainty about the impending realization of the U.S. policy rate. Time series, such as policy rates and exchange rates, exhibit different volatilities and, more importantly, time varying volatilities. Not considering time varying volatilities, will lead to misleading conclusions about the effects of monetary policy changes in the United States on the monetary policy of emerging economies. The bivariate structural GARCH-in-Mean model helps us overcome the limitations of existing studies by accounting for reverse causality as well as volatility in policy rates and exchange rates. The structural model adopted in this paper, allows the conditional variance of one or more variables in a simultaneous equations system to affect the conditional mean of one or more other variables. That is, the model assumes that the conditional variance is heteroscedastic and not homoscedastic as is done in most of the existing studies. The GARCH-in-Mean VAR model analyses the impact of U.S. monetary policy uncertainty on the monetary policy regime of each of the emerging economies through the standard VAR transmission channels and an additional channel, the volatility channel, as it is captured by the GARCH term.

Our model is based on Elder and Serletis (2010), and is a bivariate (identified) structural GARCH-in-Mean, as follows

$$\boldsymbol{B}\boldsymbol{z}_t = \boldsymbol{C} + \boldsymbol{\Gamma}_1\boldsymbol{z}_{t-1} + \boldsymbol{\Gamma}_2\boldsymbol{z}_{t-2} + ... + \boldsymbol{\Gamma}_p\boldsymbol{z}_{t-p} + \boldsymbol{\Lambda}\sqrt{\boldsymbol{H}_t} + \boldsymbol{\epsilon}_t \tag{1.1}$$

where

$$\boldsymbol{B} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}; \quad \boldsymbol{\Gamma}_i = \begin{bmatrix} \gamma_{11}^j & \gamma_{12}^j \\ \gamma_{21}^j & \gamma_{22}^j \end{bmatrix}; \quad \boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ \lambda & 0 \end{bmatrix}.$$

In the case of emerging market countries that target the inflation rate, the vector $\boldsymbol{z}_t$ includes the change in the monetary policy rate in the United States, Δf_t, and the change in the policy rate of the emerging economy, Δi_t. In the case of those emerging market countries that target the exchange rate, $\boldsymbol{z}_t$ includes Δf_t and the logged change in the exchange rate of the emerging economy, $\Delta \log s_t$. In equation (1.1), $\boldsymbol{\epsilon}_t$ is the vector of structural disturbances, and it is assumed that $\boldsymbol{\epsilon}_t \,|\Omega_{t-1} \sim \text{iid } N(\boldsymbol{0}, \boldsymbol{H}_t)$ where $\boldsymbol{0}$ is the null vector and $\boldsymbol{H}_t$ is the covariance matrix, Ω_{t-1} denotes the information set at time $t-1$, which includes variables dated $t-1$ and earlier, and $\boldsymbol{\Lambda}$ is a matrix of coefficients that relates U.S. monetary policy rate volatility to the conditional mean of the variables in the VAR. This specification allows the matrix of conditional standard deviations, denoted $\sqrt{\boldsymbol{H}_t}$, to affect the conditional mean. Testing whether uncertainty in the U.S. policy rate affects the policy rates of inflation targeting emerging economies and the exchange rates of exchange rate targeting emerging economies is a test of restrictions on the elements of $\boldsymbol{\Lambda}$, that relate the conditional standard deviation of U.S. policy rates, given by the appropriate element of $\sqrt{\boldsymbol{H}_t}$, to the conditional mean of the variables in the VAR. The system is identified by assuming that the diagonal elements of contemporaneous correlation matrix, $\boldsymbol{B}$, are unity, that $\boldsymbol{B}$ is a lower triangular matrix, and that the structural disturbances, $\boldsymbol{\epsilon}_t$, are contemporaneously uncorrelated.

The conditional variance is modeled as

$$diag\left(\boldsymbol{H}_t\right) = \boldsymbol{C}_v + \sum_{j=1}^{q} \boldsymbol{F}_j\, diag\left(\boldsymbol{\epsilon}_{t-j}\boldsymbol{\epsilon}_{t-j}'\right) + \sum_{i=1}^{r} \boldsymbol{G}_i\, diag\left(\boldsymbol{H}_{t-i}\right) \tag{1.2}$$

where *diag* is the operator that extracts the diagonal elements from a square matrix. We impose the additional restriction that the conditional variance of $\boldsymbol{z}_t$ depends only on its own past squared errors and its own past conditional variance such that the matrices $\boldsymbol{F}_j$ and $\boldsymbol{G}_i$ are also diagonal.

Impulse responses are computed as in Elder (2003). We also show one-standard error bands based on the Monte Carlo method described in Hamilton (1994). Confidence intervals are constructed by simulating 1000 impulse responses that are retrieved randomly from the sampling distribution of the maximum likelihood estimates. The covariance matrix of the maximum likelihood estimates is derived from an estimate of Fisher's information matrix.

1.5 Empirical Evidence

Each of the 12 bivariate GARCH-in-Mean VARs, consisting of equations (1) and (2), is estimated by full information maximum likelihood, thus avoiding Pagan (1984) generated regressor problems associated with estimating the variance function parameters separately from the conditional mean parameters. The procedure is to maximize the log likelihood with respect to the structural parameters — see Elder and Serletis (2010) for more details. We estimate each model after we optimally select p in equation (1) using the Akaike Information Criterion (AIC), and set $q = r = 1$ in equation (1.2).

We report the point estimates of the mean and variance function parameters in 1.3-1.8 for the emerging countries that target the inflation rate and in Tables 1.9-1.14 for those countries that target the exchange rate. The primary coefficient of interest in each of the 12 bivariate structural models is the GARCH-in-Mean coefficient, λ — the coefficient on the conditional standard deviation of the U.S. monetary policy rate in the mean equation. This coefficient indicates the effect of uncertainty in monetary policy in the United States on the monetary policy stance in each of the emerging market countries. In Table 1.15, we report the coefficient of interest and the corresponding p-value for each of the 12 bivariate models we estimate.

We also simulate the response of the monetary policy stance in each of the emerging market countries to both a positive and negative U.S. policy rate shock in order to investigate whether the responses to positive and negative U.S. monetary policy shocks are symmetric or asymmetric. Those impulse responses are shown in Figures 1.1-1.6 for the inflation-targeting emerging market countries and in Figures 1.7-1.12 for those that target the exchange rate. The impulse responses are based on a U.S. policy rate shock equal to the annualized unconditional standard deviation of the change in the U.S. policy rate and are calculated as in Elder (2003).

Table 1.3: Estimates of the GARCH-in-Mean VAR for Brazil

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ -0.002\ (0.989) & 1 \end{bmatrix}; \boldsymbol{C} = \begin{bmatrix} -0.006\ (0.594) \\ -3.478\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.0634\ (0.226) & -0.003\ (0.571) \\ -0.435\ (0.000) & 0.327\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.347\ (0.000) & 0.001\ (0.596) \\ -0.121\ (0.406) & 0.232\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_3 = \begin{bmatrix} 0.229\ (0.000) & -0.010\ (0.414) \\ 0.200\ (0.104) & 0.173\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ 19.857\ (0.000) & 0 \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 0.031\ (0.000) \\ 0.040\ (0.000) \end{bmatrix};$$

$$diag\boldsymbol{F} = \begin{bmatrix} -0.008\ (0.000) \\ 0.172\ (0.000) \end{bmatrix}; diag\boldsymbol{G} = \begin{bmatrix} 0.000\ (0.000) \\ 0.630\ (0.000) \end{bmatrix}.$$

Note: Sample period, monthly data: 1999:8 - 2018:4. Numbers in parentheses are p-values.

Table 1.4: Estimates of the GARCH-in-Mean VAR for Chile

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ \\ 0.057\ (0.280) & 1 \end{bmatrix};\ \boldsymbol{C} = \begin{bmatrix} -0.006\ (0.564) \\ \\ -0.638\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.021\ (0.596) & -0.051\ (0.018) \\ \\ 0.225\ (0.000) & 0.395\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.363\ (0.000) & -0.032\ (0.122) \\ \\ 0.615\ (0.000) & 0.059\ (0.280) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_3 = \begin{bmatrix} 0.262\ (0.000) & -0.010\ (0.729) \\ \\ 0.126\ (0.000) & 0.117\ (0.001) \end{bmatrix};$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ \\ 3.630\ (0.000) & 0 \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 0.027\ (0.000) \\ \\ 0.002\ (0.025) \end{bmatrix};$$

$$diag\boldsymbol{F} = \begin{bmatrix} -0.011\ (0.000) \\ \\ 0.301\ (0.000) \end{bmatrix};\ diag\boldsymbol{G} = \begin{bmatrix} 0.000\ (0.000) \\ \\ 0.699\ (0.000) \end{bmatrix}.$$

Note: Sample period, monthly data: 1997:3 - 2018:4. Numbers in parentheses are p-values.

Table 1.5: Estimates of the GARCH-in-Mean VAR for Mexico

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ -0.209\ (0.000) & 1 \end{bmatrix}; \ \boldsymbol{C} = \begin{bmatrix} 0.016\ (0.091) \\ -0.011\ (0.285) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.423\ (0.000) & 0.021\ (0.133) \\ 0.060\ (0.341) & 0.310\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.068\ (0.116) & 0.014\ (0.311) \\ 0.038\ (0.252) & 0.140\ (0.044) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_3 = \begin{bmatrix} 0.019\ (0.543) & -0.016\ (0.119) \\ -0.047\ (0.386) & 0.307\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_4 = \begin{bmatrix} -0.027\ (0.634) & 0.029\ (0.018) \\ -0.116\ (0.089) & -0.124\ (0.004) \end{bmatrix};$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ 0.139\ (0.001) & 0 \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 0.012\ (0.000) \\ 0.006\ (0.000) \end{bmatrix};$$

$$diag\boldsymbol{F} = \begin{bmatrix} 0.874\ (0.000) \\ 0.593\ (0.000) \end{bmatrix}; \ diag\boldsymbol{G} = \begin{bmatrix} 0.000\ (0.000) \\ 0.404\ (0.000) \end{bmatrix}.$$

Note: Sample period, monthly data: 2001:2 - 2018:4. Numbers in parentheses are p-values.

Table 1.6: Estimates of the GARCH-in-Mean VAR for Romania

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ 0.115\ (0.120) & 1 \end{bmatrix}; \boldsymbol{C} = \begin{bmatrix} 0.039\ (0.000) \\ -0.054\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.343\ (0.000) & 0.136\ (0.000) \\ 0.003\ (0.943) & 0.350\ (0.001) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.220\ (0.000) & -0.117\ (0.000) \\ -0.021\ (0.788) & 0.037\ (0.700) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_3 = \begin{bmatrix} -0.019\ (0.663) & 0.117\ (0.000) \\ 0.145\ (0.236) & 0.149\ (0.147) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_4 = \begin{bmatrix} -0.010\ (0.807) & 0.066\ (0.000) \\ -0.0204\ (0.820) & -0.014\ (0.887) \end{bmatrix};$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ 0.357\ (0.000) & 0 \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 0.005\ (0.000) \\ 0.001\ (0.000) \end{bmatrix};$$

$$diag\boldsymbol{F} = \begin{bmatrix} 0.982\ (0.000) \\ 0.276\ (0.000) \end{bmatrix}; diag\boldsymbol{G} = \begin{bmatrix} 0.000\ (0.000) \\ 0.724\ (0.000) \end{bmatrix}.$$

Note: Sample period, monthly data: 2005:2 - 2018:4. Numbers in parentheses are p-values.

Table 1.7: Estimates of the GARCH-in-Mean VAR for Serbia

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ -0.121\ (0.420) & 1 \end{bmatrix};\ \boldsymbol{C} = \begin{bmatrix} -9.9002e-005\ (0.991) \\ -0.144\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.468\ (0.000) & -1.1989e-003\ (0.978) \\ -0.203\ (0.261) & 0.447\ (0.001) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} -0.042\ (0.481) & 4.2217e-004\ (0.991) \\ -0.107\ (0.574) & -0.050\ (0.546) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_3 = \begin{bmatrix} -5.1028e-003\ (0.904) & 6.2472e-004\ (0.988) \\ -0.154\ (0.166) & 0.086\ (0.287) \end{bmatrix};$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ 0.714\ (0.000) & 0 \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 0.014\ (0.000) \\ 6.9669e-004\ (0.000) \end{bmatrix};$$

$$diag\boldsymbol{F} = \begin{bmatrix} 0.899\ (0.000) \\ 0.216\ (0.000) \end{bmatrix};\ diag\boldsymbol{G} = \begin{bmatrix} 0.000\ (0.000) \\ 0.784\ (0.000) \end{bmatrix}.$$

Note: Sample period, monthly data: 2006:2 - 2018:4. Numbers in parentheses are p-values.

Table 1.8: Estimates of the GARCH-in-Mean VAR for South Africa

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ -0.186\ (0.000) & 1 \end{bmatrix};\ \boldsymbol{C} = \begin{bmatrix} 0.002\ (0.864) \\ -0.031\ (0.009) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.463\ (0.000) & -0.026\ (0.546) \\ 0.106\ (0.014) & 0.013\ (0.872) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.056\ (0.281) & 0.012\ (0.630) \\ 0.163\ (0.000) & 0.454\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_3 = \begin{bmatrix} 0.030\ (0.425) & -0.008\ (0.860) \\ -0.030\ (0.475) & 0.201\ (0.001) \end{bmatrix};$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ 0.113\ (0.017) & 0 \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 0.020\ (0.000) \\ 0.002\ (0.000) \end{bmatrix};$$

$$diag\boldsymbol{F} = \begin{bmatrix} 0.761\ (0.000) \\ 0.127\ (0.000) \end{bmatrix};\ diag\boldsymbol{G} = \begin{bmatrix} 0.000\ (0.000) \\ 0.840\ (0.000) \end{bmatrix}.$$

Note: Sample period, monthly data: 2000:2 - 2018:4. Numbers in parentheses are p-values.

Table 1.9: Estimates of the GARCH-in-Mean VAR for Bosnia and Herzegovina

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ -0.004\ (0.072) & 1 \end{bmatrix}; \boldsymbol{C} = \begin{bmatrix} -0.004\ (0.754) \\ -0.020\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.043\ (0.009) & 0.301\ (0.660) \\ -0.011\ (0.000) & 0.350\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.363\ (0.000) & -0.370\ (0.660) \\ 0.002\ (0.000) & -0.048\ (0.388) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_3 = \begin{bmatrix} 0.227\ (0.000) & 0.880\ (0.398) \\ 0.004\ (0.266) & -0.075\ (0.225) \end{bmatrix};$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ 0.114\ (0.000) & 0 \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 0.031\ (0.000) \\ 0.000\ (0.000) \end{bmatrix};$$

$$diag\boldsymbol{F} = \begin{bmatrix} -0.012\ (0.000) \\ 0.076\ (0.001) \end{bmatrix}; diag\boldsymbol{G} = \begin{bmatrix} 0.000\ (0.000) \\ 0.726\ (0.000) \end{bmatrix}.$$

Note: Sample period, monthly data: 1999:02 - 2018:04. Numbers in parentheses are p-values.

Table 1.10: Estimates of the GARCH-in-Mean VAR for Bulgaria

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ -3.7289e-003\ (0.000) & 1 \end{bmatrix};\ \boldsymbol{C} = \begin{bmatrix} -3.5485e-003\ (0.706) \\ -0.025\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.044\ (0.000) & 0.466\ (0.000) \\ -0.012\ (0.000) & 0.342\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.365\ (0.000) & -0.402\ (0.000) \\ 3.3926e-003\ (0.000) & -0.069\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_3 = \begin{bmatrix} 0.226\ (0.000) & 0.830\ (0.000) \\ 3.6497e-003\ (0.000) & -6.6004e-003\ (0.651) \end{bmatrix};$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ 0.141\ (0.000) & 0 \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 0.031\ (0.000) \\ 1.6570e-005\ (0.000) \end{bmatrix};$$

$$diag\boldsymbol{F} = \begin{bmatrix} -0.012\ (0.000) \\ 0.049\ (0.000) \end{bmatrix};\ diag\boldsymbol{G} = \begin{bmatrix} 0.000\ (0.000) \\ 0.766\ (0.000) \end{bmatrix}.$$

Note: Sample period, monthly data: 1999:02 - 2018:04. Numbers in parentheses are p-values.

Table 1.11: Estimates of the GARCH-in-Mean VAR for Comoros

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ -4.9350e-003\ (0.015) & 1 \end{bmatrix}; \boldsymbol{C} = \begin{bmatrix} -2.8767e-003\ (0.773) \\ -6.2152e-003\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.029\ (0.432) & 0.553\ (0.468) \\ -9.4182e-003\ (0.002) & 0.345\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.292\ (0.000) & -0.060\ (0.934) \\ -6.8328e-005\ (0.977) & -0.103\ (0.040) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_3 = \begin{bmatrix} 0.300\ (0.000) & 0.641\ (0.489) \\ 2.4627e-003\ (0.469) & 8.2781e-003\ (0.887) \end{bmatrix};$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ 0.035\ (0.000) & 0 \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 0.030\ (0.000) \\ 1.5151e-005\ (0.000) \end{bmatrix};$$

$$diag\boldsymbol{F} = \begin{bmatrix} -0.015\ (0.400) \\ 0.069\ (0.000) \end{bmatrix}; diag\boldsymbol{G} = \begin{bmatrix} 0.000\ (0.000) \\ 0.760\ (0.000) \end{bmatrix}.$$

Note: Sample period, monthly data: 1994:02 - 2018:04. Numbers in parentheses are p-values.

Table 1.12: Estimates of the GARCH-in-Mean VAR for Croatia

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ -4.2732e-003\ (0.029) & 1 \end{bmatrix};\ \boldsymbol{C} = \begin{bmatrix} -4.2188e-003\ (0.672) \\ -5.1780e-003\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.036\ (0.330) & 0.430\ (0.623) \\ -8.1703e-003\ (0.004) & 0.330\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.299\ (0.000) & -0.236\ (0.752) \\ 1.7510e-004\ (0.944) & -0.010\ (0.063) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_3 = \begin{bmatrix} 0.280\ (0.000) & 0.581\ (0.548) \\ 1.6921e-003\ (0.625) & -0.030\ (0.604) \end{bmatrix};$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ 0.031\ (0.000) & 0 \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 0.029\ (0.000) \\ 7.9834e-006\ (0.000) \end{bmatrix};$$

$$diag\boldsymbol{F} = \begin{bmatrix} -0.014\ (0.474) \\ 0.016\ (0.035) \end{bmatrix};\ diag\boldsymbol{G} = \begin{bmatrix} 0.000\ (0.000) \\ 0.899\ (0.000) \end{bmatrix}.$$

Note: Sample period, monthly data: 1994:07 - 2018:04. Numbers in parentheses are p-values.

Table 1.13: Estimates of the GARCH-in-Mean VAR for Former Yugoslav Republic of Macedonia

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ -0.004\ (0.065) & 1 \end{bmatrix}; \boldsymbol{C} = \begin{bmatrix} -0.004\ (0.204) \\ -0.020\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.043\ (0.000) & 0.272\ (0.654) \\ -0.011\ (0.000) & 0.344\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.363\ (0.000) & -0.300\ (0.402) \\ 0.004\ (0.154) & -0.074\ (0.179) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_3 = \begin{bmatrix} 0.228\ (0.000) & 0.849\ (0.416) \\ 0.003\ (0.000) & -0.001\ (0.968) \end{bmatrix};$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ 0.115\ (0.000) & 0 \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 0.031\ (0.000) \\ 0.000\ (0.000) \end{bmatrix};$$

$$diag\boldsymbol{F} = \begin{bmatrix} -0.012\ (0.000) \\ 0.055\ (0.000) \end{bmatrix}; diag\boldsymbol{G} = \begin{bmatrix} 0.000\ (0.000) \\ 0.781\ (0.000) \end{bmatrix}.$$

Note: Sample period, monthly data: 1999:01 - 2018:04. Numbers in parentheses are p-values.

Table 1.14: Estimates of the GARCH-in-Mean VAR for Montenegro

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ -4.1851e-003\ (0.000) & 1 \end{bmatrix}; \boldsymbol{C} = \begin{bmatrix} -3.6297e-003\ (0.732) \\ -0.029\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.049\ (0.070) & 0.528\ (0.543) \\ -0.012\ (0.000) & 0.338\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.367\ (0.000) & -0.598\ (0.445) \\ 4.0601e-003\ (0.000) & -0.075\ (0.000) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_3 = \begin{bmatrix} 0.222\ (0.000) & 0.906\ (0.000) \\ 2.7311e-003\ (0.000) & -0.012\ (0.849) \end{bmatrix};$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 \\ 0.166\ (0.000) & 0 \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 0.031\ (0.000) \\ 1.6647e-005\ (0.000) \end{bmatrix};$$

$$diag\boldsymbol{F} = \begin{bmatrix} -0.011\ (0.000) \\ 0.064\ (0.000) \end{bmatrix}; diag\boldsymbol{G} = \begin{bmatrix} 0.000\ (0.000) \\ 0.754\ (0.000) \end{bmatrix}.$$

Note: Sample period, monthly data: 1999:02 - 2018:04. Numbers in parentheses are p-values.

Table 1.15: λ coefficient estimates from the GARCH-in-Mean VARs

Country	$\hat{\lambda}$	p-value
A. Inflation rate targeters		
Brazil	19.857	0.000
Chile	3.630	0.000
Mexico	0.139	0.001
Romania	0.357	0.000
Serbia	0.714	0.000
South Africa	0.113	0.017
B. Exchange rate targeters		
Bosnia & Herzegovina	0.114	0.000
Bulgaria	0.141	0.000
Comoros	0.035	0.000
Croatia	0.031	0.000
Former Yugoslav Republic of Macedonia	0.115	0.000
Montenegro	0.166	0.000

Figure 1.1: Impulse Response Functions for Brazil

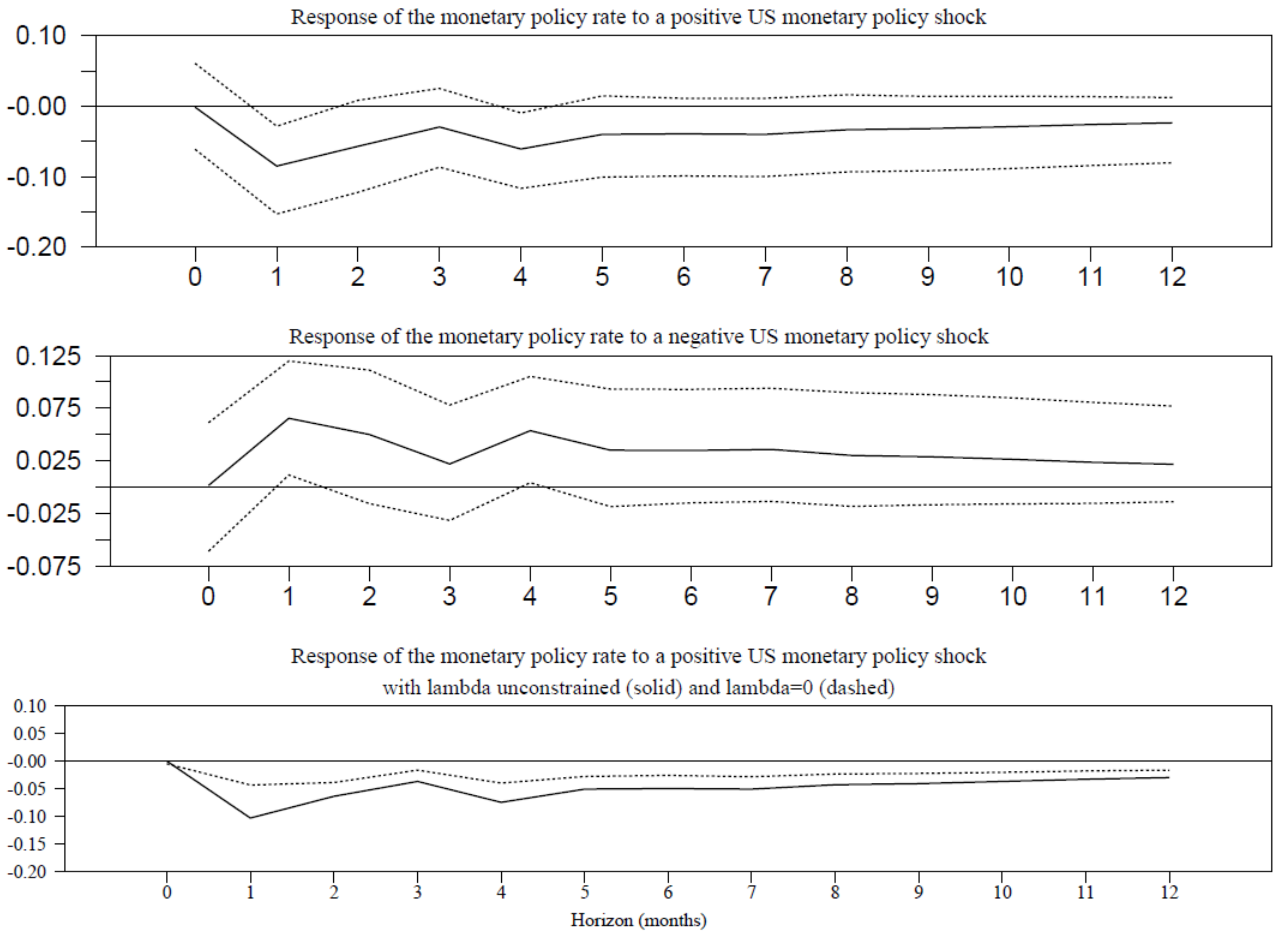


Figure 1.2: Impulse Response Functions for Chile

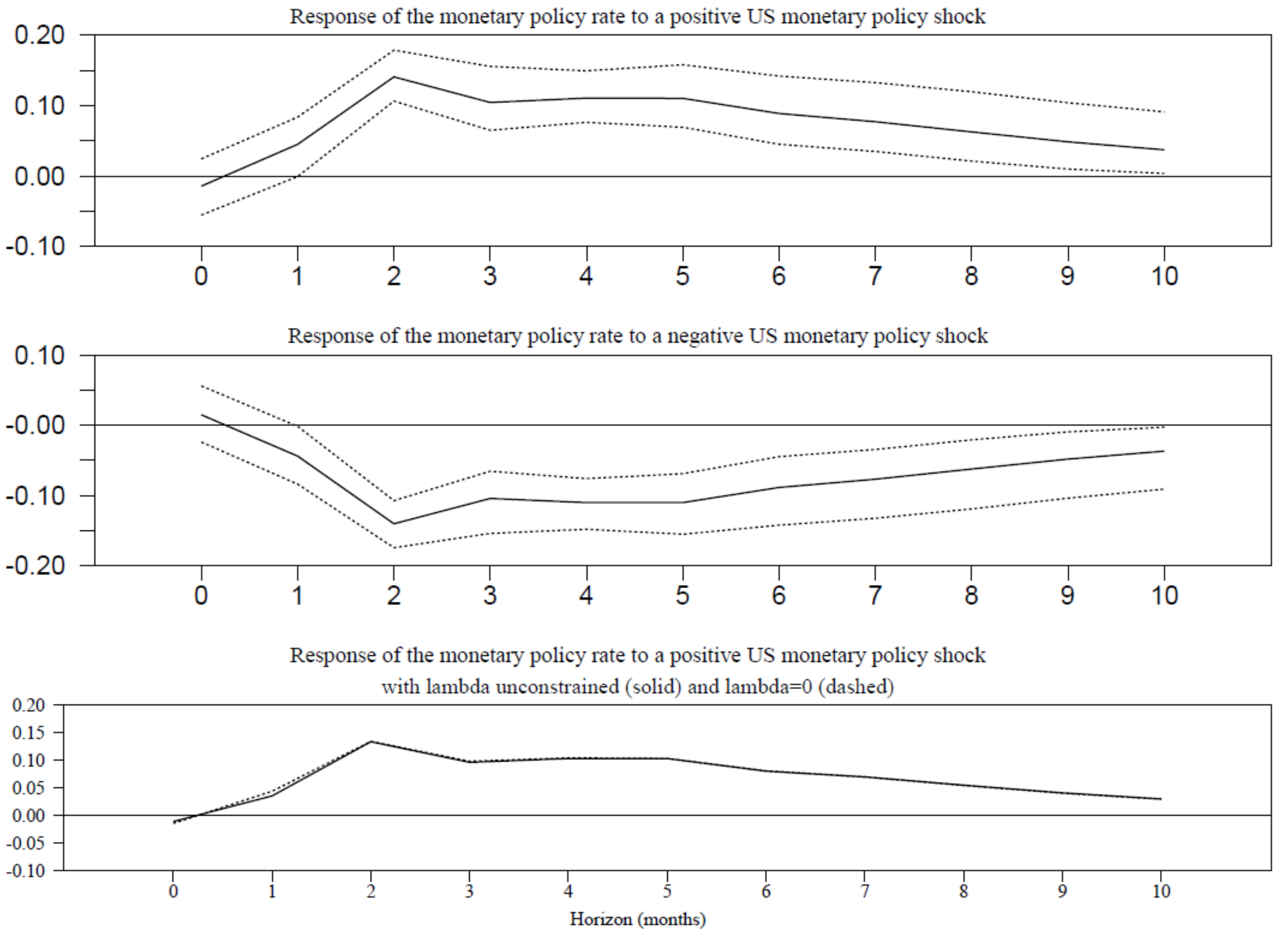


Figure 1.3: Impulse Response Functions for Mexico

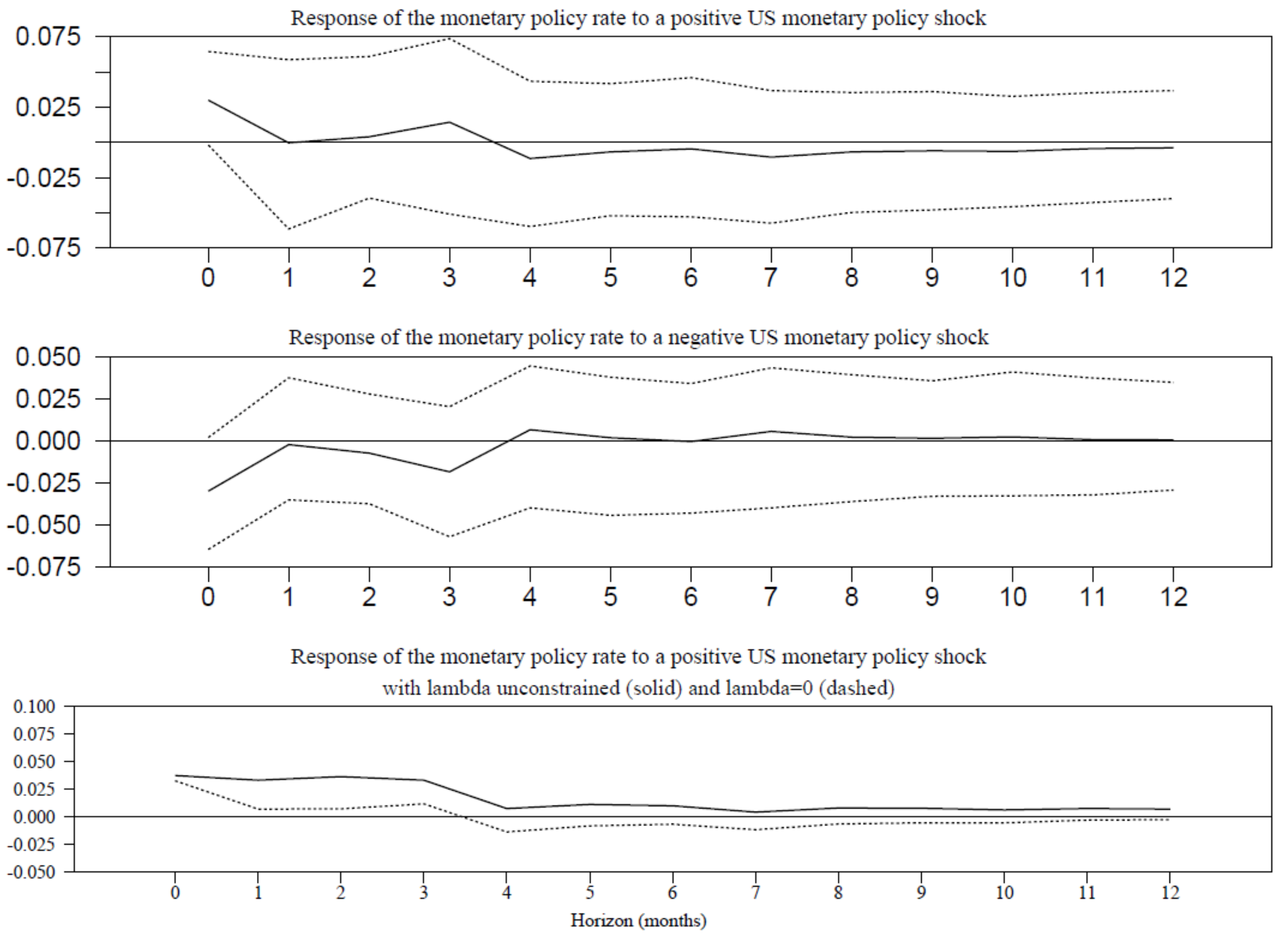


Figure 1.4: Impulse Response Functions for Romania

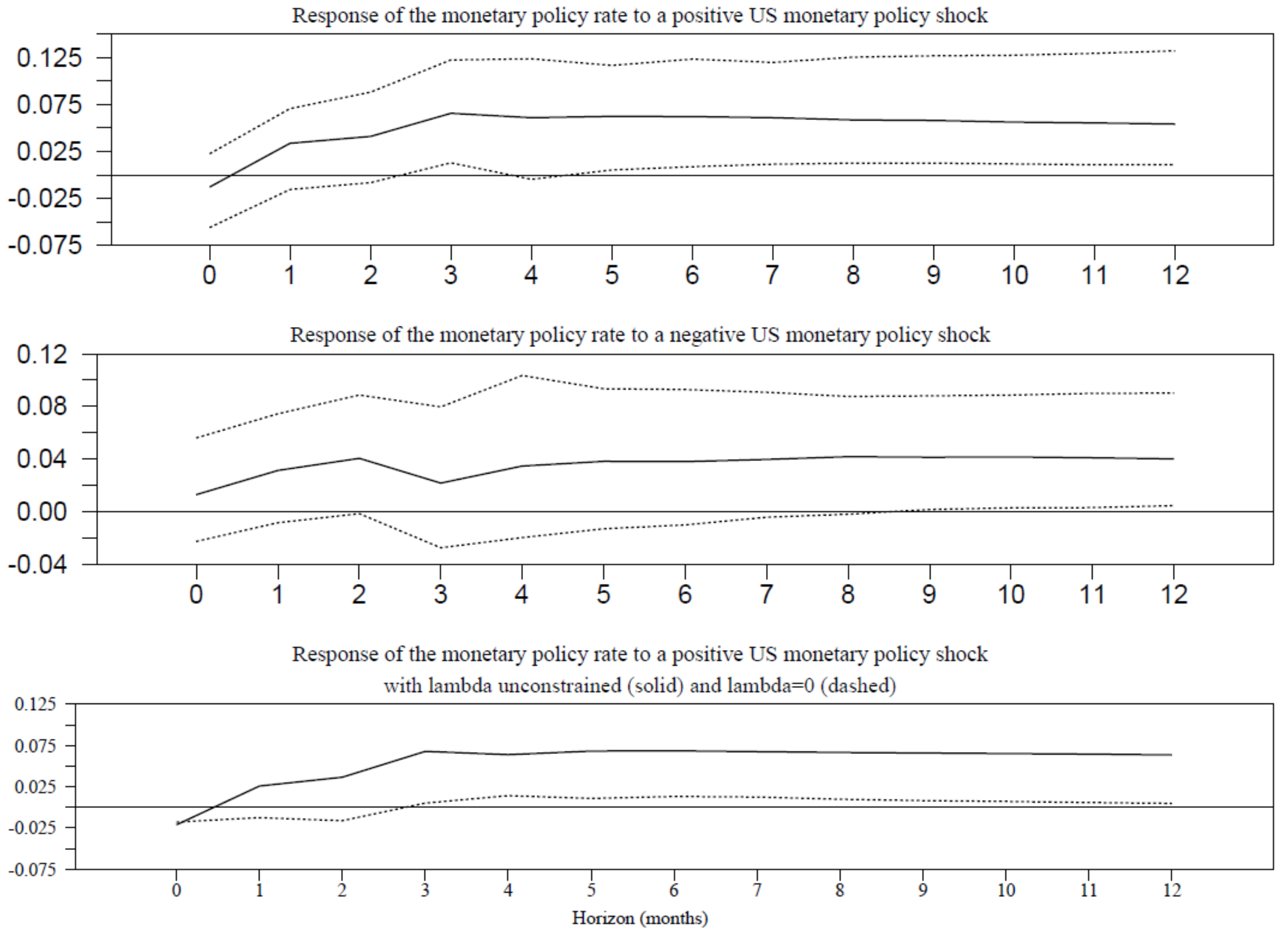


Figure 1.5: Impulse Response Functions for Serbia

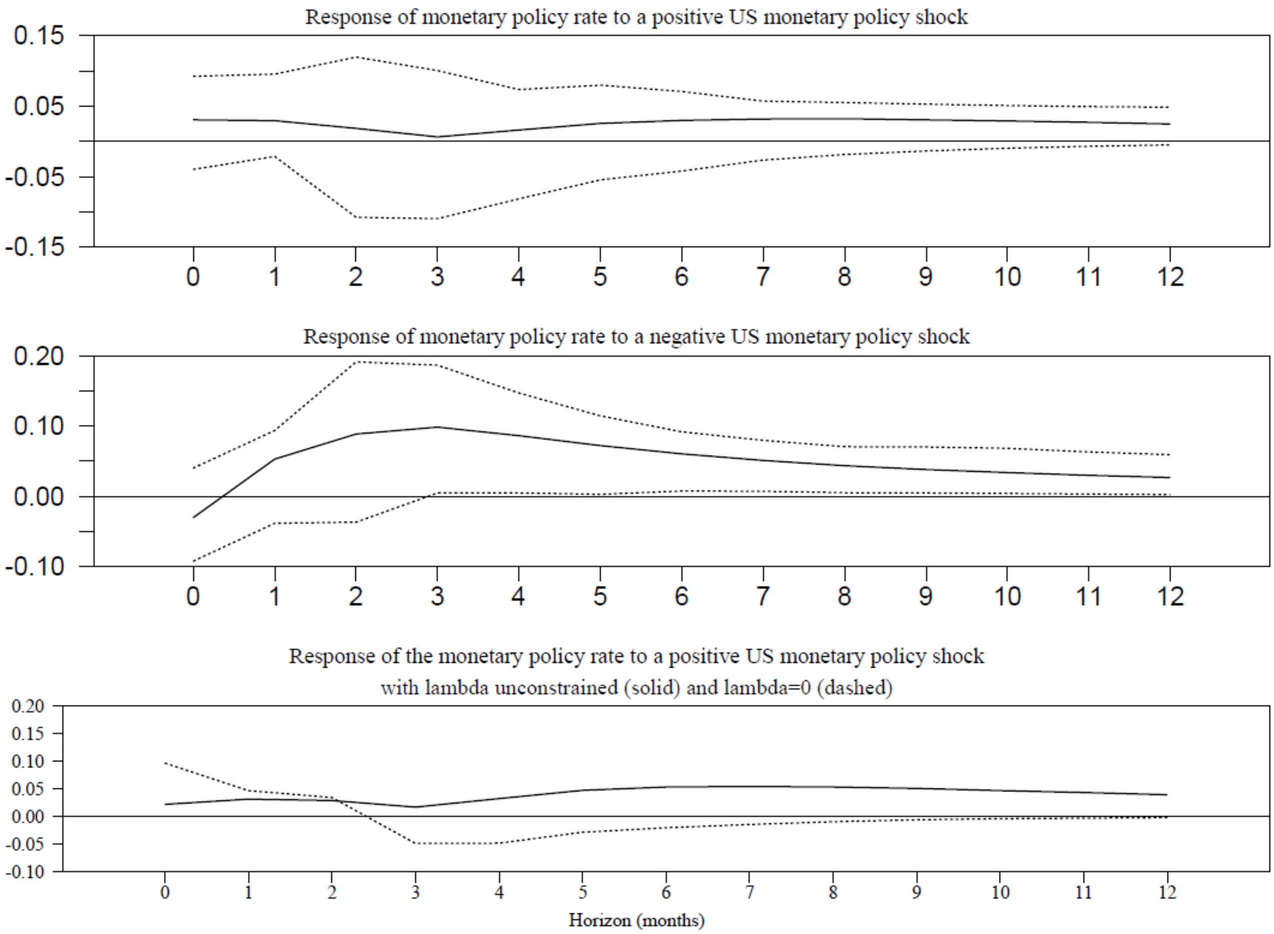


Figure 1.6: Impulse Response Functions for South Africa

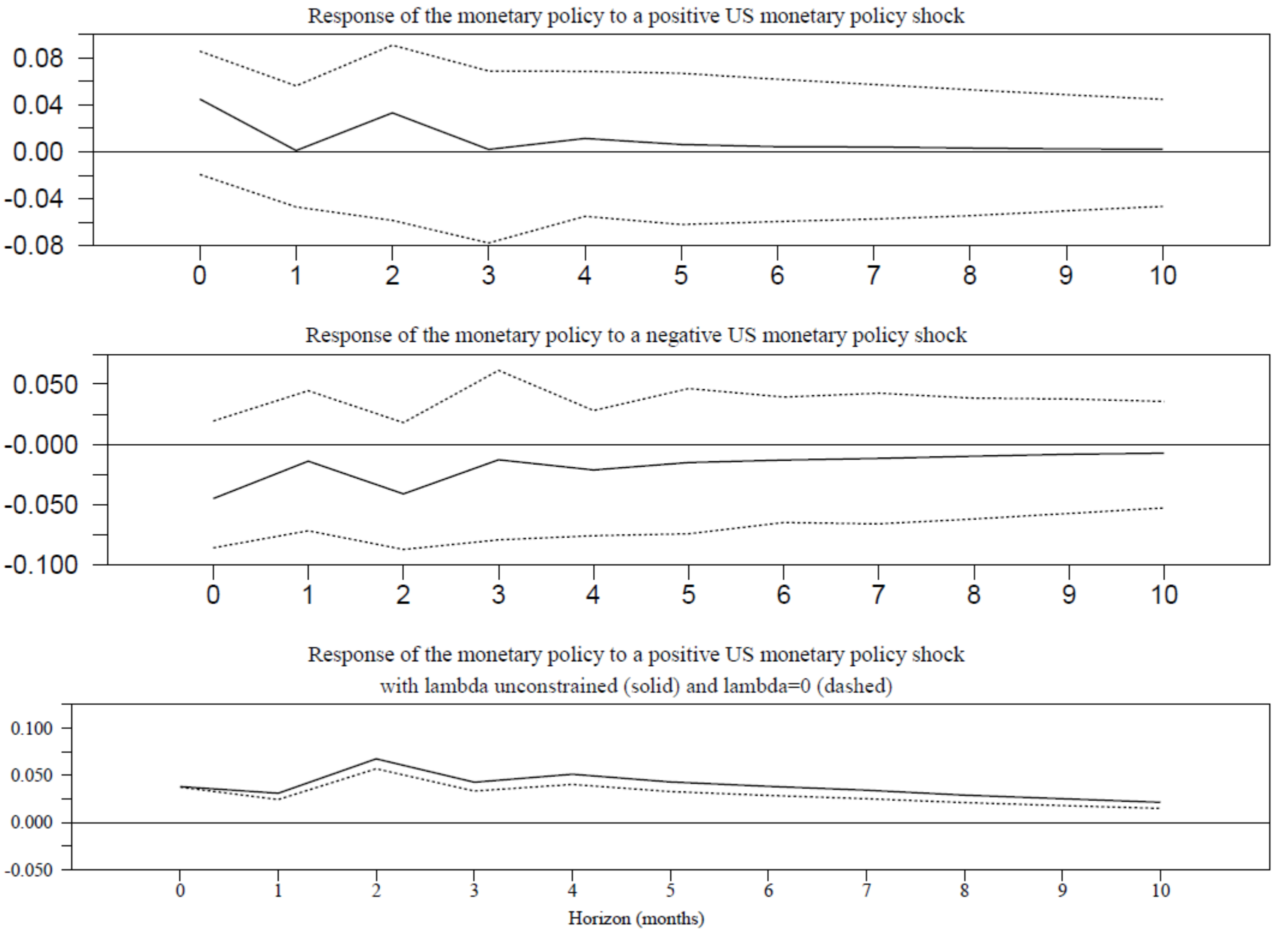


Figure 1.7: Impulse Response Functions for Bosnia and Herzegovina

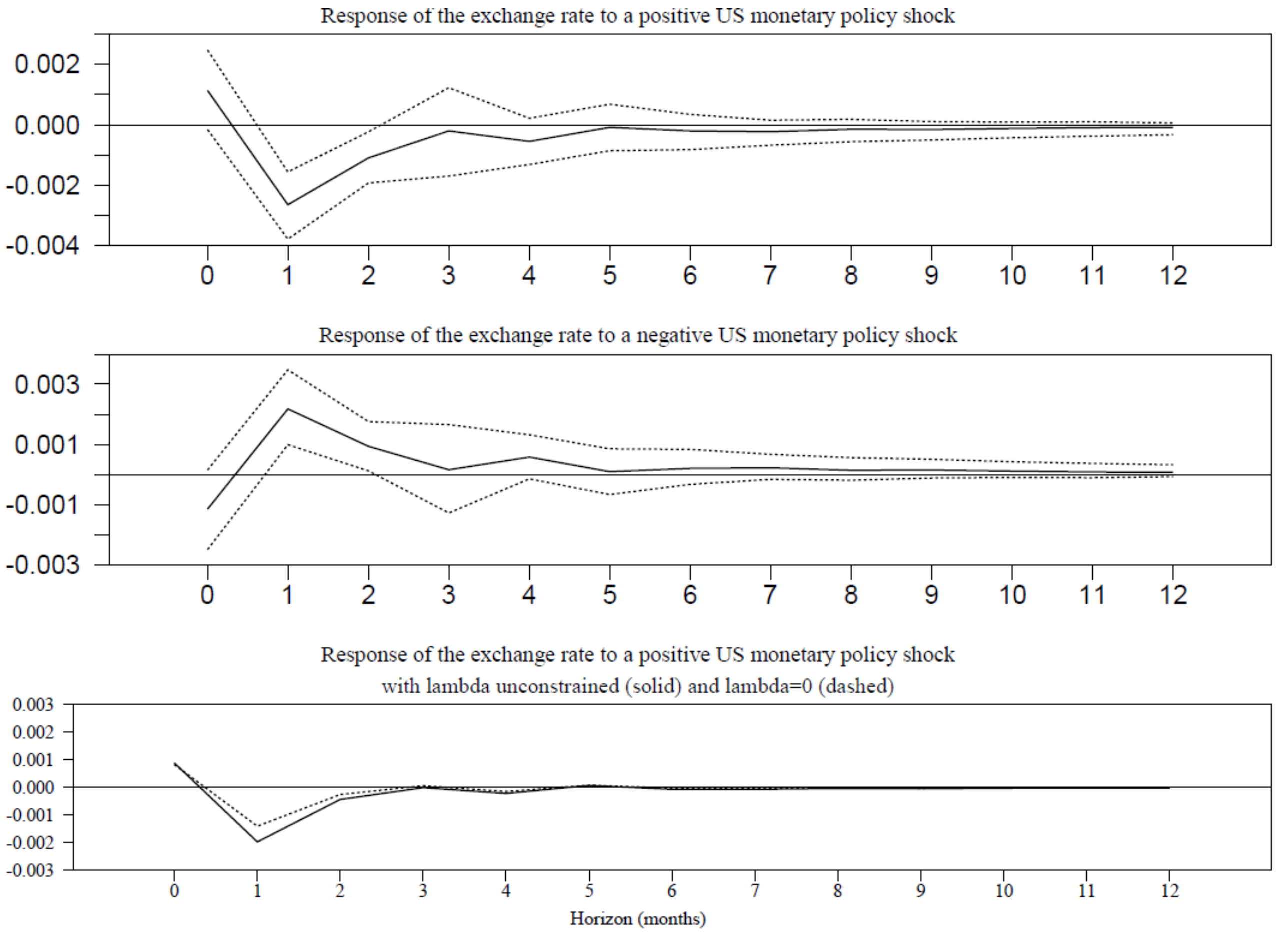


Figure 1.8: Impulse Response Functions for Bulgaria

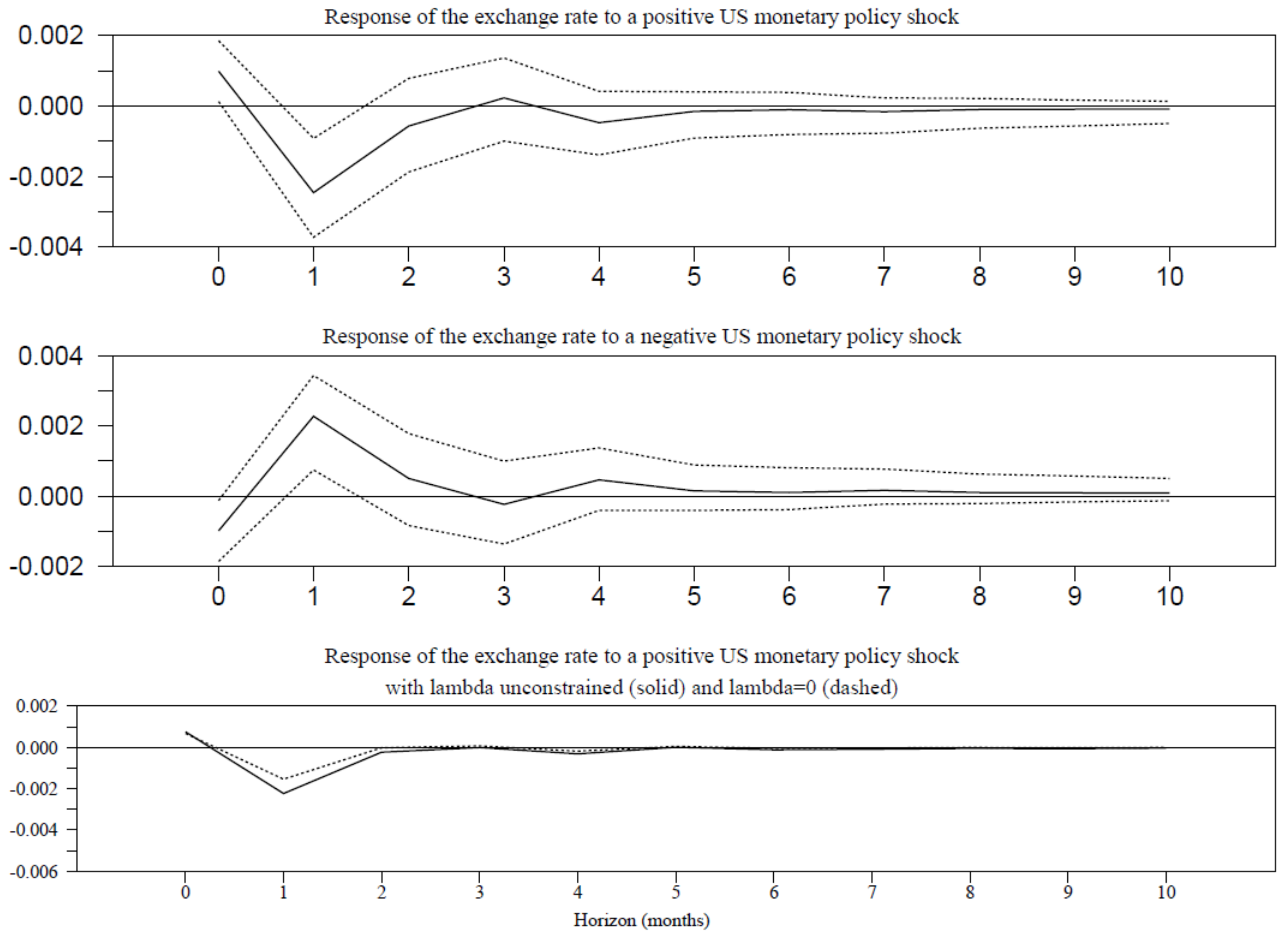


Figure 1.9: Impulse Response Functions for Comoros

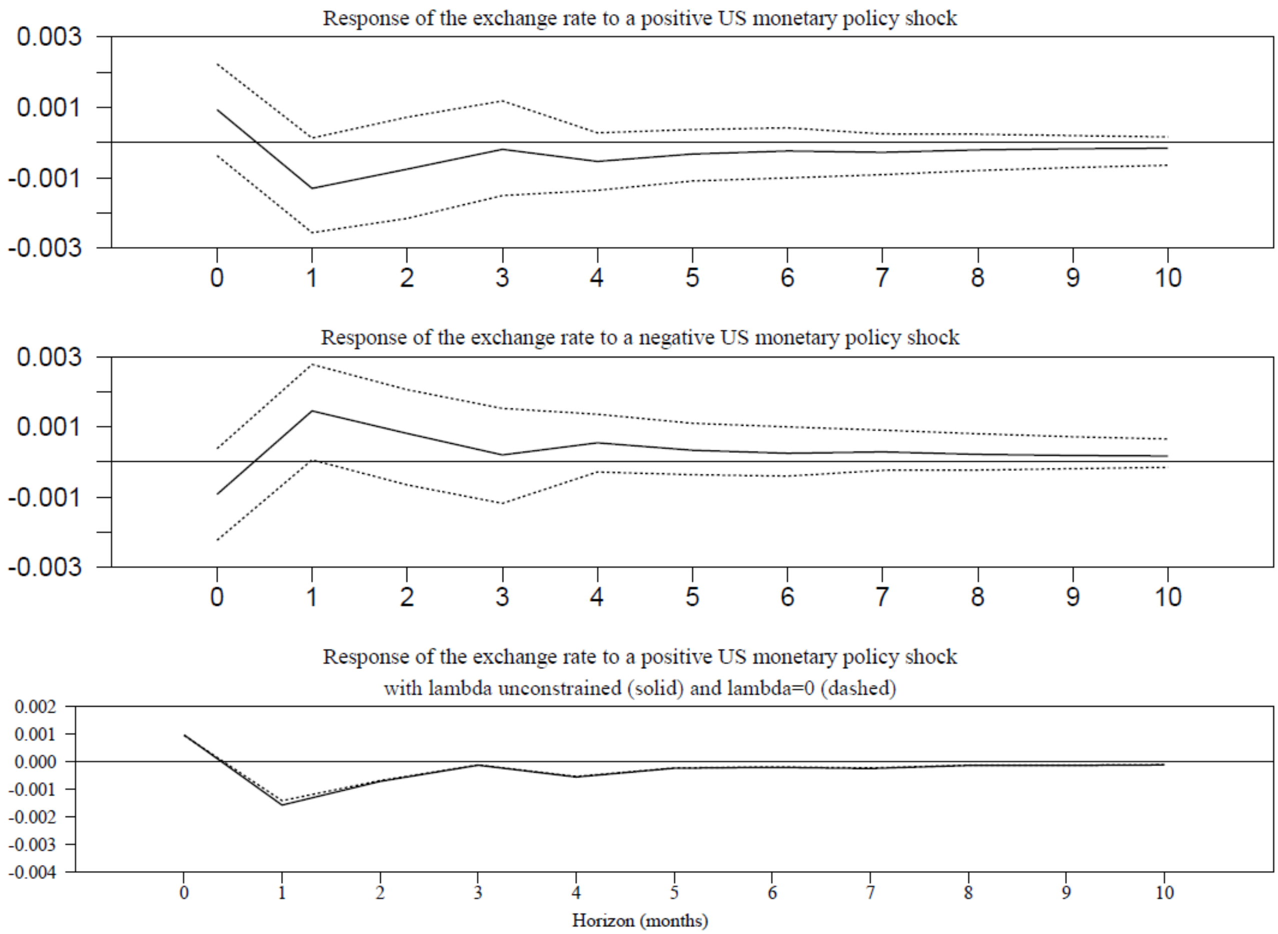


Figure 1.10: Impulse Response Functions for Croatia

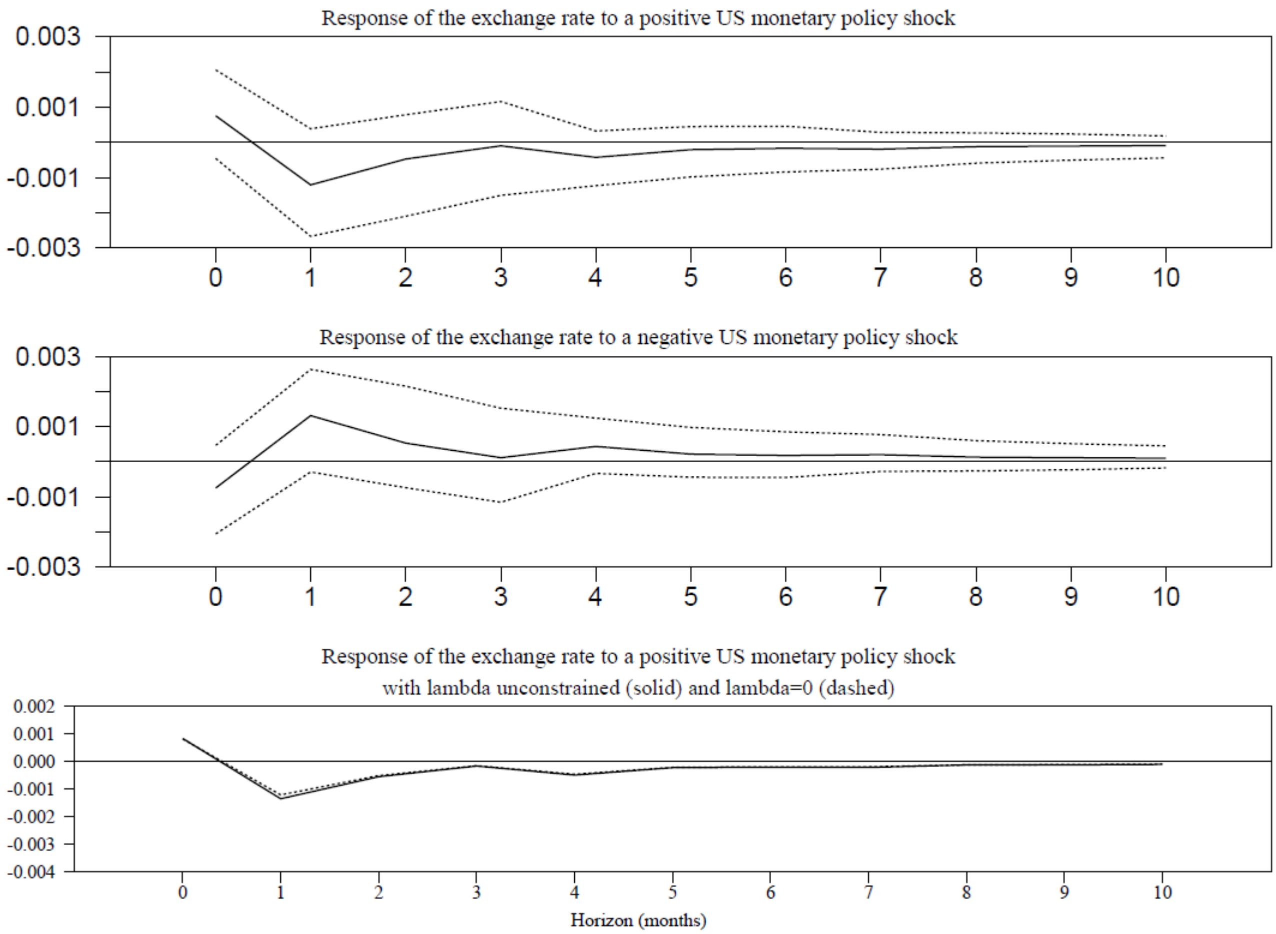


Figure 1.11: Impulse Response Functions for Former Yugoslav Republic of Macedonia

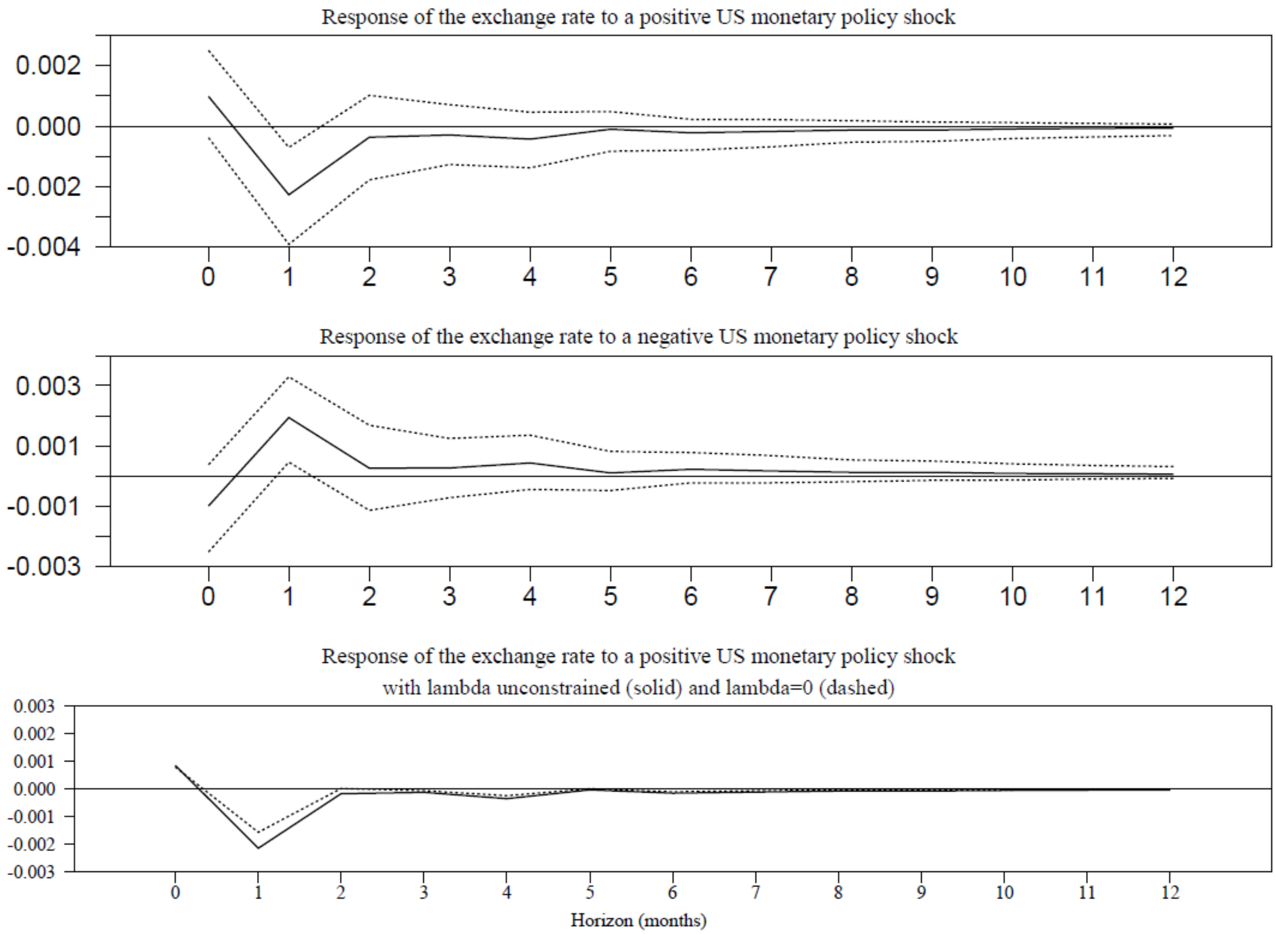
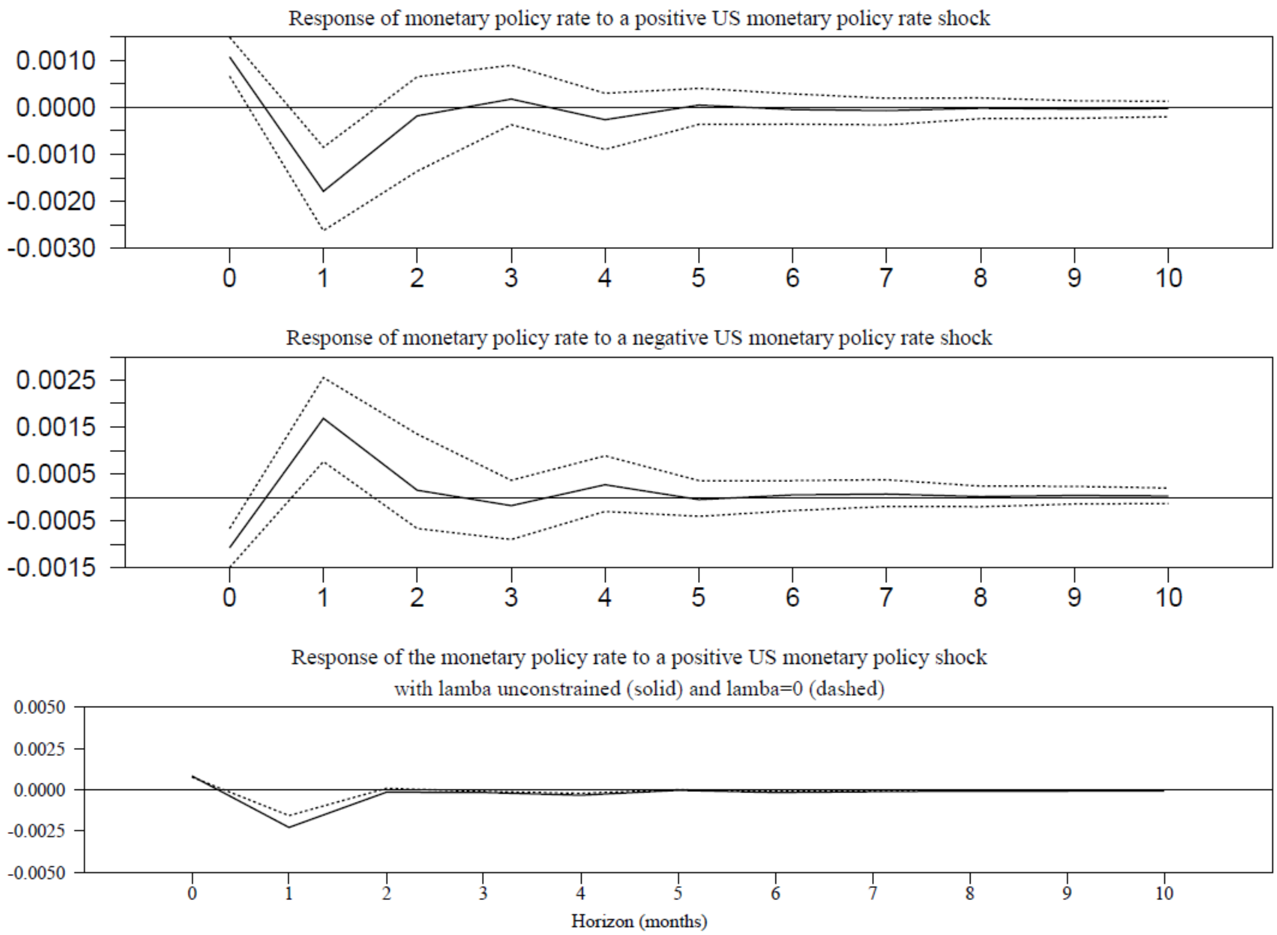


Figure 1.12: Impulse Response Functions for Montenegro



1.5.1 Inflation Targeters

Regarding countries that target the inflation rate, as can be seen in Tables 1.3-1.8 (and the summary Table 1.15), the estimated coefficient of interest $\hat{\lambda}$ is 19.857 with a p-value of 0.000 for Brazil, 3.630 with a p-value of 0.000 for Chile, 0.139 with a p-value of 0.001 for Mexico, 0.357 with a p-value of 0.000 for Romania, 0.714 with a p-value of 0.000 for Serbia, and 0.113 with a p-value of 0.017 for South Africa, respectively. The null hypothesis that the true value of $\hat{\lambda}$ is zero is rejected for all countries, indicating that uncertainty in U.S. monetary policy has a statistically significant effect on the monetary policy rate in all the inflation-targeting emerging economies in our sample. Specifically, monetary policy uncertainty in the United States has a positive and statistically significant effect on the monetary policy rate in each of Brazil, Chile, Mexico, Romania, Serbia, and South Africa.

These results are different from those reported by Nsafoah and Serletis (2019) for advanced economies; they showed that monetary policy uncertainty in the United States has a negative and statistically significant effect on the monetary policy rate in each of Canada, Denmark, the Eurozone, Japan, Switzerland, and the United Kingdom. They are, however, consistent with the findings of Canova (2005) who finds that a contractionary U.S. monetary shock induces a significant and instantaneous increase in Latin American short-term nominal interest rates. Iacoviello and Navarro (2019) also find that in emerging economies, policy rates increase in response to a contractionary monetary policy shock in the United States, and Caceres et al. (2016) argue that "the share of sovereign debt in domestic currency that is held by foreigners has been increasing substantially over the last few years, especially in emerging market economies. In this context, portfolio rebalancing by international investors following a rise in U.S. rates can potentially have a larger impact on the capital account. Central banks may then need to raise policy rates in an attempt to attenuate outflow pressures, irrespective of domestic macro conditions."

Next, we simulate the response of policy rates in inflation-targeting emerging economies to both positive and negative U.S. policy rates shocks to investigate whether the responses to positive and negative federal funds rate shocks are asymmetric or symmetric in nature. We also report one-standard error bands based on the Monte Carlo method described in Hamilton (1994). As can be seen in the first panel of Figures 1-6, accounting for the impact of uncertainty in the federal funds rate, a positive shock in the federal funds rate tends to significantly reduce the policy rate immediately in Brazil and Serbia and tends to significantly increase the policy rate immediately in each of Chile, Mexico, Romania, and South Africa. The second panel in Figures 1-6 shows that a negative shock in the U.S. policy rate immediately increases the policy rate in Brazil, Mexico, Romania, Serbia, and South Africa while in the case of Chile the policy rate tends to decrease immediately in response to a negative shock in the U.S. policy rate.

It must be noted that in the absence of a formal statistical test of the null hypothesis of symmetric impulse responses, the responses of monetary policy rates in inflation-targeting emerging economies to positive and negative shocks in the U.S. policy rate are not very informative as to whether they are symmetric or not. Finally, in the third panel of Figures 1-6 we compare the response of changes in policy rates of the inflation-targeting emerging economies to a positive shock in the U.S. federal funds rate as estimated in our model to the responses from a model in which the uncertainty in the federal funds rate has been restricted from entering the policy rate equation of the inflation-targeting emerging economy. As can be seen, accounting for uncertainty in the U.S. federal funds rate tends to have an ambiguous effect on the dynamic response of the policy rate in each of the emerging market economies to an unfavorable (positive) shock in the U.S. federal funds rate.

1.5.2 Exchange Rate Targeters

As can be seen in Tables 9-14 (and the summary Table 15), the estimated coefficient of interest $\hat{\lambda}$ is positive for all six countries. In particular, it is 0.114 with a p-value of 0.000 for Bosnia and Herzegovina, 0.141 with a p-value of 0.000 for Bulgaria, 0.035 with a p-value of 0.000 for Comoros, 0.031 with a p-value of 0.000 for Croatia, 0.115 with a p-value of 0.000 for the Former Yugoslav Republic of Macedonia, and 0.166 with a p-value of 0.000 for Montenegro. The null hypothesis that the true value of $\hat{\lambda}$ is zero is rejected at the 1% level for all countries, indicating the high level of statistical significance of $\hat{\lambda}$ in our exchange rate analysis. Thus, higher monetary policy uncertainty in the United States has a positive and statistically significant effect on the exchange rate of each of the emerging economies in our sample.

Our results are consistent with the findings of Tillman (2016) that uncertainty about future U.S. monetary policy leads to a depreciation of local currencies in emerging economies. They are also consistent with Gupta et al. (2017) who show that a surprise monetary tightening in the United States, "estimated by an increase in 2-year Treasury yield on the day of the FOMC announcement, results in exchange rate depreciation, decline in equity prices, and increase in bond yields in emerging economies." In this regard, when the domestic currency depreciates, there is a tendency for borrowers (both banks and nonfinancial firms) in emerging market financial systems to borrow less in U.S. dollars. In doing so, they assume less risk (since their assets and products are priced in domestic currency), but the domestic depreciation causes a deterioration in firms' balance sheets, because it increases the domestic currency value of debt denominated in U.S. dollars.

As with the inflation-targeting emerging economies, we simulate the response of exchange rates to both positive and negative federal funds rate shocks. The first panel of Figures 7-12 shows that, accounting for the impact of uncertainty in the federal funds rate, a positive shock in the federal funds rate tends to significantly reduce the percentage change in exchange rate, that is leads to an appreciation of the local currency for all six exchange-targeting emerging economies. Our results show that positive (contractionary) monetary policy shocks in the United States lead to appreciation of the currencies of the emerging economies on impact, with the maximum effect during the first month, before gradually depreciating to the baseline. That is the U.S. dollar depreciates against the currencies of the emerging economies in response to a contractionary monetary policy adopted by the Federal Reserve. This is in contradiction to the Dornbusch (1976) overshooting model which predicts that a contractionary monetary policy shock, led by a rise in the U.S. nominal rate of interest, should cause an instantaneous appreciation of the U.S. dollar. After the initial instantaneous appreciation, the exchange rate gradually depreciates in line with uncovered interest parity. Bjørnland (2009) finds empirical support for the Dornbusch (1976) hypothesis in the context of four advanced economies with floating exchange rates, namely Australia, Canada, New Zealand, and Sweden. Our results show that the Dornbusch (1976) hypothesis does not hold for the U.S. economy in context of bilateral spot exchange rates of exchange rate targeting emerging economies. Eichenbaum and Evans (1995) find that contractionary shocks to U.S. monetary policy lead to sharp, persistent appreciation of the U.S. nominal and real exchange rates. We find that contractionary shocks to U.S. monetary policy lead to initial sharp depreciation of the U.S. dollar against the currencies of emerging economies, before eventually appreciating to the baseline level. The second panel in Figures 7-12 shows that a negative shock to the federal funds rate tends to significantly increase the exchange rate, leading to a depreciation of the domestic currency in all six emerging economies, Bosnia and Herzegovina, Bulgaria, Comoros, Croatia, the Former Yugoslav Republic of Macedonia, and Montenegro.

Finally, in the third panel of Figures 7-12, we compare the response of the exchange rate to a positive shock in the U.S. federal funds rate as estimated in our model to the responses from a model in which $\lambda = 0$. As can be seen, accounting for uncertainty in the U.S. federal funds rate tends to amplify the negative dynamic response of exchange rate changes (i.e. higher appreciation of the domestic currency) to an unfavorable (positive) shock in the U.S. federal funds rate.

1.6 Conclusion

In this paper, we investigate spillovers from monetary policy in the United States to 12 emerging market countries. We make a distinction between two groups of emerging market economies; those that target the inflation rate — Brazil, Chile, Mexico, Romania, Serbia, and South Africa — and those that target the exchange rate — Bosnia and Herzegovina, Bulgaria, Comoros, Croatia, the Former Yugoslav Republic of Macedonia, and Montenegro. In doing so, we use the Elder and Serletis (2010) bivariate structural GARCH-in-Mean VAR and two new monthly data sets (compiled by the Bank for International Settlements), one on (central bank) monetary policy rates and the other on exchange rates (against the U.S. dollar).

We find statistically significant monetary policy spillovers from the United States to all twelve emerging economies. Some of our findings are as follows:

- Positive (negative) U.S. monetary policy shocks tend to appreciate (depreciate) the currencies of the exchange rate targeting emerging economies, but have an ambiguous effect on the policy rates of the inflation-targeting emerging economies.
- Monetary policy uncertainty in the United States leads to an increase in policy rates in those emerging economies that target the inflation rate and leads to depreciation of the currencies of those emerging economies that target the exchange rate.
- Accounting for uncertainty in U.S. monetary policy tends to amplify the appreciation of the currencies of those emerging economies that target the exchange rate, but the effect on those emerging economies that target the inflation rate is ambiguous.

In our investigation for monetary policy spillovers from the United States to emerging economies, we assumed that the dynamics of the structural VAR could be summarized by a linear function of the variables of interest and a term related to U.S. monetary policy uncertainty. That is, we ignored those variables that usually enter into a central bank's policy reaction function, such as the inflation gap and the output. Addressing this issue, in the context of a higher-dimensional structural VAR, is an area for future research.

Chapter 2

Oil Price Shocks in Major Emerging Economies[1]

Nahiyan Faisal Azad and Apostolos Serletis

2.1 Introduction

The seven largest emerging market economies (henceforth EM7) — Brazil, China, India, Indonesia, Mexico, Russia, and Turkey — could be double the size of their advanced counterparts, the G7 — Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States — by 2040, according to the estimates by Hawksworth et al. (2017). This is a massive shift in world economic power from advanced economies to emerging market economies, especially striking since two decades ago these economies were half the size of their advanced counterparts. Hawksworth et al. (2017) also estimates that by the year 2050, the EM7 economies could increase their share of world gross domestic product to 50% from approximately 35% today. In fact, based on GDP at purchasing power parity, China could be the largest economy in the world, followed by India and Indonesia in fourth place. The EM7 economies will be the primary drivers of world economic growth, growing at an estimated average rate of 3.5% per annum for every year up to 2050, dwarfing the 1.6% annual growth rate of the advanced G7 countries. See Hawksworth et al. (2017) for more details.

With the shift in global economic power to emerging market economies, it is important to examine the vulnerability of these economies to shocks that might have adverse effects on real economic activity in these economies. There is a vast empirical literature that investigates whether positive shocks in the price of oil

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lead to recessions in advanced countries like the United States — see, for example, Edelstein and Kilian (2009), Elder and Serletis (2010), and Kilian and Vigfusson (2011). Bredin et al. (2011) report that among the G7, uncertainty about oil prices has had an adverse effect on manufacturing activity in Canada, France, the United Kingdom, and the United States. Investigation of similar shocks to members of the EM7 countries has been an area in the empirical literature that has been relatively understudied. Nasir et al. (2018) employ a time-varying structural vector autoregressive (TV-SVA) framework to analyse the implications of oil prices shocks for the BRICS (Brazil, Russia, India, China and South Africa) economies. The paper finds that among the oil exporters, the Russian economy is more dependent on oil than the Brazilian economy. The paper also finds that among the oil importers the Indian economy is more vulnerable to oil prices shocks than the Chinese economy. In general, the member economies of the BRICS display asymmetries in response to oil prices shocks.

This paper contributes to the empirical literature through its investigation of how oil price shock affect economic activity in the EM7 countries, of whether oil price uncertainty affects real economic activity in the EM7, and whether the relationship between oil prices and the level of economic activity in the EM7 countries is asymmetric. In doing so, we use two classes of empirical models. In particular, we extend the Elder and Serletis (2010) model, incorporating aspects of the Kilian (2009) and Kilian and Park (2009) methodology, to investigate the effects of oil price uncertainty. We also use the Kilian and Vigfusson (2011) methodology to test for symmetry in the impulse responses of real output to positive and negative oil price shocks in the EM7 countries.

In the context of a multivariate GARCH-in-Mean VAR specification, that controls for lagged changes in global crude oil production and world economic activity, we find that oil price uncertainty has a negative and statistically significant effect on real output in India, Indonesia, Mexico, Russia, and Turkey, and a positive and statistically significant effect on real output in Brazil and China. We also find that the responses of real economic activity to oil price shocks in China, India, Indonesia, Mexico, and Turkey are symmetric and those in Brazil and Russia are asymmetric.

The remainder of the paper is organized as follows. In Section 2, we discuss the multivariate GARCH-in-Mean VAR model, incorporating demand and supply side shocks in the world crude oil market, as in Kilian (2009) and Kilian and Park (2009). In Section 3, we discuss the data and their time series properties, and in Section 4 present the empirical results regarding the effects of oil price uncertainty. In section 5, we investigate whether the relationship between real economic activity and the real oil price is nonlinear and asymmetric and in doing so we use the Kilian and Vigfusson (2011) tests of the null hypothesis of symmetric impulse responses. The final section concludes the paper.

2.2 The Multivariate GARCH-in-Mean VAR

Elder and Serletis (2010) use the Elder (2004) model and investigate the relationship between the price of oil and the level of economic activity, focusing on the role of uncertainty about oil prices. In doing so, they utilize an internally consistent bivariate GARCH-in-Mean structural VAR that accommodates an independent role for the effects of oil price volatility. They find that volatility in oil prices has had a negative and statistically significant effect on several measures of investment, durables consumption, and aggregate output. They also find that accounting for the effects of oil price volatility tends to exacerbate the negative dynamic response of economic activity to a negative oil price shock, while dampening the response to a positive oil price shock.

In this section, we follow Elder and Serletis (2010) and consider an extension of their bivariate structural GARCH-in-Mean VAR model to investigate the relationship between oil price uncertainty and real output, after controlling for global crude oil production and world economic activity, building on the work by Kilian (2009) and Kilian and Park (2009). Existing studies that analyze the relationship between the price of oil and real output in the context of bivariate models suffer from the limitation that oil prices are assumed to be strictly exogenous with respect to the global economy. In this regard, Kilian (2009) provides empirical evidence that fluctuations in global macroeconomic activity have an impact on the price of oil. Therefore, in what follows, we investigate the relationship between oil prices and domestic real output, after we control for economic variables that drive both the price of oil as well as domestic real output.

We assume that the dynamics of the structural system can be summarized by a linear function of the relevant vector of macroeconomic variables, modified to allow the conditional volatility of the real price of oil to affect the conditional mean

$$\boldsymbol{B}\boldsymbol{z}_t = \boldsymbol{C} + \boldsymbol{\Gamma}_1\boldsymbol{z}_{t-1} + \boldsymbol{\Gamma}_2\boldsymbol{z}_{t-2} + ... + \boldsymbol{\Gamma}_p\boldsymbol{z}_{t-p} + \boldsymbol{\Lambda}\sqrt{\boldsymbol{h}_t} + \boldsymbol{\epsilon}_t \tag{2.1}$$

where $\boldsymbol{z}$ is a column vector in the percentage change in global crude oil production, $\Delta \ln prod_t$, world economic activity, wea_t, percentage change in real price of oil, $\Delta \ln o_t$, and the growth rates of real output in each of the EM7 countries, $\Delta \ln y_t$. In equation (2.1), $\dim(\boldsymbol{B}) = \dim(\boldsymbol{\Gamma}_j) = (4 \times 4)$ and $\boldsymbol{\epsilon}_t\,|\Omega_{t-1} \sim$i.i.d. N($\mathbf{0}$, $\boldsymbol{H}_t$), with $\boldsymbol{H}_t$ being the variance-covariance matrix. Also,

$$\boldsymbol{B} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix}; \quad \boldsymbol{\Gamma}_j = \begin{bmatrix} \gamma_{11}^j & \gamma_{12}^j & \gamma_{13}^j & \gamma_{14}^j \\ \gamma_{21}^j & \gamma_{22}^j & \gamma_{23}^j & \gamma_{24}^j \\ \gamma_{31}^j & \gamma_{32}^j & \gamma_{33}^j & \gamma_{34}^j \\ \gamma_{41}^j & \gamma_{42}^j & \gamma_{43}^j & \gamma_{44}^j \end{bmatrix}; \quad \boldsymbol{\epsilon}_t = \begin{bmatrix} \epsilon_{\Delta \ln prod_t} \\ \epsilon_{wea_t} \\ \epsilon_{\Delta \ln o_t} \\ \epsilon_{\Delta \ln y_t} \end{bmatrix};$$

$$
\boldsymbol{H}_t = \begin{bmatrix} h_{\Delta \ln prod_t} & 0 & 0 & 0 \\ 0 & h_{wea_t} & 0 & 0 \\ 0 & 0 & h_{\Delta \ln o_t} & 0 \\ 0 & 0 & 0 & h_{\Delta \ln y_t} \end{bmatrix}; \quad \boldsymbol{h}_t = \begin{bmatrix} h_{\Delta \ln prod_t} \\ h_{wea_t} \\ h_{\Delta \ln o_t} \\ h_{\Delta \ln y_t} \end{bmatrix}; \quad \boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 & \lambda_{13} & 0 \\ 0 & 0 & \lambda_{23} & 0 \\ 0 & 0 & \lambda_{33} & 0 \\ 0 & 0 & \lambda_{43} & 0 \end{bmatrix}.
$$

The model is identified by imposing a sufficient number of exclusion restrictions on the $\boldsymbol{B}$ matrix. In this four variable structural VAR case, we estimate $n(n-1)/2 = 6$ free parameters in $\boldsymbol{B}$, subject to a rank condition, such that the diagonal elements of $\boldsymbol{B}$ are assumed to be equal to 1 and $\boldsymbol{B}$ is assumed to be lower triangular. The block-recursive structure of $\boldsymbol{B}$ implies that world crude oil production, world real economic activity, and the real price of oil are predetermined with respect to domestic real output. Global oil production is assumed to be exogenous to the other three variables (it is affected only by a shock to itself but is unaffected by instantaneous feedback from the other variables). Thus, our recursive factorization structure imposes six exclusion restrictions on the $\boldsymbol{B}$ matrix, satisfying a rank condition. The restrictions on the $\boldsymbol{B}$ matrix allow us to differentiate between three structural shocks that affect the real price of oil, namely unanticipated changes in world oil production that are referred to as supply shocks, contemporaneous changes in the demand for oil generated from structural innovations in world economic activity, referred to as aggregate demand shocks, and shocks that are unique to the demand for oil, referred to as oil-specific demand shocks.

Finally, we allow the conditional variance matrix, $\boldsymbol{H}_t$, to follow a multivariate GARCH process as follows

$$
\begin{bmatrix} h_{\Delta \ln prod_t} \\ h_{wea_t} \\ h_{\Delta \ln o_t} \\ h_{\Delta \ln y_t} \end{bmatrix} = \begin{pmatrix} C_1 + F_1 \epsilon^2_{\Delta \ln prod_{t-1}} + G_1 H_{\Delta \ln prod_{t-1}} \\ C_2 + F_2 \epsilon^2_{wea_{t-1}} + G_2 H_{wea_{t-1}} \\ C_3 + F_3 \epsilon^2_{\Delta \ln o_{t-1}} + G_3 H_{\Delta \ln o_{t-1}} \\ C_4 + F_4 \epsilon^2_{\Delta \ln y_{t-1}} + G_4 H_{\Delta \ln y_{t-1}} \end{pmatrix} \tag{2.2}
$$

The multivariate GARCH-in-Mean VAR model, consisting of equations (2.1) and (2.2), is estimated using full information maximum likelihood — see Elder and Serletis (2010) for more details. We used the RATS (version 9) software and initially attempted to estimate the model with one full year of lags, but had convergence problems in the large parameters space. To deal with this, we used the AIC criterion to optimally select the lag length.

2.3 The Data

We use industrial production data for the seven emerging economies from three different sources. For Brazil, India, Mexico, Russia, and Turkey, we use total industrial production data from the Organization for Economic Cooperation and Development (OECD) Main Economic Indicators: Production and sales database. Due to the lack of comprehensive monthly industrial production data for China, we use the monthly real GDP series constructed (and used) by Higgins et al. (2016) as a proxy for industrial production. Finally, for Indonesia, we retrieve the Industrial/Manufacturing Production growth rate from the Asia Regional Integration Center: Economic and Financial Indicators Database of the Asian Development Bank.

In our structural VAR analyses, we use the real price of oil as in Barsky and Kilian (2001), Kilian (2009), Kilian and Park (2009), Elder and Serletis (2010), and Jo (2014). We retrieve data for the variable Crude Oil (petroleum), Dated Brent, light blend 38 API, fob U.K. from the International Monetary Fund's primary commodity prices data set. The original data is in US dollars per barrel. To obtain the real price of oil in domestic currency, we first multiply the series with the exchange rate (local currency per US dollar) and then deflate the nominal data by the domestic Consumer Price Index (CPI) for all items. The data for the exchange rate and the domestic consumer price index has been retrieved from FRED. The data sources are comprehensively described in Appendix Table A.1. It is to be noted that the sample period varies from country to country due to the difference in the availability of comprehensive data for industrial production, CPI, and the exchange rate for each country. The Brent oil price data starts in 1980. For Brazil, even though the OECD industrial production data starts in 1975, we are restricted to start from 1980. All the data was downloaded on 3 April 2019.

In Figure 2.1 we plot the natural logarithm of industrial production and the corresponding growth rate for Brazil, China, India, Mexico, Russia, and Turkey, as well as the growth rate of Indonesia's industrial production. In Figure 2.2, we plot the logged real oil price (in terms of domestic currency) and its associated growth rate for each of the EM7 countries. We also use data for world oil production from the U.S. Energy Information Administration. For the world economic activity series, we use the (updated and corrected version of the) index of global real economic activity in industrial commodity markets proposed by Kilian (2009) and downloaded from Kilian's website. In Figure 2.3 we plot the natural log of the world crude oil production series and its corresponding growth rate and in Figure 2.4 the world economic activity series.[2]

We conduct a series of unit root tests in the growth rates of industrial production and the real oil price. We calculate the growth rate by taking the logarithmic first difference of the original series and multiplying by 100, except for Indonesia. For Indonesia, the original series requires no transformation, since the original

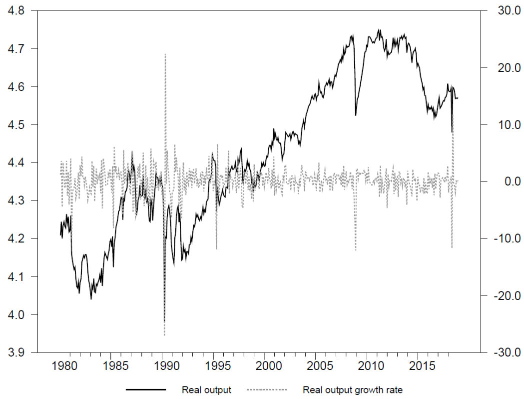
[2] In this model, and for purposes of achieving convergence, we use the world economic activity series multiplied by 12/100.

data represents the Industrial/Manufacturing Production growth rate. The data transformations are shown in Appendix Table A.2. Specifically, we carry out three tests to test for the presence of unit roots in our time series, namely the Augmented Dickey-Fuller (ADF) test [see Dickey and Fuller (1981)], the Phillips-Perron unit root test [see Phillips and Perron (1988)], and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test [see Kwiatkowski et al. (1992)]. We assume a constant and a trend for all three unit root tests. The null hypothesis for the ADF and PP tests is that a unit root is present in a time series sample, while the null hypothesis for the KPSS test is that the data is stationary.

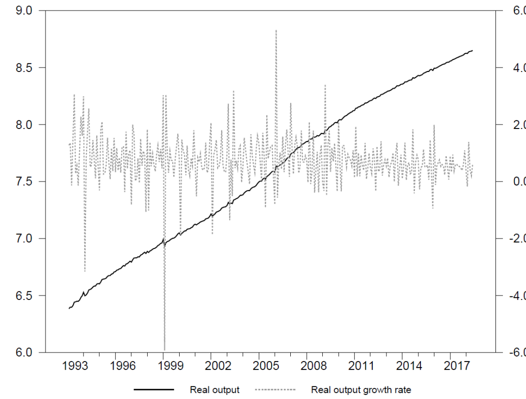
We report the p-values for the ADF and PP tests and the KPSS test statistics in Table 2.1 (in panel A for the growth rate of industrial production and in panel B for the growth rate of the real oil price). As can be seen, the null hypothesis of the presence of unit root is rejected at the 1% significance level by both the ADF and PP tests, while the null hypothesis of stationarity cannot be rejected at the 1% significance level by the KPSS test. We conclude that the industrial production and real oil price growth rates of the EM7 countries are all stationary. In panel C of Table 2.1, we also carry out the unit root and stationarity tests on the growth rate of world oil production, $\Delta \ln prod_t$, and on the series of world economic activity. Kilian and Zhou (2018) state that the global real activity index is "constructed as a business cycle index and, hence, must not be differenced or otherwise transformed." The p-values for the ADF tests are 0.000 for $\Delta \ln prod_t$ and 0.003 for the global economic activity series. The p-values for the PP tests are 0.000 for $\Delta \ln prod_t$ and 0.015 for the global economic activity series. Thus, the null hypothesis of a unit root is rejected at conventional significance levels by both the ADF and PP tests. The KPSS test statistics are 0.040 for $\Delta \ln prod_t$ and 0.132 for the global economic activity series, suggesting that the null hypothesis of stationarity cannot be rejected at the 1% significance level.

Figure 2.1: Real output and its growth rate for the EM7 countries

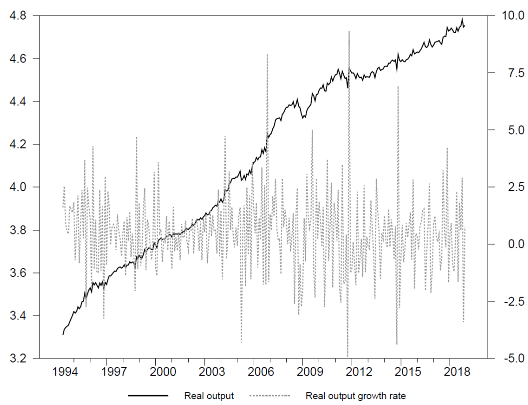
(a) Brazil



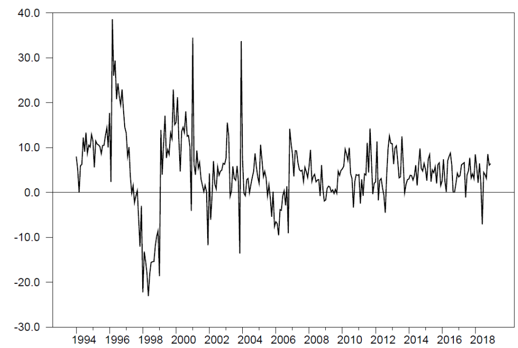
(b) China



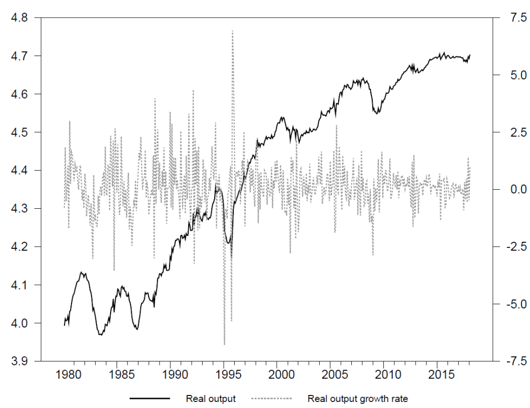
(c) India



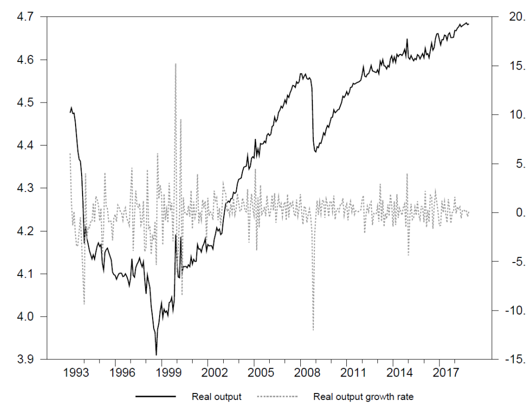
(d) Indonesia



(e) Mexico



(f) Russia



(g) Turkey

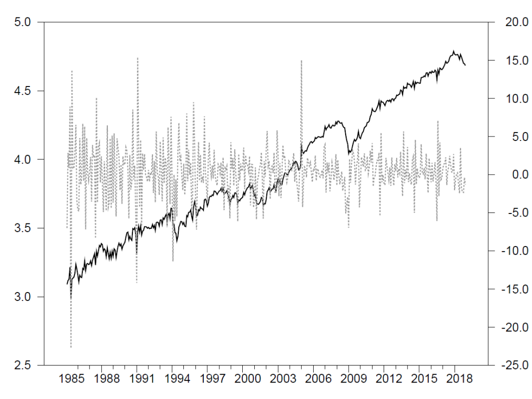
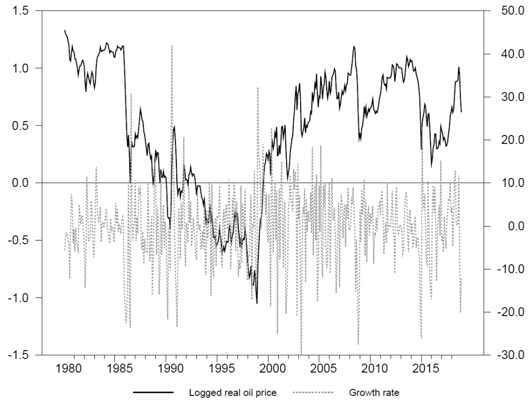
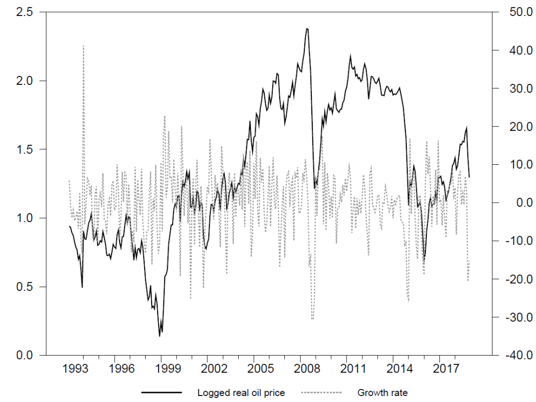


Figure 2.2: Brent crude oil price and its growth rate for the EM7 countries

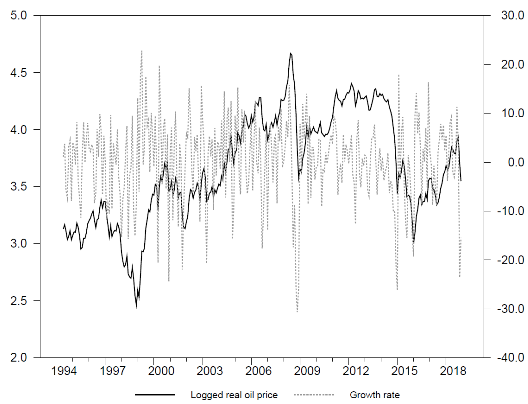
(a) Brazil



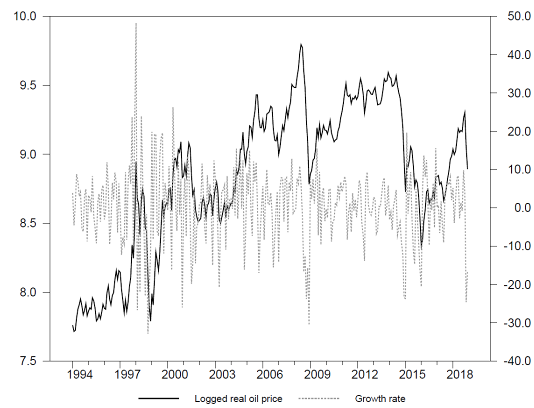
(b) China



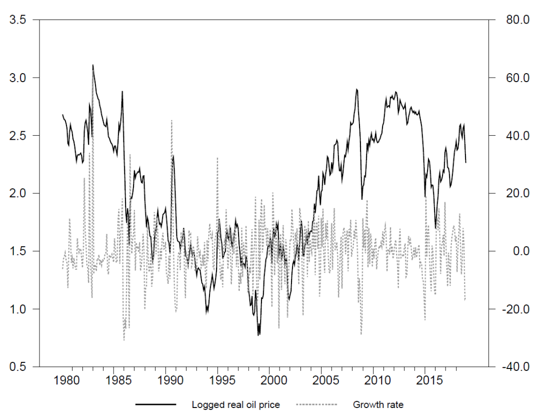
(c) India



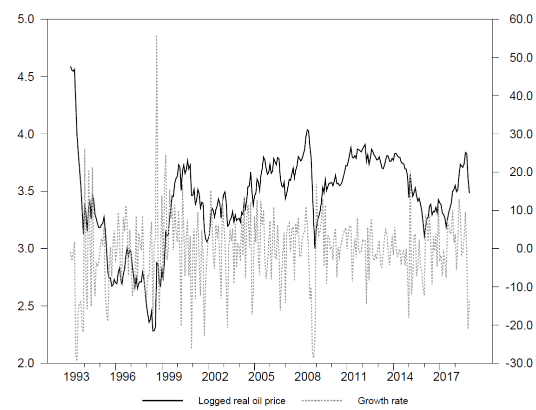
(d) Indonesia



(e) Mexico



(f) Russia



(g) Turkey

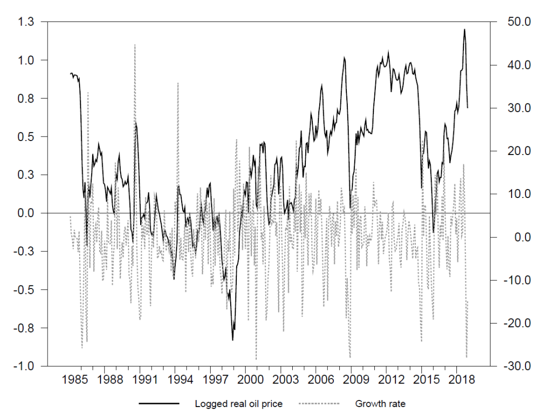


Figure 2.3: World crude oil production and its growth rate

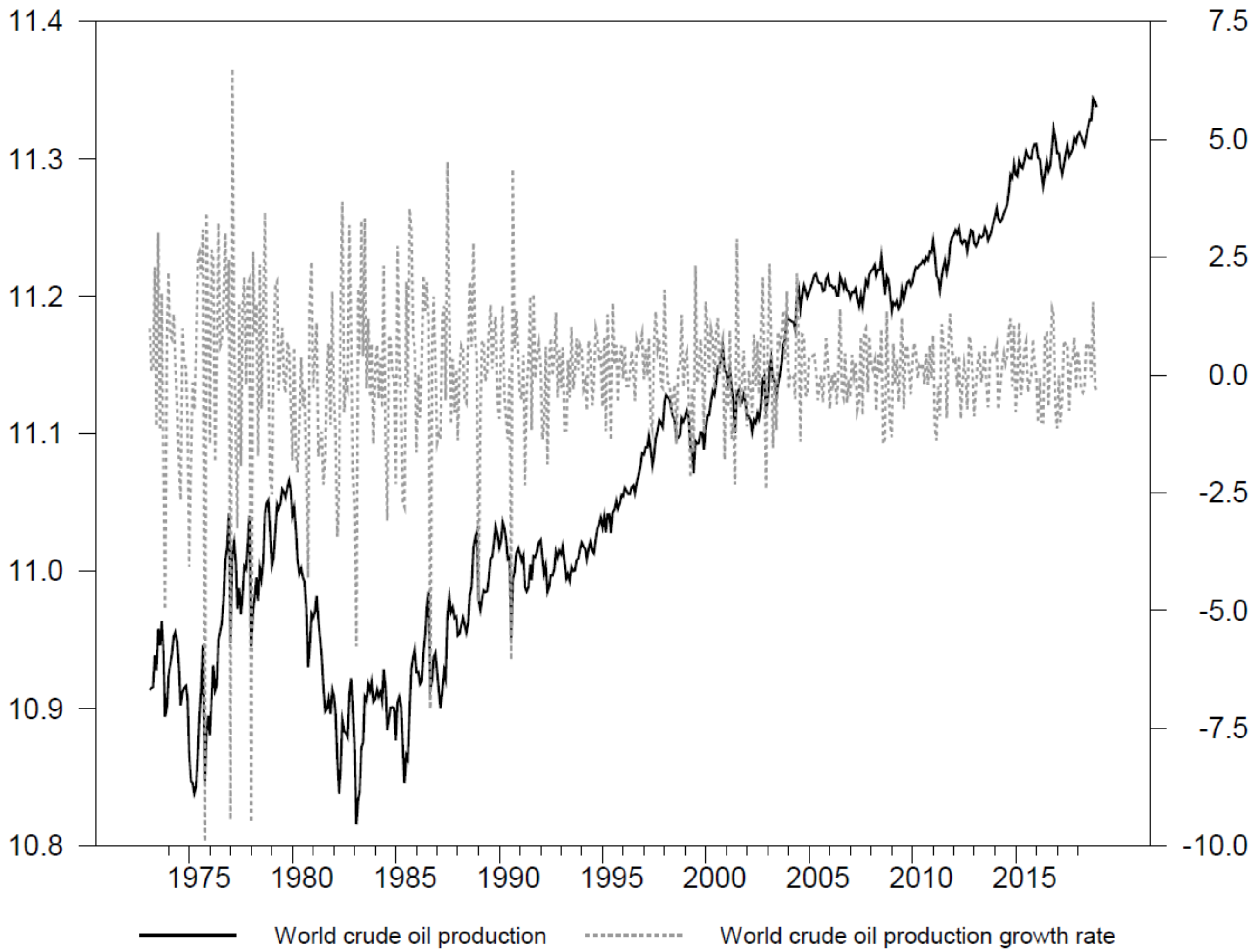


Figure 2.4: World economic activity

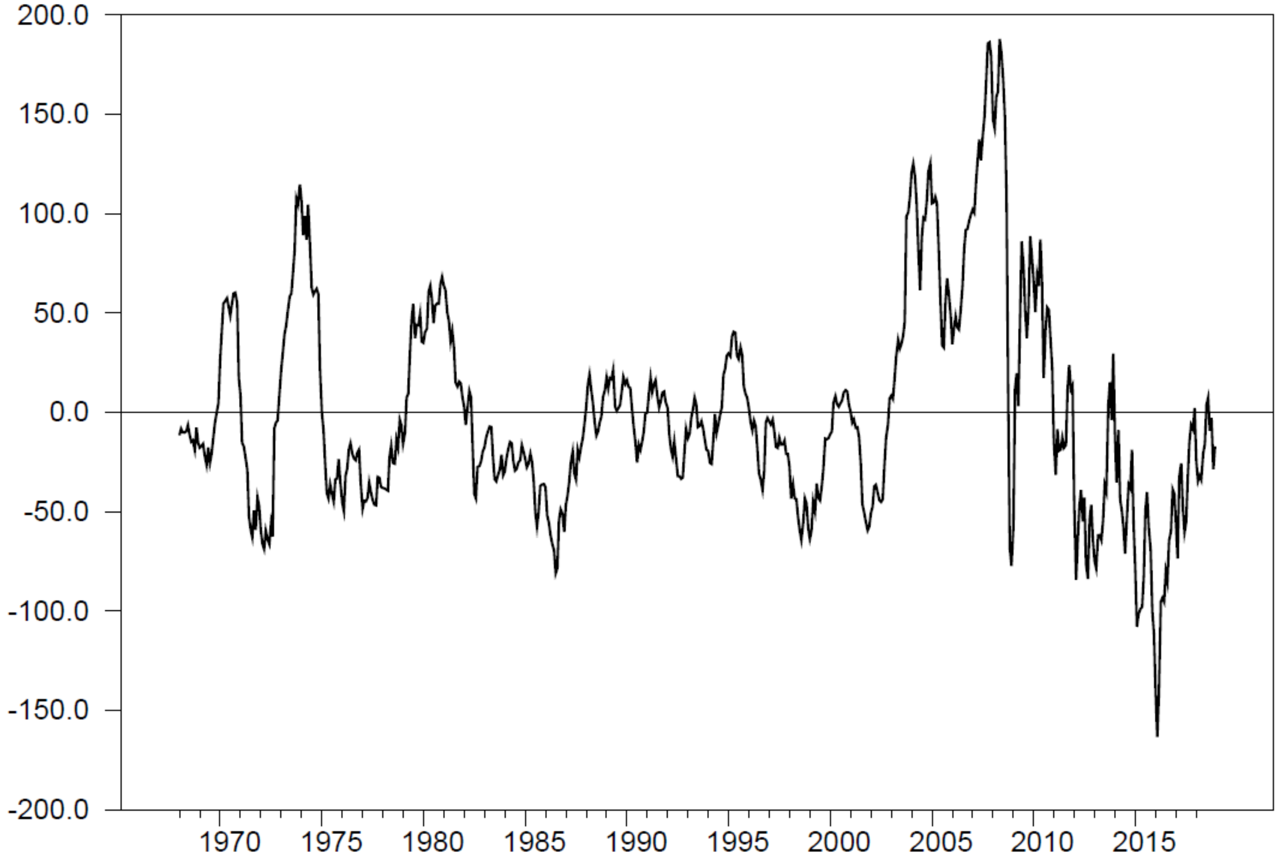


Table 2.1: Unit root and stationarity tests on the logged difference series

Country	ADF	PP	KPSS
	(A.) Industrial production		
Brazil	0.000	0.000	0.072
China	0.000	0.000	0.179
India	0.000	0.000	0.068
Indonesia	0.019	0.000	0.061
Mexico	0.000	0.000	0.040
Russia	0.000	0.000	0.175
Turkey	0.000	0.000	0.040
	(B.) Brent crude oil price		
Brazil	0.000	0.000	0.058
China	0.000	0.000	0.056
India	0.000	0.000	0.043
Indonesia	0.000	0.000	0.019
Mexico	0.000	0.000	0.049
Russia	0.000	0.000	0.129
Turkey	0.000	0.000	0.045

Notes: The first two columns report the p-values from the ADF and PP tests and the last column reports the KPSS test statistics. The 1% asymptotic critical value for the KPSS test is 0.216 for all the series.

Table 2.2: SIC values for the standard VAR and the multivariate GARCH-in-Mean VAR

Country	Homoscedastic VAR	GARCH-in-mean VAR
Brazil	17 951.151	16 886.016
China	9887.456	9498.109
India	10 386.066	10 183.709
Indonesia	9765.700	9299.102
Mexico	16 188.878	15 159.769
Russia	11 339.744	842.184
Turkey	15 884.714	15 189.324

Table 2.3: Coefficients of interest, λ_{41} and λ_{43}, from the multivariate GARCH-in-Mean model

Country	Optimal lag length	$\hat{\lambda_{13}}$	$\hat{\lambda_{43}}$
Brazil	4	-0.024	0.021
		(0.000)	(0.021)
China	2	-0.044	0.013
		(0.000)	(0.072)
India	2	-0.056	-0.070
		(0.000)	(0.000)
Indonesia	3	-0.010	-0.030
		(0.012)	(0.000)
Mexico	2	-0.031	-0.065
		(0.000)	(0.000)
Russia	2	-0.006	-0.040
		(0.162)	(0.054)
Turkey	2	-0.035	-0.046
		(0.000)	(0.000)

Note: Numbers in parentheses are p values

2.4 Empirical Evidence

We start by reporting in Table 2.2 the SIC values for a conditional homoscedastic VAR and our multivariate GARCH-in-Mean VAR. As can be seen in the table, the multivariate GARCH-in-Mean VAR captures more important features of the data than its homoscedastic counterpart, with the SIC values being considerably lower than that for the conventional homoscedastic VAR.

In the third column of Table 2.3, we report the maximum likelihood estimates of the primary coefficient of interest, $\hat{\lambda}_{43}$, with p-values in parenthesis, for each of the EM7 countries. $\hat{\lambda}_{43}$ gives the effect of uncertainty in the real oil price on domestic real output, after accounting for the supply side and demand side shocks to the real oil price. As can be seen, the coefficient of interest, $\hat{\lambda}_{43}$, is 0.021 with p-value of 0.021 for Brazil, 0.013 with a p-value of 0.072 for China, -0.070 with a p-value of 0.000 for India, -0.030 with a p-value of 0.000 for Indonesia, -0.065 with p-value of 0.000 for Mexico, -0.040 with a p-value of 0.054 for Russia, and -0.046 with a p-value of 0.000 for Turkey. More specifically, oil price uncertainty has a negative effect on real output in India, Indonesia, Mexico, Russia, and Turkey, and a positive and statistically significant effect on real output in Brazil and China.

In the fourth column of Table 2.3, we also report the estimates of the λ_{13} coefficient (with p-values in parentheses) for each of the EM7 countries; $\hat{\lambda}_{13}$ gives the effect of real oil price uncertainty on world oil production. Looking at the point estimates and their corresponding p-values, we see that oil price uncertainty has a negative and statistically significant effect on world crude oil production in six emerging market countries, namely Brazil, China, India, Indonesia, Mexico, and Turkey, and a negative and statistically insignificant effect on world crude oil production in Russia. Thus, we can also conclude that oil price uncertainty has in general an adverse effect on world crude oil production.

It is to be kept in mind that we should be cautious in interpreting results for China, since our time series is monthly interpolated real GDP growth data from quarterly frequency. Interpolated data has been criticized in the literature for giving spurious regression results — see Kilian and Park (2009). Chinese data has also been criticized heavily in the literature for intentional falsification and overstatement. In this regard, Zheng (2001) states that "there is serious weakness in some fields of national accounts such as transportation, real estate, education, and science and technology; in the price system underpinning the national accounts; and in the breakdown of the GDP accounts into components (e.g.,consumption and other segments of aggregate expenditure). China has barely begun to work on methods of incorporating environmental issues into the system of national accounts. The quarterly GDP estimates are crudely calculated with heavy reliance on estimates and excessive aggregation." Finally, Rawski (2001) argues that official statistics of Chinese real output growth beginning in 1998 are subject to major exaggerations. They claim that "the standard data contain numerous inconsistencies. Chinese commentaries castigate widespread falsification at lower levels and question the authenticity of figures emanating from the central statistical authorities. The author speculates that cumulative GDP growth during 1997/2001 was no more than one-third of official claims, and possibly much smaller." More recently, Chen et al. (2019) estimate that official growth in China's GDP was overstated by 1.7 percentage points in the period from 2008 to 2016 and the investment and savings rates in 2016 were overstated by 7 percentage points.

In this regard, panel (b) of Figure 2.1 may provide some hints regarding this issue. In particular, output in China has grown steadily over the sample period, with little variation that might be expected to be associated with cyclical expansions and contractions. We are therefore not surprised that oil price uncertainty does not have a negative effect on Chinese output growth. As for Brazil, the puzzling result might be due to the fact that Brazil is a large methanol producer and the methanol output can be influenced by the crude oil price. In fact, Brazil is the second largest producer of ethanol in the world after the United States. As of 2017, the U.S. and Brazil produce 85% of the world's ethanol (see https://afdc.energy.gov). A hike in the price of the substitute, crude oil, would increase the demand for ethanol. According to Hira and De Oliveira (2009), "Brazil has been able to substitute petroleum for ethanol for 20% of automotive fuel and 80% of Brazilian cars can take various blends of gas and ethanol."

2.5 On the (A)symmetric Relationship

Over the years, it has been argued that the relationship between oil prices and real economic activity is asymmetric, with the correlation between oil price increases and real output significantly different than the correlation between oil price decreases and real output — see, for example, Mork (1989) and Hamilton (2003). This is consistent with our evidence in the previous section that oil price uncertainty has a significant effect on all seven countries. More recently, Kilian and Vigfusson (2011) develop a formal statistical test of the null hypothesis of symmetric impulse responses to positive and negative oil price shocks, based on impulse response functions. As Kilian and Vigfusson (2011) put it, "what is at issue in conducting this impulse-response-based test is not the existence of asymmetries in the reduced form parameters, but the question of whether possible asymmetries in the reduced form imply significant asymmetries in the impulse response function."

In this section, we use the Kilian and Vigfusson (2011) symmetry test to check for symmetry in the responses of real output to positive and negative oil price shocks. The test is carried out by estimating the following non-linear structural model

$$\Delta \ln o_t = \alpha_{10} + \sum_{j=1}^{p} \beta_{11}(j)\Delta \ln o_{t-j} + \sum_{j=1}^{p} \beta_{12}(j)\Delta \ln y_{t-j} + u_{1t}$$

$$\Delta \ln y_t = \alpha_{20} + \sum_{j=0}^{p} \beta_{21}(j)\Delta \ln o_{t-j} + \sum_{j=1}^{p} \beta_{22}(j)\Delta \ln y_{t-j} + \sum_{j=0}^{p} \delta_{21}(j)\tilde{o}_{t-j} + u_{2t}$$

where $\tilde{o}_t$ is a non-linear function of the growth rate of the real oil price

$$\tilde{o}_t = \max\left[0, \ln o_t - \max\left\{\ln o_{t-1}, \ln o_{t-2}, \ln o_{t-3}, \cdots, \ln o_{t-12}\right\}\right].$$

The null hypothesis of symmetric impulse responses of $\Delta \ln y_t$ to positive and negative real oil price growth rate shocks of the same size is

$$H_0 : I_y(h, \delta) = -I_y(h, -\delta) \quad \text{for } h = 0, 1, ..., H$$

and tests whether the response of $\Delta \ln y_t$ to a positive shock in the oil price growth rate of size δ is equal to the negative of the response of y_t to a negative shock in the oil price growth rate of the same size, $-\delta$, for horizons $h = 0, 1, ..., H$. For a detailed discussion of the methodology, see Kilian and Vigfusson (2011).

In Table 2.4, we report p-values of the null hypothesis and since the test depends on the size of the shock, we report results for both small shocks (one standard deviation shocks, $\delta = \hat{\sigma}$) and large shocks (two standard deviation shocks, $\delta = 2\hat{\sigma}$). The test is conducted for 12 months, based on 10,000 simulations and 50 histories. As can be seen in Table 4, in general the null hypothesis of a symmetric relationship between the growth rates of the real oil price and real output cannot be rejected at conventional significance levels for China, India, Indonesia, Mexico, and Turkey. The null hypothesis, however, is rejected for Brazil and Russia.

Table 2.4: p-values for statistical test of the null hypothesis of symmetric impulse responses to positive and negative oil price shocks

	Brazil		China		India		Indonesia		Mexico		Russia		Turkey	
h	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$
0	0.591	0.600	0.226	0.243	0.411	0.410	0.020	0.026	0.122	0.120	0.000	0.000	0.022	0.017
1	0.001	0.002	0.271	0.302	0.334	0.324	0.067	0.082	0.074	0.073	0.001	0.000	0.060	0.045
2	0.001	0.002	0.297	0.332	0.527	0.518	0.142	0.171	0.073	0.072	0.001	0.001	0.131	0.102
3	0.003	0.005	0.438	0.478	0.687	0.677	0.240	0.281	0.137	0.135	0.002	0.002	0.213	0.164
4	0.006	0.009	0.578	0.618	0.792	0.792	0.309	0.355	0.222	0.220	0.003	0.002	0.323	0.257
5	0.012	0.017	0.670	0.718	0.849	0.838	0.426	0.477	0.226	0.221	0.005	0.004	0.441	0.366
6	0.021	0.030	0.760	0.808	0.901	0.899	0.515	0.563	0.317	0.312	0.005	0.004	0.558	0.478
7	0.034	0.046	0.839	0.877	0.800	0.832	0.623	0.669	0.416	0.407	0.009	0.008	0.652	0.573
8	0.050	0.066	0.889	0.919	0.868	0.890	0.717	0.755	0.506	0.493	0.010	0.009	0.744	0.671
9	0.070	0.093	0.932	0.952	0.916	0.932	0.786	0.821	0.601	0.588	0.012	0.010	0.820	0.753
10	0.068	0.089	0.879	0.923	0.948	0.960	0.829	0.866	0.680	0.670	0.016	0.013	0.878	0.823
11	0.094	0.122	0.921	0.952	0.969	0.977	0.835	0.865	0.752	0.740	0.024	0.018	0.919	0.877

Note Results are based on 10,000 impulse responses (R=10,000) and 50 histories (T=50)

In the previous section, we found that oil price uncertainty has a negative and statistically significant effect on real output in India, Indonesia, Mexico, Russia, and Turkey, and a positive and statistically significant effect on real output in Brazil and China, implying that the impulse-responses are asymmetric for all these countries. However, the Kilian and Vigfusson (2011) test for symmetry rejects the null of symmetry only Brazil and Russia. This could be because the Kilian and Vigfusson (2011) test is a generalized test for symmetry and will have lower power against any specific alternative. It could be that the failure to reject symmetry for China, India, Indonesia, Mexico, and Turkey could simply be due to low power with respect to this particular alternative. In this regard, as Jo (2014) put it, "the consensus in the literature is that there is no compelling evidence of asymmetric responses at the aggregate level in the U.S. or in other industrialized economies, whereas the evidence at the disaggregate level is mixed. While there is evidence of an uncertainty effect for oil producers in Texas, as shown by Kellogg (2010), tests for asymmetric responses of industrial production at the sectoral level show only limited asymmetries and not necessarily in energy intensive industries, as theory would have suggested."

We conclude that different countries respond differently to oil price shocks, and as noted by Serletis and Istiak (2013), this could be attributed to price and wage rigidities, varieties of macroeconomic policies in the different countries, and the nature of oil price shocks. In fact, as Kilian and Lewis (2011) put it in the case of the United States, "oil price shocks are best viewed as symptoms of deeper structural shocks in oil markets. One would expect the Federal Reserve to respond differently to oil price shocks associated with, say, unexpected booms in global demand, than oil supply disruptions. An unexpected demand boom driven by the global business cycle, for example, will stimulate the US economy in the short run, whereas an unanticipated oil supply disruption will not, calling for different policy responses depending on the composition of the oil demand and oil supply shocks underlying the oil price shock."

2.6 Conclusion

In recent years, emerging and developing economies accounted for about 70 percent of global growth in output and consumption, and in the aftermath of the global financial crisis, with advanced economies experiencing a slow recovery, the contribution of emerging market and developing economies to global growth has been even higher. Although the relationship between the price of oil and the level of economic activity in advanced economies has attracted considerable attention in the literature, there are relatively few studies that investigate the effects of oil price uncertainty and oil price shocks in emerging market economies. In this paper, we contribute to this literature by investigating the relationship between oil prices and the level of economic activity in the seven largest emerging market countries — Brazil, China, India, Indonesia, Mexico, Russia, and Turkey.

In the context of a multivariate GARCH-in-Mean VAR specification, that controls for lagged changes in global crude oil production and world economic activity, we find that oil price uncertainty has a negative effect on real output in India, Indonesia, Mexico, Russia, and Turkey, and a positive and statistically significant effect on real output in Brazil and China. This evidence is broadly consistent with the evidence that is available for advanced economies — see, for example, Bredin et al. (2011). In our investigation of whether the responses of real output in the EM7 countries to positive and negative oil price shocks are symmetric or asymmetric, we use the Kilian and Vigfusson (2011) impulse response function test and provide evidence of a symmetric relation in China, India, Indonesia, Mexico, and Turkey and of an asymmetric relation in Brazil and Russia.

Chapter 3

Spillovers of U.S. Monetary Policy Uncertainty on Inflation Targeting Emerging Economies[1]

NAHIYAN FAISAL AZAD AND APOSTOLOS SERLETIS

3.1 Introduction

With more integrated financial markets and more correlated business cycles across countries, the monetary policy in a large economy like the United States will spill over to other countries. In a recent paper, Nsafoah and Serletis (2019) contribute to this literature by estimating the Elder and Serletis (2010) bivariate structural (identified) GARCH-in-Mean VAR in the U.S. policy rate (the target federal funds rate) and the policy rate in a number of other advanced economies — Canada, Denmark, the Eurozone, Japan, Sweden, Switzerland, and the United Kingdom. They find empirical support for the view that monetary policy uncertainty in the United States has negative and statistically significant effects on the policy rate in each of the other countries, suggesting that monetary policy independence is less that what traditional macroeconomic theory suggests.

In this paper, we investigate how monetary policy uncertainty in the United States affects the monetary policy of seven inflation targeting emerging economies — Brazil, Chile, Colombia, Indonesia, Mexico, Poland,

[1]Published as Azad, Nahiyan Faisal, and Apostolos Serletis (2021). "Spillovers of U.S. Monetary Policy Uncertainty on Inflation Targeting Emerging Economies." *Emerging Markets Review*, forthcoming.

and South Africa. We restrict the analysis to the inflation targeting period for each of these countries, because of data availability issues, and (unlike Nsafoah and Serletis (2019)) control for the traditional Taylor rule type variables, such as the (domestic) inflation and output gaps. We carry out our investigation in the context of two classes of empirical models. We consider a multivariate extension of the Elder and Serletis (2010) GARCH-in-Mean VAR model in real output growth, the inflation rate, the U.S. policy rate, and the domestic policy rate in each of the emerging economies. In the context of this model, we associate the U.S. policy rate VAR residual (after controlling for lagged changes in the U.S. policy rate and the domestic real output growth rate, inflation rate, and policy rate of each emerging economy) with exogenous U.S. monetary policy shocks, use the conditional standard deviation of the forecast error for the change in the U.S. policy rate as a measure of monetary policy uncertainty in the United States, and investigate the relationship between the U.S. policy rate and the policy rate (as well as some macroeconomic fundamentals) in each of the seven emerging countries.

We also use a different proxy for U.S. monetary policy uncertainty to investigate how monetary policy uncertainty in the United States affects macroeconomic and financial fundamentals in emerging economies. In particular, we use the Baker et al. (2016) monetary policy uncertainty index in the context of a different multivariate structural VAR model — the Bjørnland and Leitemo (2009) model identified by a combination of short-run and long-run restrictions. In recent years, various risk and uncertainty measures have been proposed in the literature. As Cascaldi-Garcia et al. (2020) put it, "researchers, policymakers, and market participants have become increasingly focused on the effects of uncertainty and risk on financial market and economic outcomes." Increased uncertainty typically leads to declines in real GDP, consumption, investment, employment, inflation and interest rates — see, for example, Bloom (2009), Elder and Serletis (2010), Mumtaz and Zanetti (2013), Jurado et al. (2015), Fernández-Villaverde et al. (2015), Bloom et al. (2018), Davis (2019), Caldara et al. (2016), Caldara et al. (2020), and Dery and Serletis (2021), among others.

In this regard, Fernández-Villaverde et al. (2011), in their investigation of the macroeconomic effects of the volatility in the real interest rate at which emerging economies borrow, also argue that these economies rely on foreign debt to smooth consumption and to hedge against idiosyncratic productivity shocks. When the volatility in the real interest rate increases, the economy becomes exposed to real interest rate fluctuations, and debt becomes riskier. To reduce this exposure, the economy cuts consumption to lower its outstanding debt. Also, investment declines, reducing output and, through a fall in the marginal productivity of labour, hours worked. To counter these recessionary shocks, the central banks of small open emerging economies, lower their policy rates to help stimulate economy activity. This is consistent with the notion that uncertainty is countercyclical and confirms the role of uncertainty in stimulating a synchronized contraction in the U.S. economy as well as in small open emerging economies.

Our paper contributes to two literatures. First, it contributes to the uncertainty literature. High uncertainty, whether caused by political unrest, trade restrictions, or the Covid-19 crisis, generally has a negative effect on the level of economic activity. Second, it contributes to the growing international monetary policy spillovers literature — see, for example, Canova (2005), Maćkowiak (2007),Georgiadis (2016), Chen et al. (2016), Anaya et al. (2017), and Nsafoah and Serletis (2019), among others. In this regard, although there is some literature regarding the international transmission of U.S. monetary policy shocks in advanced economies, research regarding the transmission in emerging market economies has been fairly limited — see, for example, Azad and Serletis (2020).

The paper is organized as follows. In Section 2, we present the multivariate structural GARCH-in-Mean VAR, discuss the data, and present the empirical results and carry out a number of robustness checks. In Section 3, we present the multivariate structural VAR model with short-run and long-run identification and present the empirical evidence as well as some other robustness checks. The final section provides a brief conclusion.

3.2 The Multivariate GARCH-in-Mean VAR

We extend the bivariate structural GARCH-in-Mean VAR model developed by Elder and Serletis (2010) to a higher dimensional structural VAR model. In doing so, we utilize an internally consistent model that accommodates an independent role for the effects of monetary policy uncertainty in the United States. In the context of our multivariate structural GARCH-in-Mean VAR, we investigate the relationship between U.S. monetary policy uncertainty and the policy rates of inflation targeting emerging economies, after controlling for domestic inflation and the domestic growth rate.

Our choice of domestic variables is guided by the variables included in the traditional Taylor rule. According to the standard Taylor Rule, for an inflation targeting central bank, the domestic policy rate, is determined by the output gap and the inflation gap. A natural addition to the model might be the exchange rate. Leitemo and Söderström (2005) use a new-Keynesian open economy model to show that augmenting an optimized Taylor policy rule with the exchange rate, offers only slight improvements in terms of volatility in key macroeconomic variables. The paper concludes that since the gains are so small, using the output and inflation gaps is sufficient as indicators for monetary policy in the open economy. In line of that finding, we exclude the exchange rate from our GARCH-in-Mean model and include the standard variables in a Taylor rule, the domestic output growth rate, inflation rate, and domestic policy rate, in addition to the U.S. shadow rate.

We assume that the dynamics of the structural system can be summarized by a linear function of the relevant vector of macroeconomic variables, modified to allow the conditional volatility of the U.S. policy rate to affect the conditional mean

$$\boldsymbol{B}\boldsymbol{z}_t = \boldsymbol{C} + \boldsymbol{\Gamma}_1\boldsymbol{z}_{t-1} + \boldsymbol{\Gamma}_2\boldsymbol{z}_{t-2} + ... + \boldsymbol{\Gamma}_p\boldsymbol{z}_{t-p} + \boldsymbol{\Lambda}\sqrt{\boldsymbol{H}_t} + \boldsymbol{\epsilon}_t \tag{3.1}$$

where $\boldsymbol{z}$ is a column vector in the percentage change in real output, $\Delta \ln y_t$, the domestic inflation rate, π_t, the first difference of the U.S. policy rate, Δi_t^*, and the first difference of the domestic policy rate, Δi_t. That is, $\boldsymbol{z}_t = [\Delta \ln y_t \ \pi_t \ \Delta i_t^* \ \Delta i_t]'$. In equation (3.1), $\dim(\boldsymbol{B}) = \dim(\boldsymbol{\Gamma}_j) = (4 \times 4)$ and $\boldsymbol{\epsilon}_t \,|\Omega_{t-1} \sim$i.i.d. N($\boldsymbol{0}$, $\boldsymbol{H}_t$), with $\boldsymbol{H}_t$ being the variance-covariance matrix. $\sqrt{\boldsymbol{H}_t}$ is the conditional standard deviation of the U.S. policy rate. Also,

$$\boldsymbol{B} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix}; \quad \boldsymbol{\Gamma}_j = \begin{bmatrix} \gamma_{11}^j & \gamma_{12}^j & \gamma_{13}^j & \gamma_{14}^j \\ \gamma_{21}^j & \gamma_{22}^j & \gamma_{23}^j & \gamma_{24}^j \\ \gamma_{31}^j & \gamma_{32}^j & \gamma_{33}^j & \gamma_{34}^j \\ \gamma_{41}^j & \gamma_{42}^j & \gamma_{43}^j & \gamma_{44}^j \end{bmatrix}; \quad \boldsymbol{\epsilon}_t = \begin{bmatrix} \epsilon_{\Delta \ln y_t} \\ \epsilon_{\pi_t} \\ \epsilon_{\Delta i_t^*} \\ \epsilon_{\Delta i_t} \end{bmatrix};$$

$$\boldsymbol{H}_t = \begin{bmatrix} h_{\Delta \ln y_t} & 0 & 0 & 0 \\ 0 & h_{\pi_t} & 0 & 0 \\ 0 & 0 & h_{\Delta i_t^*} & 0 \\ 0 & 0 & 0 & h_{\Delta i_t} \end{bmatrix}; \quad \boldsymbol{h}_t = \begin{bmatrix} h_{\Delta \ln y_t} \\ h_{\pi_t} \\ h_{\Delta i_t^*} \\ h_{\Delta i_t} \end{bmatrix}; \quad \boldsymbol{\Lambda} = \begin{bmatrix} 0 & 0 & \lambda_{13} & 0 \\ 0 & 0 & \lambda_{23} & 0 \\ 0 & 0 & \lambda_{33} & 0 \\ 0 & 0 & \lambda_{43} & 0 \end{bmatrix}.$$

The model is identified by imposing a sufficient number of exclusion restrictions on the $\boldsymbol{B}$ matrix. In this four variable structural VAR case, we estimate $n(n-1)/2 = 6$ free parameters in $\boldsymbol{B}$, subject to a rank condition, such that the diagonal elements of $\boldsymbol{B}$ are assumed to be equal to 1 and $\boldsymbol{B}$ is assumed to be lower triangular

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ b_{21} & 1 & 0 & 0 \\ b_{31} & b_{32} & 1 & 0 \\ b_{41} & b_{42} & b_{43} & 1 \end{bmatrix}.$$

The block-recursive structure of $\boldsymbol{B}$ implies that the macroeconomic variables do not react to the policy variables in the short run, while the policy variables are allowed to contemporaneously react to the macroeconomic variables. By placing the U.S. policy rate and the domestic policy rate at the bottom of the system, our identification strategy assumes that innovations in the U.S. policy rate, $\epsilon_{\Delta i_t^*}$, and the domestic policy rates, $\epsilon_{\Delta i_t}$, affect the growth rate of real output and the inflation rate with a lag. This identification strategy closely follows the one used by Uribe and Yue (2006) who investigate the impact of U.S. interest rate shocks and domestic country spread shocks on domestic macroeconomic fundamentals in emerging economies. The core assumption of their identification scheme is that fundamental shocks generated from both international and domestic financial markets take a period to affect real domestic macroeconomic fundamentals, whereas innovations in domestic markets are picked up by financial markets in the short run. Our identification scheme is also standard in the monetary VAR literature — see, for example, Christiano et al. (1998), Christiano et al. (2005) and Bjørnland and Leitemo (2009).

Finally, we allow the conditional variance matrix, $\boldsymbol{H}_t$, to follow a multivariate GARCH process as follows

$$\begin{bmatrix} H_{\Delta \ln y_t} \\ H_{\pi_t} \\ H_{\Delta i_t^*} \\ H_{\Delta i_t} \end{bmatrix} = \begin{pmatrix} C_1 + F_1 \epsilon^2_{\Delta \ln y_{t-1}} + G_1 H_{\Delta \ln y_{t-1}} \\ C_2 + F_2 \epsilon^2_{\pi_{t-1}} + G_2 H_{\pi_{t-1}} \\ C_3 + F_3 \epsilon^2_{\Delta i^*_{t-1}} + G_3 H_{\Delta i^*_{t-1}} \\ C_4 + F_4 \epsilon^2_{\Delta i_{t-1}} + G_4 H_{\Delta i_{t-1}} \end{pmatrix}. \tag{3.2}$$

That is, we allow contemporaneous U.S. monetary policy volatility to affect the domestic policy rate of the emerging economies according to the coefficient matrix $\boldsymbol{\Lambda}$. If U.S. monetary policy uncertainty adversely affects the domestic policy rate, then we would get a negative and statistically significant coefficient, λ_{43}. We follow Elder (2004) and impose the restriction that the structural disturbances are orthogonalized so that $\boldsymbol{H}_t$ is diagonal. This helps to simplify the conditional variance system.

The multivariate GARCH-in-Mean VAR model, consisting of equations (3.1) and (3.2), is estimated using full information maximum likelihood — see Elder and Serletis (2010) for more details. We use the econometric software RATS (version 9.0) to estimate the model.[2] The optimal lag length is chosen using the Schwarz Information Criterion (SIC).

3.2.1 The Data

We use the industrial production index as a proxy for real output in each of the seven emerging market economies. For each of Brazil, Chile, and Poland, we use the total industrial production data from the Organization for Economic Cooperation and Development (OECD) Main Economic Indicators. For Indonesia, we use the year-over-year percentage growth rate of industrial/manufacturing production from the Asia Regional Integration Center: Economic and Financial Indicators Database of the Asian Development Bank. Finally, for Colombia, Mexico, and South Africa, we use the industrial production series from the World

[2] Note that for the country-specific models for Chile, Colombia, and South Africa, in the construction of the output growth rate and inflation rate we multiply the logarithmic first differences of the industrial production index and the consumer price index, respectively, by 1200 (instead of 100), for convergence purposes.

Bank's Global Economic Monitor (and convert it to domestic terms). Except for Indonesia, we use the logarithmic first differences of the industrial production indices.

We use country specific consumer price indices from FRED and take the logarithmic first difference to get the inflation rate series. We use the domestic policy rate series for the seven emerging inflation targeting economies from the central bank policy rates database of the Bank for International Settlements (BIS). We also use the Wu and Xia (2016) United States shadow rate which is a better proxy for the monetary policy stance of the Federal Reserve than the federal funds rate. In this regard, Wu and Xia (2016) state that the structural break in the effective federal funds rate when the policy rate hits the zero lower bound, prevents meaningful interpretation of research conducted using vector autoregressions in samples that cover the zero lower bound period. The continuity of the shadow rate series in the zero lower bound period allows us to overcome this problem. The comprehensive url list of the data sources is available in Appendix Table B.1.

Our sample period varies from country to country, with the beginning of the sample period dictated by the start of the inflation targeting regime and the end of the sample period dictated by the availability of data from our multiple sources. Table 3.1 summarizes the sample period for each country and the names of their respective central banks that have adopted the inflation targeting regime. Our sample of countries is restricted to these seven emerging economies due to data availability, degrees of freedom issues, and start of adoption of inflation targeting regime.

We conduct a series of unit root and stationarity tests in the growth rates of the industrial production series, $\Delta \ln y_t$, the inflation rate, π_t, the first difference of the domestic policy rates, Δi_t, of the inflation targeting emerging economies, and the first difference of the U.S. shadow rate, Δi_t^*. The data transformations are summarized in Appendix Table B.2. In particular, we use the Augmented Dickey-Fuller (ADF) unit root test [see Dickey and Fuller (1981)], the Phillips-Perron unit root test [see Phillips and Perron (1988)], and the Kwiatkowski *et al.* (KPSS) stationarity test [see Kwiatkowski et al. (1992)], to test the presence of unit roots in our converted series. For all tests, we assume an intercept and a linear trend. The null hypothesis of the ADF and PP tests is that a unit root is present in the data while the null hypothesis for the KPSS test is that the data is stationary about the trend.

We report the t-statistics for the ADF and PP tests in panels A and B and the KPSS test statistics in panel C of Appendix Table B.3. As can be seen, the null hypothesis of the presence of a unit root is rejected at the 1% significance level by both the ADF and PP tests, while the null hypothesis of stationarity about the trend in the KPSS test cannot be rejected at the 1% significance level, for all series. We conclude that the growth rates of industrial production, the inflation rate, and the first differences of the domestic policy rates and the U.S. shadow rate are all stationary. We also conducted similar tests on the logged levels of industrial production, $\ln y_t$, and the consumer price index, $\ln P_t$, and on the levels of the domestic policy rates, i_t, and the U.S. shadow rate series, i_t^*. We find that all these series have a unit root. These results are not displayed here but are available upon request.

Table 3.1: Countries, central banks and sample period

Country	Central bank	Sample period
Brazil	Central Bank of Brazil	1999:10 - 2020:11
Chile	Central Bank of Chile	1999:10 - 2020:11
Colombia	Central Bank of Colombia	1999:10 - 2020:12
Indonesia	Bank of Indonesia	2006:01 - 2020:02
Mexico	Bank of Mexico	2001:09 - 2020:12
Poland	National Bank of Poland	1999:01 - 2020:11
South Africa	South African Reserve Bank	2000:05 - 2020:12

3.2.2 Empirical Evidence

To confirm that our specifications in equations (3.1) and (3.2) are consistent with the data, for each of the seven country-specific models that we estimate, we calculate the SIC value for a conditional homoscedastic VAR and our multivariate GARCH-in-Mean VAR. As can be seen in Appendix Table B.4, the SIC values in each of the GARCH-in-Mean VAR models are lower than those in the homoscedastic VAR models, suggesting that our GARCH-in-Mean VAR model provides a better description of the data.

In the third column of Table 3.2, we report the λ_{43} estimates — the coefficient on the conditional standard deviation of the U.S. shadow rate in the mean equation of the domestic policy rate, for each of the seven country-specific models. This is the coefficient on the conditional standard deviation of the U.S. policy rate in the fourth mean equation. As can be seen, $\hat{\lambda}_{43}$ is -0.948 with a p-value of 0.000 for Brazil, -0.255 with a p-value of 0.000 for Chile, -0.326 with a p-value of 0.000 for Colombia, -0.019 with a p-value of 0.612 for Indonesia, -0.156 with a p-value of 0.000 for Mexico, -0.110 with a p-value of 0.000 for Poland, and -0.453 with a p-value of 0.000 for South Africa. The null hypothesis that the true value of λ_{43} is zero is rejected for six out of the seven countries. More specifically, we see that our measure of U.S. monetary policy uncertainty has a negative and statistically significant effect on the policy rates of Brazil, Chile, Colombia, Mexico, Poland, and South Africa, but no effect on the policy rate of Indonesia. In this regard, Bhattarai et al. (2020) state that central banks of some emerging economies, such as the Reserve Bank of India, maintained their policy rate despite a fall in inflation and output during heightened international monetary policy uncertainty. This might have been a strategy to counter future volatility of capital flows, and might explain why for another Asian economy, Indonesia, we find no statistically significant effect of U.S. monetary policy uncertainty on the policy rate. Thus, the "fear of capital flows" might have been a driver of maintaining the policy rate of Indonesia.

Table 3.2: λ_{43} coefficient estimates from the multivariate GARCH-in-Mean VAR

Country	Optimal lag length	$\hat{\lambda_{43}}$
Brazil	1	-0.948 (0.000)
Chile	1	-0.255 (0.000)
Colombia	1	-0.326 (0.000)
Indonesia	1	-0.019 (0.612)
Mexico	1	-0.156 (0.000)
Poland	2	-0.110 (0.000)
South Africa	1	-0.453 (0.000)

Note: Numbers in parentheses are p values

Our results are consistent with the findings by Lastauskas and Minh (2021). They also provide evidence that U.S. interest rate volatility leads to larger downward shifts in interest rates across their sample of emerging and advanced economies. Nilavongse et al. (2020) investigate the impact of domestic and foreign economic policy uncertainty shocks on the economy of the United Kingdom. They find that domestic interest rates fall after economic policy uncertainty increases at home and in the United States. Neely (2015) provides evidence that unconventional policies enacted by the Federal Reserve significantly reduce the 10-year nominal yields of Australia, Canada, Germany, Japan, and the United Kingdom. Carrière-Swallow and Céspedes (2013) report that global uncertainty shocks lead to a more severe and persistent fall in investment and private consumption in emerging economies compared to advanced economies.

3.2.3 Robustness

Sensitivity to the Ordering of the Variables

In our first robustness check, we run each of the seven country-specific GARCH-in-Mean models, with the U.S. shadow rate as the first variable in $\boldsymbol{z}_t$, that is $\boldsymbol{z}_t = [\Delta i_t^* \; \Delta \ln y_t \; \pi_t \; \Delta i_t]'$. By placing the U.S. policy rate above the domestic output growth rate, inflation rate, and policy rate, we are assuming that uncertainty originating from the Federal Reserve affects the macroeconomic and financial variables of a small open economy contemporaneously, but itself remains unaffected in the short run from shocks originating from macroeconomic fundamentals and the financial market of the small economy. In Appendix Table B.5, we report the SIC values for a standard homoscedastic VAR and our GARCH-in-Mean VAR. We again find that our GARCH-in-Mean model specification is superior to a standard homoscedastic VAR.

In Table 3.3, we report the estimates of the λ_{41} coefficients. We find, consistent with our results from the previous section, that U.S. monetary policy uncertainty has a negative effect on the policy rates of Brazil, Chile, Colombia, Mexico, Poland and South Africa, and no effect on the policy rate of Indonesia. Thus, our primary results still hold, that higher uncertainty associated with the actions taken by the Federal Reserve has a negative effect on the policy rate of inflation targeting emerging economies.

Table 3.3: λ_{41} coefficient estimates from the multivariate GARCH-in-Mean VAR with US shadow rates ordered first

Country	Optimal lag length	$\hat{\lambda}_{41}$
Brazil	1	-0.953 (0.000)
Chile	1	-0.242 (0.000)
Colombia	1	-0.236 (0.000)
Indonesia	1	-0.016 (0.659)
Mexico	1	-0.159 (0.000)
Poland	2	-0.109 (0.000)
South Africa	1	-0.442 (0.000)

Note: Numbers in parentheses are p values

Sensitivity to the Policy Rate

We also carry out a robustness check to assess the sensitivity of our findings to alternative measures of the U.S. policy rate. In particular, we use the BIS policy rate for the United States, instead of the Wu and Xia (2016) shadow rate, as a proxy for the monetary policy stance of the Federal Reserve. We carry out our multivariate GARCH-in-Mean analysis with the same domestic variables and our original ordering, $\boldsymbol{z}_t = [\Delta \ln y_t \; \pi_t \; \Delta i_t^* \; \Delta i_t]'$. Again, the optimal lag length for each of the country specific models is chosen using the SIC criterion. In Appendix Table B.6, we first report the SIC values for a standard homoscedastic VAR and our GARCH-in-Mean VAR for each of the seven country specific models. We find that the SIC values from our GARCH-in-Mean VAR are considerably lower than the SIC values from the standard VAR; as noted earlier, lower SIC values provide support in favour of our model specification.[3]

In Table 3.4, we report the estimates of the λ_{43} coefficients, in the same fashion as those in Table 3.3. Again, the λ_{43} coefficient tells us the impact of U.S. monetary policy uncertainty on the domestic policy rate. As can be seen, $\hat{\lambda}_{43}$ is -0.259 with p-value of 0.001 for Brazil, -0.056 with p-value of 0.002 for Chile, -0.350 with p-value of 0.000 for Colombia, -0.076 with p-value of 0.011 for Indonesia, -0.110 with p-value of 0.420 for Mexico, 0.091 with a p-value 0.252 for Poland, and -0.353 with p-value of 0.000 for South Africa. We see that U.S. monetary policy uncertainty has a negative effect on the policy rates of Brazil, Chile, Colombia, Indonesia, and South Africa. Thus, consistent with our earlier results, higher U.S. monetary policy uncertainty, in general, has a negative effect on the policy rates of inflation targeting emerging economies.

Sensitivity to Different Monetary Policy Strategies

BRICS is an association of leading emerging economies, namely Brazil, Russia, India, China, and South Africa. So far, we have robustly shown that for each of Brazil and South Africa, U.S. monetary policy uncertainty has a negative effect on the domestic policy rate. Due to the large size in terms of the macroeconomic fundamentals of India, China and Russia, an interesting question might be the impact of U.S. monetary policy uncertainty on policy rates on these big economies.

Russia and India started targeting the inflation rate only recently (in 2014 and 2016, respectively). Conducting analysis on these economies, during the period for which inflation targeting has been adopted and running, would lead to degree of freedom problems, because of the relatively small sample period. To choose a more reasonable sample period for Russia, we focus on the period after the 1998 Russian financial

[3]Note that to achieve convergence, in our country-specific models for Brazil, Chile, Colombia, Poland, and South Africa, in the construction of the output growth rate and inflation rate we multiply the logarithmic first differences of the industrial production index and the consumer price index, respectively, by 1200, instead of 100.

Table 3.4: λ_{43} coefficient estimates from the multivariate GARCH-in-Mean VAR with BIS policy rates

Country	Optimal lag length	$\hat{\lambda_{43}}$
Brazil	1	-0.259
		(0.001)
Chile	1	-0.056
		(0.002)
Colombia	1	-0.350
		(0.000)
Indonesia	1	-0.076
		(0.011)
Mexico	1	-0.110
		(0.420)
Poland	2	0.091
		(0.252)
South Africa	1	-0.353
		(0.000)

Note: Numbers in parentheses are p values

crisis (more commonly known as the Russian ruble crisis). Thus, our sample period for Russia is from 1999:1 to 2020:11. We proxy output growth in Russia, by using the growth rate of the industrial production series from the Organization for Economic Cooperation and Development (OECD) Main Economic Indicators. For India, we use the entire period for which data is available, from 1995:4 to 2020:11. As we did for Indonesia, for India we use the year-over-year percentage growth rate of industrial/manufacturing production from the Asia Regional Integration Center: Economic and Financial Indicators Database of the Asian Development Bank.

China, another big emerging economy, targets monetary aggregates.[4] The sample period for China is from 2006:10 to 2020:11. Sun (2018) shows that near the end of 2006, different measures for forecasting GDP growth suffer from a structural break. The paper states that this corresponds to a period in which the central bank of China, the People's Bank of China, started to aggressively use the required reserve ratio to help lower excessive liquidity. Thus, we start our sample period from the last quarter of 2006. We proxy China's real output growth rate with the growth rate of the monthly real GDP series constructed by the Centre for Quantitative Economic Research of the Federal Reserve Bank of Atlanta as part of the database of China's Macroeconomy: Time Series Data. For all three countries, China, India, and Russia, we use the

[4]See `https://www.elibrary-areaer.imf.org/Documents/YearlyReport/AREAER_2020.pdf`

growth rate of the consumer price index series retrieved from FRED, to measure the inflation rate. For the three emerging economies, we retrieve the domestic policy rates from BIS and for the United States, we use the Wu and Xia (2016) shadow policy rate. We take the first differences of both the policy rates as well as the shadow rates to render the data stationary (the unit root tests are available upon request).

We run our GARCH-in-Mean VAR with the same model specification as in Section 2, where we choose the optimal lag length using the SIC criterion. The output growth rate is placed at the top of the VAR ordering, followed by the inflation rate, the first difference of the U.S. shadow rate, and finally the first difference of the domestic policy rate. The λ_{43} coefficient is -0.039 with a p-value of 0.155 for China, 0.185 with a p-value of 0.000 for India, and -2.380 with a p-value of 0.000 for Russia. Thus, higher U.S. monetary policy uncertainty has no effect on the policy rate in China, a positive effect on the policy rate of India, and a negative effect on the policy rate of Russia. These results must be interpreted with caution as the central banks of these three economies have not been using the interest rate as the operating target of monetary policy for the entire sample period; in fact, as already mentioned, India and Russia started targeting the inflation only recently and China has been targeting the money supply.

We also estimated the GARCH-in-Mean VAR, for China, India, and Russia using the ordering $\boldsymbol{z}_t = [\Delta i_t^* \; \Delta \ln y_t \; \pi_t \; \Delta i_t]'$ with the U.S, shadow rate ordered first. As already noted, this VAR ordering assumes that U.S. monetary policy affects the domestic macroeconomic fundamentals of the emerging economies contemporaneously but prevents instantaneous feedback from the macroeconomic variables of the emerging economies to the U.S. shadow rate. This is consistent with the assumption that all three of these emerging economies are small open economies. The optimal lag length is chosen using the SIC criterion. For this ordering of the variables, the λ_{43} coefficient is -0.040 with a p-value of 0.146 for China, 0.187 with a p-value of 0.070 for India, and 0.300 with a p-value of 0.000 for Russia. The results are contrary to what we find for our seven inflation targeting emerging economies in the previous sections, where higher U.S. monetary policy uncertainty has a negative effect on domestic policy rates implemented by central banks of inflation targeting emerging economies.

3.3 The Bjørnland and Leitemo (2009) VAR

In this section, we use a different measure of U.S. monetary policy uncertainty, and the structural VAR model implemented by Bjørnland and Leitemo (2009), to explore for spillovers from monetary policy uncertainty in the United States to our sample of inflation targeting emerging economies. Based on the inconclusive evidence in the previous section for China, India, and Russia, in this section we do not investigate these three countries.

We use the monthly monetary policy uncertainty index for the United States, constructed by Baker et al. (2016), and retrieved from FRED. This monetary policy uncertainty index is constructed from hundreds of daily newspapers covered by Access World News, after flagging articles that contain the triple of terms satisfying the uncertainty, economy, and policy categories and in addition terms related to monetary policy, such as Federal Reserve, central bank, overnight lending rate, and federal funds rate. SeeBaker et al. (2016) for more details.

Our VAR model uses monthly data on the real output growth rate, $\Delta \ln y_t$, the inflation rate, π_t, the monetary policy uncertainty index, U_t, the first difference of the domestic policy rate, Δi_t, and the percentage growth rate of real share prices, $\Delta \ln s_t$; we include share prices as the stock market is a barometer of future economic conditions. The share price series are retrieved from FRED and are deflated by the consumer price index (also retrieved from FRED). We also test for unit roots and stationarity in the U_t and $\Delta \ln s_t$ series, using the ADF, PP and KPSS tests, in the same fashion as in Table 2 for the $\Delta \ln y_t$, π_t, and Δi_t series. Results not reported here (but available on request) indicate that the null hypothesis of a unit root is rejected at conventional significance levels by both the ADF and PP tests and that the KPSS test cannot reject the null hypothesis of stationarity at the 1% level of significance for all the series. Thus all five series, $\Delta \ln y_t$, π_t, U_t, $\Delta \ln s_t$, and Δi_t used in our empirical analysis are stationary; as noted by Bjørnland and Leitemo (2009), if the variables used in the VAR are non-stationary, the moving average representation of the VAR maybe is non-convergent. We also conduct basic diagnostic tests to show that is no evidence of autocorrelation or heteroscedasticity in the model residuals.

Following Bjørnland and Leitemo (2009), who investigate the interdependence between interest rates and stock prices by imposing both short-run and long-run zero restrictions, we assume $\boldsymbol{z}_t$ to be the 5×1 vector of our macroeconomic variables, ordered as

$$\boldsymbol{z}_t = [\Delta \ln y_t, \pi_t, U_t, \Delta \ln s_t, \Delta i_t]'$$

Specified in this order, our structural VAR is assumed to be stable, invertible and written in its moving average representation as

$$\boldsymbol{z}_t = \boldsymbol{B}(L)\boldsymbol{v}_t \tag{3.3}$$

where $\boldsymbol{v}_t$ is a 5×1 vector of reduced-form residuals, assumed to be identically and independently distributed, $\boldsymbol{v}_t \sim \text{iid}(\boldsymbol{0}, \boldsymbol{\Omega})$, with $\boldsymbol{\Omega}$ being the positive-definite covariance matrix. $\boldsymbol{B}(L)$ is the 5×5 convergent matrix polynomial in the lag operator, L, $\boldsymbol{B}(L) = \boldsymbol{B}_0 + \boldsymbol{B}_1 L^1 + \boldsymbol{B}_2 L^2 + ...$

The underlying orthogonal structural disturbances, $\boldsymbol{\varepsilon}_t$, can be written as a linear combination of the reduced-form innovations, $\boldsymbol{v}_t = \boldsymbol{S}\boldsymbol{\varepsilon}_t$, where $\boldsymbol{S}$ is the 5×5 contemporaneous matrix. Equation (3.3) can be written in terms of the structural shocks, $\boldsymbol{\varepsilon}_t$, as

$$\boldsymbol{z}_t = \boldsymbol{C}(L)\boldsymbol{\varepsilon}_t \tag{3.4}$$

where $\boldsymbol{C}(L) = \boldsymbol{B}(L)\boldsymbol{S}$. In our identification scheme for $\boldsymbol{S}$, the underlying orthogonal structural disturbances, $\boldsymbol{\varepsilon}_t$, are normalized to have unit variance, the vector of the uncorrelated structural shocks is ordered as $\boldsymbol{\varepsilon}_t = [\varepsilon_t^{\Delta \ln y}, \varepsilon_t^{\pi}, \varepsilon_t^{U}, \varepsilon_t^{\Delta \ln s}, \varepsilon_t^{\Delta i}]'$, and the remaining shocks are identified from their respective equations, but are left uninterpreted. ε_t^U represents the U.S. monetary policy uncertainty shock. From the covariance structure we also get the following relationship

$$\boldsymbol{\Omega} = E\left[\boldsymbol{v}_t\boldsymbol{v}_t'\right] = \boldsymbol{S}E\left[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'\right]\boldsymbol{S}' = \boldsymbol{S}\boldsymbol{S}'. \tag{3.5}$$

Following the standard VAR literature — see, for example, Christiano et al. (1998), Christiano et al. (2005) and Bjørnland and Leitemo (2009) — we assume that the macroeconomic aggregates do not contemporaneously react to the financial markets, while a simultaneous reaction from the macroeconomic environment to the financial markets is allowed for. We achieve this identification by placing the two macroeconomic aggregates, $\Delta \ln y_t$ and π_t, above the U.S. monetary policy uncertainty variable, U_t, the share prices growth rate, $\Delta \ln s_t$, and the domestic policy rate, Δi_t, in the structural VAR ordering and assuming two zero restrictions on the relevant coefficients in the fifth column of the $\boldsymbol{S}$ matrix, namely $S_{15} = S_{25} = 0$. We follow Uribe and Yue (2006) in placing the U.S. monetary policy uncertainty variable, U_t, after the domestic output growth rate and inflation rate. We follow Bjørnland and Leitemo (2009) and impose similar recursive restrictions on the relationship between share prices and our macroeconomic aggregates and the U.S. monetary policy uncertainty variable, by imposing three zero restrictions on the $\boldsymbol{S}$ matrix, namely $S_{14} = S_{24} = S_{34} = 0$. These restrictions reflect the assumption that macroeconomic aggregates and U.S. monetary policy uncertainty do not contemporaneously react to share price shocks. By imposing no zeros in the fourth row of the $\boldsymbol{S}$ matrix, we allow share prices to contemporaneously react to shocks originating from the macroeconomic aggregates and U.S. monetary policy uncertainty. Specifically,

$$\begin{bmatrix} \Delta \ln y_t \\ \pi_t \\ U_t \\ \Delta \ln s_t \\ \Delta i_t \end{bmatrix} = \boldsymbol{B}(L) \begin{bmatrix} S_{11} & 0 & 0 & 0 & 0 \\ S_{21} & S_{22} & 0 & 0 & 0 \\ S_{31} & S_{32} & S_{33} & 0 & 0 \\ S_{41} & S_{42} & S_{43} & S_{44} & S_{45} \\ S_{51} & S_{52} & S_{53} & S_{54} & S_{55} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\Delta \ln y} \\ \varepsilon_t^{\pi} \\ \varepsilon_t^{U} \\ \varepsilon_t^{\Delta \ln s} \\ \varepsilon_t^{\Delta i} \end{bmatrix}. \tag{3.6}$$

In order to account for two-way causation, we allow for interaction between the domestic interest rate and share prices by following Bjørnland and Leitemo (2009) and assuming that domestic policy rate shock do not have any effect on real share prices in the long run. We impose this restriction by setting the sum of the infinite number of relevant lag coefficients in equation (3.4) equal to zero, $\sum_{j=0}^{\infty} C_{45,j} = 0$. From the relationship $\boldsymbol{C}(L) = \boldsymbol{B}(L)\boldsymbol{S}$, we know that $B(1)\boldsymbol{S} = C(1)$. Here, $C(1) = \sum_{j=0}^{\infty} C_j$ and $B(1) = \sum_{j=0}^{\infty} B_j$ represent the 5×5 long run matrix of $C(L)$ and $B(L)$, respectively. Therefore, the long run restriction $C_{45}(1) = 0$ implies that

$$B_{41}(1)S_{15} + B_{42}(1)S_{25} + B_{43}(1)S_{35} + B_{44}(1)S_{45} + B_{45}(1)S_{55} = 0.$$

The system becomes just identifiable. For a structural VAR with n $(= 5)$ variables, we need $n(n-1)/2$ $(= 10)$ restrictions for identification. We achieve that in our system by imposing nine short-run restrictions and one long-run restriction. In short, since share prices and the interest rate appear at the bottom of the system, the identification strategy assumes that innovations in the interest rate, ε_t^{R}, and share prices, $\varepsilon_t^{\Delta s}$, percolate into the domestic economy with a lag. On the other hand, real domestic shocks, $\varepsilon_t^{\Delta y}$, $\varepsilon_t^{\Delta c}$, and $\varepsilon_t^{\Delta i}$, affect the financial markets contemporaneously.

3.3.1 Empirical Evidence

For each emerging economy, we estimate the model over the sample period shown in Table 3.1 using stationary variables (as confirmed by the unit root tests). We also use the SIC criterion to determine the optimal lag length in the VAR; it is chosen to be equal to 1 for each country.[5] The shocks are normalized so that the U.S. monetary policy uncertainty shock increases the monetary policy uncertainty index by 1 percentage point in the first month. Figures 3.1-3.7 show the impulse responses for the growth rate of real output, the inflation rate, the domestic policy rate, and share prices, from an unanticipated increase in monetary policy

[5] We rerun the structural VAR with a lag length of 3 and our results (available upon request) are qualitatively the same.

uncertainty in the United States. We graph the responses with probability bands represented as 0.16 and 0.84 fractiles. More specifically we use the Bayesian simulated distribution from Monte Carlo integration where the draws are made directly from the estimated VAR coefficients as suggested by Doan (2004).

We observe that an unanticipated increase in U.S. monetary policy uncertainty leads to a decline in the domestic policy rate in Chile, Colombia, Indonesia, Mexico, Poland, and South Africa. The results are consistent with our findings from the multivariate GARCH-in-Mean VAR model implemented in Section 2. That is, uncertainty about the future path taken by U.S. monetary policy, in general, has a negative effect on policy rates in inflation targeting emerging economies. In this regard, Hofmann and Takáts (2015) argue that there might be policy spillovers from the United States to smaller advanced and emerging economies. In particular, they argue that a possible reason why the monetary policies of these small economies closely follow monetary policy in the United States, might be to prevent large interest rate differentials with the United States which will cause a fall in trade competitiveness by appreciating the exchange rate. Another possible reason why these economies might want to avoid large interest rate differentials with the United States is to prevent speculative short-term capital inflows which will cause financial stability risks. Due to these two reasons, the policy rates of these economies will be closely tied to those in the United States, and through the rest of the yield curve, other short- and long-term interest rates will follow a similar path.

Innovations in U.S. monetary uncertainty also lead to a decline in real output in Brazil, Chile, Colombia, Mexico, Poland, and South Africa. Our results are consistent with the findings of Stockhammar and Österholm (2017), who document that U.S. policy uncertainty shocks have a negative effect on GDP growth of all five Nordic economies (Denmark, Finland, Iceland, Norway, and Sweden). Also, Colombo (2013) empirically shows that a one standard deviation shock to U.S. economic policy uncertainty has a negative effect on European industrial production. Fernández-Villaverde et al. (2011) find that real interest rate volatility, the interest at which emerging economies borrow, stimulates a fall in output, consumption, investment, and hours worked in four Latin American economies (Argentina, Ecuador, Venezuela, and Brazil). The share prices experience an immediate decline in response to an increase in uncertainty about the future path taken by the monetary policy conducted by the Federal Reserve. For some economies, share prices experience an increase after the initial decline, before settling back to the steady-state level. This might be because heightened uncertainty regarding U.S. monetary policy leads to an initial fall in global demand, but gradually stimulates foreign demand away from the United States to these emerging economies.

Figure 3.1: Responses of domestic variables in Brazil to a U.S. monetary policy uncertainty shock

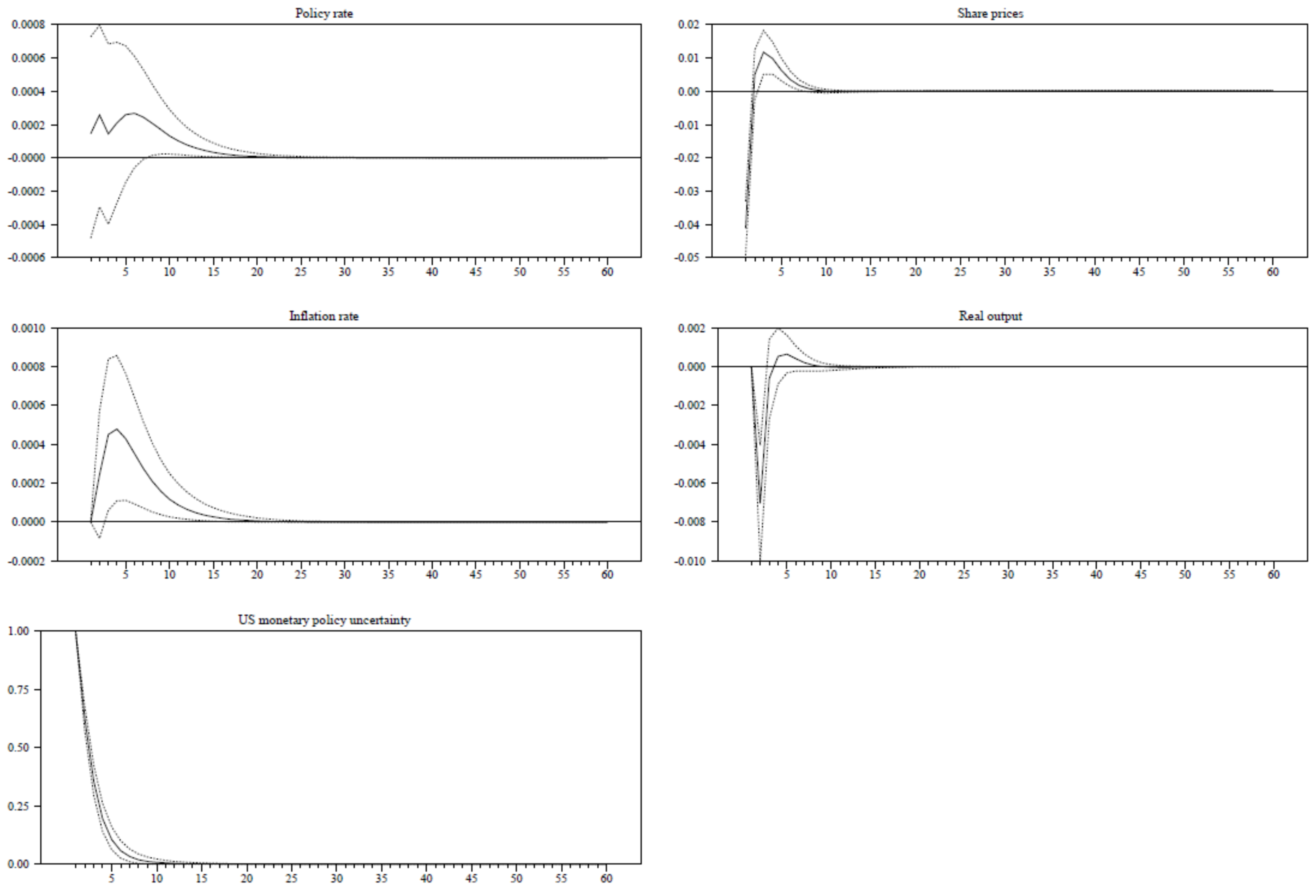


Figure 3.2: Responses of domestic variables in Chile to a U.S. monetary policy uncertainty shock

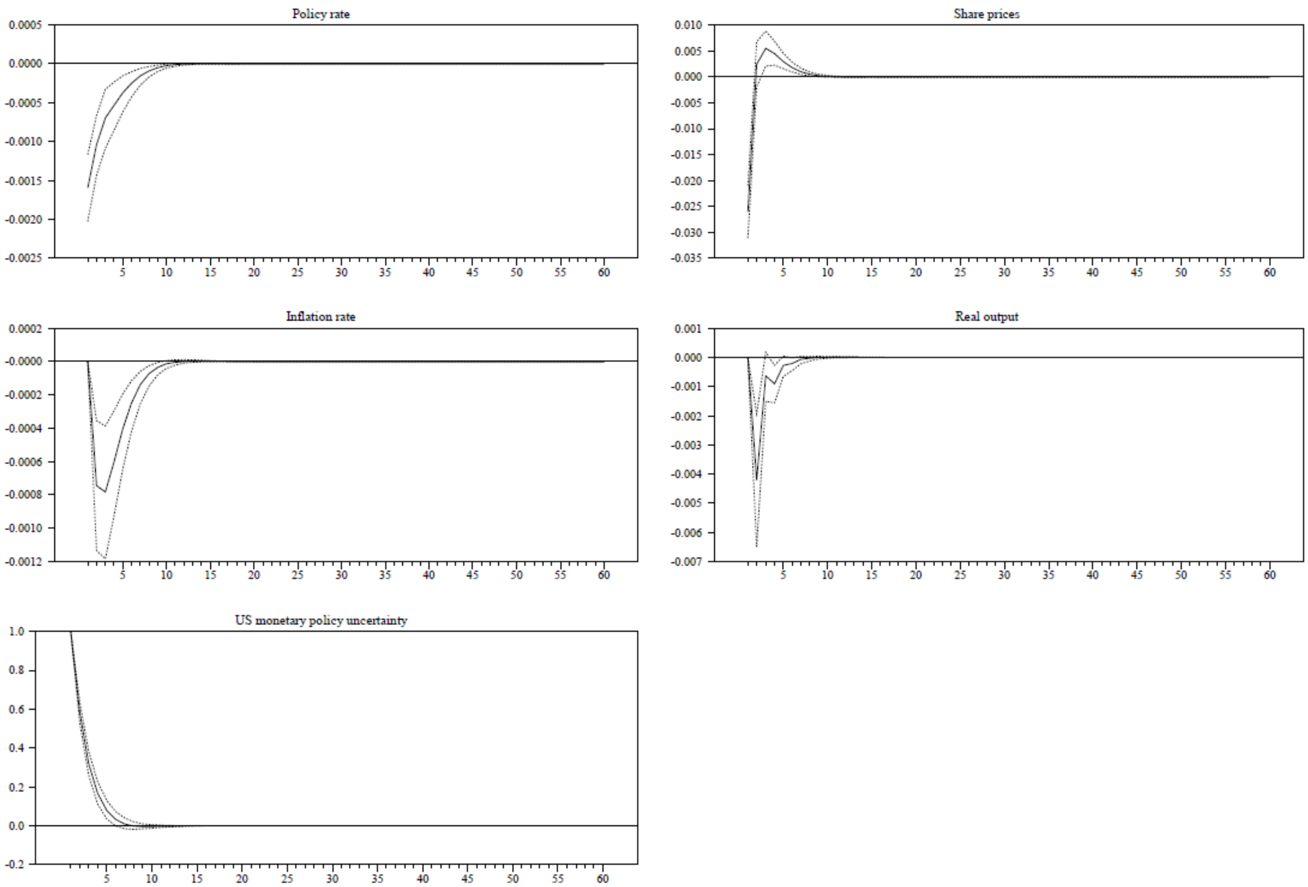


Figure 3.3: Responses of domestic variables in Colombia to a U.S. monetary policy uncertainty shock

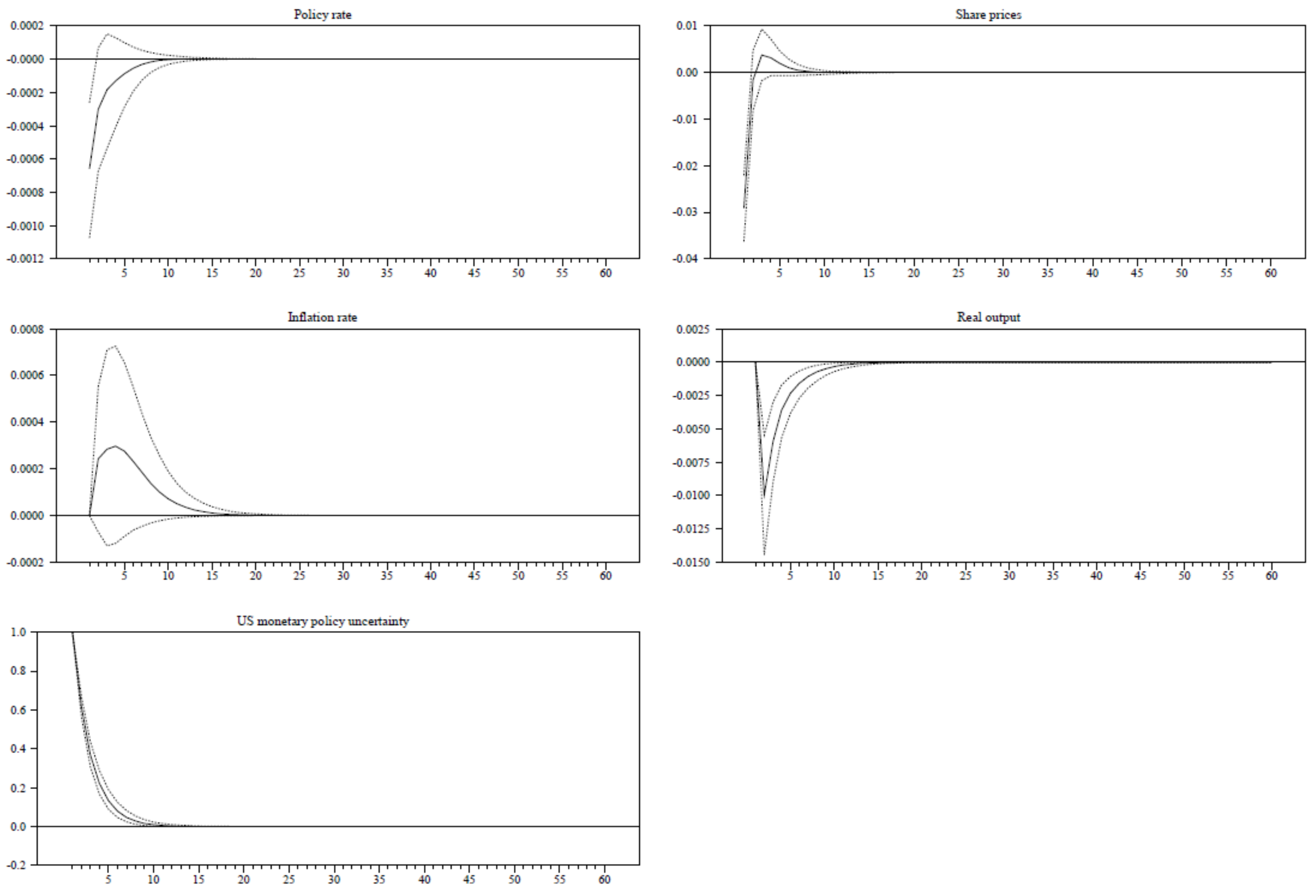


Figure 3.4: Responses of domestic variables in Indonesia to a U.S. monetary policy uncertainty shock

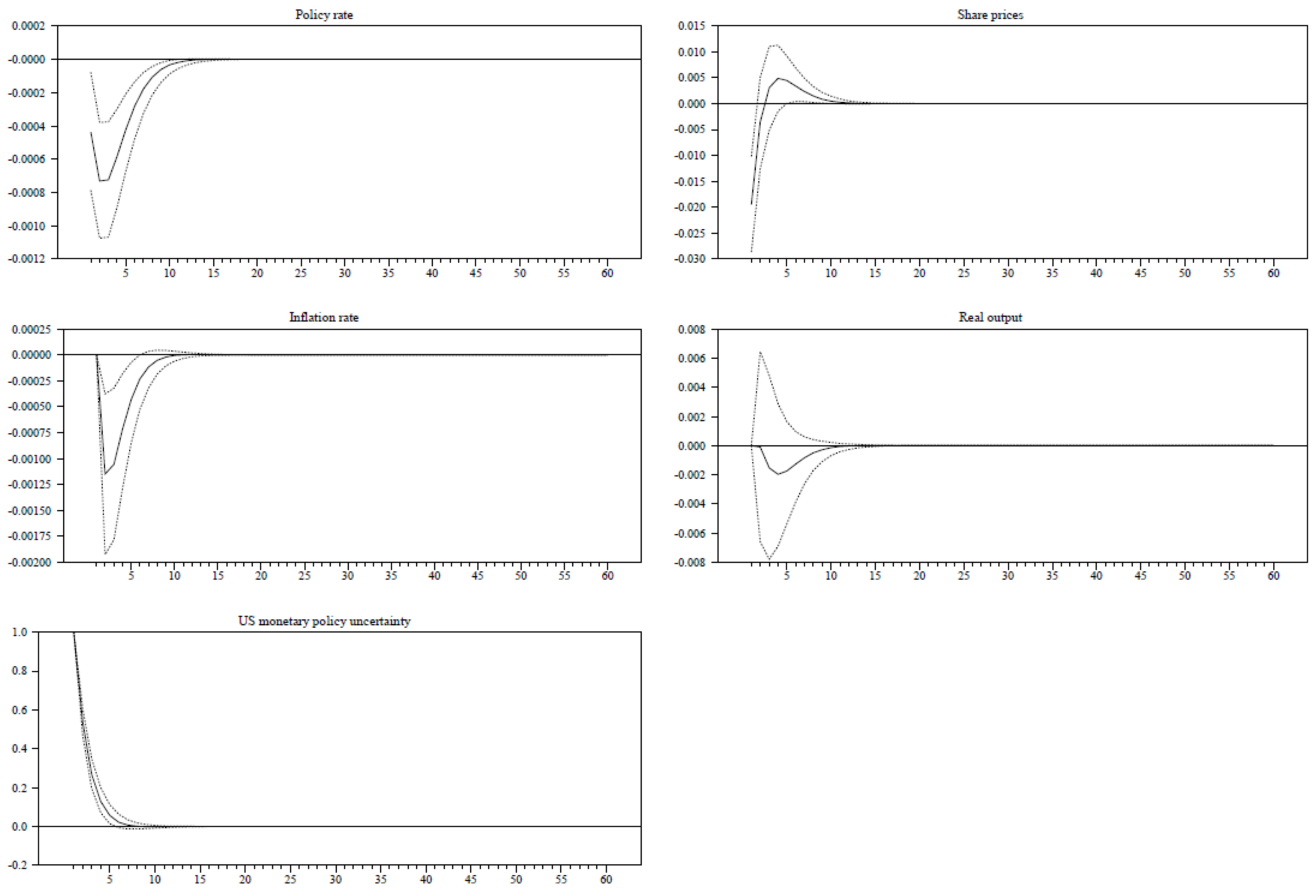


Figure 3.5: Responses of domestic variables in Mexico to a U.S. monetary policy uncertainty shock

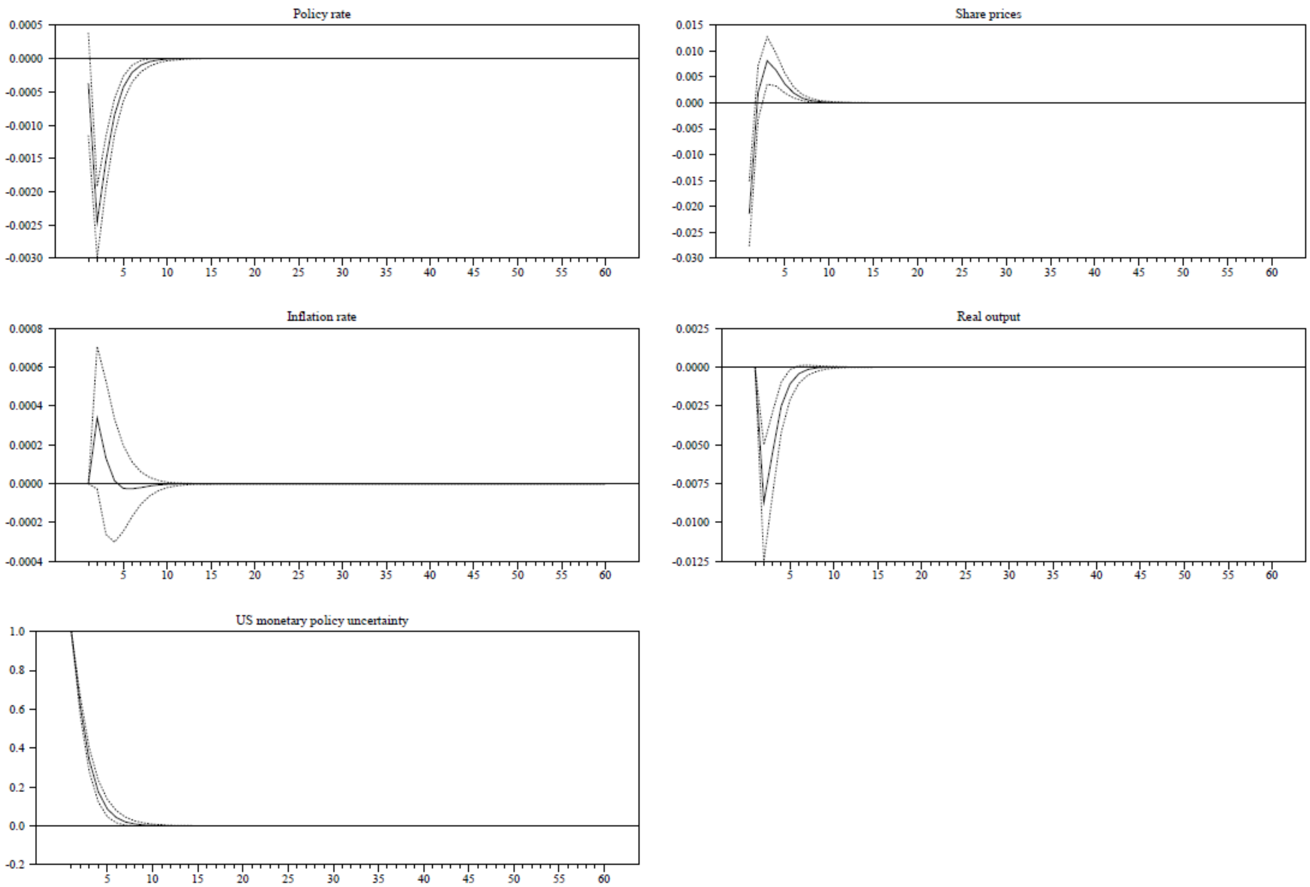


Figure 3.6: Responses of domestic variables in Poland to a U.S. monetary policy uncertainty shock

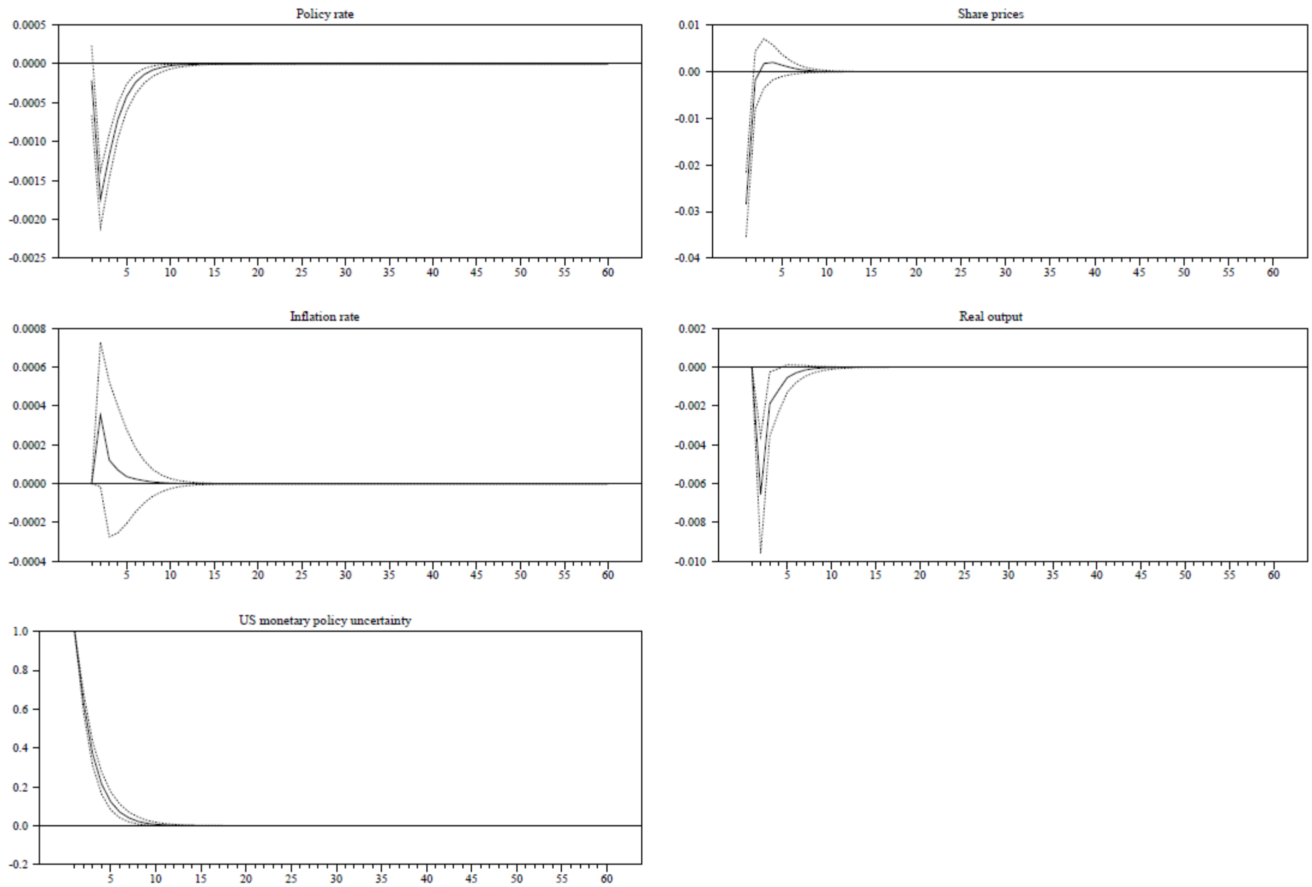
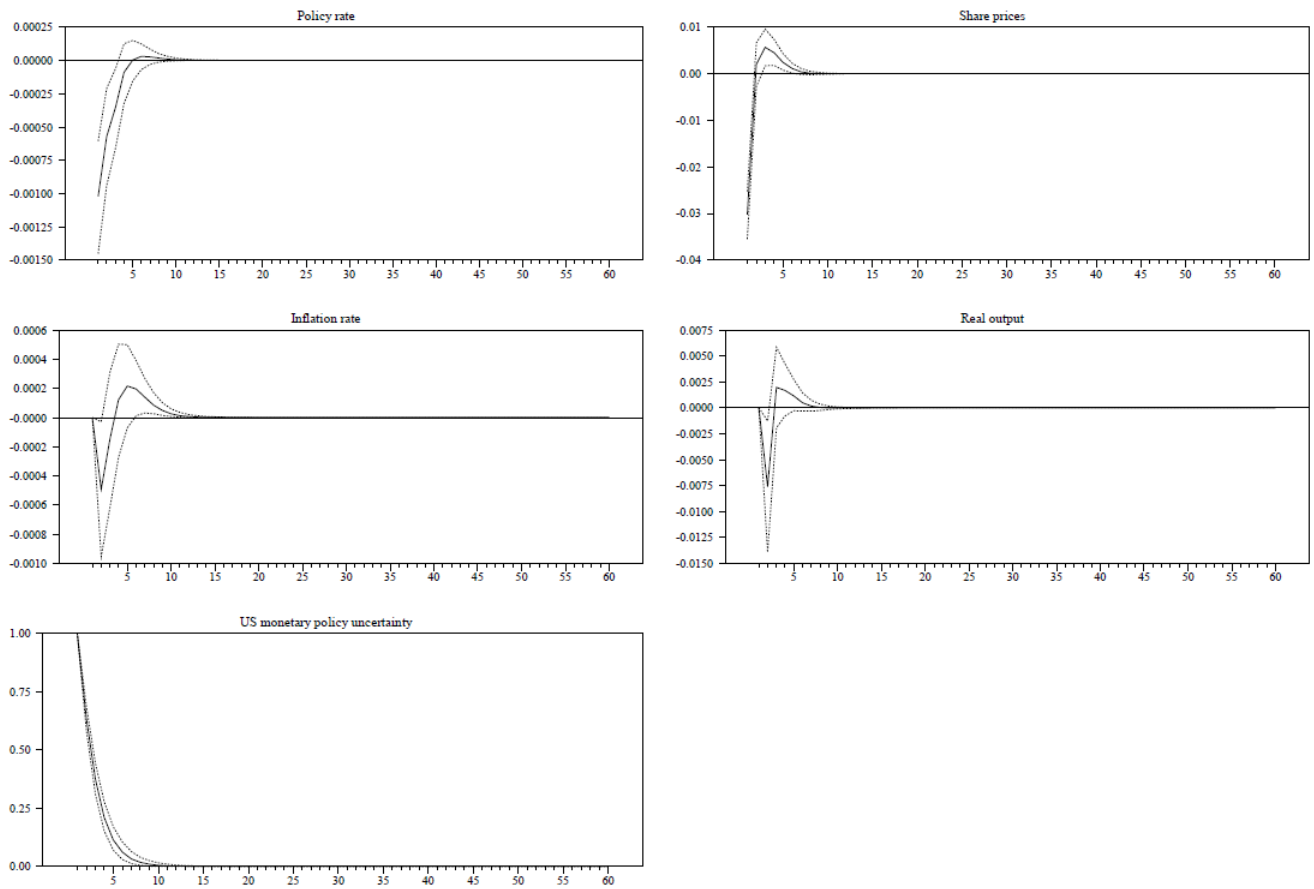


Figure 3.7: Responses of domestic variables in South Africa to a U.S. monetary policy uncertainty shock



3.3.2 Robustness

In this section, we carry out a series of robustness checks to assess the sensitivity of our key findings. More specifically, we check the sensitivity of our main findings to the ordering of the variables in the structural VAR and an alternative measure of U.S. monetary policy uncertainty.

Sensitivity to the Ordering of the Variables

We rerun the baseline model with the U.S. monetary policy uncertainty index placed at the top of the structural VAR ordering. That is the vector of macroeconomic and financial variables, $\boldsymbol{z}_t$, is ordered as $\boldsymbol{z}_t = [U_t, \Delta \ln y_t, \pi_t, \Delta \ln s_t, \Delta i_t]'$. By placing U.S. monetary policy uncertainty at the top of the structural VAR ordering, we are assuming that uncertainty about U.S. monetary policy affects the macroeconomic and financial variables of a small open emerging economy both in the short run as well as in the long run, but itself remains unaffected by instantaneous feedback from the other variables. We identify the domestic monetary policy shock and share price shock using the same methodology as before. To allow for a possible interaction between domestic monetary policy and share prices, we follow Bjørnland and Leitemo (2009), and impose the restriction that a domestic monetary policy shock can have no long-run effects on the level of real share prices.

We report the impulse responses to an unanticipated U.S. monetary policy uncertainty shock in Figures 3.8-3.14, in the same fashion as those in Figures 3.1-3.7. The shocks are again normalized so that the U.S. monetary policy uncertainty shock increases the monetary policy uncertainty index by one percentage point in the first month. We find that an increase in uncertainty about the future monetary policy path of the U.S. leads to a decline in the policy rates of Chile, Colombia, Indonesia, Mexico, Poland, and South Africa. For Brazil, the uncertainty regarding future U.S. monetary policy does not affect the domestic policy rate. We see that share prices in the emerging economies experience a sharp instantaneous decline after an unanticipated heightened uncertainty in the U.S. monetary policy. For Brazil, Chile, Mexico, and South Africa, share prices actually go up after the initial decline before converging to the steady-state level. This might be attributed to the fact that U.S. monetary policy uncertainty is usually correlated with higher global uncertainty and so leads to an initial decline in share prices with lower global demand, but eventually, as investors move their investments away from the more volatile U.S. economy to the emerging economies, the demand for shares from firms in these emerging economies shoots up, leading to higher foreign direct investment as well. We also find that for Brazil, Colombia, Mexico, and South Africa, domestic output first rises before declining. This might be due to the fact higher U.S. monetary policy uncertainty leads to a fall in the domestic policy rates which stimulates the initial rise in domestic output due to the expansionary reaction of domestic monetary policy. The eventual decline in the output of these small emerging economies might be due to the international spillovers of heightened U.S. monetary policy uncertainty. Thus, our main results still hold, even after the reordering of the structural VAR variables.

Sensitivity to the Uncertainty Index

Finally, we run another robustness check by using the Economic Policy Uncertainty index, constructed by Baker et al. (2016), instead of the Monetary Policy Uncertainty index, in our structural VAR model. In this case, our vector of macroeconomic variables is $\boldsymbol{z}_t = [\Delta \ln y_t, \pi_t, U_t, \Delta \ln s_t, \Delta i_t]'$, where U_t is the original Baker et al. (2016) Economic Policy Uncertainty index. We report the impulse responses to a positive U.S. economic policy uncertainty shock in Figures 3.15-3.21, in the same fashion as those in Figures 3.1-3.7. We find again that heightened uncertainty about U.S. economic policy has in general a negative effect on policy rates in emerging economies. We also find that higher economic policy uncertainty has a negative effect on real output and stock market. Thus, we can conclude that our main finding, that higher uncertainty originating from U.S. monetary policy has a negative effect on policy rates of inflation targeting economies.

Figure 3.8: Responses of domestic variables in Brazil to a U.S. monetary policy uncertainty shock after reordering of variables

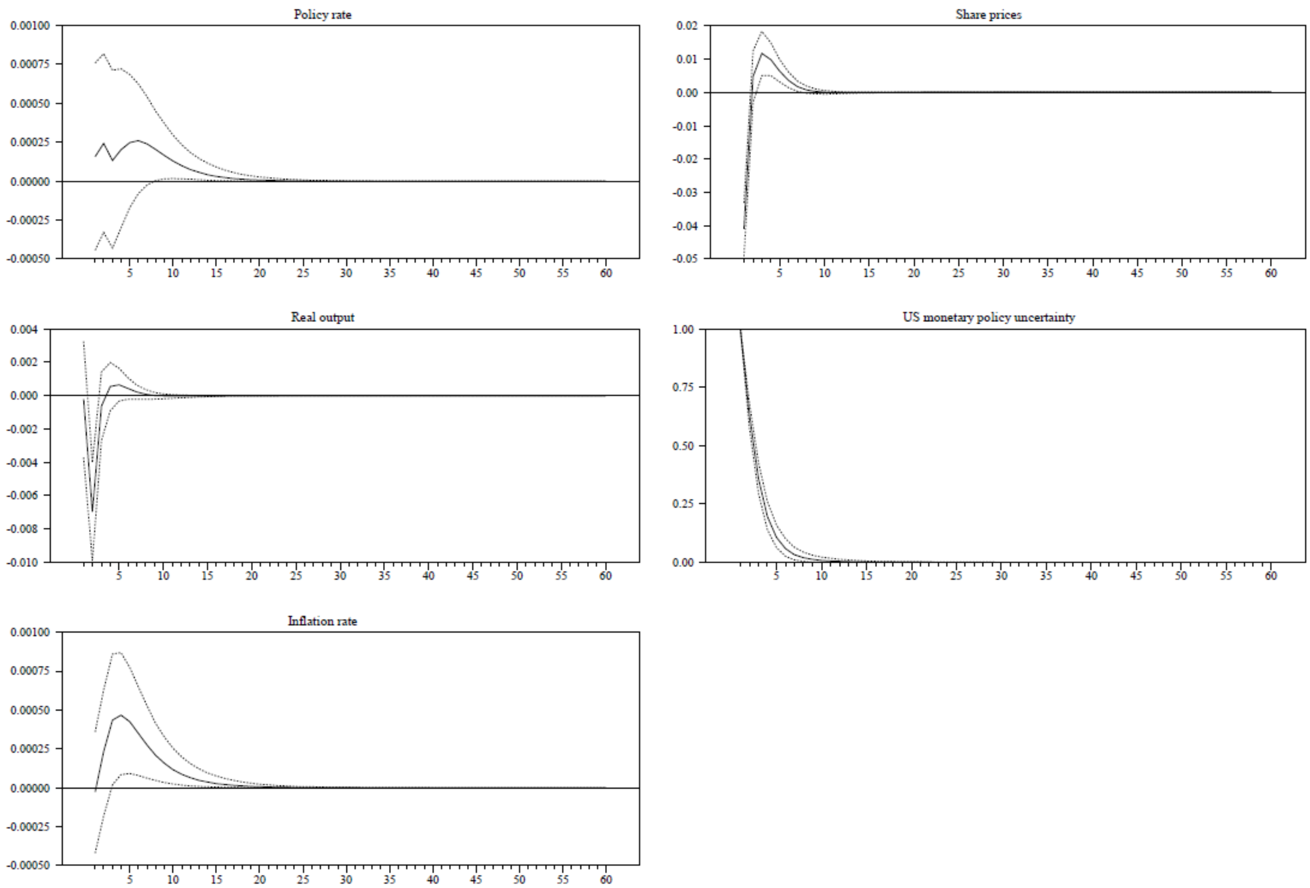


Figure 3.9: Responses of domestic variables in Chile to a U.S. monetary policy uncertainty shock after reordering of variables

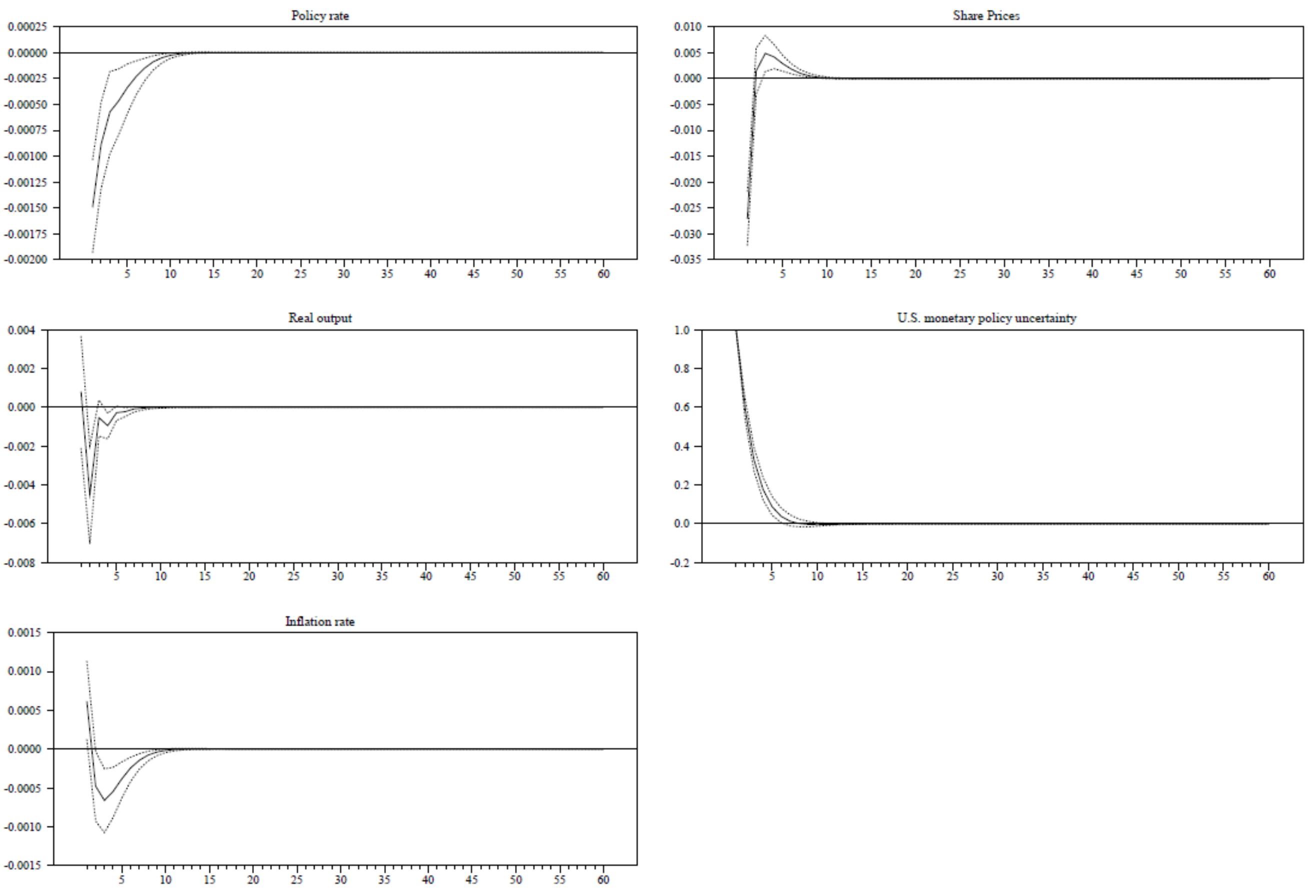


Figure 3.10: Responses of domestic variables in Colombia to a U.S. monetary policy uncertainty shock after reordering of variables

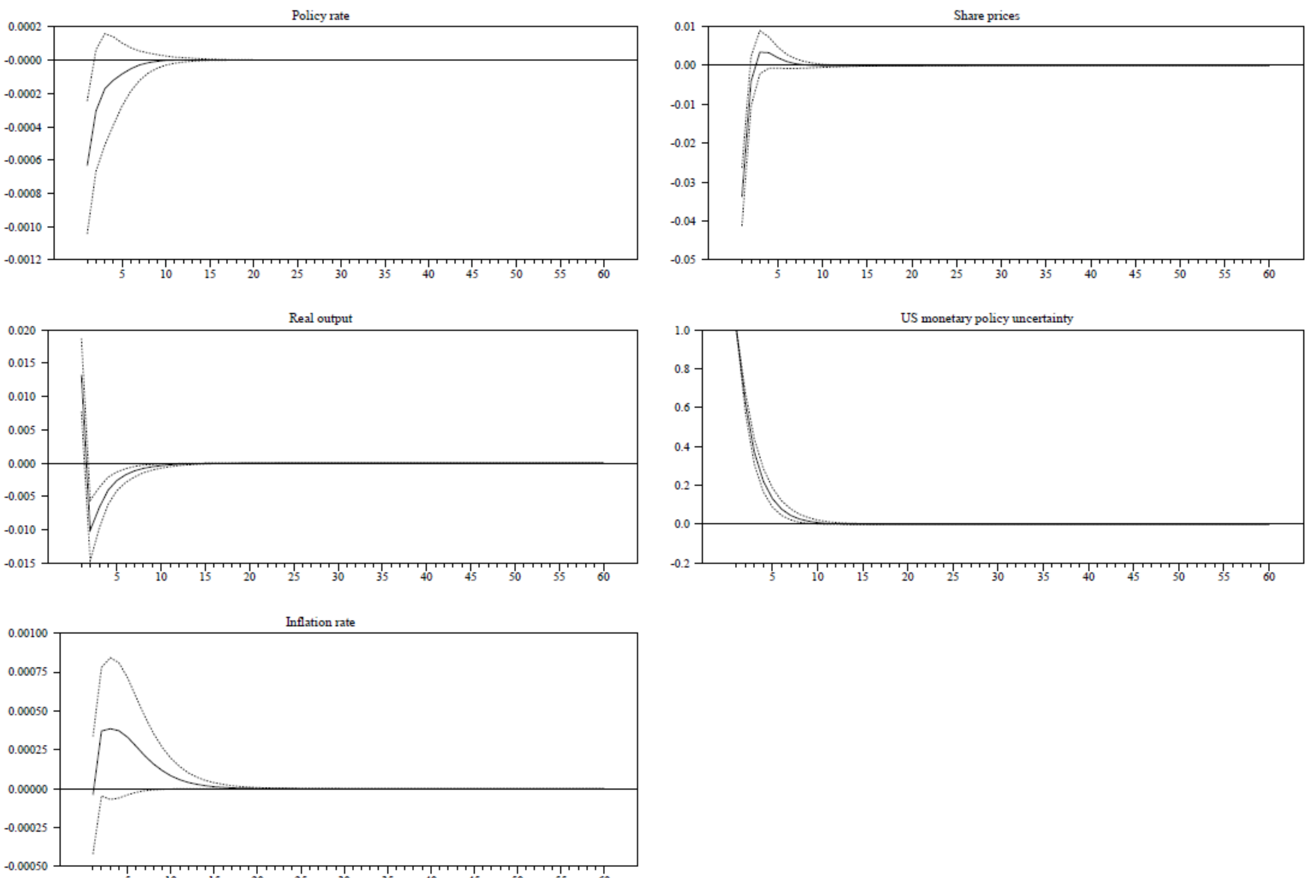


Figure 3.11: Responses of domestic variables in Indonesia to a U.S. monetary policy uncertainty shock after reordering of variables

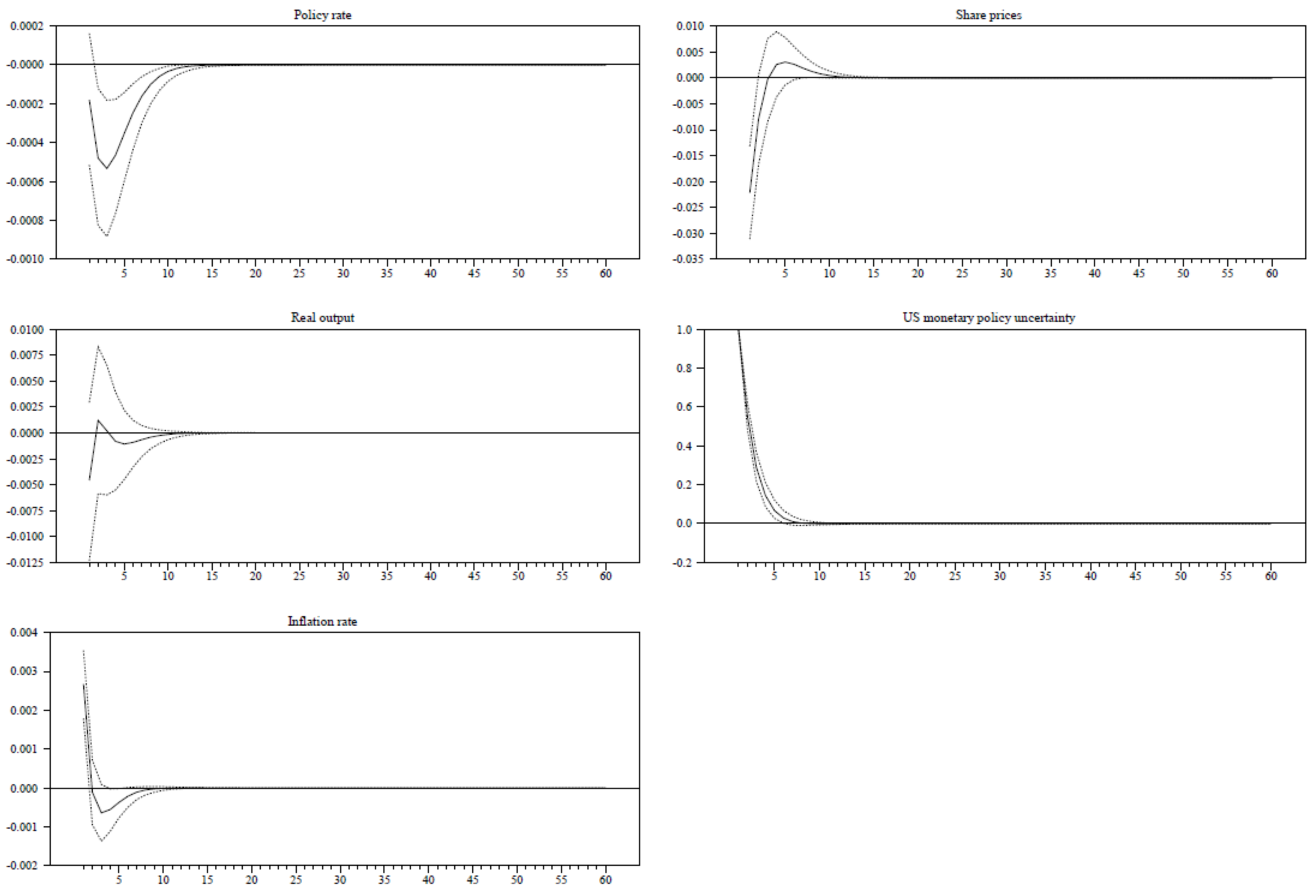


Figure 3.12: Responses of domestic variables in Mexico to a U.S. monetary policy uncertainty shock after reordering of variables

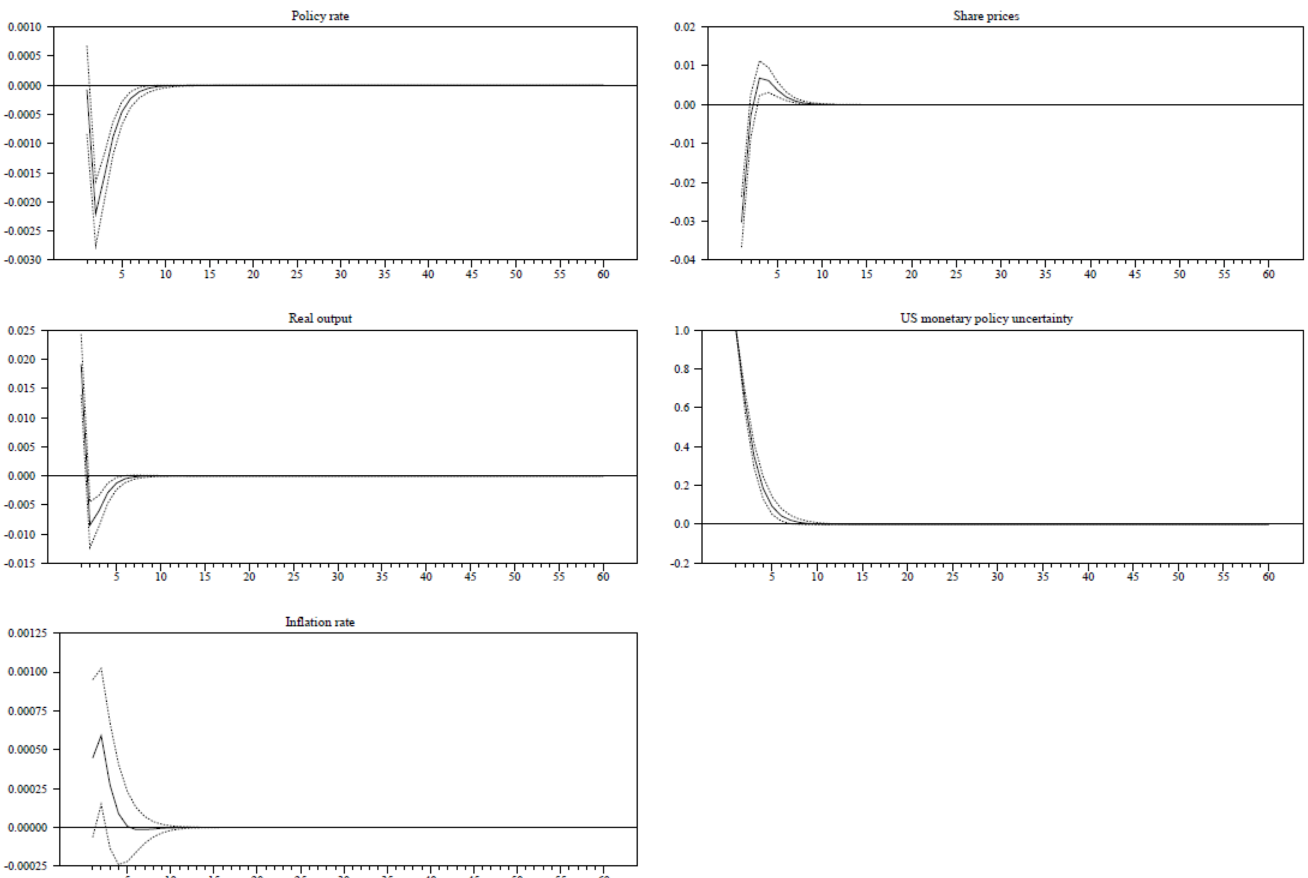


Figure 3.13: Responses of domestic variables in Poland to a U.S. monetary policy uncertainty shock after reordering of variables

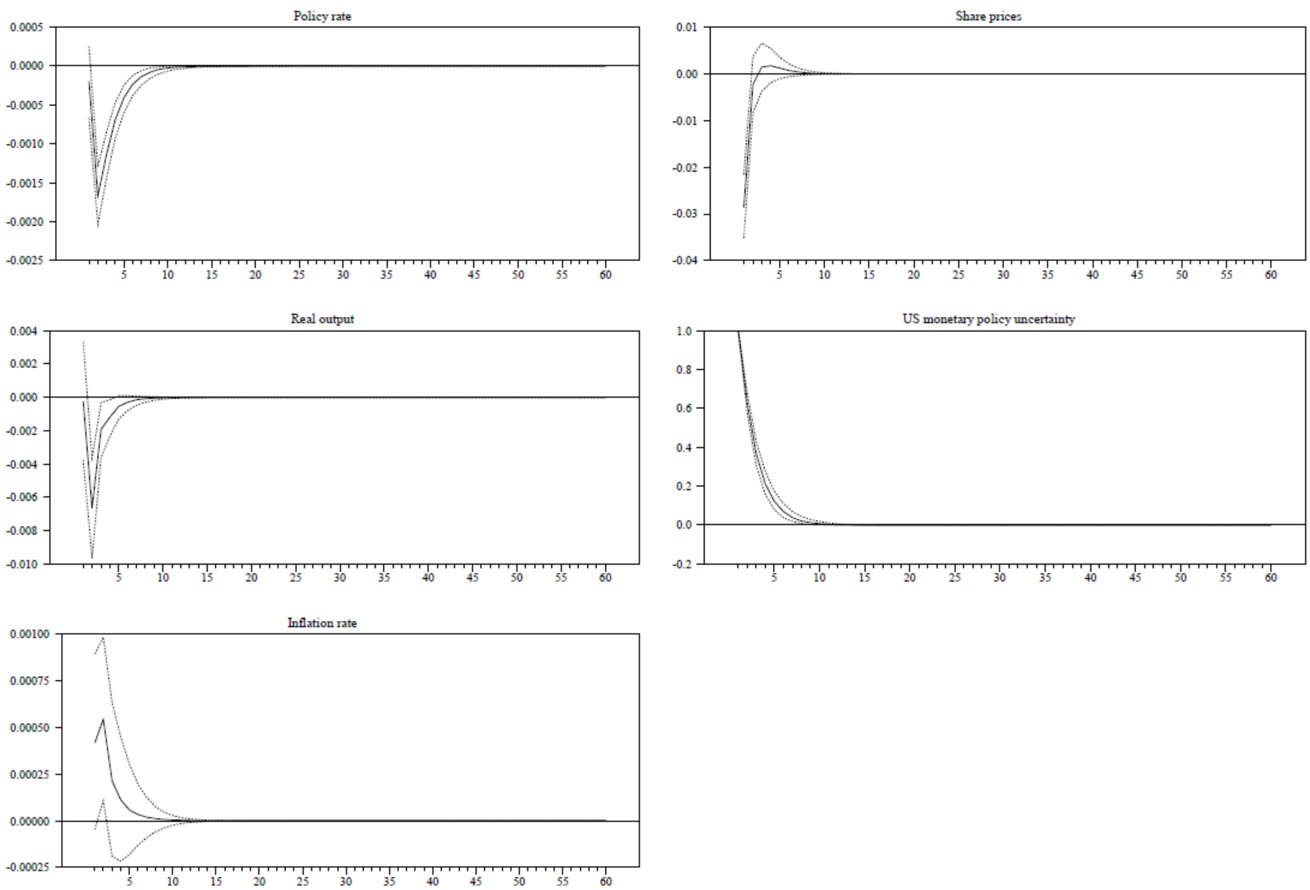


Figure 3.14: Responses of domestic variables in South Africa to a U.S. monetary policy uncertainty shock after reordering of variables

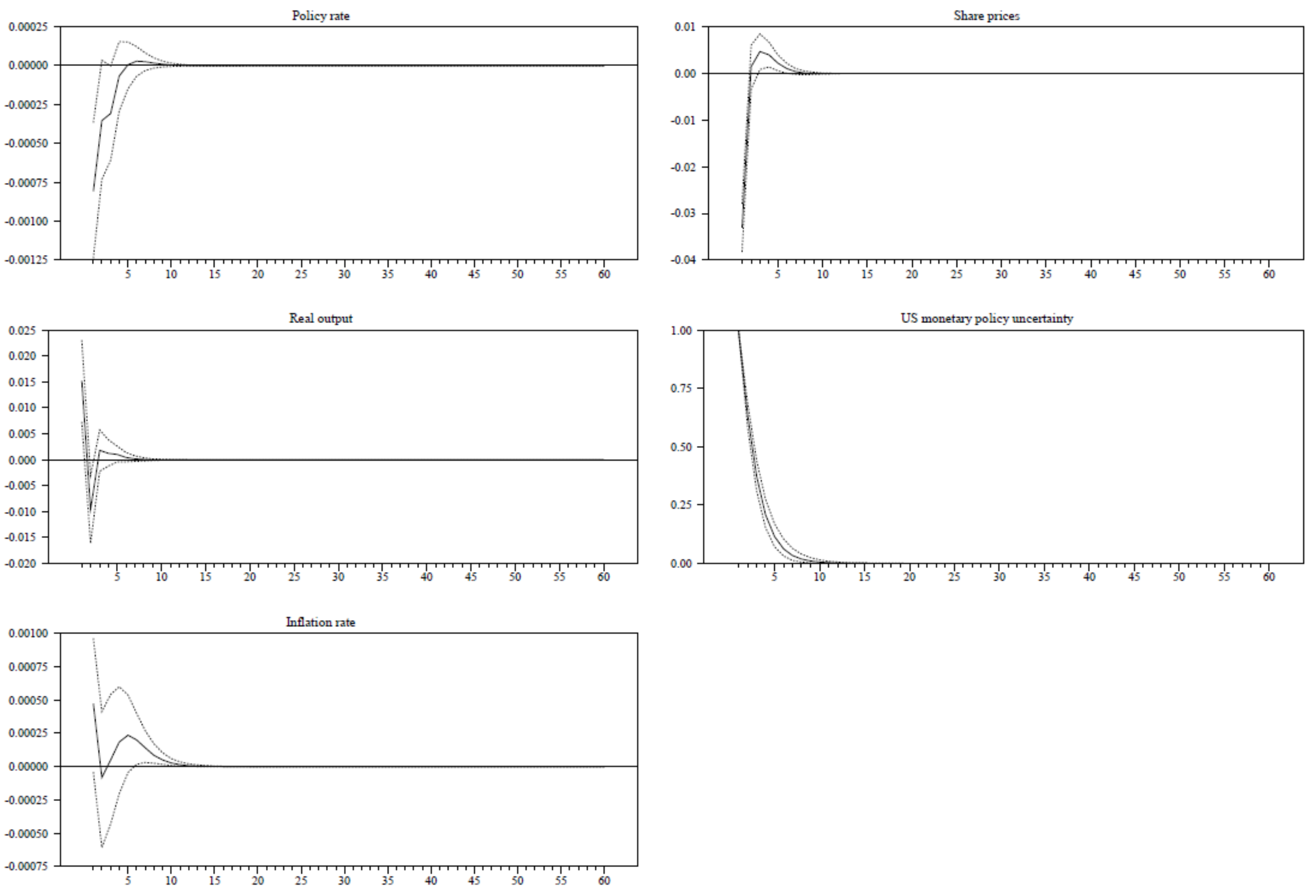


Figure 3.15: Responses of domestic variables in Brazil to a U.S. economic policy uncertainty shock

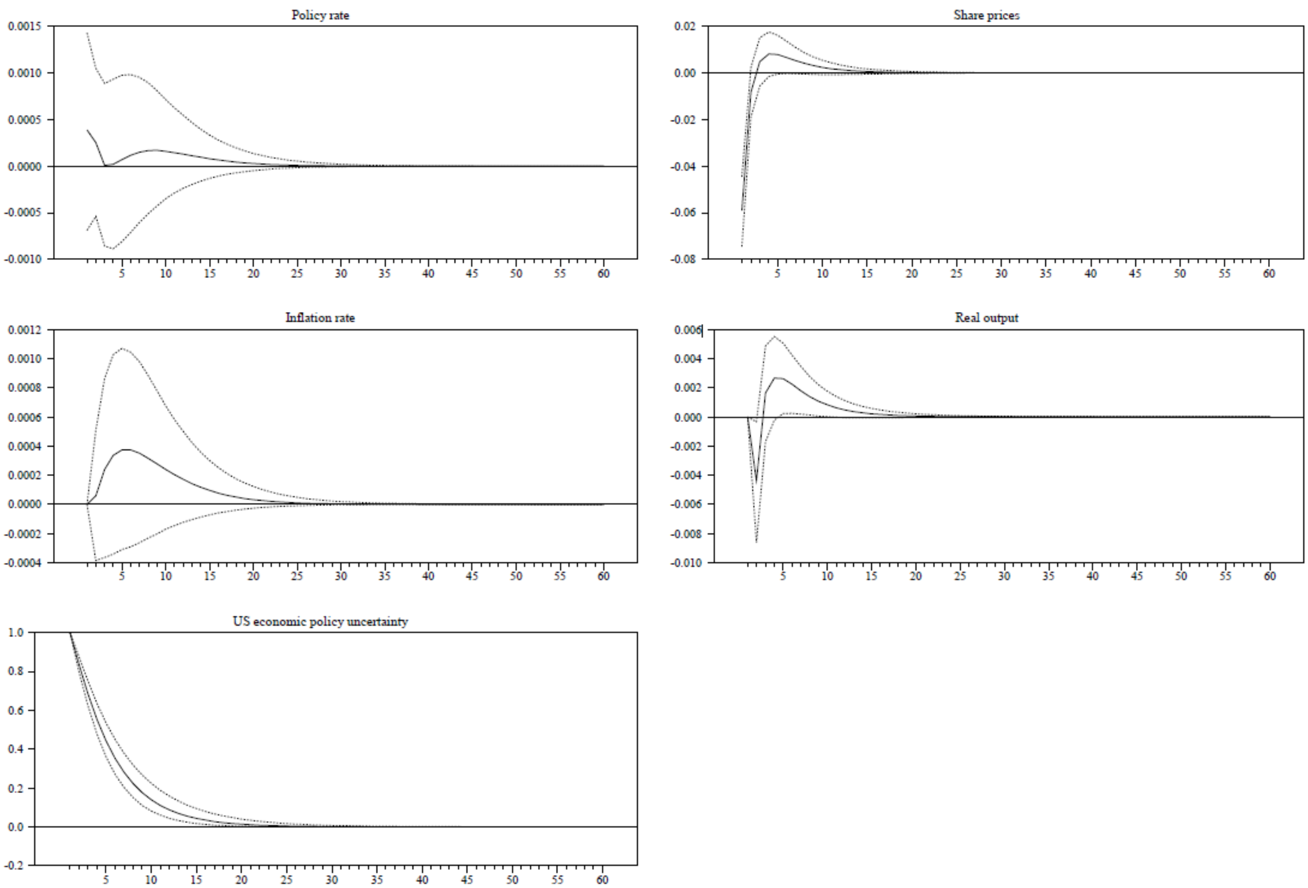


Figure 3.16: Responses of domestic variables in Chile to a U.S. economic policy uncertainty shock

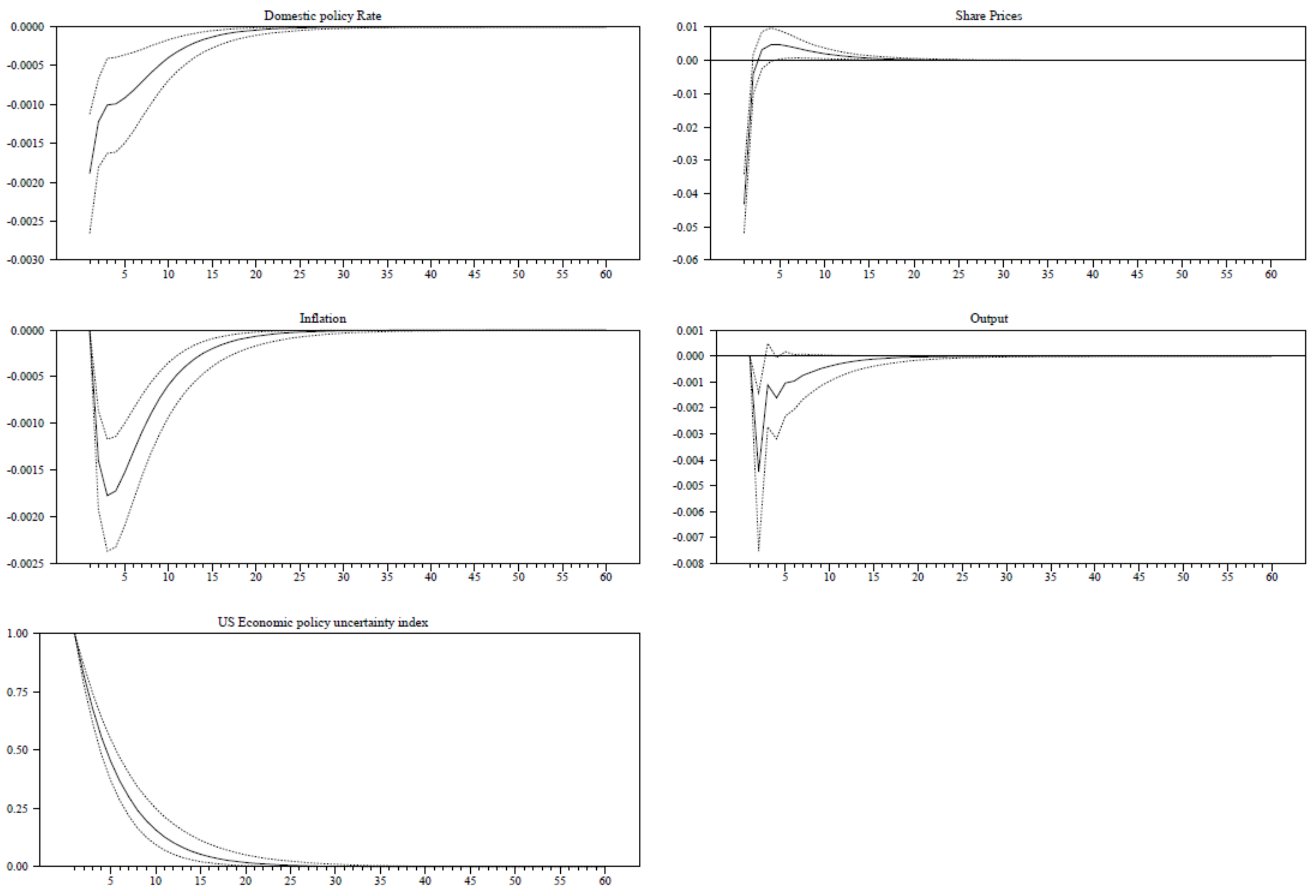


Figure 3.17: Responses of domestic variables in Colombia to a U.S. economic policy uncertainty shock

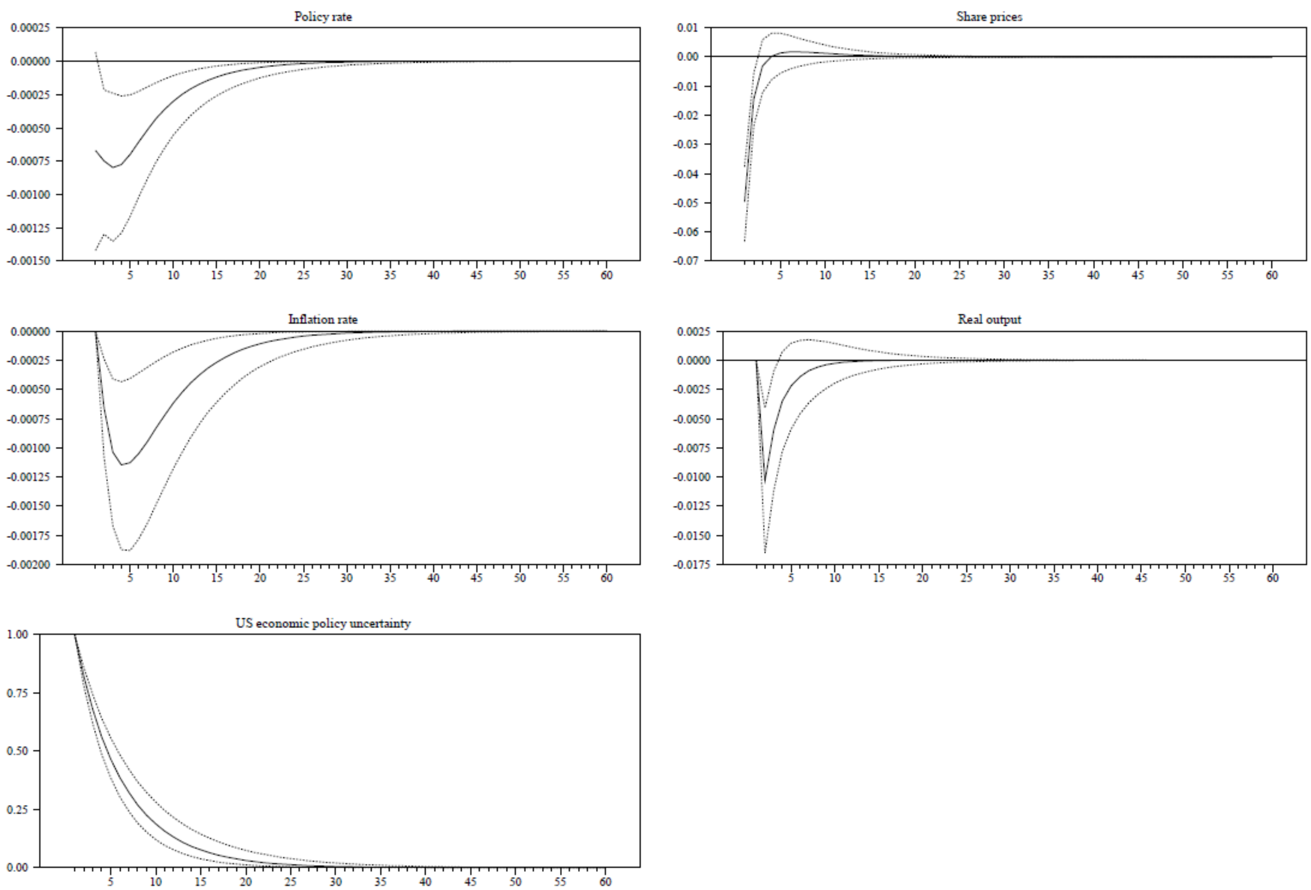


Figure 3.18: Responses of domestic variables in Indonesia to a U.S. economic policy uncertainty shock

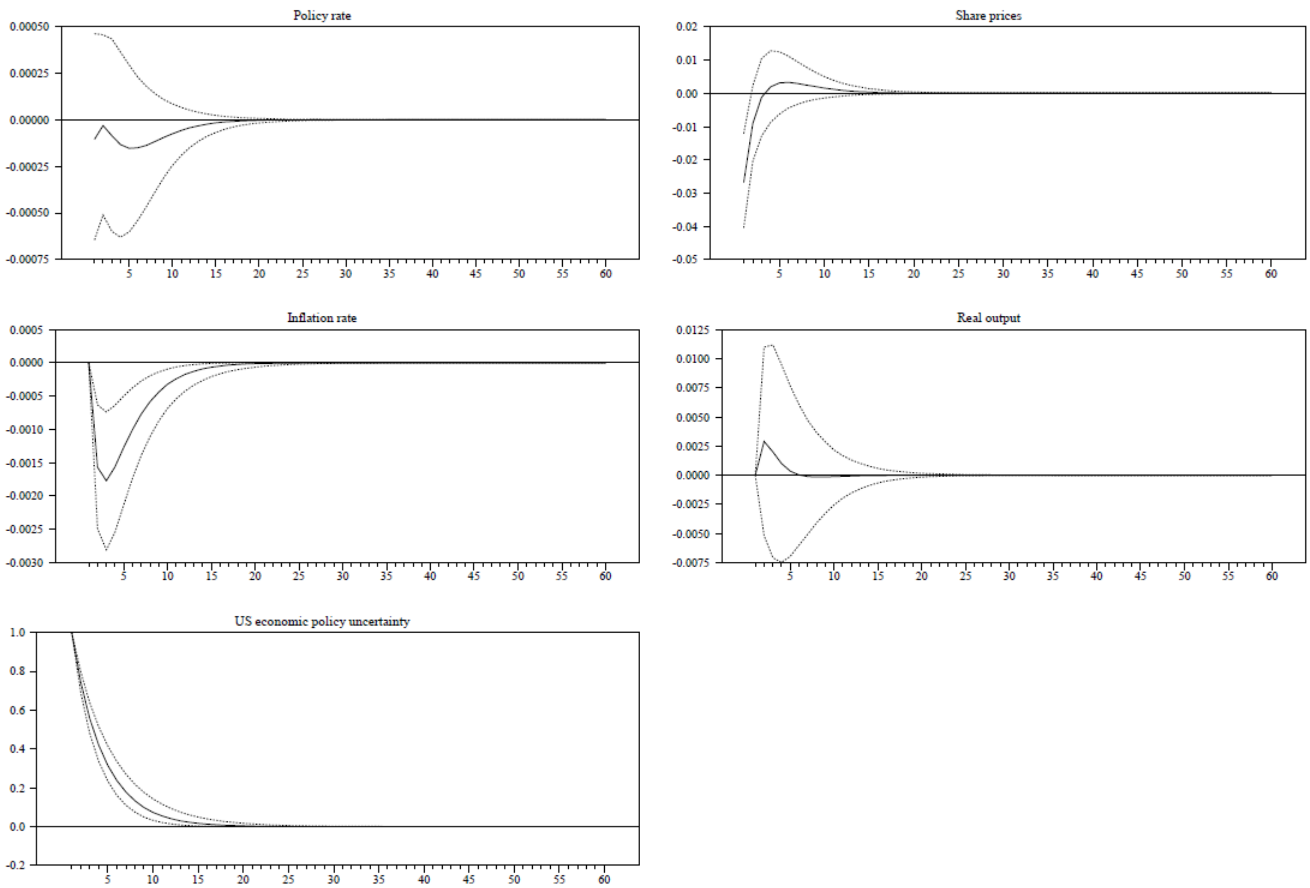


Figure 3.19: Responses of domestic variables in Mexico to a U.S. economic policy uncertainty shock

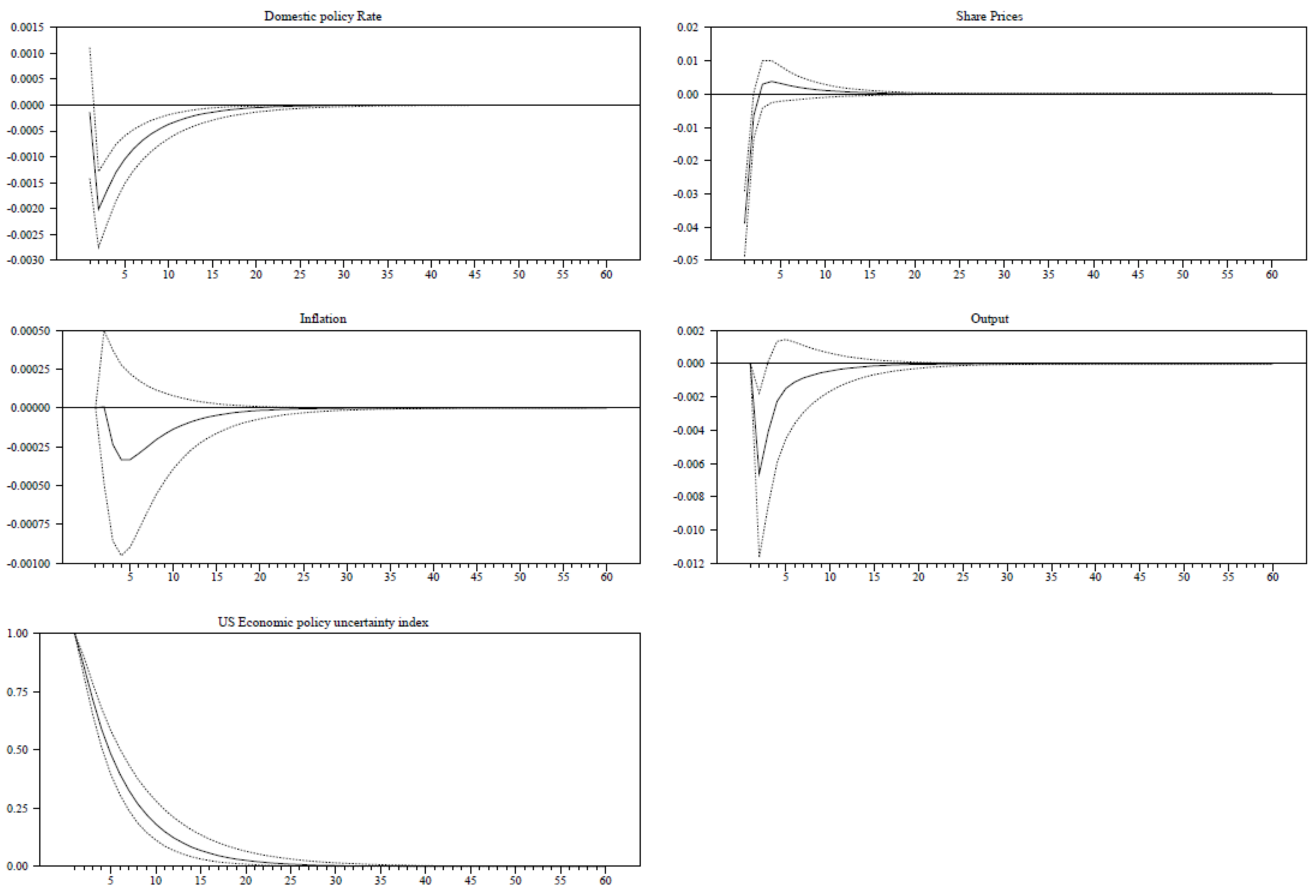


Figure 3.20: Responses of domestic variables in Poland to a U.S. economic policy uncertainty shock

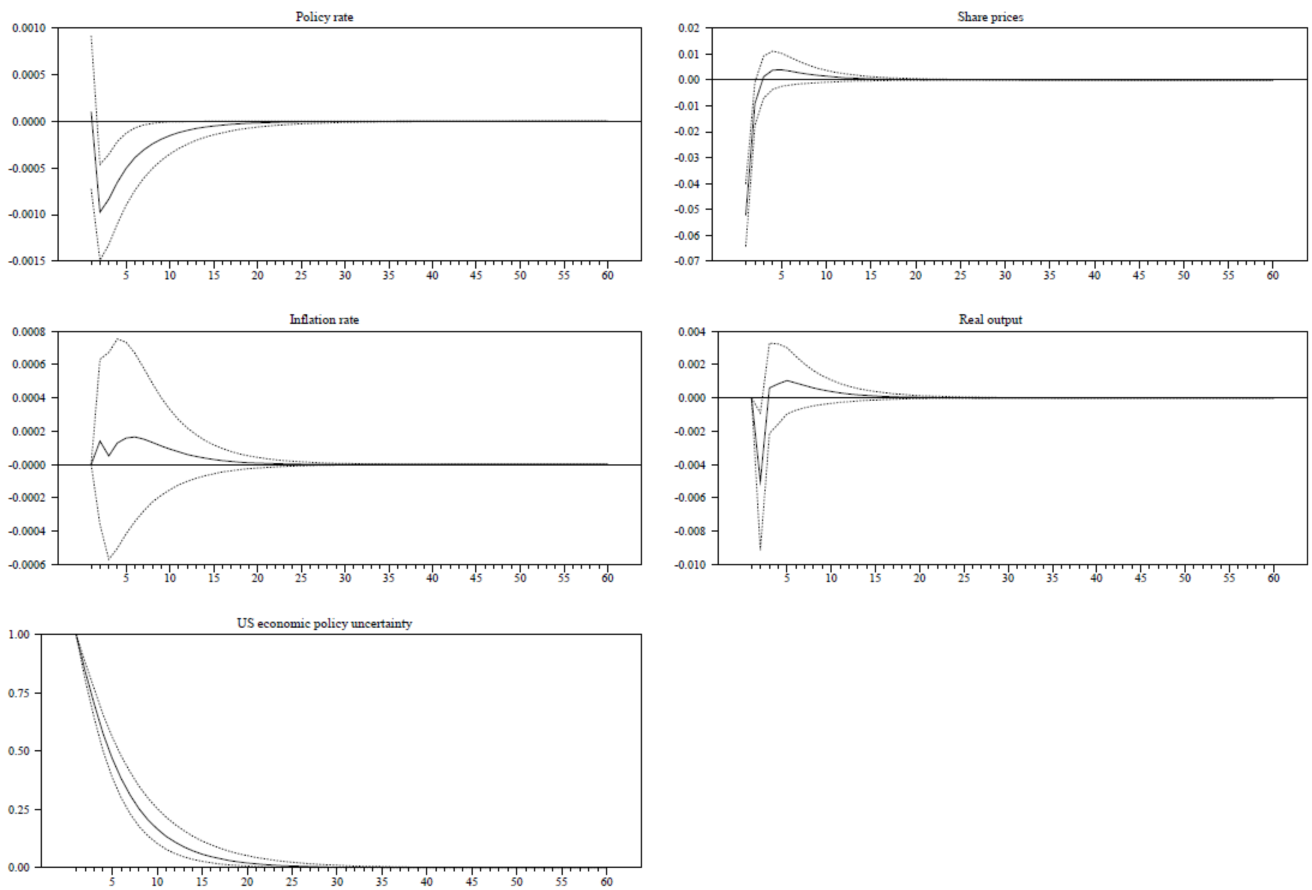
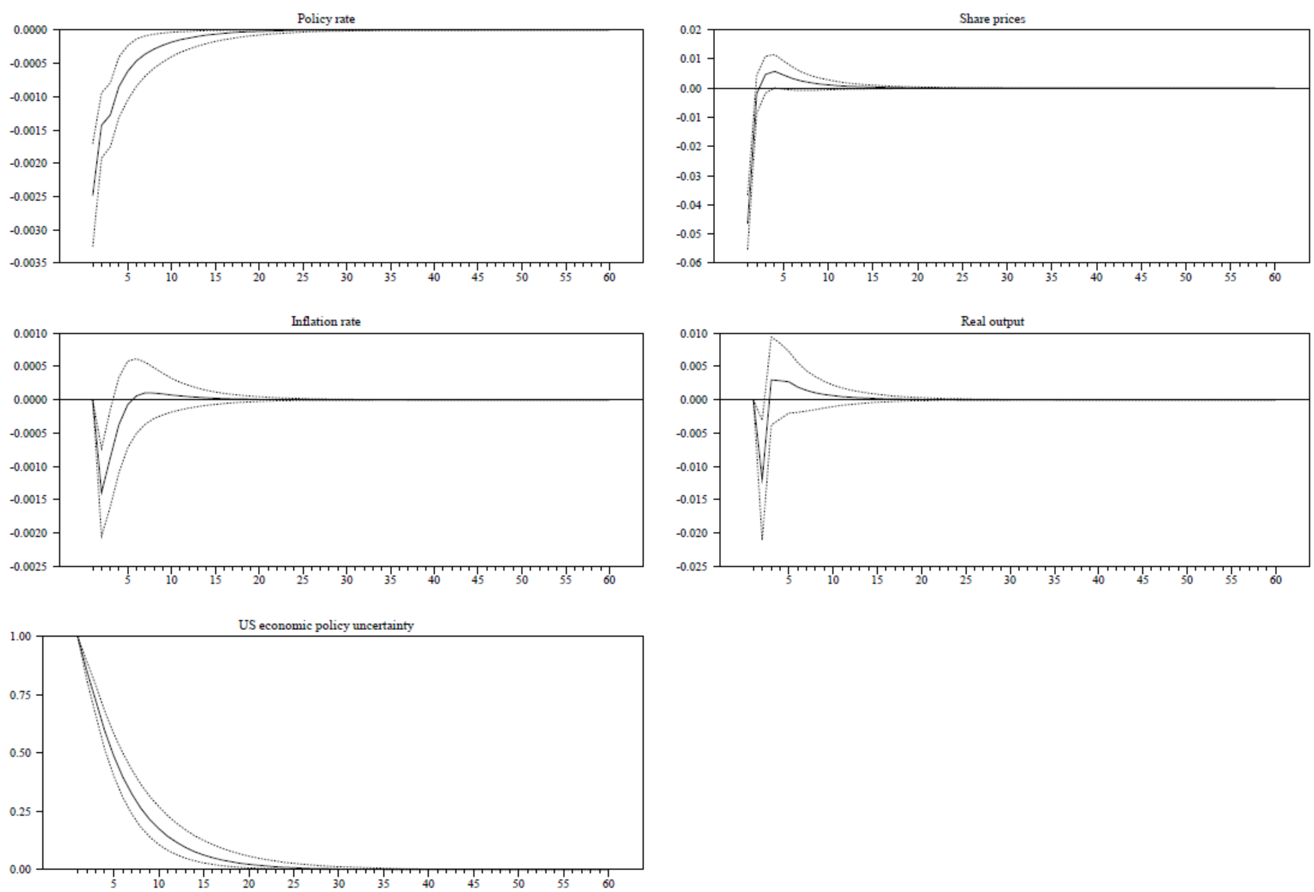


Figure 3.21: Responses of domestic variables in South Africa to a U.S. economic policy uncertainty shock



Sensitivity to Exchange Rates

As a final robustness check, we redo our analysis of investigating the impact of U.S. monetary policy uncertainty on policy rates of inflation targeting emerging economies, after controlling for the exchange rate, E_t. We retrieve the exchange rate series (national currency per U.S. dollar) from FRED and use the growth rate of the series. We implement the country-specific structural VAR models with the vector of variables, $\boldsymbol{z}_t$, ordered as follows, $\boldsymbol{z}_t = [\Delta \ln y_t \ \pi_t \ U \ \Delta i_t \ \Delta \ln E_t]'$. Our contemporaneous $\boldsymbol{S}$ matrix is

$$\begin{bmatrix} \Delta \ln y_t \\ \pi_t \\ U \\ \Delta i_t \\ \Delta \ln E_t \end{bmatrix} = B(L) \begin{bmatrix} S_{11} & 0 & 0 & 0 & 0 \\ S_{21} & S_{22} & 0 & 0 & 0 \\ S_{31} & S_{32} & S_{33} & 0 & 0 \\ S_{41} & S_{42} & S_{43} & S_{44} & 0 \\ S_{51} & S_{52} & S_{53} & S_{54} & S_{55} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\Delta \ln y} \\ \varepsilon_t^{\pi} \\ \varepsilon_t^{U} \\ \varepsilon_t^{\Delta i} \\ \varepsilon_t^{\Delta \ln E} \end{bmatrix} \tag{3.7}$$

Our identification scheme assumes that the macroeconomic variables do not react to the financial markets and the exchange rates in the short run, but affect both markets in the short and long run. We place the output growth rate and inflation rate above the U.S. monetary policy uncertainty variable, the domestic policy rate, and the growth rate of the exchange rate. We set $S_{45} = 0$, which reflects the assumption that the domestic policy rate does not contemporaneously react to the growth rate of the exchange rate. We allow the exchange rate to be affected by the policy rate both in the short run and the long run. This is consistent with the view that these inflation targeters have a flexible exchange rate regime.

We estimate the seven country-specific models with the optimal lag length chosen using the SIC criterion. We observe that our primary results hold, that monetary policy uncertainty originating from the United States has in general a negative effect on policy rates of these inflation targeting emerging economies. More specifically, Chile, Colombia, Indonesia, Mexico, Poland, and South Africa, experience a drop in their policy rates. We also find that, in general, output declines in these economies. These results are available upon request.

3.4 Conclusion

In this paper, we investigate for spillovers from monetary policy uncertainty in the United States to policy rates of seven inflation targeting emerging economies — Brazil, Chile, Colombia, Indonesia, Mexico, Poland, and South Africa. We use a multivariate identified structural GARCH-in-Mean VAR model, controlling for the traditional Taylor rule type variables, such as the domestic inflation rate and output gap. In the context of this model, monetary policy uncertainty in the United States is measured by the conditional standard deviation of the one-period ahead forecast error of the change in the Wu and Xia (2016) U.S. shadow rate. We find that the multivariate GARCH-in-Mean VAR embodies a better description of the data and is preferred over a homoscedastic VAR. Our main empirical result is that U.S. monetary policy uncertainty has a negative and statistically significant effect on the policy rates of the inflation targeting emerging economies. This finding is robust to the use of the BIS policy rate for the United States, instead of the Wu and Xia (2016) U.S. shadow rate.

We also investigate robustness by using the Bjørnland and Leitemo (2009) structural VAR and the Baker et al. (2016) monetary policy uncertainty index for the United States, achieving identification by a combination of short-run and long-run restrictions. Consistent with our findings based on the multivariate GARCH-in-Mean VAR model, with the Bjørnland and Leitemo (2009) model we reach the same conclusion, that uncertainty about the future policy path taken by the Federal Reserve leads to the adoption of lower policy rates by inflation targeting central banks in emerging economies. We also find that higher U.S. monetary policy uncertainty has a negative effect on output growth and the stock market in emerging economies. These effects are robust to several alternative model specifications and data.

A natural extension of our analysis would be to extend our sample period back, to include a period before inflation targeting was adopted and conduct a comparative analysis on pre- and-post inflation targeting periods. However, BIS data on policy rates starts in 1997:2 for Chile, in 1995:4 for Colombia, in 2005:8 for Indonesia, in 1998:11 for Mexico, and in 1993:1 for Poland. Also, the Wu and Xia (2016)shadow rate series for the United States starts in 1990:1. Looking at our sample period in Table 3.1, we can see that due to data availability issues and degree of freedom problems, we cannot conduct a meaningful analysis using a pre-inflation targeting sample period, and this is the reason that we restricted our analysis on the post-inflation targeting sample periods indicated in Table 3.1. As a result, our analysis of the impact of U.S. monetary policy uncertainty on the policy rates of inflation targeting emerging economies is not able to answer the following interesting questions. Did U.S. monetary policy uncertainty have negative and statistically significant effects on country level variables before embracing inflation targeting? If it had, did the implementation of inflation targeting aggravated or alleviated the size of these effects? Or, is precisely the implementation of inflation targeting the trigger of these effects? This is an area for potentially productive future research.

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Appendix A

Appendix of Tables and Figures - Chapter 2

Table A.1: Data sources

	Variable	Source
Brazil	Industrial production	https://data.oecd.org/industry/industrial-production.htm
	Consumer Price Index: All Items	https://fred.stlouisfed.org/series/BRACPIALLMINMEI
	National Currency to US Dollar Exchange Rate: Average of Daily Rates	https://fred.stlouisfed.org/series/CCUSMA02BRM618N
China	Real GDP	https://www.frbatlanta.org/cqer/research/china-macroeconomy.aspx?panel=3
	Consumer Price Index: All Items	https://fred.stlouisfed.org/series/CHNCPIALLMINMEI
	National Currency to US Dollar Exchange Rate: Average of Daily Rates	https://fred.stlouisfed.org/series/CCUSMA02CNM618N

	Variable	Source
India	Industrial production	https://data.oecd.org/industry/industrial-production.htm
	Consumer Price Index: All Items	https://fred.stlouisfed.org/series/INDCPIALLMINMEI
	National Currency to US Dollar Exchange Rate: Average of Daily Rates	https://fred.stlouisfed.org/series/CCUSMA02INM618N
Indonesia	Industrial production	https://aric.adb.org/database/economic-financial-indicators
	Consumer Price Index: All Items	https://fred.stlouisfed.org/series/IDNCPIALLMINMEI
	National Currency to US Dollar Exchange Rate: Average of Daily Rates	https://fred.stlouisfed.org/series/CCUSMA02IDM618N
Mexico	Industrial production	https://data.oecd.org/industry/industrial-production.htm
	Consumer Price Index: All Items	https://fred.stlouisfed.org/series/MEXCPIALLMINMEI
	National Currency to US Dollar Exchange Rate: Average of Daily Rates	https://fred.stlouisfed.org/series/CCUSMA02MXM618N
Russia	Industrial production	https://data.oecd.org/industry/industrial-production.htm
	Consumer Price Index: All Items	https://fred.stlouisfed.org/series/RUSCPIALLMINMEI
	National Currency to US Dollar Exchange Rate: Average of Daily Rates	https://fred.stlouisfed.org/series/CCUSMA02RUM618N

	Variable	Source
Turkey	Industrial production	https://data.oecd.org/industry/industrial-production.htm
	Consumer Price Index: All Items	https://fred.stlouisfed.org/series/TURCPIALLMINMEI
	National Currency to US Dollar Exchange Rate: Average of Daily Rates	https://fred.stlouisfed.org/series/CCUSMA02TRM618N
Oil price	Crude Oil (petroleum), Dated Brent, light blend 38 API, fob U.K., US$ per barrel	https://www.imf.org/en/Research/commodity-prices
Oil production	Crude Oil Production, World (Thousand Barrels per Day)	https://www.eia.gov/totalenergy/data/browser/?tbl=T11.01B#/?f=M&start=200001
Economic activity	Global real economic activity index	https://sites.google.com/site/lkilian2019/research/data-sets

Table A.2: Data description

Series	Transformation in baseline and alternative models	Description
$\triangle IP$	$100 * [ln(IP_t) - ln(IP_{t-1})]$	Industrial production growth rate
$\triangle PROD$	$100 * [ln(PROD_t) - ln(PROD_{t-1})]$	World crude oil production growth rate
$\triangle OIL$	$100 * [ln(OIL_t) - ln(OIL_{t-1})]$	Real price of crude oil (in domestic currency) growth rate
WEA	$12/100 * (WEA)$	Index of global real economic activity in industrial commodity markets

Appendix B

Appendix of Tables and Figures - Chapter 3

Table B.1: Data sources

	Variable	Source
Brazil	Industrial production	https://data.oecd.org/industry/industrial-production.htm
	Consumer Price Index: All items	https://fred.stlouisfed.org/series/BRACPIALLMINMEI
	Total share prices for all shares	https://fred.stlouisfed.org/series/SPASTT01BRM661N
Chile	Industrial production	https://data.oecd.org/industry/industrial-production.htm
	Consumer Price Index: All items	https://fred.stlouisfed.org/series/CHLCPIALLMINMEI
	Total share prices for all shares	https://fred.stlouisfed.org/series/SPASTT01CLM661N
Colombia	Industrial production	https://datacatalog.worldbank.org/dataset/global-economic-monitor
	Consumer Price Index: All items	https://fred.stlouisfed.org/series/COLCPALTT01IXOBM
	National currency to U.S. dollar exchange rate	https://fred.stlouisfed.org/series/COLCCUSMA02STM
	Total share prices for all shares	https://fred.stlouisfed.org/series/COLSPASTT01IXOBM

	Variable	Source
Indonesia	Industrial production	https://aric.adb.org/database/economic-financial-indicators
	Consumer Price Index: All items	https://fred.stlouisfed.org/series/IDNCPIALLMINMEI
	Total share prices for all shares	https://fred.stlouisfed.org/series/SPASTT01IDM661N
Mexico	Industrial production	https://datacatalog.worldbank.org/dataset/global-economic-monitor
	Consumer Price Index: All items	https://fred.stlouisfed.org/series/MEXCPIALLMINMEI
	National currency to U.S. dollar exchange rate	https://fred.stlouisfed.org/series/EXMXUS
	Total share prices for all shares	https://fred.stlouisfed.org/series/SPASTT01MXM661N
Poland	Industrial production	https://data.oecd.org/industry/industrial-production.htm
	Consumer Price Index: All items	https://fred.stlouisfed.org/series/POLCPIALLMINMEI
	Total share prices for all shares	https://fred.stlouisfed.org/series/SPASTT01PLM661N
South Africa	Industrial production	https://datacatalog.worldbank.org/dataset/global-economic-monitor
	Consumer Price Index: All items	https://fred.stlouisfed.org/series/ZAFCPIALLMINMEI
	National currency to U.S. dollar exchange rate	https://fred.stlouisfed.org/series/EXSFUS
	Total share prices for all shares	https://fred.stlouisfed.org/series/SPASTT01ZAM661N
United States	Consumer Price Index: Total all items	https://fred.stlouisfed.org/series/CPALTT01USM661S
Shadow rate	Wu-Xia Shadow Federal Funds Rate	https://www.frbatlanta.org
Policy uncertainty indices	Economic Policy Uncertainty Index for United States	https://fred.stlouisfed.org/series/USEPUINDXM
	Categorical uncertainty Index: Monetary policy	https://fred.stlouisfed.org/series/EPUMONETARY
Policy rate	Central bank policy rates	https://www.bis.org/statistics/cbpol.htm

Table B.2: Data transformations

Series	Transformation	Description
$\Delta ln\ IPI_t$	$100 * [ln(IPI_t) - ln(IPI_{t-1})]$	Industrial production growth rate
π_t	$100 * [ln(CPI_t) - ln(CPI_{t-1})]$	Inflation rate
$\triangle i^*{}_t$	$i^*{}_t - i^*{}_{t-1}$	First difference of US policy rate
$\triangle i_t$	$i_t - i_{t-1}$	First difference of domestic policy rate
$\Delta ln\ s_t$	$100 * [ln(s_t) - ln(s_{t-1})]$	Share prices growth rate

Table B.3: Unit root and stationarity tests

Country	Δlny_t	π_t	Δi_t	Δi_t^*
		A. ADF test		
Brazil	−15.269	−7.589	−5.347	−6.528
Chile	−16.012	−9.940	−9.467	−6.528
Colombia	−15.890	−8.848	−6.192	−6.559
Indonesia	−8.633	−8.856	−6.803	−9.027
Mexico	−12.352	−9.482	−7.189	−7.020
Poland	−14.076	−10.592	−5.337	−6.530
South Africa	−16.819	−10.153	−4.792	−6.461
		B. Phillips-Perron test		
Brazil	−15.394	−7.748	−9.097	−10.471
Chile	−26.017	−9.875	−9.673	−10.472
Colombia	−15.980	−7.279	−10.896	−10.606
Indonesia	−8.712	−8.548	−6.955	−9.345
Mexico	−14.879	−9.493	−15.062	−10.828
Poland	−19.433	−10.614	−15.383	−10.706
South Africa	−16.971	−10.297	−13.949	−10.851
		C. KPSS test		
Brazil	0.031	0.105	0.053	0.116
Chile	0.033	0.040	0.037	0.116
Colombia	0.113	0.098	0.134	0.116
Indonesia	0.120	0.048	0.109	0.130
Mexico	0.043	0.021	0.058	0.159
Poland	0.024	0.186	0.071	0.113
South Africa	0.053	0.105	0.059	0.135

Notes: The first two panels report the $t - statistics$ from the ADF and PP tests and the last panel reports the KPSS test statistics. The 1% asymptotic critical value for the KPSS test is 0.216 for all the series.

Table B.4: SIC values for standard and multivariate GARCH-in-Mean VARs

Country	Homoscedastic VAR	GARCH-in-Mean VAR
Brazil	3077.173	2511.273
Chile	7708.534	7137.020
Colombia	8191.305	7848.758
Indonesia	1844.229	1644.605
Mexico	3152.962	2237.383
Poland	2933.481	2022.586
South Africa	8598.093	8214.576

Table B.5: SIC values for standard and multivariate GARCH-in-Mean VARs with US shadow rates ordered first

Country	Homoscedastic VAR	GARCH-in-Mean VAR
Brazil	8106.624	7540.853
Chile	2679.083	2104.763
Colombia	8734.977	8205.292
Indonesia	5694.357	5217.242
Mexico	3152.962	2236.885
Poland	8121.966	7204.408
South Africa	3687.918	3280.938

Table B.6: SIC values for the standard and multivariate GARCH-in-Mean VARs with BIS policy rates

Country	Homoscedastic VAR	GARCH-in-Mean VAR
Brazil	8091.395	7523.117
Chile	7728.011	7150.937
Colombia	8222.072	7824.675
Indonesia	1843.612	1386.888
Mexico	7706.825	6784.277
Poland	8103.417	7246.303
South Africa	8592.168	8158.895