Ambiguity, Global Financial Risk, and Emerging Market Business Cycles*

Brendan Epstein† Rahul Mukherjee‡ Musa Orak§ Alessandro Peri¶

September 8, 2026

Abstract

This paper examines the impact of ambiguity (Knightian uncertainty) in U.S. financial markets on real economic activity in Emerging Market Economies (EMEs). Using a panel structural vector autoregression framework, we identify ambiguity shocks in U.S. equity markets and assess their transmission to EMEs. We find that an increase in ambiguity leads to a significant and persistent boom in EME GDP and investment. We attribute this result to international investors' portfolio reallocations: heightened ambiguity in U.S. stock returns increases demand for relatively safer corporate bonds, lowering borrowing costs and boosting economic activity in EMEs. We also document a negative response of U.S. stock market ambiguity to structurally identified global financial risk shocks, uncovering a key role of global financial risk in shaping the evolution of investors beliefs. Variance decompositions underscore the role of ambiguity as a key driver of EME business cycles, comparable in importance to global financial risk and interest rate shocks.

Keywords: Emerging market economies, ambiguity, uncertainty, global financial conditions, international business cycles .

JEL Codes: F41, E44, D81, G15.

*We thank Yehuda Izhakian and Jay Horvath for sharing their data and code with us. We also thank Max Croce, Cosmin Ilut, Felipe Saffie, and Yangwei Song for helpful discussions, and Chris Machol, who provided excellent research assistance. The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

†Department of Economics, University Massachusetts at Lowell. Falmouth Hall, Room 302. One University Avenue, Lowell, MA 01854, United States. E-mail: epsteinb@gmail.com.

‡University of Nottingham. B31 Sir Clive Granger Building, University Park, Nottingham, NG7 2RD, United Kingdom. E-mail: Rahul.Mukherjee@nottingham.ac.uk.

§Board of Governors of the Federal Reserve System, 20th St. and Constitution Ave. NW, Washington, D.C. 20551, United States. E-mail: musa.orak@frb.gov.

¶Department of Economics, University of Colorado Boulder, CO 80302, United States. E-mail: Alessandro.Peri@Colorado.edu.

1 Introduction

Assessing how real economic activity in Emerging Market Economies (EMEs) responds to external financial factors is a central question in the international finance literature, with implications for policymakers and investors alike. Prior research has examined the interplay between real economic activity in EMEs and financial factors, such as the U.S. real interest rate, country-specific interest rate spreads, and global financial conditions. Since Akıncı (2013), this literature has emphasized the key role of global financial risk in driving EME fluctuations. Despite these advances, little is known about the impact of ambiguity -henceforth defined as Knightian uncertainty (Knight, 1921)- in foreign financial conditions on EME business cycles. A clear view of this transmission channel is crucial, as ambiguity captures a qualitatively distinct form of uncertainty that extends beyond the traditional notion of risk.[1] This paper fills this gap by employing a panel structural vector autoregression approach to study the extent to which Knightian uncertainty in U.S. financial markets spills over to EME economies.

In the last decades, U.S. listed companies have accounted for nearly 40% of the world's equity market capitalisation and over 60% of that within OECD countries (World Bank, 2025), highlighting a prominent role in global financial markets. This paper investigates the extent to which fluctuations in Knightian uncertainty in U.S. equity markets—defined as ambiguity about the probability distribution of returns—have real effects on EMEs. To motivate this exploration, Panels (a) and (b) of Figure 1.1 show that our measure of Knightian uncertainty in the U.S. stock markets is positively correlated with the cyclical components of aggregated EME GDP growth (with a pairwise coefficient of correlation of 0.30) and investment growth (with a pairwise coefficient of correlation of 0.25), suggesting that periods with rising ambiguity in U.S. equity markets coincide with increased EME activity. We interpret this pattern

[1] In the context of decision-making, risk is associated with situations where uncertainty lies in the realization of outcomes whose probability distribution is known. On the other hand, ambiguity represents a distinct form of uncertainty where unique probabilities cannot be assigned to potential outcomes, so that their probability distribution is unknown or unknowable. While a large literature has documented meaningful real and financial effects of uncertainty shocks (e.g., Bloom, 2009; Jurado et al., 2015; Ludvigson et al., 2021; Ilut et al., 2024), much less is known about how Knightian uncertainty, as distinct from risk, transmits internationally to emerging economies.

as reflecting a portfolio rebalancing mechanism. As ambiguity in U.S. equity markets rises, international financial markets are likely to respond, triggering portfolio reallocation that ease EME borrowing constraints, stimulating their economic activity. Panel (c) supports this interpretation, showing that ambiguity negatively comoves with EME country spreads (with a pairwise coefficient of correlation of -0.37), which in turn have strong and negative correlations with EME macroeconomic aggregates (Panel (d)), in line with the findings of Neumeyer and Perri (2005) and Uribe and Yue (2006)).[2]

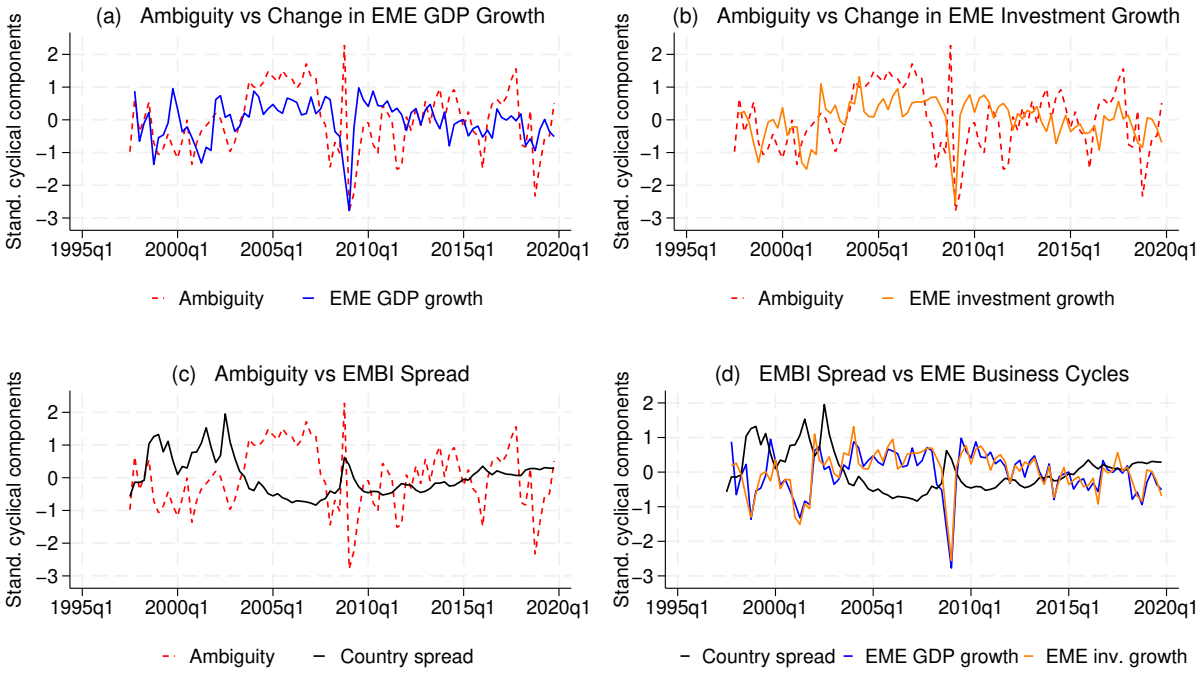


Figure 1.1: Ambiguity, EMBI spread, and EME business cycles

Note: The panels show standardized cyclical components. EME GDP and investment growth are averages of six countries. Data start from 1997:Q1 as this is the first year we have GDP and investment data for all six countries.

This motivating evidence highlights the presence of a link between ambiguity in U.S. equity markets and borrowing-constrained EMEs' activity. To rigorously assess this relationship, we empirically model the complex joint dynamics of U.S. equity markets' ambiguity, global financial risk, and EME business cycles within a panel structural vector autoregression framework in order to identify the real and financial effects of structurally identified U.S.

[2]The pairwise coefficient of correlations between the cyclical component of EMBI spread and EME GDP growth and EME investment growth are -0.49 and -0.56, respectively.

ambiguity shocks on EMEs.

We quantify the degree of ambiguity in U.S. equity markets by adopting the ambiguity index developed by Izhakian (2020) and Brenner and Izhakian (2018). This index measures the degree of Knightian uncertainty associated with the probability distribution of U.S. equity returns, which it is derived within the expected utility with uncertain probabilities theory developed by Izhakian (2017).[3] An increase in ambiguity can be interpreted as an increase in the disagreement among international investors regarding the probability distributions of stock returns. We choose this index for three reasons. First, it provides an empirical measure of the degree of ambiguity that is independent of both risk and agents' attitudes towards risk and ambiguity. This property is key to our analysis, as it allows us to isolate shocks in the degree of ambiguity that are orthogonal to changes in the U.S. stock market risk, including those potentially correlated with global financial risk previously examined in the literature (Akıncı, 2013).[4] Second, this index has been shown to have important implications for U.S. financial variables—such as, expected stock returns (Brenner and Izhakian, 2018) and the pricing of credit default swaps (Augustin and Izhakian, 2020)—that extend beyond those captured by traditional risk measures (e.g., VIX). Third, it is publicly available and independently constructed, facilitating replication and comparability with the literature.

Our empirical framework builds on Uribe and Yue (2006) and Akıncı (2013), and uses a 7-variable panel structural vector autoregression (PSVAR) model with: *(i)* four country-specific variables, which include three EME business cycle indicators (namely, GDP, investment, and the trade balance) and one financial variable (the country spread); and *(ii)* three global financial variables given by the 3-month U.S. Treasury yield as a measure of the risk free rate, the BAA corporate bond spread as a measure of global financial risk, and the Izhakian (2020)'s ambiguity index as a measure of the degree of Knightian Uncertainty in U.S. stock markets. Our estimated PSVAR identifies four structural shocks: a U.S. risk-free interest rate shock, a global financial risk shock, a country spread shock, and a U.S. equity markets' ambiguity shock. Our identification scheme relies on few key restrictions, which

[3] See Section 2 for more details.

[4] The index of ambiguity presents indeed a negligible correlation (-0.03) with the BAA corporate spread, utilized by (Akıncı, 2013) to capture global financial risk.

extends assumptions previously made in the literature to our framework. First, we assume that the evolution of global financial variables are exogenous to country-specific developments in EMEs, extending the restrictions in Uribe and Yue (2006) and Akıncı (2013) to the U.S. ambiguity index. Following these studies, we impose a "Cholesky" structure to the contemporaneous relations among global financial variables by assuming that the risk free rate is the most exogenous variable, followed by global financial risk, while the ambiguity measure is the least exogenous of the three.[5] Specifically, we assume that the risk free rate affects both global financial risk and ambiguity contemporaneously, while global financial risk is assumed to affect only ambiguity contemporaneously. All the global financial variables of the PSVAR influence each other in lags. Last, we assume that EME financing conditions–proxied by country-specific EMBI+ sovereign bond spreads–react to contemporaneous shocks in own-country fundamentals (GDP, investment and trade balance, which are the other three variables entering the PSVAR) while the latter react to all financial variables only with a lag.

We estimate the parameters of the above-described PSVAR and assess the impact of the four identified shocks by computing impulse response functions. Moreover, we quantify the relevance of the four identified shocks in explaining movements across the variables in our model using variance decompositions. Our analysis yields four main results.

First, an identified unexpected increase in the degree of ambiguity in U.S. equity markets leads to a surprisingly prominent, significant, and protracted *boom* (not bust) in EME GDP and investment. This stands in apparent contrast to the literature which generally finds negative transmission of U.S. uncertainty shocks (see e.g., Bhattarai et al., 2020).[6] Crucially, U.S. ambiguity shocks still yield contractionary responses in U.S. GDP and investment, in line with earlier findings on both ambiguity and uncertainty shocks (e.g., Ilut and Schneider, 2014; Jurado et al., 2015). This contrast uncovers a previously undocumented asymmetry in business cycle responses to U.S. ambiguity shocks: while ambiguity shocks depress economic

[5]The ordering of the risk free rate and global financial risk is in line with earlier literature, while the position of ambiguity is supported by our empirical analysis.

[6]Additional analysis in which we replace ambiguity with a host of other measures of uncertainty in our benchmark SVAR shows that these other measures are indeed contractionary for EME GDP and investment, and therefore in line with the existing literature.

activity in the U.S., their international transmission boost EMEs activity, in sharp contrast with the impact of previously examined uncertainty (but not ambiguity) shocks.

Second, we reconcile the puzzling "expansionary" response of EME macroeconomies to a U.S. stock market ambiguity shock by providing supporting evidence for a portfolio rebalancing mechanism that relaxes EMEs' external borrowing constraints. In particular, we find the identified ambiguity shock in U.S. equity markets to lead a deep and significant decline in BAA corporate yields but only a shallow, short lived, and insignificant decline in the U.S. safe interest rate. This result is consistent with a portfolio reallocation in response to a US stock market ambiguity shock towards relatively less risky assets (corporate bonds) but not a full-blown "flight to safety" (T-bills).[7] Crucially, this portfolio rebalancing affects EMEs' external costs of financing, whose spread jumps in response to the ambiguity shock and thereafter shows a protracted decline below trend. The joint dynamics of country spread and EME GDP and investment are consistent with the virtuous feedback loop documented in the literature (Uribe and Yue, 2006 and Akıncı, 2013): improved economic conditions reduce borrowing rates, which in turn help sustaining longer periods of above-trend EME GDP and investment. By and large, this analysis suggests that in response to greater ambiguity in the U.S. stock market, international investors shift investments to only somewhat relatively less risky avenues at the global level, which drives an increase in demand for BAA corporate bonds and greater investment and GDP in EME countries.

Third, an identified positive shock to BAA corporate yields leads to a sharp and significant decline in ambiguity. We provide suggestive evidence that shows this finding to be consistent with global financial risk playing a key role in influencing investors *beliefs* about the underlying return generating process and through that the degree of ambiguity. Our analysis suggests that an unanticipated widening of corporate credit spreads provides a strong signal of a worsening outlook for real economic activity (e.g. Gertler and Lown, 1999; Gilchrist and Zakrajšek, 2012), stirring investors beliefs towards a narrower set of priors with

[7] For the sake of clarity, we emphasize here that identified innovations to BAA corporate yields—such as the one investigated in Akıncı (2013)—are distinct from endogenous dynamics of the BAA corporate yield in response to other conceptually different uncertainty shocks, such as innovations to the U.S. stock market ambiguity which we are examining in this paper.

greater weight on bad economic states, thereby dissipating Knightian uncertainty (ambiguity). In doing so, we uncover a new channel through which global financial risks shocks affect EMEs, by acting as a coordination mechanism of international investors' beliefs.

Last, forecast error variance decomposition (FEVD) analysis reveals that the inclusion of ambiguity in the structural VAR analyses is critical in explaining EME aggregate activity in more recent years. Innovations to ambiguity emerge as the dominant driver, accounting for about 6 percent of GDP fluctuations, versus roughly 2 percent each for global financial risk and the country spread (together explaining 10 percent of GDP variance). For investment, ambiguity and the country spread are the largest contributors (totaling about 9 percent), while global financial risk adds only 1 percent. While this appears to be at odds with earlier literature, an expanding-window analysis shows that earlier samples (ending 2011) attribute far more variance to global financial shocks (global financial risk and U.S. interest rates) and country-spread shocks (up to 27 percent for GDP). As more recent data are added, the role of financial shocks diminishes, while ambiguity becomes the most important factor.

The rest of the paper proceeds as follows. Related literature is addressed in the following subsection. In section 2, we outline our methodology and data. Section 3 presents the results of our SVAR analysis using impulse response functions and FEVDs. We then discuss a number of robustness analyses in section 4 before concluding with section 5.

Related Literature

Our paper contributes to two strands of research: the literature on macro–financial implications of ambiguity—particularly for the U.S. economy—and the work examining the role of global financial conditions in shaping EME business cycles.

On the financial implications of ambiguity, prior studies show that ambiguity influences asset pricing, portfolio allocation, and market dynamics (Epstein and Wang, 1994; Chen and Epstein, 2002; Epstein and Miao, 2003; Cao et al., 2005; Garlappi et al., 2007; Benigno and Nisticò, 2009; Ju and Miao, 2012; Brenner and Izhakian, 2018; Ui, 2023; Millner, 2024). These studies highlight how ambiguity helps explain puzzles such as limited market

participation, equity-home bias, and equity premium, and find that ambiguity may drive global financial allocations in ways relevant for EME vulnerabilities. From a macroeconomic perspective, increases in ambiguity have been found to generate economic contractions in closed-economy settings or advanced economies (Ilut and Schneider, 2014; Bianchi et al., 2018; Altug et al., 2020; Ilut et al., 2024).[8] We build on this work by studying whether, and how, ambiguity originating in U.S. financial markets transmits internationally, particularly to EME business cycles.

In doing so, we contribute to the large empirical literature that explore the importance of *global financial conditions* for EME business cycles. Early work by Diaz-Alejandro (1985), Calvo et al. (1993), and Calvo (2002) stress the role of external financial factors, such as financial liberalization and global financial risk appetite, for EMEs. Subsequent research demonstrates U.S. monetary policy shocks have been important drivers of economic dynamics and fluctuations in EMEs (Canova, 2005; Mackowiak, 2007; Uribe and Yue, 2006; Fink and Schüler, 2015; Miranda-Agrippino and Rey, 2020). Several other studies show that U.S. uncertainty shocks (Bhattarai et al., 2020) and unconventional monetary policy (Anaya et al., 2017) have strong effects on EME asset prices, capital flows, and output; while global financial risk (Akıncı, 2013; Rey, 2015; Caballero et al., 2019; Epstein et al., 2019) accounts for a meaningful share of EME credit spreads and business cycles.[9]

Among the work in this literature, the closest papers to ours are Uribe and Yue (2006) and Akıncı (2013), who use panel SVAR frameworks to show that U.S. interest rate and global financial risk shocks drive EME cycles. We build directly on their framework by introducing *U.S. financial ambiguity shocks* as a novel external factor. In doing so, our contribution is threefold. First, we isolate the effects of ambiguity shocks from those of conventional risk and uncertainty measures. Second, we document a novel *expansionary* response of EME GDP and investment to U.S. ambiguity shocks, in sharp contrast with the contractionary

[8] Ilut and Schneider (2022) provide a wide-ranging survey on modeling uncertainty as ambiguity in macroeconomics and finance, emphasizing its role in pricing, welfare, and business cycles. Their insights strengthen the foundations of our empirical framework.

[9] Further work has refined these results. Horvath and Yang (2024) propose that the transmission of global financial risk shocks to EMEs occurs mainly through international capital flows, with countries experiencing larger capital inflows being more affected, while Horvath and Rothman (2021) identify the U.S. mortgage spread as the key driver of EME business cycles.

effects of standard uncertainty shocks.[10] Third, we uncover interactions between ambiguity and global financial risk, showing that ambiguity is an increasingly important driver of EME business cycles in recent decades.

2 Data and Methodology

Our empirical model builds directly on Uribe and Yue (2006) and Akıncı (2013). In particular, we estimate the following PSVAR:

$$Ay_{i,t} = \alpha_i + \sum_{k=1}^{p} B_k y_{i,t-k} + \epsilon_{i,t}, \tag{2.1}$$

where i indexes countries and t indexes time, A is a square matrix summarizing the contemporaneous relationships between the endogenous variables, and

$$y_{i,t} = \left[gdp_{i,t}, inv_{i,t}, tby_{i,t}, R_t^{US}, GR_t, ambig_t, R_{i,t}\right]', \tag{2.2}$$

where, for EMEs, $gdp_{i,t}$ is real GDP, $inv_{i,t}$ is real investment, and $tby_{i,t}$ is the trade balance to GDP ratio. Also, R_t^{US} is the gross U.S. real interest rate (the 3-month real gross U.S. Treasury Bill rate deflated by a measure of expected inflation - in line with Akıncı, 2013), GR_t is the gross BAA corporate bond spread measured using data from Moody's (a shock to which, in line with earlier literature, is interpreted as an innovation to global financial risk), $ambig_t$ is ambiguity (in U.S. equity markets), and $R_{i,t}$ is the gross EME country spread (measured using EMBI spread data from J.P. Morgan).[11] In addition, α_i is a vector of country fixed effects, B_k are square matrices summarizing the effect of lagged variables of

[10] Broad-based uncertainty indices and cross-country uncertainty spillovers suggest that *uncertainty shocks* tend to be contractionary in EMEs (Jurado et al., 2015; Mumtaz and Theodoridis, 2017)—a contrast to our finding of expansionary effects from ambiguity shocks.

[11] The ordering of U.S. real interest rate and global financial risk in the foreign block is the same as in Akıncı (2013), which we augment using Granger causality test to determine the position of ambiguity, as mentioned previously.

order p, and $\epsilon_{i,t}$ is the vector of innovations

$$\epsilon_{i,t} = \left[\epsilon_{i,t}^{gdp}, \epsilon_{i,t}^{inv}, \epsilon_{i,t}^{tby}, \epsilon_{t}^{R^{US}}, \epsilon_{i,t}^{GR}, \epsilon_{t}^{ambig}, \epsilon_{i,t}^{R}\right]'.$$

Except for $tby_{i,t}$ all data are in natural logarithms. Also, all data are in the form of deviations from a linear trend.

Turning to our identifying assumptions, we build on Uribe and Yue (2006) and Akıncı (2013). First, we assume that the contemporaneous-effects matrix A is lower triangular with unit diagonal elements.[12] As such, regarding EME variables, these restrictions imply that: GDP is the most exogenous variable and does not contemporaneously react to any other variable in the system; investment reacts contemporaneously to GDP, exclusively; the trade balance reacts contemporaneously only to GDP and investment; and the country spread reacts contemporaneously to EME-specific variables and foreign financial variables (the gross U.S. real interest rate, global financial risk, and degree of ambiguity in U.S. equity markets).

As a baseline, following Akıncı (2013), we specify the model with two lags and assume foreign financial variables constitute an exogenous shock block: $A_{ij} = B_{1,ij} = B_{2,ij} = 0$ for $i = 4, 5, 6$ and $j = 1, 2, 3, 7$. This restriction implies that $\left[R_t^{US}, GR_t, ambig_t\right]'$ are not affected simultaneously or in lags by country-specific EME macroeconomic aggregates. Moreover, $A_4 j = 0$ for all $j \neq 4$, $A_5 j = 0$ for all $j \neq 4, 5$ and $A_6 j = 0$ for all $j \neq 4, 5, 6$. This implies that: the real U.S. rate does not react contemporaneously to global financial risk or ambiguity; the BAA corporate bond spread reacts contemporaneously only to the real U.S. rate; and ambiguity reacts contemporaneously to both the real U.S. rate and the BAA corporate bond spread. Therefore, within the shock block, the U.S. rate is the most exogenous variable followed by global financial risk, while ambiguity is the least exogenous of the foreign financial variables. Since we do not impose any further restrictions on $\{B_k\}$, country-specific EME variables respond with lags to foreign financial variables.[13]

[12] We follow Akıncı (2013) in ordering the variables in the vector $y_{i,t}$ in equation (2.2), while the position of ambiguity is informed using Granger causality tests.

[13] See Online Appendix B for a summary of matrix specifications resulting from these restrictions.

Our baseline PSVAR estimation uses pooled quarterly data from the same set of countries as Akıncı (2013) (Argentina, Brazil, Mexico, Peru, South Africa and Turkey) and, on net, our sample ranges from 1993:Q4 through 2019:Q4. This dataset allows for straightforward comparison of results with earlier literature and nets out potentially confounding dynamics owing to the pandemic period and its immediate aftermath. In addition, also in line with Akıncı (2013) and for similar reasons (time span considerably larger than country sample size), we use the least squares dummy variables estimator.

Since relative to earlier work our analysis incorporates ambiguity, we discuss this measure in greater detail here, while additional information on the rest of our data can be found in Online Appendix A. We quantify the degree of ambiguity in U.S. equity markets ($ambig_t$) using the ambiguity index from Izhakian (2020). This index is theory-based and assumes the presence of a representative investor who: *(i)* aggregates the set of priors of all investors in the economy (henceforth, international investors; *(ii)* makes decisions according to the expected utility with uncertain probabilities model (EUUP model henceforth) of Izhakian (2017) when confronted with uncertainty over outcomes and outcomes' probabilities. Specifically, in the EUUP model international investors respond to the two-tier uncertainty (over outcomes and outcomes' probabilities) by forming their perceived probabilities with respect to their payoff-relevant events and then use these certainty-equivalent probabilities (capacities) to assess expected stock market returns - gains or losses - with respect to the risk free interest rate (which is used as a reference point). Crucially for our analysis, the EUUP framework specializes the Choquet Expected Utility framework (Schmeidler, 1989) and Cumulative Prospect Theory (Wakker and Tversky, 1993) to derive a measure of the degree of ambiguity, which is independent of risk as well as individuals' attitudes towards ambiguity and risk. This empirically appealing separation is reached by assuming that investors' preferences for ambiguity (such as ambiguity aversion) do not depend on the stock return outcomes and apply exclusively to the uncertain probabilities associated with these outcomes.[14]

[14]In the EUUP model, agents preferences for ambiguity are formalized by agents' preferences for mean preserving spreads in uncertain probabilities, mirroring the canonical formalization of preferences for risk as agents' preferences for mean preserving spreads in lotteries' outcomes (Rothschild and Stiglitz, 1978). This assumption replaces the assumption that agents preferences for ambiguity are represented by agents' preferences for mean preserving spreads in certainty equivalent utilities (e.g., Klibanoff et al., 2005; Seo,

Operationally, the Izhakian (2020) index is constructed from intraday (5-minute frequency) data on the Standard & Poor's Depositary Receipt (SPDR)[15]. These high-frequency data are used to generate daily probability distributions of stock returns (outcomes), yielding an *endogenous* set of distinct (and equally likely) intra-month probability priors. Assuming daily stock returns are normally distributed, and after appropriately partitioning the stock return support, Izhakian (2020) measures the degree of ambiguity as the expected volatility of probabilities across all outcomes in the (discretized) stock returns support.[16] For our purposes, an increase in the ambiguity index measures an increase in the dispersion of the international investors' beliefs over stock return outcomes, as measured by an increase in the expected volatility of uncertain probabilities over outcomes.

3 Benchmark Analysis

We present our main findings from the estimated PSVAR using impulse response functions (IRFs) and forecast error variance decompositions (FEVDs). Section 3.1 reports IRFs given structurally identified shocks to the degree of ambiguity in U.S. equity markets - the novel element of our analysis. Section 3.2 does the same for shocks to global financial risk, the U.S. interest rate, and the country spread. In addition, Section 3.4 presents FEVD results. All IRF figures display responses to a positive, unanticipated, one standard deviation shock, along with 95% and 68% confidence bands.[17]

3.1 Impulse Response Functions: Ambiguity

Figure (3.1) shows IRFs to an unanticipated one standard deviation shock to the degree of ambiguity in U.S. equity markets. Jointly, the IRFs suggest that given higher ambiguity investors rebalance portfolios by shifting to positions that may be perceived as less risky

2009; Hayashi and Miao, 2011), which yields measures of ambiguity that are not independent of risk and preferences for risk.

[15]The SPDR is a frequently traded index designed to replicate the (relatively less liquid) S&P 500.

[16]See Izhakian (2020) for more details regarding the construction of the index.

[17]To place our findings in context, Online Appendix C.1 reviews key findings from Akıncı (2013)—the framework we build on—and compares them with our results.

compared to U.S. equities, but not positions that are perceived as entirely riskless. Put another way, the shock to ambiguity can be interpreted as decreasing appetite for risk in relative, but not absolute, terms, as a full-fledged flight to safety does not take place. In line with this, as shown in panel (e) of the figure, the BAA spread (labeled "global risk") exhibits a steep decline that is significant at the 95 percent level, with a trough at about 0.1 percentage points below trend a few quarters after the shock. As in Akıncı (2013), an innovation to BAA spread is a proxy for a global financial risk shock. In contrast, the response of the BAA spread to shocks in other variables is intuitively in line with reflecting endogenous bond market dynamics. In the present case, with investors shifting to assets that are relatively less risky, the decline in the BAA spread suggests higher demand for BAA corporate bonds.

Also in line with a shift to positions that may be temporarily perceived as relatively less risky, even if not fully riskless, EME investment exhibits a prominent and protracted increase that is significant at the 95 percent level, peaking at roughly 1 percent above trend around six quarters after the shock. In line with this, EME GDP follows similar dynamics, peaking at nearly 0.4 percent above trend. Consistent with foreign capital inflows, the behavior of the trade balance is dominated by a decrease below trend that is significant at the 68 percent level. Finally, the country spread ("EMBI spread") dynamics are dominated by a protracted decline below trend that is significant at the 68 percent level. This response is consistent with the boom in EME GDP and investment taking place in tandem with EMEs being perceived as less risky in relative terms. Moreover, the joint response of the EME real variables and the country spread reflect an important virtuous feedback loop that was previously emphasized by Uribe and Yue (2006) and Akıncı (2013). Indeed, stronger economic conditions lead to a lower country spread, which in turn helps keep EME GDP and investment above trend longer than would otherwise be the case.

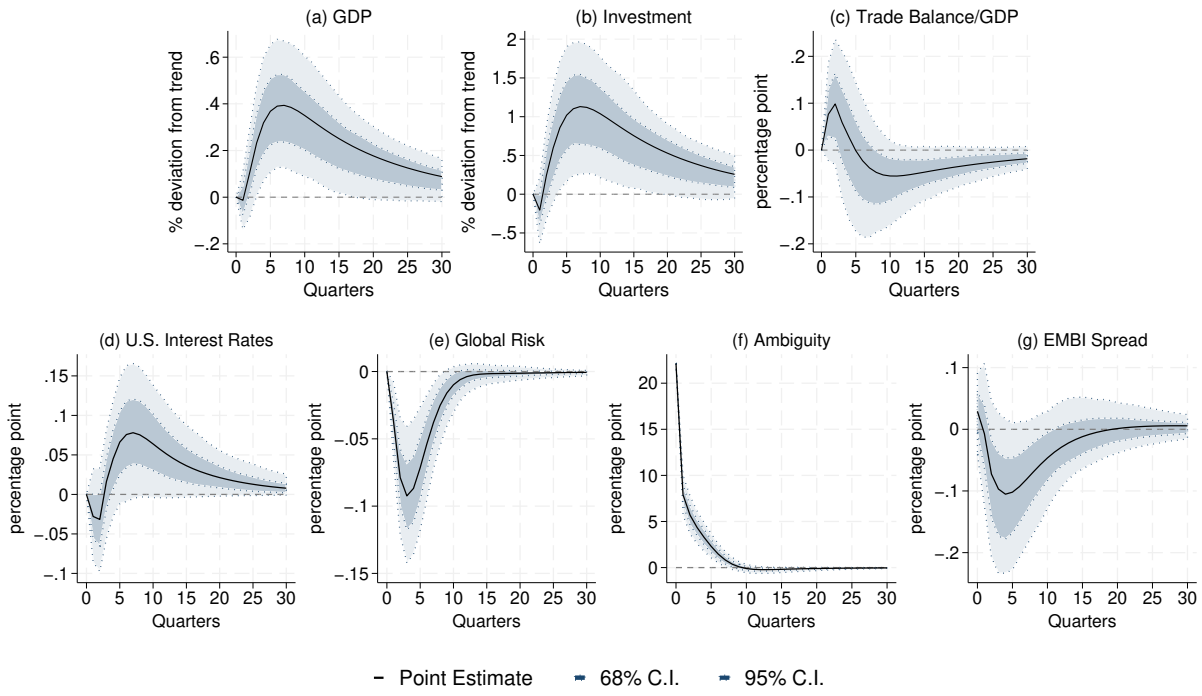


Figure 3.1: IRFs to one std. dev. shock to ambiguity

3.2 Additional Impulse Response Functions

As shown in Figures 3.2 through 3.4 the following results are in line with the 6-variable PSVAR from Akıncı (2013) and, therefore, unaffected by the inclusion of ambiguity in the analysis. Shocks to global financial risk and the country spread generate significant contractions in EMEs, while dynamics in the case of a U.S. interest rate shock are not significant, even if, in this case, also contractionary as in Uribe and Yue (2006).[18]

That said, there are important dynamics of ambiguity against the backdrop of overall system behavior. Indeed, as shown in Figure 3.2, a shock to global financial risk leads to a sharp and significant decline in ambiguity. This is in line with the shock to global financial risk signaling worldwide economic deterioration strongly enough so that uncertainty (in the Knightian sense) about conditions in U.S. equity market actually dissipates. Further in line with this, Section 3.3.3 presents suggestive evidence that global financial risk plays a central role in shaping investors *beliefs* about the underlying return generating process for

[18] Online Appendix C.1 complements the analysis presented here by running the Akıncı (2013) 6-variable PSVAR with our own benchmark data.

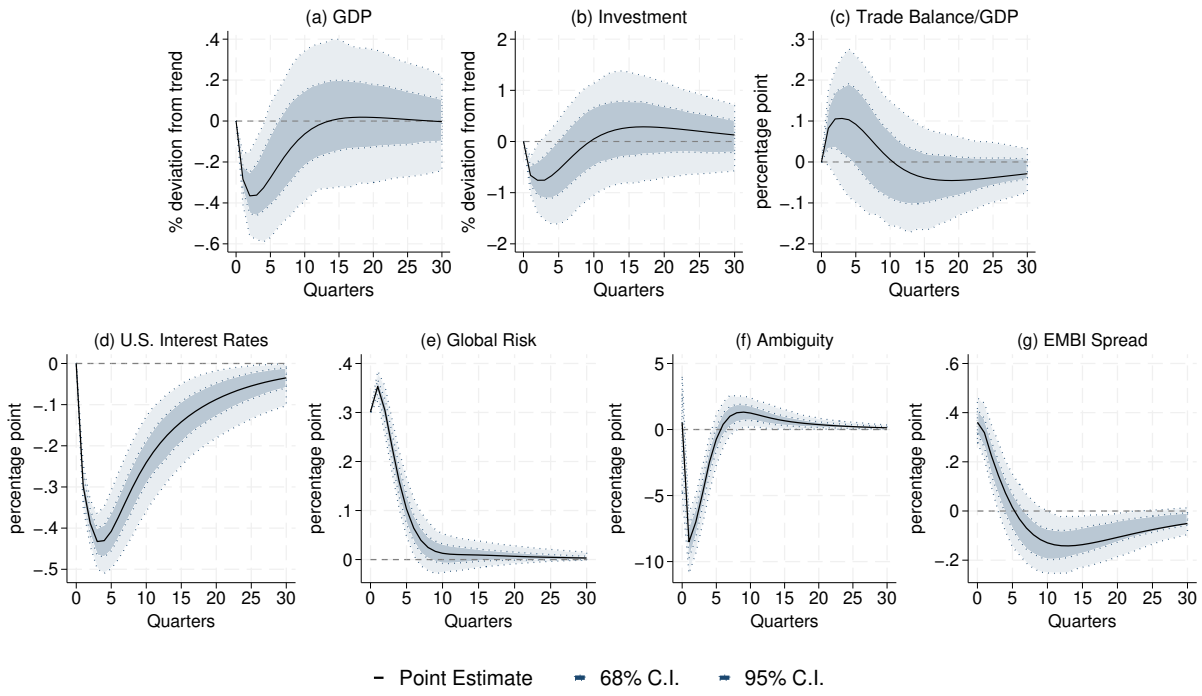


Figure 3.2: IRFs to one std. dev. shock to BAA spread

U.S. equity returns and, through this channel, reduces the degree of ambiguity. Beyond these dynamics, the shock to global financial risk triggers a flight to safety that is reflected by an increase in the EMBI spread and, consistent with foreign capital outflows, declines in EME GDP and investment alongside an initial increase in the trade balance. Flight-to-safety dynamics are, in this case, further underscored by a steep decline in the U.S. real interest rate.[19]

As anticipated, Figure 3.3 shows that, in line with Uribe and Yue (2006), a shock to the U.S. interest rate is contractionary for EMEs but, in line with Akıncı (2013), these dynamics are not significant. Intuitively, given an unexpected increase in the yield of U.S. bonds, controlling for BAA corporate bonds helps shed light on the fact that in this case asset reallocation dynamics within the system are largely restricted to bond markets. In line with this, a higher U.S. interest rate triggers lower demand for other debt instruments, including BAA corporate bonds and EME sovereign bonds, which is reflected in a higher BAA spread and a higher country spread. (Recall that, while an exogenous shock to the BAA spread is,

[19]The decline in the U.S. real rate in response to a global financial risk shock is in line with other studies that build on Akıncı (2013), such as Epstein et al. (2019).

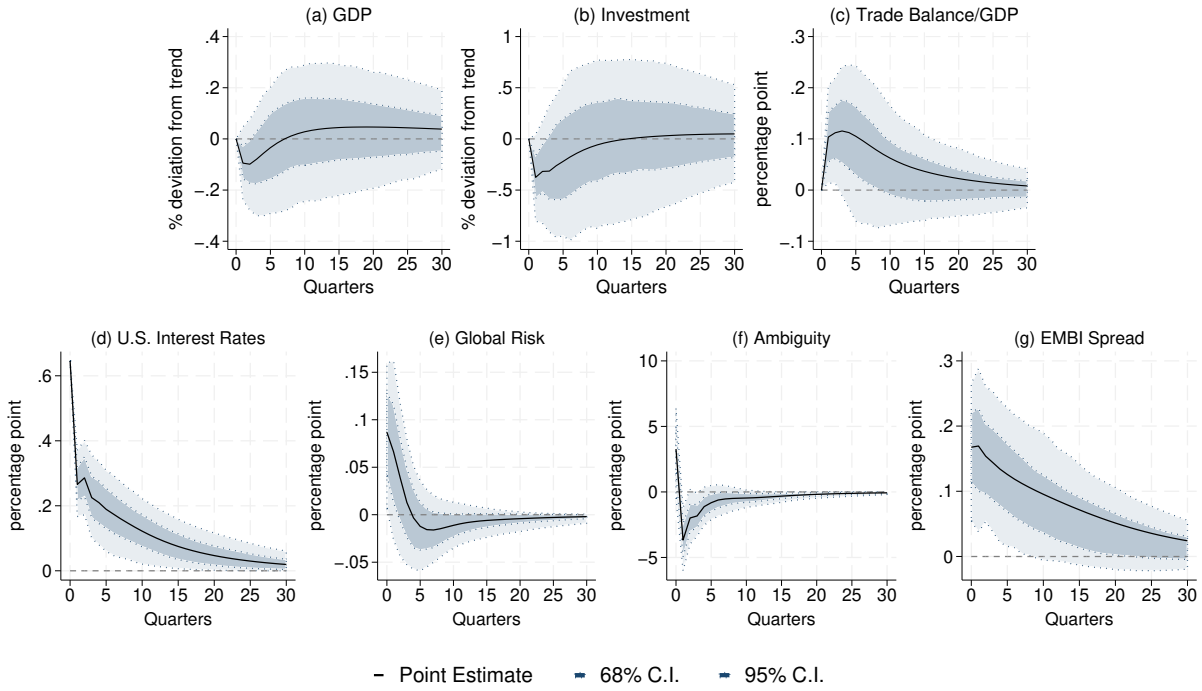


Figure 3.3: IRFs to one std. dev. shock to U.S. interest rate

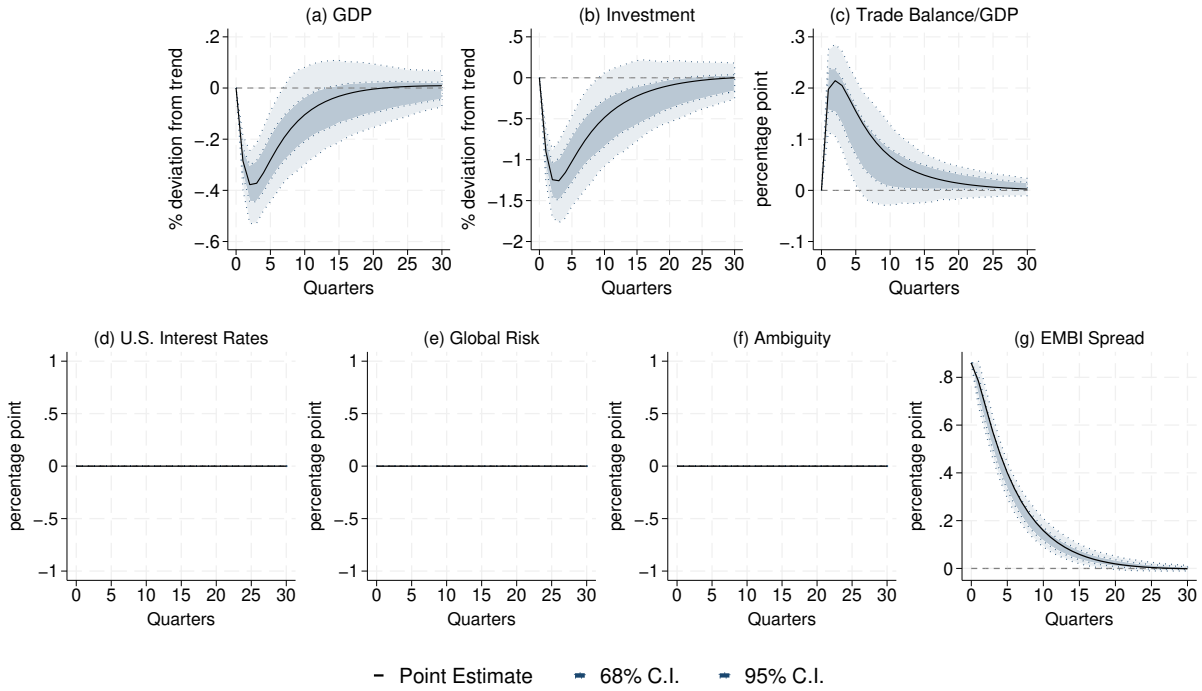


Figure 3.4: IRFs to one std. dev. shock to country spread

intuitively, a proxy for heightened global financial risk, dynamics in the BAA spread that stem from shocks to other variables are best interpreted as reflecting endogenous changes in BAA corporate bond markets.) Further in line with overall dynamics centering around bond markets, ambiguity in U.S. equity markets oscillates a bit before returning quickly to trend, and these short oscillations are relatively small compared to the standard deviation of ambiguity (see Figure 3.1 for reference).[20]

Finally, and also as anticipated, as shown in Figure 3.4 a shock to the EME country spread is strongly and significantly contractionary. Intuitively, heightened risk in EMEs as reflected by an exogenous increase in the risk premium of sovereign bonds results in foreign capital outflows, with the trade balance rising significantly above trend. This occurs in tandem with EME GDP and investment dropping significantly by about 0.4 and 1.25 percent below trend, respectively. By construction, given the nature of the shock block, there is no response in the U.S. rate, global financial risk, or ambiguity.

3.3 Inspecting the Mechanism

In Section 3.1 we document that an unexpected surge in the degree of ambiguity in U.S. equity markets has surprisingly prominent, significant, protracted, and *counterintuitive* expansionary effects on EME GDP and investment. The point estimate dynamics of the EME trade balance further suggests a medium- to long-term surge in foreign capital inflows into EMEs in response to heightened uncertainty in U.S. equity markets. Importantly, these patterns are accompanied by a prolonged decline in the BAA corporate yields and country spreads. Taken together, these dynamics are consistent with a financial market channel in which international investors, faced with hightend uncertainty, reallocate resources towards relatively safer assets: BAA corporate bonds and domestic investment in EMEs.

In this section we conduct additional analysis to investigate the underlying financial market mechanisms at work and to clarify the unique role of ambiguity. We proceed in four

[20]In the baseline analysis in Akıncı (2013) a U.S. interest rate shock triggers an insignificant decrease in the BAA corporate spread. However, Akinci attributes this to the Global Financial Crisis comprising an important fraction of the baseline sample period, noting that the BAA spread rises if analysis is run with a pre-Global Financial Crisis subsample of the data.

steps. First, we examine whether a shock to the degree of ambiguity in U.S. equity markets generates "push" factors stirring resources away from U.S. financial markets. Second, we assess the extent to which the BAA corporate bond markets amplifies the effect of ambiguity shocks for EMEs. Third, to shed light on the feedback effect between the corporate bond market and equity market ambiguity, we provide suggestive evidence about the dynamics of investor beliefs. Finally, we test whether the effects of ambiguity in U.S. equity markets are distinct from those of other U.S.-centric measures of uncertainty commonly used in the literature.

3.3.1 U.S. Real and Financial Effects of U.S. Ambiguity Shocks.

What are the real and financial consequences of an increase in ambiguity in U.S. equity market for the U.S. economy? Addressing this question is central to our analysis for three reasons. First, the response of the U.S. stock market provides a test of our portfolio rebalancing mechanism, whereby resources flow out of U.S. equity markets towards corporate bonds and EMEs. Second, it allows to verify that the response of U.S. real variables (GDP and investment) to hightened U.S. uncertainty aligns with the detrimental effect documented in the literature (e.g., Ilut and Schneider, 2014; Jurado et al., 2015), alleviating concerns that our results may be an artifact of the particular measure of ambiguity used. To address this question we modify our benchmark specification by replacing the U.S. interest rate, in turn, with the SPYD's expected returns, U.S. GDP, and U.S. investment.

Figure 3.5 shows the impact of a shock to ambiguity after swapping out the U.S. interest rate for expected SPYD returns.[21] Hightened ambiguity leads to a decline in expected SPYD returns, consistent with our portfolio rebalancing mechanism, which predicts a flow of funds away from U.S. stock markets. We find that ambiguity, on average, has a significantly positive effect on expected returns as in Brenner and Izhakian (2018). The dynamics of all other variables remains unchanged relative to the benchmark model.

Next, we show the impact of a shock to ambiguity after swapping out the U.S. rate, in

[21] The ordering of the shock block now assumes that global financial risk is the most exogenous variable. Then, since the construction of the ambiguity variable is based off the behavior of the stock market, in the shock block ambiguity goes last, preceded by expected SPYD returns.

turn, for U.S. real GDP (Figures 3.6) and investment (Figure 3.7).[22] The figures show that ambiguity shocks trigger a contraction in U.S. GDP and investment, respectively. As before, the response of other variables is in line with the benchmark model.

Together with the findings in Section 3.1, this analysis underscores a previously undocumented asymmetry in business cycle responses to U.S. ambiguity shocks: while ambiguity shocks depress U.S. economic activity, their international transmission stimulates EMEs' activity, in sharp contrast to the effects of previously examined uncertainty (but not ambiguity) shocks (e.g., Bhattarai et al., 2020).

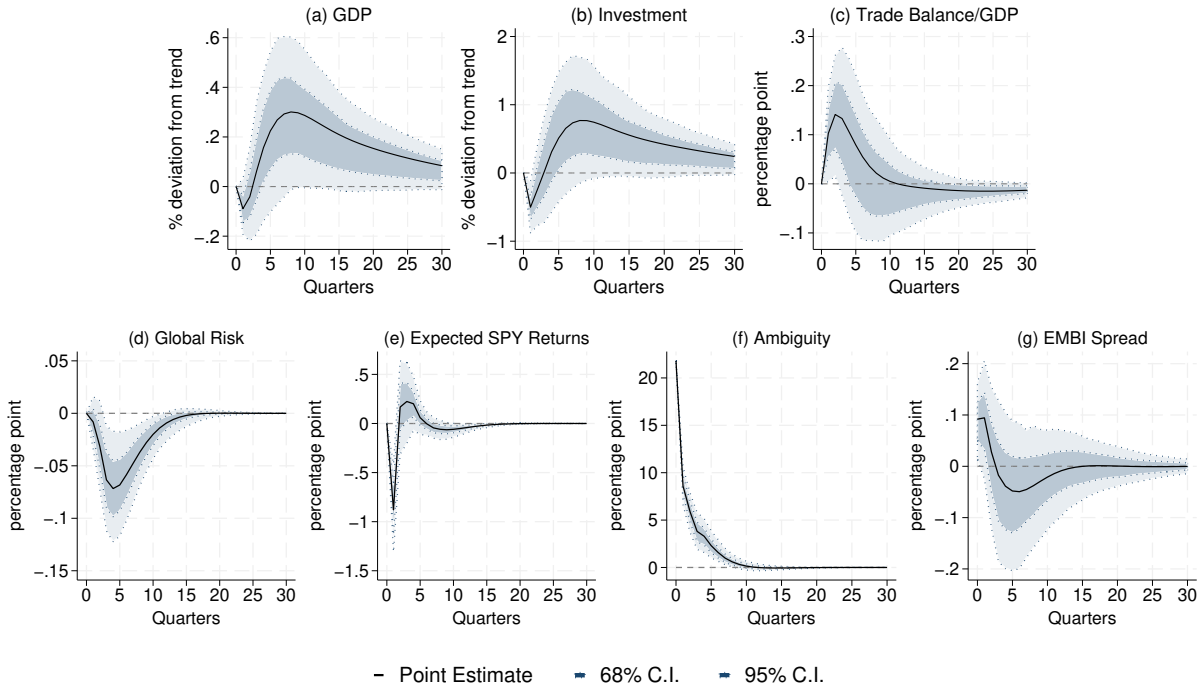


Figure 3.5: IRFs to one std. dev. shock to ambiguity with U.S. interest rate replaced by expected SPYD returns

3.3.2 Amplification through Bonds Markets

In this section we explore the extent to which the Baa corporate bond market serves as a transmission channel of the shock to ambiguity. To this end, we generate IRFs from the benchmark model (without reestimating it) but assuming that the Baa spread is simply an

[22]For consistency with the analysis of expected SPYD returns from above, we incorporate U.S. GDP and investment as the third variable in the shock block.

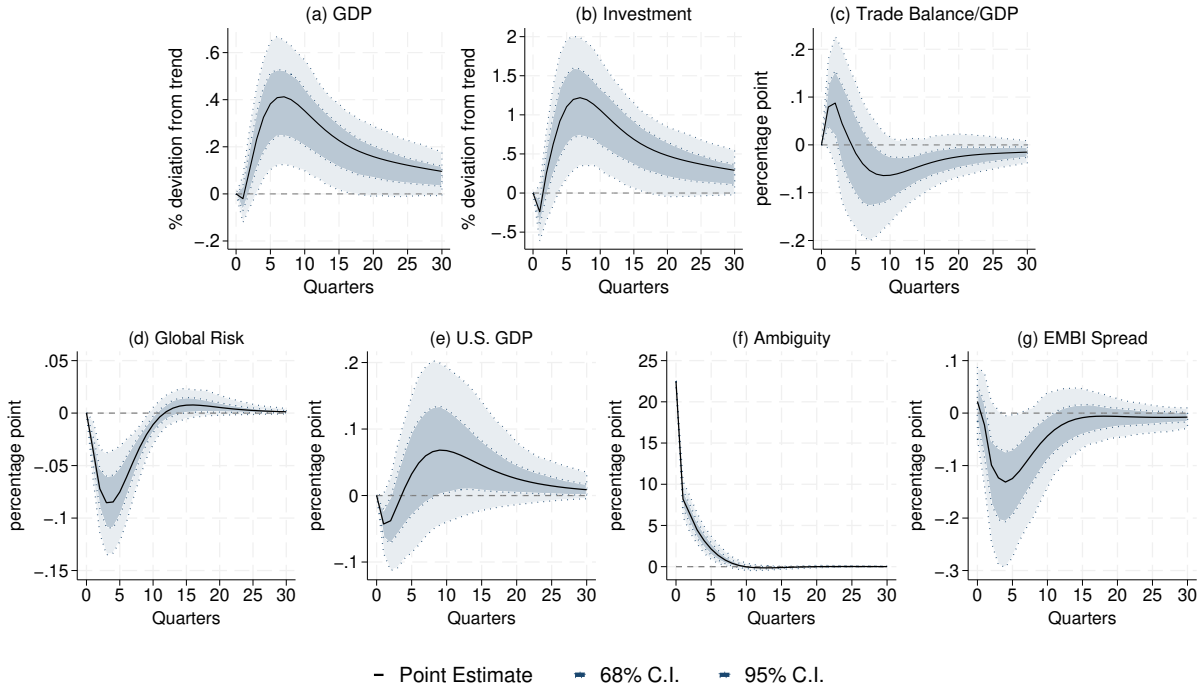


Figure 3.6: IRFs to one std. dev. shock to ambiguity with U.S. interest rate replaced by U.S. GDP

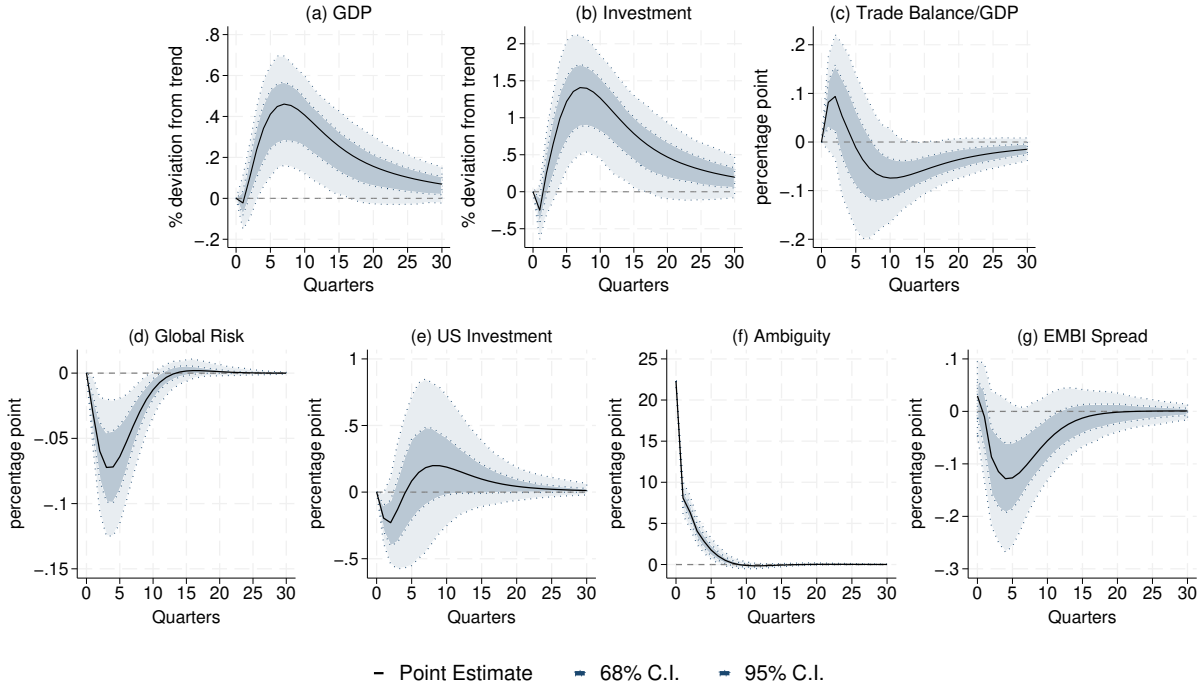


Figure 3.7: IRFs to one std. dev. shock to ambiguity with U.S. interest rate replaced by U.S. investment

AR2 process not depending on the global financial variables, the U.S. interest and ambiguity. As such, in the Baa equation we set the R^{US}_{t-j} coefficients equal to zero for $j = 0, 1, 2$ and the $ambig_{t-j}$ coefficients equal to zero for $j = 1, 2$ (note that in the benchmark case the ambiguity coefficient is already zero for $j = 0$ in the case of the Baa equation), while keeping everything else the same as in the benchmark model. Overall, as shown in Figures C.22 and C.23 in the Online Appendix C.5, the results of this exercise are in essence the same as in our baseline analysis in the case of the Baa and U.S. interest rate shocks. However, in the case of a shock to ambiguity, compared to the benchmark analysis the expansion in EME GDP and investment is muted and becomes significant at the 95 percent level in later periods and, in addition, the declines in the U.S. interest rate and the country spread following the shock are not significant (the fact that the country spread is not significant is consistent with a lesser improvement in EME economic conditions compared to the benchmark case). This suggests that the Baa spread acts as a transmission channel of the ambiguity shock. Intuitively, in the benchmark analysis, following the ambiguity shock, as investors seek out relatively safer investments in the form of Baa bonds (although riskier than U.S. bonds), the yields on these bonds decline, and this decline in yields boosts incentives to seek out additional lucrative opportunities, therefore shifting more allocation to EMEs than otherwise. Put another way, if the shock to ambiguity has no impact on Baa yields, then in response to the ambiguity shock investors do not have an incentive to move as many resources to EMEs than otherwise precisely because returns on Baa bonds remain as lucrative as before the ambiguity shock. Ultimately, this result suggests that investors may view investment in EMEs as riskier compared to investment in Baa corporate bonds.

3.3.3 Global Financial Risk, Investors Beliefs, and Ambiguity.

We showed earlier (Figure 3.2) that a shock to global financial risk leads to a sharp and significant decrease in ambiguity. We suggested that this is consistent with global financial risk playing a key role in influencing investors *beliefs* about the underlying return generating process and, through this channel, affecting the degree of ambiguity. To explore this possible mechanism, we estimate in Online Appendix C.2 a three-variable VAR including global

financial risk (proxied by the BAA spread), the degree of ambiguity in U.S. equity markets, and a measure of dispersion of investors' beliefs, proxied by the difference between the highest and the lowest values of expectations of S&P return over the next year from the CFO survey of Duke University and Federal Reserve Banks of Richmond and Atlanta.[23] Online Appendix Table C.1 shows that global financial risk Granger causes investors' beliefs, which in turn Granger causes ambiguity. Crucially, panel (a) of Online Appendix Figure C.7 shows that an unanticipated increase in BAA spreads widens the range of expected returns across CFO respondents. In turn, panel (b) shows that a widening of the range of expected returns across CFO investors reduces ambiguity.

This suggestive evidence is consistent with a scenario in which an unanticipated widening of BAA spreads provides a strong signal of a worsening outlook for real economic activity (e.g. Gertler and Lown, 1999; Gilchrist and Zakrajšek, 2012), stirring investors beliefs towards a narrower set of priors with greater weight on bad economic states, thereby dissipating Knightian uncertainty (ambiguity).We illustrate this mechanism with a simple example adopted from Brenner and Izhakian (2018). Suppose stock returns follow a discrete binomial distribution, with payoff $b = -5$ in the bad state and $g = 5$ in the good state. Assume a representative investor holds the following equally likely beliefs: $(P_1(b), P_1(g)) = (.5, .5)$, $(P_2(b), P_2(g)) = (.4, .6)$, $(P_3(b), P_3(g)) = (.34, .66)$ and $(P_4(b), P_4(g)) = (.22, .78)$, corresponding to expected returns 0, 1, 1.6 and 2.8, respectively. Now, consider an unexpected increase in the BAA spread that signals a worsening in economic conditions, captured by a lowering of the payoff in the bad state to $b = -30$, while keeping $g = 5$.[24] Crucially, assume further that an increase in global financial risk provides key information regarding the worsening of the economic outlook (e.g. Gertler and Lown, 1999; Gilchrist and Zakrajšek, 2012), spurring the representative investor to update its priors towards a narrower set of

[23] Giglio et al. (2021) show that both the level and the variation of the CFO survey are quite similar to the average beliefs they derived from a newly-designed survey administered to a large panel of wealthy retail investors, and hence can be used as a proxy for investors' beliefs over 1-year ahead market returns.

[24] Among others, Gilchrist and Zakrajšek (2012) discusses a mechanism through which an increase in corporate credit spreads (bond market) may affect outcomes in the stock market. In particular, a widening of corporate credit spreads may signal a worsening in credit intermediary balance sheets, which, in turn, reduces the supply of credit, raises the cost of firms' external finance, and thereby curtails production and investment, ultimately worsening future profitability.

distributions that put more weights on bad economic outcomes, represented by the following smaller set of equally likely beliefs: $(P_1(b), P_1(g)) = (.5, .5)$ and $(P_2(b), P_2(g)) = (.4, .6)$. In this setting, an increase in the BAA spread produces an increase in the dispersion of expected returns, from $2.8 = 2.8 - 0$ to $3.5 = -9 - (-12.5)$, while simultaneously reducing the degree of ambiguity, from 0.10 to 0.05, as a result of the alignment of investors' beliefs about the bad outcome. This analysis contributes to the international finance literature—which highlights the role of global financial risks for EMEs (Akıncı, 2013)— by uncovering a novel channel through which unexpected shocks to BAA spreads act as a coordination mechanism of international investors' beliefs, with important consequences for EMEs.

3.3.4 Is Ambiguity Different? Analysis with Alternative Uncertainty Measures

To assess the extent to which accounting for ambiguity can yield unique insights relative to other common used measures of U.S.-centric uncertainty, we estimate the benchmark model by swapping out ambiguity for, each in turn, the Chicago Board Options Exchange Volatility Index (VIX), financial uncertainty, macro uncertainty, and real uncertainty. As shown in Online Appendix Figure **??**, in contrast to the effect of ambiguity, a shock to any one of these variables leads to a contraction in economic activity in EMEs along with an increase in the country spread and, importantly, sharp and protracted decreases in the U.S. interest rate and considerable increases in the Baa spread. These results suggest that shocks to any one of these uncertainty variables decreases risk appetite substantially, with asset allocations shifting strongly towards U.S. bonds. This effect is distinct from the shock to ambiguity, which, as discussed at length above, results in a rotation of assets towards relatively less risky investments although still riskier than U.S. bonds. Taken together, results suggest that these other U.S.-centric measures capture aspects of uncertainty quite similar to the Baa or global risk shock; and that ambiguity has a unique impact on EME economic activity compared to other measures of uncertainty.

3.4 Variance Decomposition

Figure 3.8 presents forecast error variance decompositions (FEVDs) from our benchmark model (Eq. (2.1)) at different horizons for the following EME variables: GDP, investment, trade balance and country spreads. Each panel corresponds to one of the variables and reports the percentage contributions of global financial risk shocks (solid black lines), country spread shocks (dashed red lines), the U.S. real interest rate shock (short-dashed blue lines), and the ambiguity shocks (dash-dotted purple lines) to the variance of the k-quarter-ahead forecast errors.

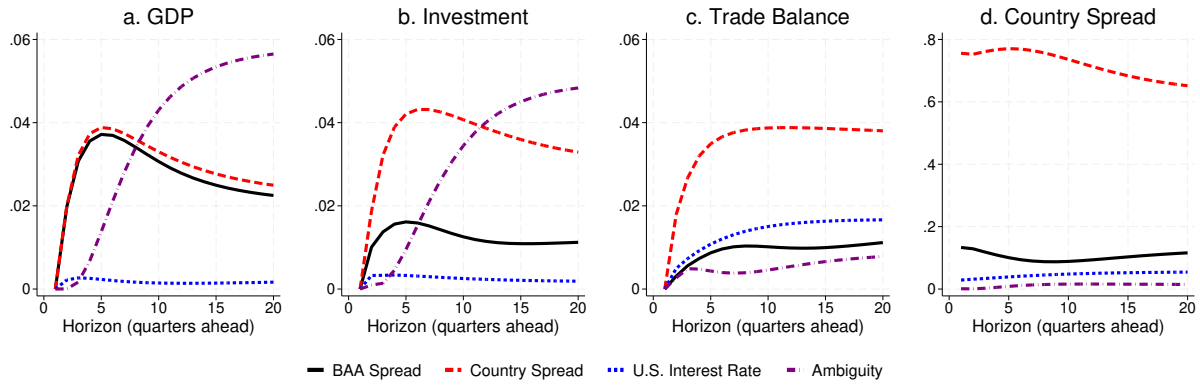


Figure 3.8: Forecast Error Variance Decomposition

Note: This chart shows the fraction of the variance of the forecasting error accounted by the BAA spread (the solid black lines), the country spreads (the dashed red lines), the U.S. real interest rate (the short-dashed blue lines), and the ambiguity (the dash-dotted purple lines) at each horizon.

Panel (a) shows that innovations to ambiguity are the most important factor in explaining the movements in the EME domestic economic activity, accounting for 6 percent of the variations in emerging markets GDP. The global financial risk (the BAA spread) and the country spread appear to be significantly less important, with each equally explaining about 2 percent of the fluctuations in domestic economic activity in the EMEs. Overall, these three factors explain about 10 percent of GDP fluctuations in emerging market economies. Shocks to the U.S. interest rate, on the other hand, do not have a material impact on the EME GDP.

Similarly, Panel (b) shows that shocks to ambiguity, global financial risk, and the country spread jointly explain a total of about 9 percent of movements in emerging market invest-

ment, with innovations to ambiguity and country spread having the largest effects. The contribution of global financial risk is only around 1 percent for investment.

Panel (c) shows that country spread shocks are the main driver of EME trade balance fluctuations, accounting for as much as the combined contribution of ambiguity, global financial risk, and U.S. interest rate shocks—about 4 percent. Panel (d) concludes by showing that global financial risk shocks are the most important driver of fluctuations in the country spread, though much less so than the country spreads' own innovations.

While ambiguity emerges as the dominant factor in explaining the fluctuations in emerging markets' GDP and investment, the total contribution of the four shocks discussed above is significantly smaller than the one reported in the literature. For instance, Akıncı (2013) finds that global financial risk and country spread shocks account for around 40 percent of business cycle fluctuations in the emerging market economies. Similarly, Uribe and Yue (2006) report that around one third of business cycles in emerging economies can be explained by innovations in the U.S. interest rate and country spread shocks.

To investigate whether these differences stems from the sample period used in these earlier studies, we generate 20-quarters ahead FEVDs for sample periods ending at different dates, beginning with the first quarter of 2011 and expanding one quarter at a time. Figure 3.9 presents the results from this exercise, where each year shows the average FEVDs of the respective variable obtained by running the estimation through each quarter of that year.

Our results align reasonably well with this earlier literature when the sample ends around 2011. In this earlier window, the BAA spread, country spreads, the U.S. interest rate, and ambiguity jointly account for 27 percent of the movements in EME domestic activity, with the BAA spread and country spreads playing the most important roles (left panel). Similarly, these four factors explain nearly 20 percent of fluctuations in emerging markets' investment (middle panel) and 15 percent of the fluctuations in the trade balance (right panel). However, as more data are added to the sample, the contributions from the BAA spread and country spreads to EME GDP and investment's fluctuations fall substantially, reducing the overall explanatory power of these variables while increasing the relative importance of ambiguity shocks. This exercise underscore the growing role of Knightian uncertainy in U.S. equity

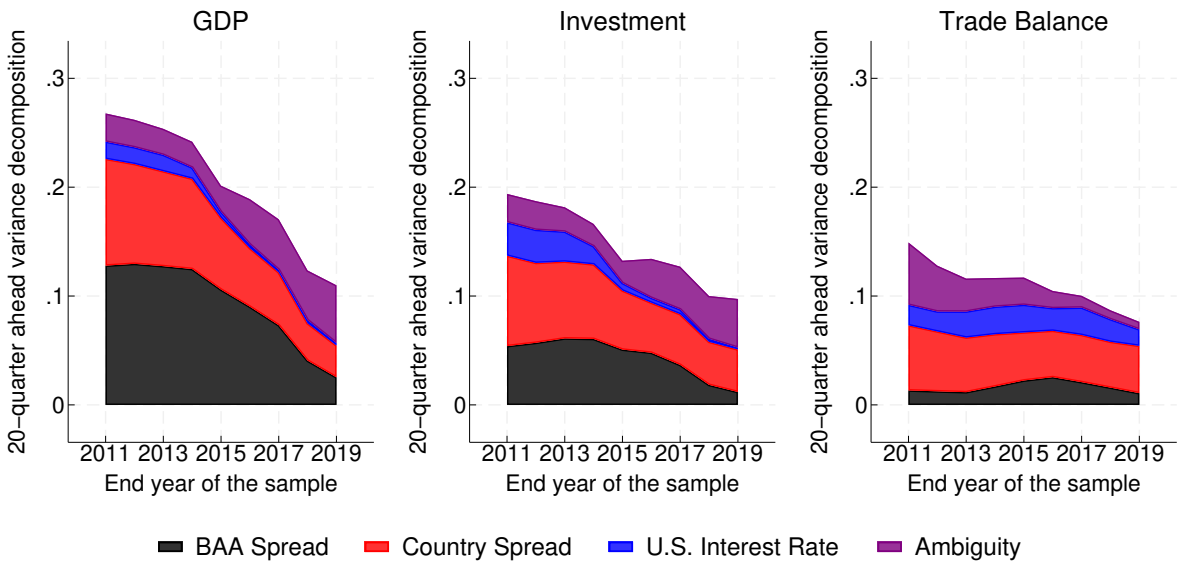


Figure 3.9: 20-Quarter Ahead Forecast Error Variance Decomposition
(for different sample period ends)

Note: This chart shows 20-quarters ahead forecast error variance decomposition for an expanding window of the sample period. Each region represents the fraction of the variance of the forecasting error accounted by the BAA spread (the black areas), the country spreads (the red areas), the U.S. real interest rate (the blue areas), and the ambiguity (the purple areas). Each year shows the averages obtained by running the estimation through each quarter of that year.

markets for emerging market business cycles in more recent years.

4 Robustness and Additional Analysis

This section performs a battery of robustness checks including: alternative filters, lag orders, exogenous block specifications, and sample of countries.

4.1 Alternative Filters

Our benchmark analysis uses data that is linearly detrended. Figures C.8-C.13 in Online Appendix C.3 show that results are robust to relaxing this assumption, by allowing for a degree of curvature in the trend component using, alternatively: the Baxter-King filter, the Christiano-Fitzgerald filter, and the HP filter. When looking at ambiguity shocks, the HP filter yields responses that are the closest to our baseline analysis; the Christiano-Fitzgerald filter results in a more protracted expansion in EME GDP and investment and the Baxter-King filter results in a somewhat less protracted response in these variables. Turning to global financial risk shocks, again the HP filter yields results closest to our baseline analysis, while the contraction of EME GDP and investment is shallower with the Christiano-Fitzgerald filter and deeper with the Baxter-King filter.

4.2 Alternative Lag Orders

Information criteria suggest that the optimal lag order of our benchmark PSVAR in Equation (2.1) is 2, in line with Akıncı (2013). We perform robustness analysis by re-estimating the model with 1 and 3 lags. Figures C.14-C.17 in the Online Appendix C.4 report the results.

In the case of one lag, a shock to global financial risk yields results in line with our benchmark analysis. Nonetheless, in contrast to our baseline results, a shock to the U.S. interest rate results in a very deep, protracted, and significant decline in EME GDP and investment. A shock to ambiguity results in IRFs that are qualitatively and quantitatively in line with our benchmark results, but the expansion in EME GDP and investment is now

significant only at the 68 percent level. That said, a shock to the country spread yields the unintuitive and arguably implausible result that there is no significant response in any of the other variables in the model neither at the 95 or 68 percent levels. This suggests that 1 lag is not appropriate to correctly capture the underlying economic dynamics, making the point that, in line with our baseline analysis, at least 2 lags are appropriate.

In the case of 3 lags, results are in line with those from our benchmark analysis. That said, on net IRFs are estimated with considerably more precision as reflected by notably tighter confidence bands at both the 68 and 95 percent levels. Interestingly, this additional precision results in it being the case that, in the aftermath of a global financial risk shock, there is a significant rebound in EME GDP and investment that is accompanied by a significant decline in the country spread.

4.3 Alternative Exogenous Block Specifications

4.3.1 Endogenous Global Financial Variables

In the baseline model, global financial variables—U.S. interest rate, global financial risk, and ambiguity in U.S. equity markets—are treated as exogenous to all country-specific variables. We relax this block-exogeneity assumption by allowing all variables, including the global financial variables, to interact endogenously (while preserving their baseline ordering). Figures C.18 and C.19 in Online Appendix C.5 show that the results remain consistent with our benchmark specification.

4.3.2 Ambiguity: Exogenous to Other Global Financial Variables

To assess the extent to which the endogenous dependence of ambiguity from U.S. interest rate and global financial risk affect the results, we examine the case in which ambiguity does not depend on these variables. To do so, we set the R^{US}_{t-j} and GR_{t-j} coefficients equal to zero for $j = 0, 1, 2$ in the ambiguity equation, while keeping everything else the same as in the benchmark model. Figures C.20 and C.21 in the Online Appendix C.5, show that the IRFs are in essence the same as in our baseline analysis, suggesting that endogenous spillover

effects from the U.S. rate and the Baa spread to ambiguity are not a critical driver of the IRF dynamics observed in our benchmark analysis.

4.3.3 U.S. Interest Rate: Exogenous to Other Global Financial Variables

To assess the extent to which the endogenous dependence of the U.S. interest rate from global financial risk and the degree of ambiguity affect the results, we examine the case in which the U.S. interest rate does not depend on these variables. To do so, we set the $ambig_{t-j}$ and GR_{t-j} coefficients equal to zero for $j = 1, 2$ in the interest rate equation (note that in the benchmark case these coefficients are already zero for $j = 0$), while keeping everything else the same as in the benchmark model. Figures C.24 and C.25 in the Online Appendix C.5, show that the IRFs are in essence the same as in our baseline analysis in the case of the ambiguity and U.S. interest rate shocks. That said, in response to a global financial risk shock, the benchmark analysis shows an initial significant contraction in GDP and investment, followed by a rebound significant at the 68 percent level. By contrast, when we set $ambig_{t-j}$ and R_{t-j} to zero for $j = 1, 2$, no such rebound occurs. This suggests that the rebound observed in the baseline case reflects the dissipation of the global financial risk shock: as U.S. bond yields revert back to trend after their initial decline, markets shifts investment from this safe asset to relatively riskier avenues, including EMEs.

4.3.4 Country Spread: Exogenous to Global Financial Variables

To examine the extent to which the interaction of the exogenous block variables with the country spread have an impact on results, we examine the case in which the country spread does not depend on these variables. As such, in the country spread equation we set $ambig_{t-j}$, GR_{t-j} and R^{US}_{t-j} equal to zero for $j = 0, 1, 2$ while keeping everything else the same as in the benchmark model. Regarding IRfs, recall that in the baseline case a shock to Baa leads to a jump in the country spread, which drives a significant decline in EME GDP and ambiguity. However, as shown in Figures C.26 and C.27 in the Online Appendix C.5 in the present case GDP declines significantly and in response to this the spread rises, although insignificantly. Against this backdrop, GDP declines but also insignificantly. Remaining dynamics

are similar to those in the benchmark analysis. Also, in the present case given a shock to ambiguity, with it being the case that on impact the country spread does not respond, the expansion in EME GDP and investment is more pronounced in terms of significance at the 95 percent level compared to the benchmark analysis, later leading to a more significant decline in the country spread driven by improvement in EME economic conditions. This is intuitive because in the baseline analysis on impact of the ambiguity shock the country spread jumps (albeit insignificantly), which mutes the expansion in EMEs compared to the present case in which the country spread does not respond on impact. Lastly, as also shown in the Appendix, in the present case the response to a U.S. interest rate shock is similar as in the benchmark analysis, with EME GDP and investment declining significantly against the backdrop of insignificant country spread dynamics.

4.3.5 Country Spread: Exogenous to other Country-Specific Real Variables

To assess the extent to which the endogenous dependence of the country spreads from country-specific variables—GDP, investment, trade balance— affect the results, we examine the case in which the country spread does not depend on these variables. To do so, we set the coefficients on $gdp_{i,t-j}$, $inv_{i,t-j}$ and $R^tby_{i,t-j}$ equal to zero for $j = 0, 1, 2$ in the country spread equation, while keeping everything else the same as in the benchmark model. Figures C.28 and C.29 in the Online Appendix C.5 show that an ambiguity shock still trigger an expansion in EME GDP and investment, but the effect is somewhat muted relative to the baseline, and the country spread does not fall significantly below trend. The intuition is straightforward. In the baseline case, the joint endogenous dynamics of country spread and EME GDP and investment are consistent with the virtuous feedback loop documented in the literature (Uribe and Yue, 2006; Akıncı, 2013): improved economic conditions reduce borrowing rates, which in turn help sustaining longer periods of above-trend EME GDP and investment. By severing this feedback loop, our current assumptions mute this inherent amplification mechanism. For similar reasons, the responses of EME macroeconomic variables to global financial risk and U.S.interest shocks are also somewhat weaker than in the benchmark analysis.

4.3.6 Alternative Exogenous Block Orderings

We examine the robustness of our main results by ordering the exogenous block across all possible five remaining permutations (relative to the baseline specification) and re-estimating the model. IRFs in Figures C.30 to C.39 in the Online Appendix C.5 show that our baseline results are robust to these alternative specifications.

4.4 Larger sample of countries

For comparability, our paper focuses on the set of emerging economies considered in Akıncı (2013): Argentina, Brazil, Mexico, Peru, South Africa and Turkey. Figures C.40 and C.41 in the Online Appendix C.6 show that our results strengthen when we expand the sample to 12 countries, adding Chile, Colombia, Ecuador, Malaysia, Philippines, and Thailand to the baseline set.

5 Conclusion

This paper provides new empirical evidence on the role of Knightian uncertainty (ambiguity) in U.S. equity markets as a driver of business cycles in EMEs. While prior literature has emphasized the impact of global risk and U.S. interest rates on EMEs, we isolate and quantify the distinct influence of ambiguity associated with investors beliefs over U.S. stock market returns in shaping macroeconomic and financial dynamics in EMEs. Using a panel SVAR framework, we identify ambiguity shocks in U.S. equity markets and analyze their spillover effects on EME output, investment, trade balance and country risk premia.

In contrast to previously examined uncertainty shocks, which typically depress economic activity, we show that ambiguity shocks in U.S. financial markets are followed by economic expansions in EMEs. This novel and counterintuitive result is explained by a portfolio reallocation channel, where greater ambiguity in U.S. equities induces investors to shift toward relatively safer assets, including corporate bonds. The resulting compression in global credit spreads lowers EME borrowing costs, fueling investment and GDP growth. Our results also

reveal a virtuous feedback loop: improved domestic conditions reinforce lower financing costs, which, in turn, prolong the expansionary effects of ambiguity shocks. Moreover, our analysis quantifies the interplay between ambiguity in U.S. equity markets and global financial risk—the key driver of EME business cycle identified in the literature. We find that increases in global financial risk tend to reduce ambiguity, consistent with risk shocks providing investors with clear signals of a worsening economic outlook, which dissipates Knightian uncertainty. Last, variance decomposition analysis confirms that ambiguity is as important as global risk and U.S. interest rates in explaining fluctuations in EME business cycles.

Overall, our study underscores a previously underappreciated role of ambiguity in U.S. equity markets in the global financial transmission of uncertainty shocks. Future research could explore the heterogeneity of these effects across different EMEs and extend the analysis to incorporate policy responses to ambiguity-driven fluctuations.

References

Akinci, O. (2013): "Global financial conditions, country spreads and macroeconomic fluctuations in emerging countries," *Journal of International Economics*, 91, 358–371.

Altug, S., C. Cakmakli, F. Collard, S. Mukerji, and H. Ozsoylev (2020): "Ambiguous Business Cycles: A Quantitative Assessment," *Review of Economic Dynamics*, 38, 220–237.

Anaya, P., M. Hachula, and C. J. Offermanns (2017): "Spillovers of U.S. unconventional monetary policy to emerging markets: The role of capital flows," *Journal of International Money and Finance*, 73, 275–295.

Augustin, P. and Y. Izhakian (2020): "Ambiguity, volatility, and credit risk," *The Review of Financial Studies*, 33, 1618–1672.

Benigno, P. and S. Nisticò (2009): "International Portfolio Allocation under Model Uncertainty," *NBER Working Paper No. 14734*, accessed August 21, 2025.

Bhattarai, S., A. Chatterjee, and W. Y. Park (2020): "Global spillover effects of US uncertainty," *Journal of Monetary Economics*, 114, 71–89.

Bianchi, F., C. L. Ilut, and M. Schneider (2018): "Uncertainty shocks, asset supply and pricing over the business cycle," *The Review of Economic Studies*, 85, 810–854.

Bloom, N. (2009): "The Impact of Uncertainty Shocks," *Econometrica*, 77, 623–685.

Brenner, M. and Y. Izhakian (2018): "Asset pricing and ambiguity: Empirical evidence," *Journal of Financial Economics*, 130, 503–531.

Caballero, J., A. Fernández, and J. Park (2019): "On corporate borrowing, credit spreads and economic activity in emerging economies: An empirical investigation," *Journal of International Economics*, 118, 160–178.

Calvo, G. A. (2002): "Presidential address: Globalization hazard and delayed reform in emerging markets," *Economia*, 2, 1–29.

Calvo, G. A., L. Leiderman, and C. M. Reinhart (1993): "Capital Inflows and Real Exchange Rate Appreciation in Latin America: The Role of External Factors," *Staff Papers (International Monetary Fund)*, 40, 108–151.

Canova, F. (2005): "The transmission of US shocks to Latin America," *Journal of Applied Econometrics*, 20, 229–251.

Cao, H. H., T. Wang, and H. H. Zhang (2005): "Model uncertainty, limited market participation, and asset prices," *The Review of Financial Studies*, 18, 1219–1251.

Chen, Z. and L. Epstein (2002): "Ambiguity, risk, and asset returns in continuous time," *Econometrica*, 1403–1443.

Diaz-Alejandro, C. (1985): "Good-bye financial repression, hello financial crash," *Journal of Development Economics*, 19, 1–24.

Epstein, B., A. Finkelstein Shapiro, and A. González Gómez (2019): "Global financial risk, aggregate fluctuations, and unemployment dynamics," *Journal of International Economics*, 118, 351–418.

Epstein, L. and T. Wang (1994): "Intertemporal asset pricing under Knightian uncertainty," *Econometrica*, 62, 283–322.

Epstein, L. G. and J. Miao (2003): "A two-person dynamic equilibrium under ambiguity," *Journal of economic Dynamics and control*, 27, 1253–1288.

Fink, F. and Y. S. Schüler (2015): "The transmission of US systemic financial stress: Evidence for emerging market economies," *Journal of International Money and Finance*, 55, 6–26, macroeconomic and financial challenges facing Latin America and the Caribbean after the crisis.

Garlappi, L., R. Uppal, and T. Wang (2007): "Portfolio selection with parameter and model uncertainty: A multi-prior approach," *The Review of Financial Studies*, 20, 41–81.

Gertler, M. and C. S. Lown (1999): "The information in the high-yield bond spread for the business cycle: evidence and some implications," *Oxford Review of economic policy*, 15, 132–150.

Giglio, S., M. Maggiori, J. Stroebel, and S. Utkus (2021): "Five Facts about Beliefs and Portfolios," *American Economic Review*, 111, 1481–1522.

Gilchrist, S. and E. Zakrajšek (2012): "Credit spreads and business cycle fluctuations," *American economic review*, 102, 1692–1720.

Hayashi, T. and J. Miao (2011): "Intertemporal substitution and recursive smooth ambiguity preferences," *Theoretical Economics*, 6, 423–472.

Horvath, J. and P. Rothman (2021): "Mortgage spreads, asset prices, and business cycles in emerging countries," *Journal of International Money and Finance*, 115, 102370.

Horvath, J. and G. Yang (2024): "Global Financial Risk, Equity Returns and Economic Activity in Emerging Countries," *Oxford Bulletin of Economics and Statistics*, 86, 672–689.

Ilut, C. L., P. Krivenko, and M. Schneider (2024): "Uncertainty or Frictions? A Quantitative Model of Scarce Safe Assets," NBER Working Papers 32198, National Bureau of Economic Research, Inc.

Ilut, C. L. and M. Schneider (2014): "Ambiguous business cycles," *American Economic Review*, 104, 2368–2399.

——— (2022): "Ambiguity and Economic Activity: A Survey," NBER Working Paper 29915, National Bureau of Economic Research, accessed August 21, 2025.

Izhakian, Y. (2017): "Expected utility with uncertain probabilities theory," *Journal of Mathematical Economics*, 69, 91–103.

——— (2020): "A theoretical foundation of ambiguity measurement," *Journal of Economic Theory*, 187, S0022053120300090.

Ju, N. and J. Miao (2012): "Ambiguity, Learning, and Asset Returns," *Econometrica*, 80, 559–591.

Jurado, K., S. C. Ludvigson, and S. Ng (2015): "Measuring uncertainty," *American Economic Review*, 105, 1177–1216.

Klibanoff, P., M. Marinacci, and S. Mukerji (2005): "A smooth model of decision making under ambiguity," *Econometrica*, 73, 1849–1892.

Knight, F. H. (1921): "Risk, uncertainty and profit," *Hart, Schaffner and Marx*.

Ludvigson, S. C., S. Ma, and S. Ng (2021): "Uncertainty and business cycles: exogenous impulse or endogenous response?" *American Economic Journal: Macroeconomics*, 13, 369–410.

Mackowiak, B. (2007): "External shocks, U.S. monetary policy and macroeconomic fluctuations in emerging markets," *Journal of Monetary Economics*, 54, 2512–2520.

Millner, A. (2024): "Variational Ambiguity Preferences and Long-Run Risk," NBER Working Paper 33291, National Bureau of Economic Research, accessed August 21, 2025.

Miranda-Agrippino, S. and H. Rey (2020): "U.S. Monetary Policy and the Global Financial Cycle," *The Review of Economic Studies*, 87, 2754–2776.

Mumtaz, H. and K. Theodoridis (2017): "Common and Country Specific Economic Uncertainty," *Journal of International Economics*, 105, 205–216.

Neumeyer, P. A. and F. Perri (2005): "Business cycles in emerging economies: the role of interest rates," *Journal of monetary Economics*, 52, 345–380.

Rey, H. (2015): "Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence," NBER Working Papers 21162, National Bureau of Economic Research, Inc.

Rothschild, M. and J. E. Stiglitz (1978): "Increasing risk: I. A definition," in *Uncertainty in economics*, Elsevier, 99–121.

Schmeidler, D. (1989): "Subjective probability and expected utility without additivity," *Econometrica: Journal of the Econometric Society*, 571–587.

Seo, K. (2009): "Ambiguity and second-order belief," *Econometrica*, 77, 1575–1605.

Ui, T. (2023): "Strategic Ambiguity in Global Games," *arXiv preprint arXiv:2303.12263*, accessed August 21, 2025.

Uribe, M. and V. Z. Yue (2006): "Country spreads and emerging countries: Who drives whom?" *Journal of International Economics*, 69, 6–36.

Wakker, P. and A. Tversky (1993): "An axiomatization of cumulative prospect theory," *Journal of risk and uncertainty*, 7, 147–175.

World Bank (2025): "Market Capitalization of Listed Domestic Companies (Current US$)," https://data.worldbank.org/indicator/CM.MKT.LCAP.CD, accessed: July 20th 2025.

Online Appendix

A Data Details

A.1 Common Variables Across Countries

US real GDP: span: 1993:Q4-2022:Q4; source: U.S. Bureau of Economic Analysis, Real Gross Domestic Product [GDPC1], retrieved from FRED, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/GDPC1). **BAA corporate spread**: span: 1993:Q4-2022:Q4; source: Federal Reserve Bank of St. Louis, Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity [BAA10Y], retrieved from FRED, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/BAA10Y). **Ambiguity index**: span: 1993:Q4-2021:Q3 ; source: Izhakian (2020). **U.S. nominal interest rate (3-month US Treasury yield)**: span: 1993:Q4-2022:Q4; source: Board of Governors of the Federal Reserve System (US), Market Yield on U.S. Treasury Securities at 3-Month Constant Maturity, Quoted on an Investment Basis [DGS3MO], retrieved from FRED, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/DGS3MO). **U.S. gross real interest rate**: calculated as the ratio of the U.S. gross nominal interest rate to U.S. gross expected inflation, where gross expected inflation is annualized. Following Akıncı (2013), U.S. (annualized) gross expected inflation is calculated by regressing the inverse of the (annualized) gross inflation in period $t+1$ (obtained using the U.S. CPI) on a constant and two lags. **VIX**: span: 1993:Q4-2022:Q4; source: retrieved from FRED, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/vixcls).

A.2 Country Specific Variables

- ***Argentina***. **Real GDP**: span: 2004:Q1-2022:Q4; source: The National Institute of Statistics and Censuses of Argentina (INDEC). **Real investment**: span: 2004:Q1-2022:Q4; source: The National Institute of Statistics and Censuses of Argentina (INDEC). **Price level**: span: 2012:Q3-2022:Q4; source: The National Institute of Statistics and Censuses of Argentina (INDEC). **Real exports**: span: 2004:Q1-2022:Q4;

source: The National Institute of Statistics and Censuses of Argentina (INDEC). **Real imports**: span: 2004:Q1-2022:Q4; source: The National Institute of Statistics and Censuses of Argentina (INDEC).[25] **Real trade balance**: ratio net exports to GDP. **Country spread**: span: 1993:Q4 - 2024:Q1; source: The J.P. Morgan Emerging Markets Bond Index Plus (EMBI+).

- ***Brazil***. **Real GDP**: span: 1994:Q1-2022:Q4; source: Brazilian Institute of Geography and Statistics. **Real investment**: span: 1994:Q1-2022:Q4; source: Brazilian Institute of Government and Statistics. **Price level**: span: 1994:Q1-2022:Q4; source: Brazilian Institute of Geography and Statistics and Uribe and Yue (2006). **Real exports**: span: 1994:Q1-2022:Q4; source: Brazilian Institute of Geography and Statistics. **Real imports**: span: 1994:Q1-2022:Q4; source: Brazilian Institute of Geography and Statistics. **Real trade balance**: ratio net exports to GDP. **Country spread**: span: 1994:Q2 - 2024:Q1; source: The J.P. Morgan Emerging Markets Bond Index Plus (EMBI+).

- ***Mexico***. **Real GDP**: span: 1994:Q1-2022:Q4; source: National Statistical and Geographic Information System of Mexico (INEGI). **Real investment**: span: 1994:Q1-2022:Q4; source: National Statistical and Geographic Information System of Mexico (INEGI). **Price level**: span: 1994:Q1-2022:Q4; source: National Statistical and Geographic Information System of Mexico (INEGI). **Real exports**: span: 1994:Q1-2022:Q4; source: National Statistical and Geographic Information System of Mexico (INEGI). **Real imports**: span: 1994:Q1-2022:Q4; source: National Statistical and Geographic Information System of Mexico (INEGI). **Real trade balance**: ratio net exports to GDP. **Country spread**: span: 1993:Q4 - 2024:Q1; source: The J.P. Morgan Emerging Markets Bond Index Plus (EMBI+).

- ***Peru***. **Real GDP**: span: 1994:Q1-2022:Q4; source: Central Reserve Bank of Peru. **Real investment**: span: 1994:Q1-2022:Q4; source: Central Reserve Bank of Peru.

[25] In all cases for data from national statistics agency please see https://www.indec.gob.ar/ and https://www.indec.gob.ar/indec/web/Institucional-Indec-InformacionDeArchivo-5

Price level: Central Reserve Bank of Peru. **Real exports**: span: 1994:Q1-2022:Q4; source: Central Reserve Bank of Peru. **Real imports**: span: 1994:Q1-2022:Q4; source: Central Reserve Bank of Peru. **Real trade balance**: ratio net exports to GDP. **Country spread**: span: 1997:Q2 - 2024:Q1; source: The J.P. Morgan Emerging Markets Bond Index Plus (EMBI+) and Uribe and Yue (2006).

- ***South Africa***. **Real GDP**: span: 1994:Q1-2022:Q4; source: Statistics South Africa (Stats SA). **Real investment**: span: 1994:Q1-2022:Q4; source: South African Reserve Bank. **Price level**: span: 1994:Q1-2022:Q4; source: Statistics South Africa (Stats SA). **Real exports**: span: 1994:Q1-2022:Q4; source: South African Reserve Bank. **Real imports**: span: 1994:Q1-2022:Q4. source; South African Reserve Bank. **Real trade balance**: ratio net exports to GDP. **Country spread**: span: 1994:Q4 - 2021:Q1; source:The J.P. Morgan Emerging Markets Bond Index Plus (EMBIG+).

- ***Turkey***. **Real GDP**: span: 1993:Q4-2022:Q4; source: Turkish Statistical Institute (TURKSTAT). **Real investment**: span: 1998:Q1-2022:Q4; sources: Turkish Statistical Institute (TURKSTAT) and Organisation for Economic Co-operation and Development (OECD) VPVOBARSA. **Price level**: span: 1993:Q4-2022:Q4; source: Turkish Statistical Institute (TURKSTAT). **Real exports**: span: 1998:Q1-2022:Q4; sources: Turkish Statistical Institute (TURKSTAT) and OECD CARSA. **Real imports**: span: 1998:Q1-2022:Q4; sources: Turkish Statistical Institute (TURKSTAT) and OECD CARSA. **Real trade balance**: ratio net exports to GDP. **Country spread**: span: 1996:Q3 - 2021:Q1; source: The J.P. Morgan Emerging Markets Bond Index Plus (EMBI+).

B Matrix Specifications

In this subsection, we present a summary of the matrix forms from the restrictions we imposed on the model specification in equation 2.1. More specifically, we estimate the

following structural panel vector autoregression model with two lags:

$$Ay_{i,t} = \alpha_i + B_1 y_{i,t-1} + B_2 y_{i,t-2} + \epsilon_{i,t}, \tag{B.1}$$

where the order of variables is as follows:

$$y_{i,t} = \begin{bmatrix} gdp_{i,t} \\ inv_{i,t} \\ tby_{i,t} \\ R_t^{US} \\ GR_t \\ ambig_t \\ R_{i,t} \end{bmatrix}.$$

After imposing all the restrictions discussed in the paper, the matrix summarizing the contemporaneous relationships, A, becomes:

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ A_{21} & 1 & 0 & 0 & 0 & 0 & 0 \\ A_{31} & A_{32} & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & A_{54} & 1 & 0 & 0 \\ 0 & 0 & 0 & A_{64} & A_{64} & 1 & 0 \\ A_{71} & A_{72} & A_{73} & A_{74} & A_{75} & A_{76} & 1 \end{bmatrix}$$

Following two matrices summarize the restrictions put on the first (B_1) and the second (B_2) lags, respectively:

$$B_1 = \begin{bmatrix} B_{1,11} & B_{1,12} & B_{1,13} & B_{1,14} & B_{1,15} & B_{1,16} & B_{1,17} \\ B_{1,21} & B_{1,22} & B_{1,23} & B_{1,24} & B_{1,25} & B_{1,26} & B_{1,27} \\ B_{1,31} & B_{1,32} & B_{1,33} & B_{1,34} & B_{1,35} & B_{1,36} & B_{1,37} \\ 0 & 0 & 0 & B_{1,44} & B_{1,45} & B_{1,46} & 0 \\ 0 & 0 & 0 & B_{1,54} & B_{1,55} & B_{1,56} & 0 \\ 0 & 0 & 0 & B_{1,64} & B_{1,65} & B_{1,66} & 0 \\ B_{1,71} & B_{1,72} & B_{1,73} & B_{1,74} & B_{1,75} & B_{1,76} & B_{1,77} \end{bmatrix}$$

$$B_2 = \begin{bmatrix} B_{2,11} & B_{2,12} & B_{2,13} & B_{2,14} & B_{2,15} & B_{2,16} & B_{2,17} \\ B_{2,21} & B_{2,22} & B_{2,23} & B_{2,24} & B_{2,25} & B_{2,26} & B_{2,27} \\ B_{2,31} & B_{2,32} & B_{2,33} & B_{2,34} & B_{2,35} & B_{2,36} & B_{2,37} \\ 0 & 0 & 0 & B_{2,44} & B_{2,45} & B_{2,46} & 0 \\ 0 & 0 & 0 & B_{2,54} & B_{2,55} & B_{2,56} & 0 \\ 0 & 0 & 0 & B_{2,64} & B_{2,65} & B_{2,66} & 0 \\ B_{2,71} & B_{2,72} & B_{2,73} & B_{2,74} & B_{2,75} & B_{2,76} & B_{2,77} \end{bmatrix}$$

C Robustness and Additional Analysis

C.1 Comparison with the results of Akinci (2013)

To assess the hypothesis that global financial risk plays an important role in driving country spreads and aggregate fluctuations in EMEs, Akıncı (2013) sets up a 6-variable structural panel VAR for a large set of EME countries with the following variables: EME real GDP, EME real investment, EME trade balance, U.S. rate, global financial risk (measured by the BAA corporate spread), and the country spread (measured by the EMBI). With the variables in this order, the VAR uses the typical Sims restrictions and in addition imposes that U.S. rate and global financial risk have an impact on all other variables but not the other way around. Recall that we build on this modeling strategy for our own analysis. For her benchmark analysis, Akinci uses quarterly data for Argentina, Brazil, Mexico, Peru,

South Africa and Turkey from 1994 through 2011, included. The model is estimated using the least square dummy variable (LSDV) estimator. Recall also that our own benchmark analysis uses quarterly data for the same set of countries as Akinci but extends her sample through the pre-pandemic period: the fourth quarter of 2019.

For the purposes of comparison to our benchmark 7-variable PSVAR, we present results from using Akinci's 6-variable model with our own benchmark data. On net, results are consistent with Akinci's findings. Figures C.1 to C.3 show IRF results from an unanticipated one standard deviation shock to: the country spread (Figure C.1), the U.S. rate (Figure C.2) and global financial risk (Figure C.3).

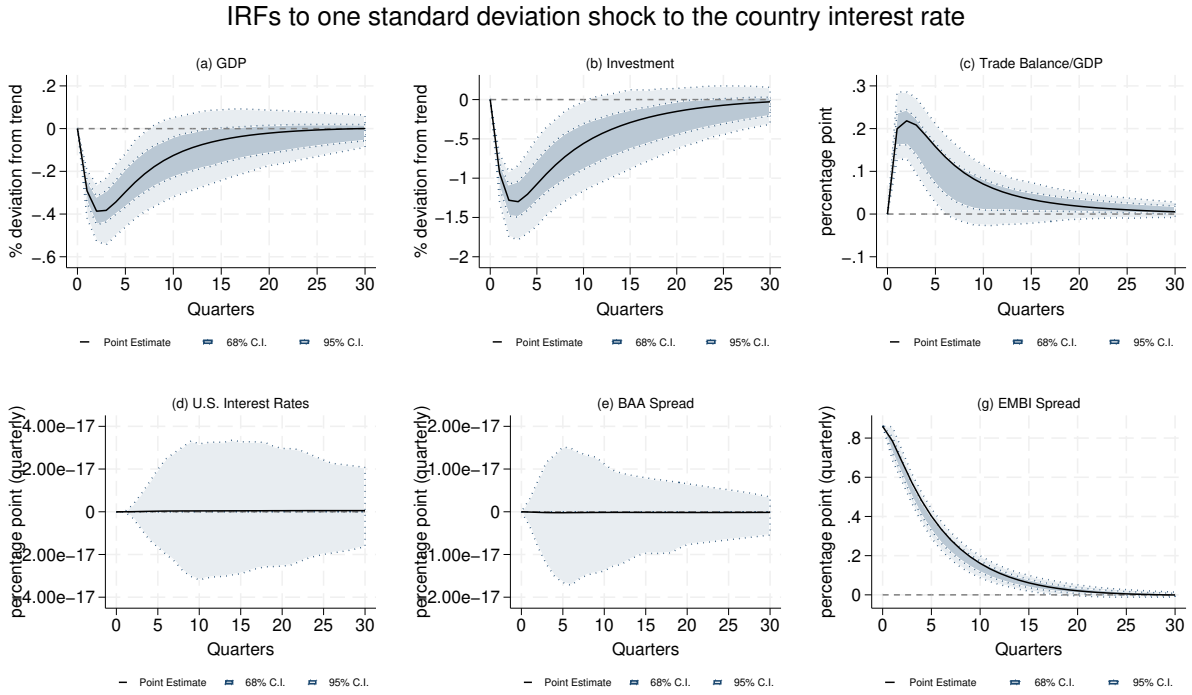


Figure C.1: IRFs to one std. dev. shock to country spread

Note: Estimated using our data through 2019:Q4 and the Akıncı (2013) specification with six variables.

As shown in Figure C.1, a shock to the country spread results in a contraction of EME GDP and investment and an expansion of the EME trade balance. These results are intuitive, as a shock to the country spread is in line with borrowing rates rising exogenously. As shown in Figure C.2, a shock to the U.S. rate yields similar results for GDP, investment, and the trade balance, although arguably of somewhat less significance. That said, this shock also

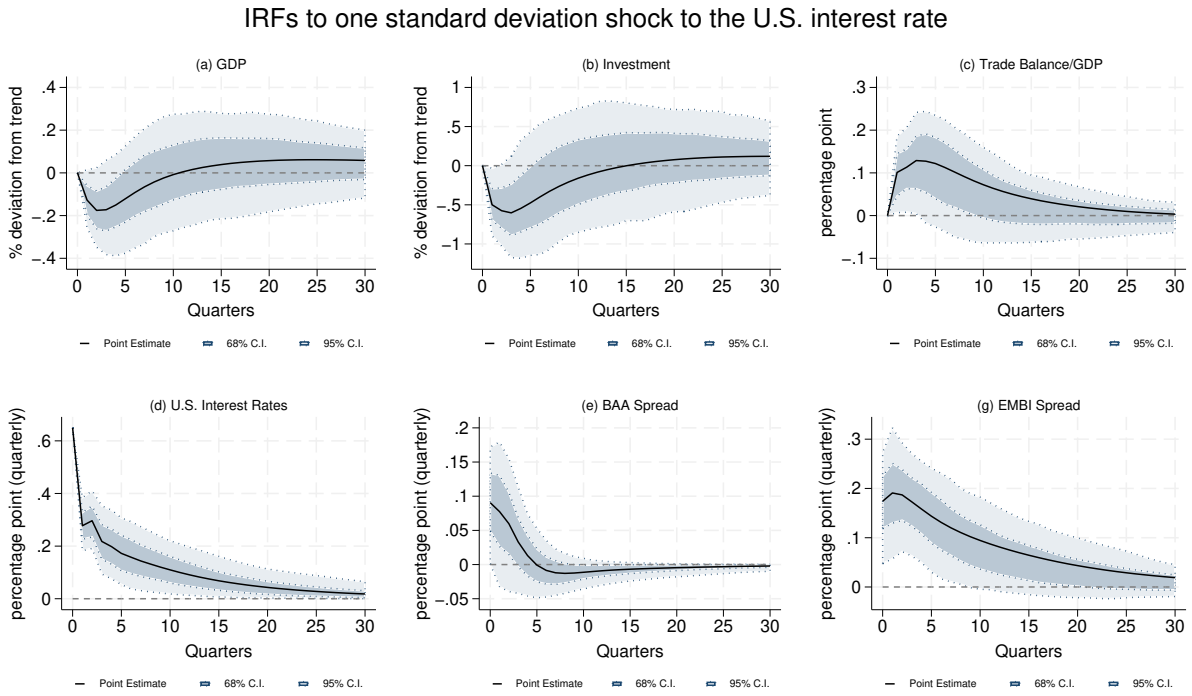


Figure C.2: IRFs to one std. dev. shock to U.S. interest rate

Note: Estimated using our data through 2019:Q4 and the Akıncı (2013) specification with six variables.

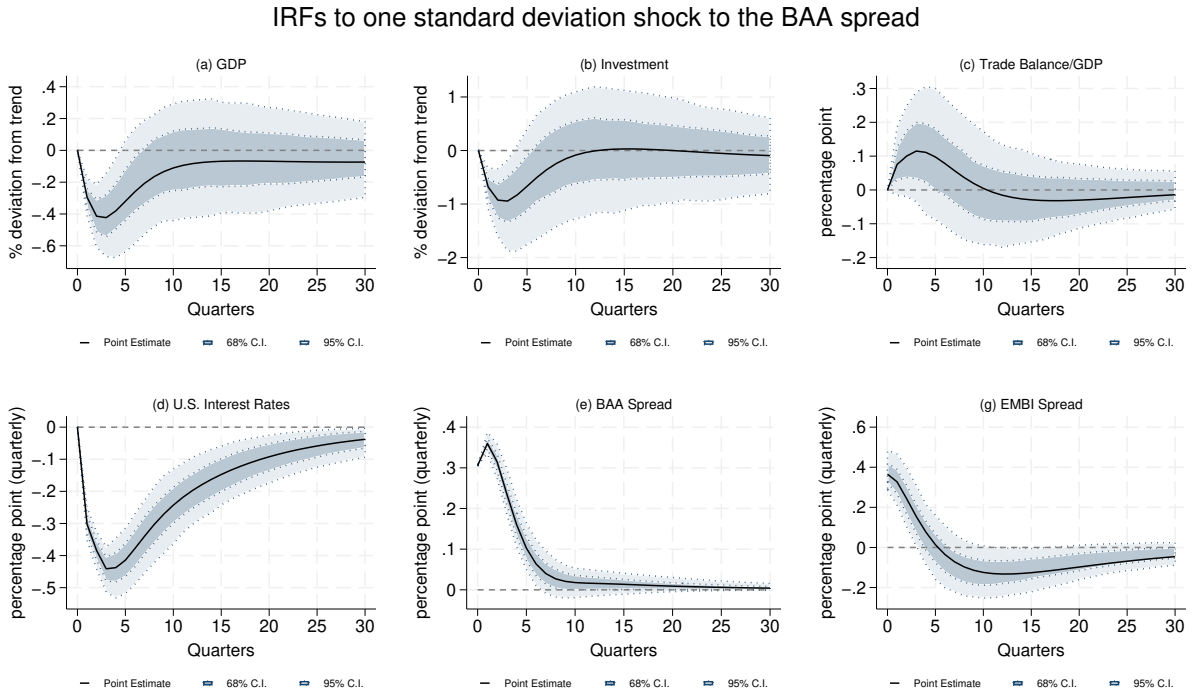


Figure C.3: IRFs to one std. dev. shock to BAA spread

Note: Estimated using our data through 2019:Q4 and the Akıncı (2013) specification with six variables.

generates a jump in the country spread and global financial risk. Intuitively, the shock to the U.S. rate can be interpreted as resulting in a rotation away from relatively riskier bonds—in the case of the model, BAA corporate bonds and EME country bonds—to the relatively safer U.S. sovereign bonds whose interest rate is now higher. As such, with lower relative demand for BAA corporate bonds and EME country bonds, their yields increase. Ultimately, the ensuing higher borrowing costs for EMEs drive similar dynamics in country variables as in the case of the shock to the country spread. (Akinci's benchmark result to a U.S. interest rate shock does not match our owing regarding BAA-spread dynamics due to the fact that her the Global Financial crisis composes a prominent fraction of her data's time span. Nonetheless, our BAA-spread results match up with Akinci's own analysis when Akinci uses pre- and post- Global Financial Crisis data between 1994 and 2011.)

Finally, Figure C.3 shows the impact of a shock to the BAA spread, which can be interpreted as an exogenous shock to global financial risk. Against this backdrop there is a flight to safety to U.S. **sovereign** bonds, which drives a substantial and significant decline in the U.S. interest rate. The retreat to safer assets lowers demand for EME country bonds, which increases the country spread and, therefore, EME borrowing costs resulting in EME GDP and investment decreasing and doing so by a greater amount, both quantitatively and in terms of significance, compared to the case of the country interest rate and U.S. rate shocks. (As shown in Figures C.4 to C.6, in all cases restricting the sample to Akinci's time frame tends to, on net, magnify the significance of results.)

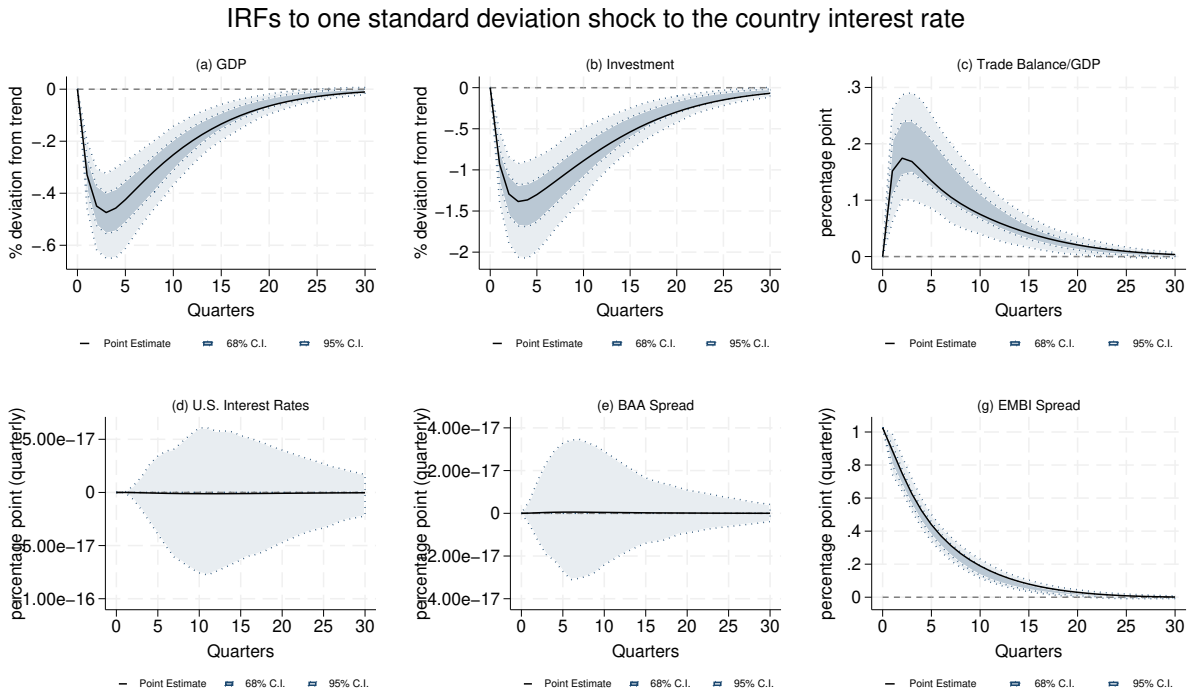


Figure C.4: IRFs to one std. dev. shock to country spread through 2011:Q4

Note: Estimated using our data through 2011:Q4 and the Akıncı (2013) specification with six variables.

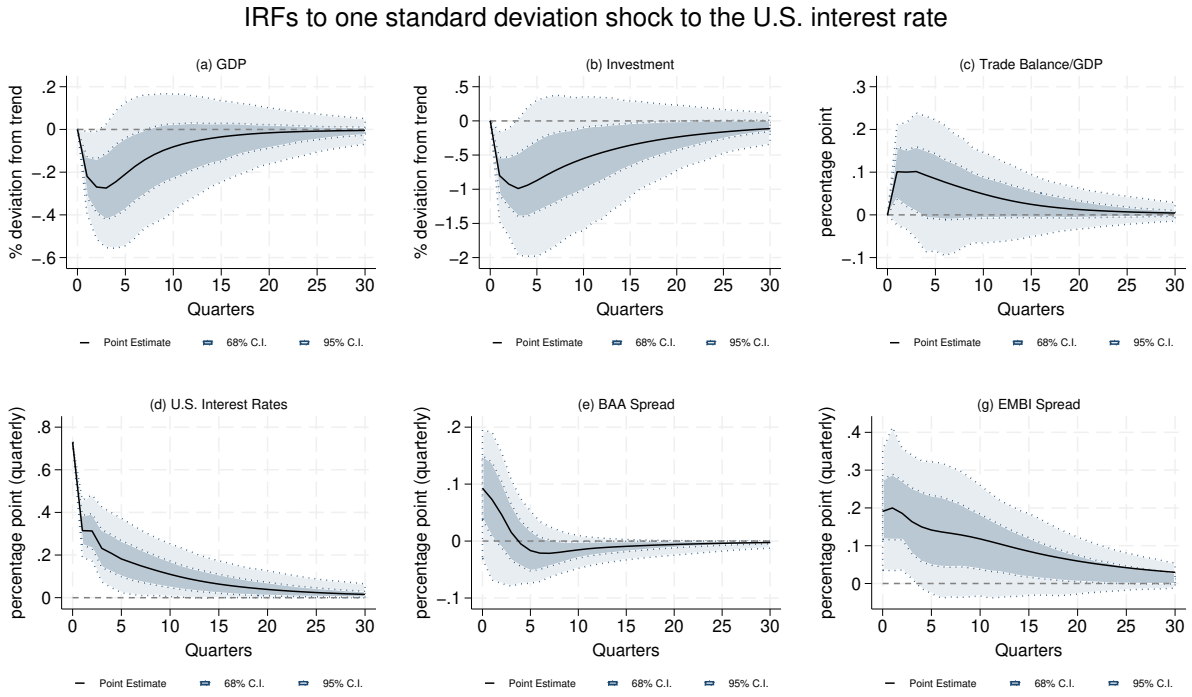


Figure C.5: IRFs to one std. dev. shock to U.S. interest rate through 2011:Q4

Note: Estimated using our data through 2011:Q4 and the Akıncı (2013) specification with six variables.

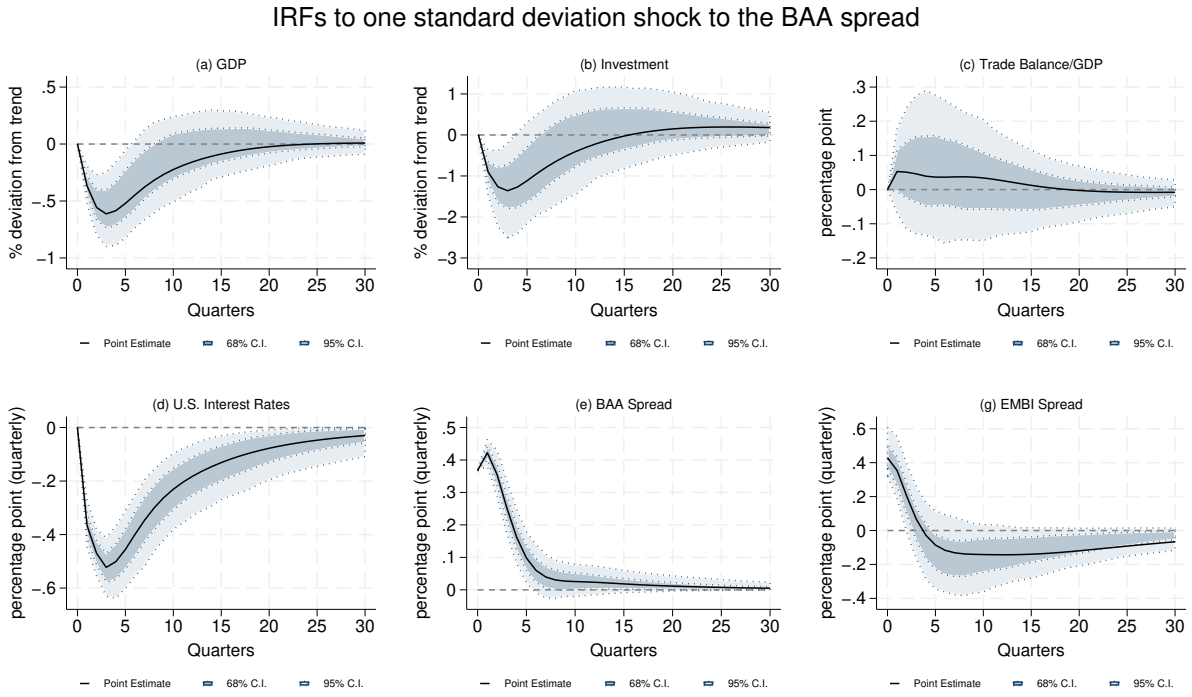


Figure C.6: IRFs to one std. dev. shock to BAA spread through 2011:Q4

Note: Estimated using our data through 2011:Q4 and the Akıncı (2013) specification with six variables.

C.2 Global risk, ambiguity, and dispersion of beliefs

In this subsection, we explore how an unexpected increase in global financial risk (proxied by an increase in BAA spread) leads to a decline in the degree of ambiguity in U.S. equity markets. Our proposed mechanism suggest that global financial risk influence investors beliefs about expected market returns, which in turn, affects the degree of ambiguity. To provide suggestive evidence for this mechanism, we estimated a VAR with three variables: *(i)* global financial risk (proxied by the BAA spread); *(ii)* U.S. equity markets' ambiguity; and *(iii)* a measure of dispersion of investors' beliefs, proxied by the difference between the highest and the lowest values of expectations for the return of the S&P 500 over the next year from the CFO survey of Duke University and Federal Reserve Banks of Richmond and Atlanta. Table C.1 and figure C.7 present the results suggesting that an increase in the BAA spread leads to rise in dispersion of beliefs, which in turn reduces ambiguity.

Dependent variable	**Regressor**	**p-value**
Belief dispersion	*BAA spread*	0.002***
	Ambiguity	0.126
BAA Spread	*Belief dispersion*	0.365
	Ambiguity	0.552
Ambiguity	*Belief dispersion*	0.000***
	BAA spread	0.001***

Table C.1: Granger Causality Wald Tests

Note: This table reports p-values of the Wald statistics of the traditional Granger-causality test. The statistics are based on a 3-variable VAR with two lags. *** denotes that the null hypothesis that the regressor does not Granger-cause the dependent variable can be rejected at 1 percent significance level.

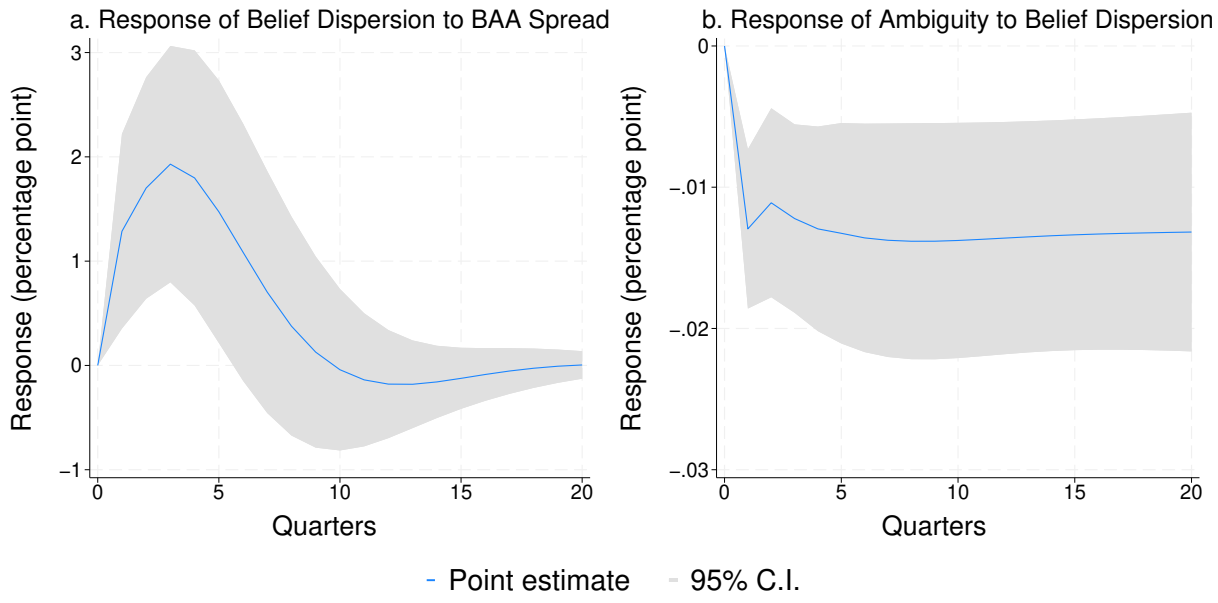


Figure C.7: Impulse Response Functions from 3-Variable VAR

Note: These panels show selected impulse response functions from a 3-variable VAR with the BAA spread, dispersion of beliefs, and U.S. equity markets' ambiguity. All variables are detrended using a time-trend and the lag order of estimation is 2.

C.3 Alternative filters

We assess the implications of relaxing the assumption of the benchmark linear trend by allowing for curvature on the margin using the HP filter with smoothing parameter 10^5 and the Baxter-King (BK) and Christiano-Fitzgerald (CF) filters with lower band equal to 2 and upper band equal to 250. These parameter choices allow for some, but not excessive, curvature in the trend component relative to its linear counterpart. Of note, regarding the BK and CF filters the lower band of 2 quarters captures short-term fluctuations, while the upper band of 250 quarters includes longer-term components, introducing moderate curvature. Results are shown below for all shocks across these different filters.

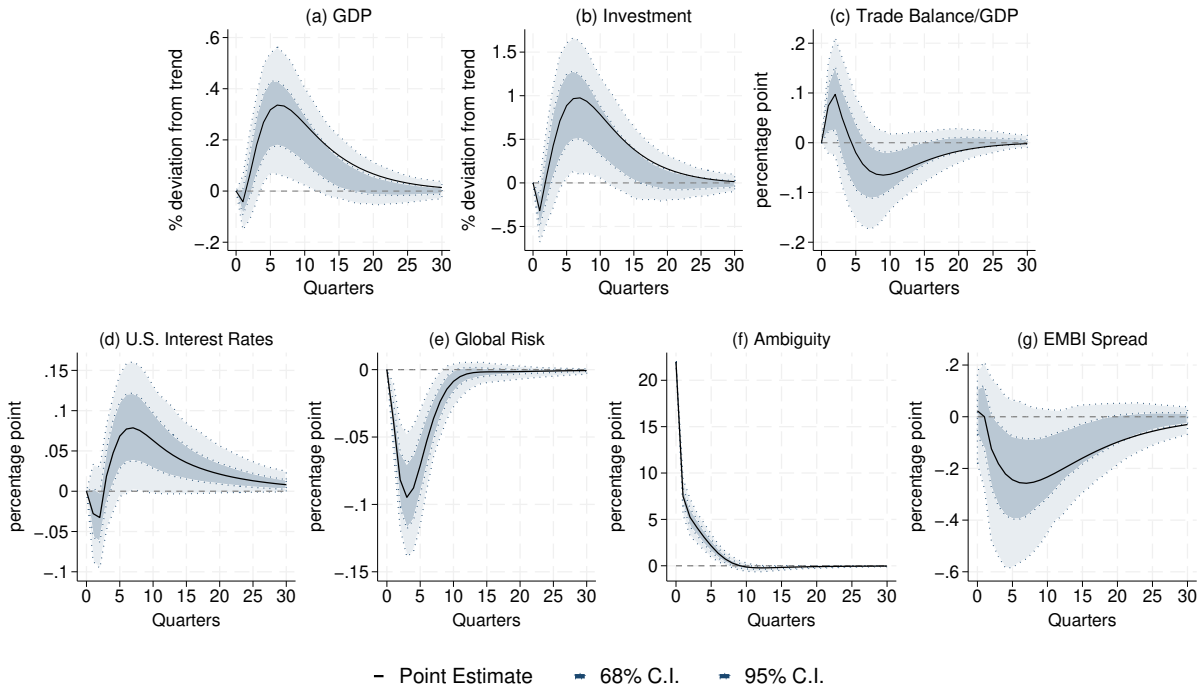


Figure C.8: IRFs to one std. dev. shock to ambiguity

Note: Baseline model with HP filtered data.

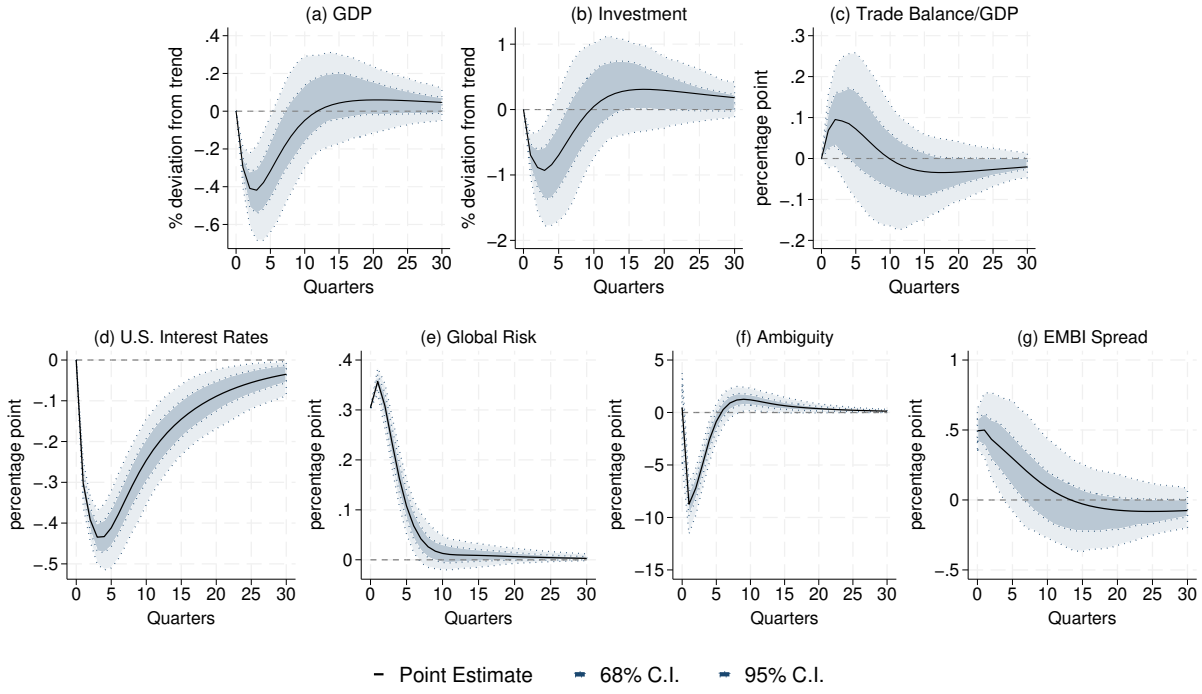


Figure C.9: IRFs to one std. dev. shock to BAA spread

Note: Baseline model with HP filtered data.

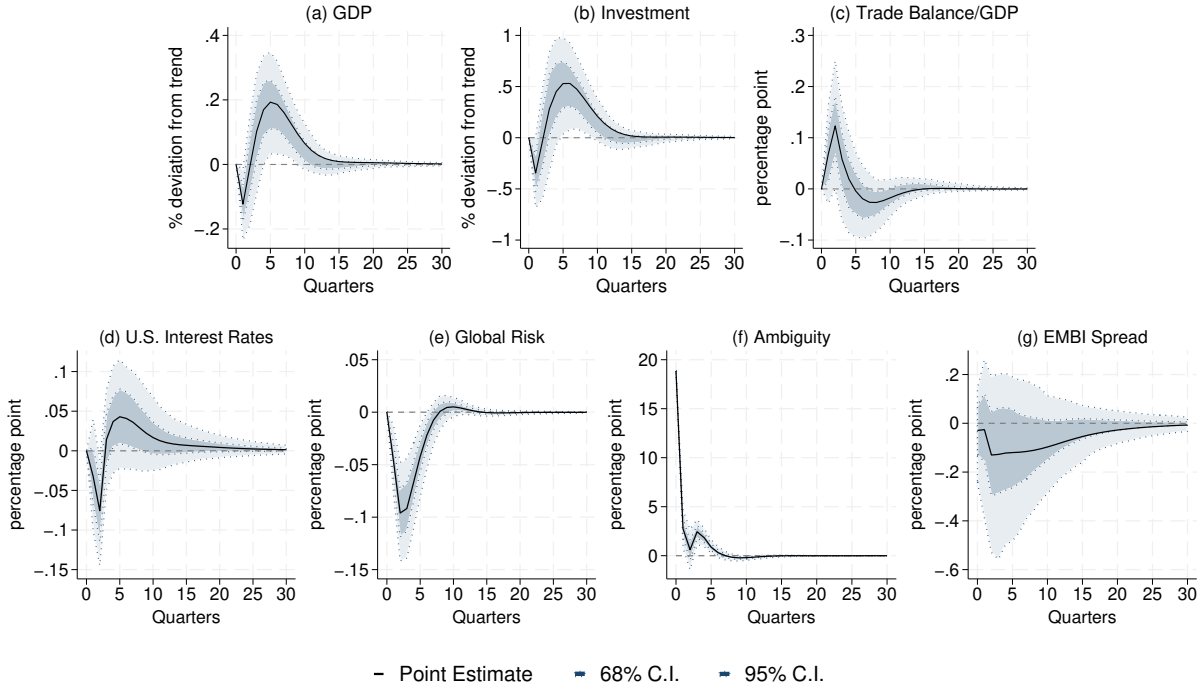


Figure C.10: IRFs to one std. dev. shock to ambiguity

Note: Baseline model with Baxter-King filtered data.

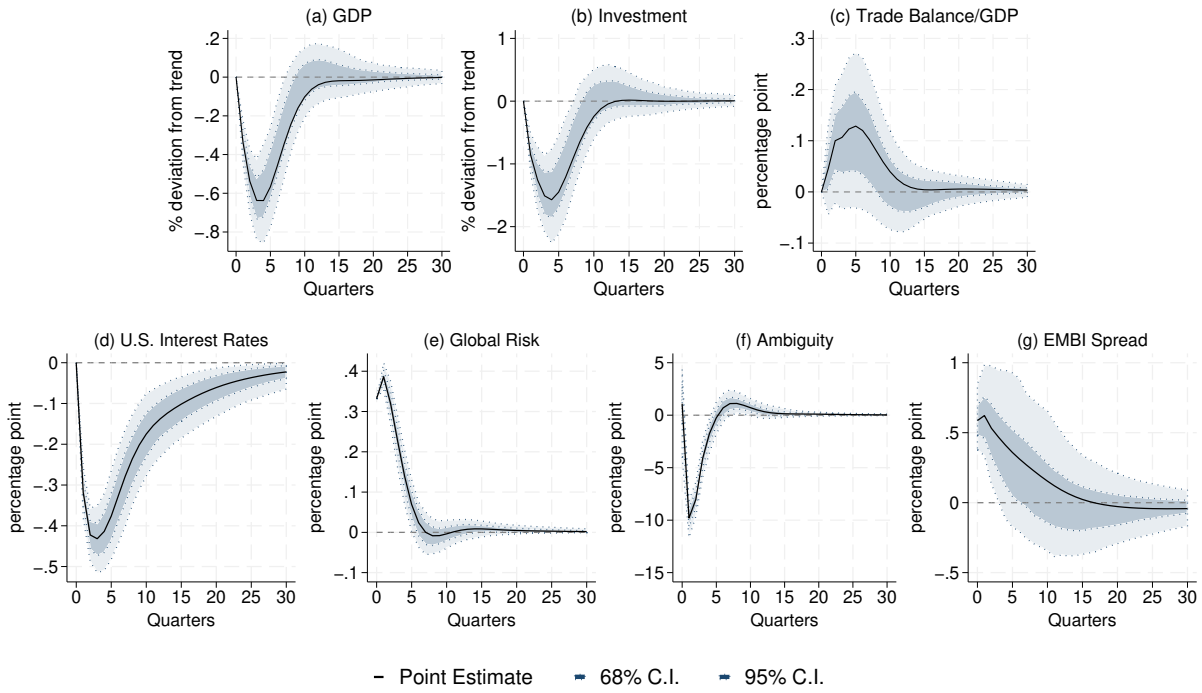


Figure C.11: IRFs to one std. dev. shock to BAA spread

Note: Baseline model with Baxter-King filtered data.

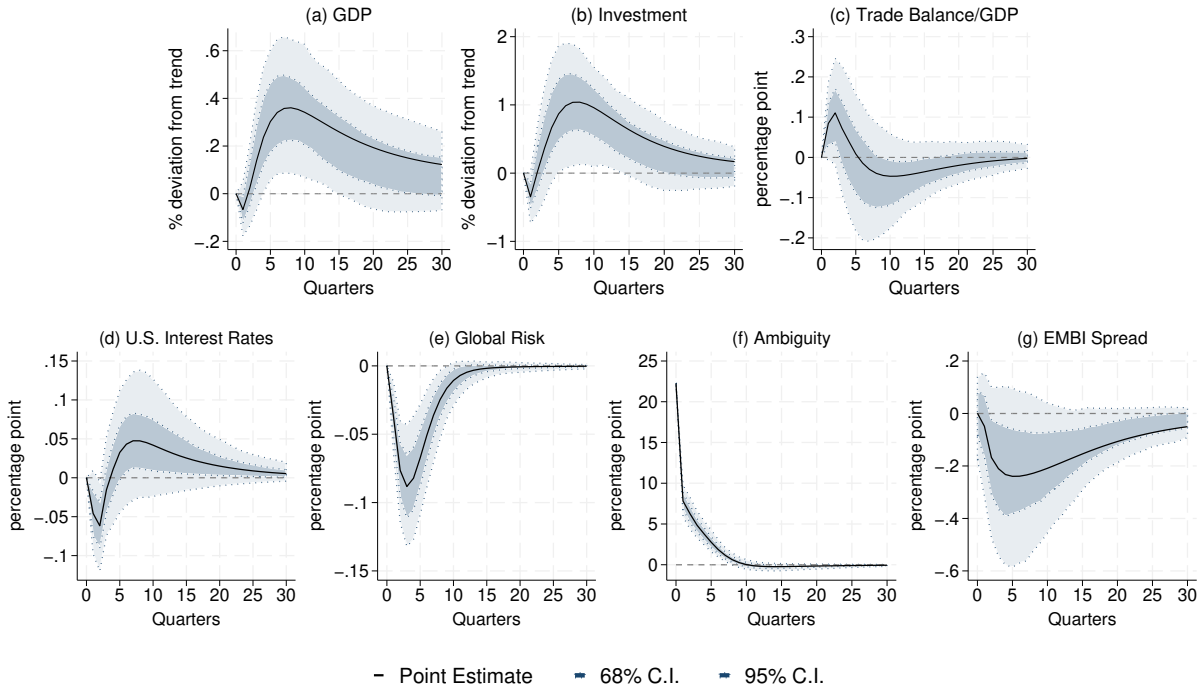


Figure C.12: IRFs to one std. dev. shock to ambiguity

Note: Baseline model with Christiano-Fitzgerald filtered data.

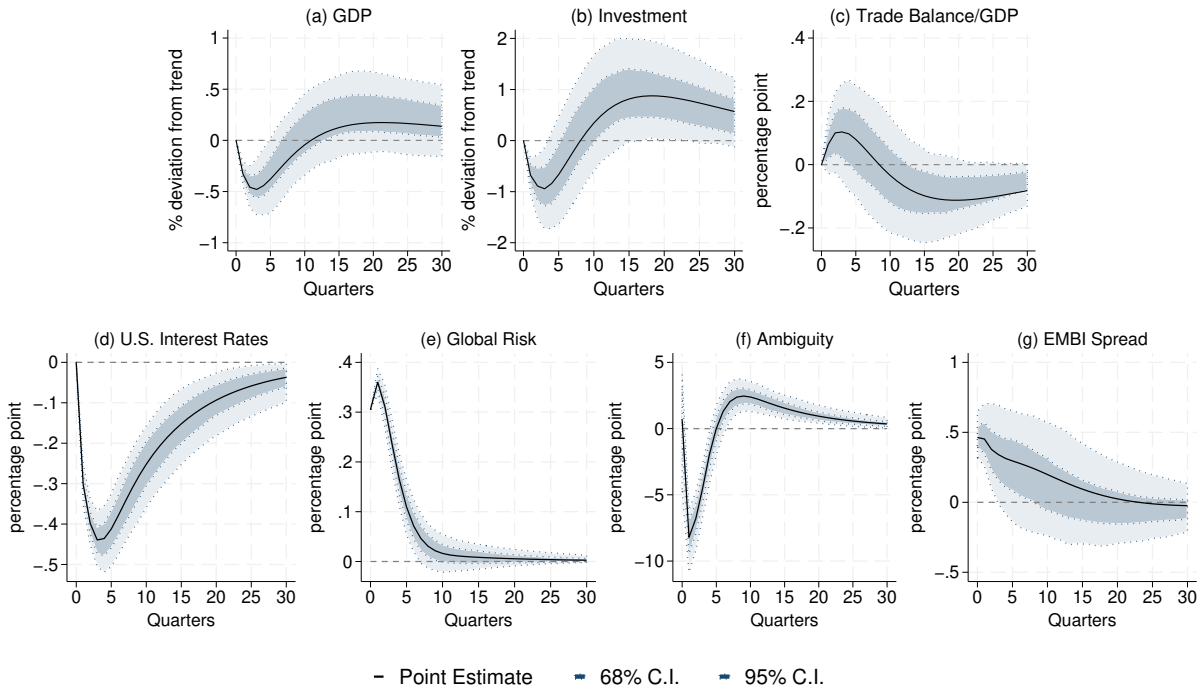


Figure C.13: IRFs to one std. dev. shock to BAA spread

Note: Baseline model with Christiano-Fitzgerald filtered data.

C.4 Alternative lag orders

The figures below show results from estimation with, alternatively, 1 and 3 lags.

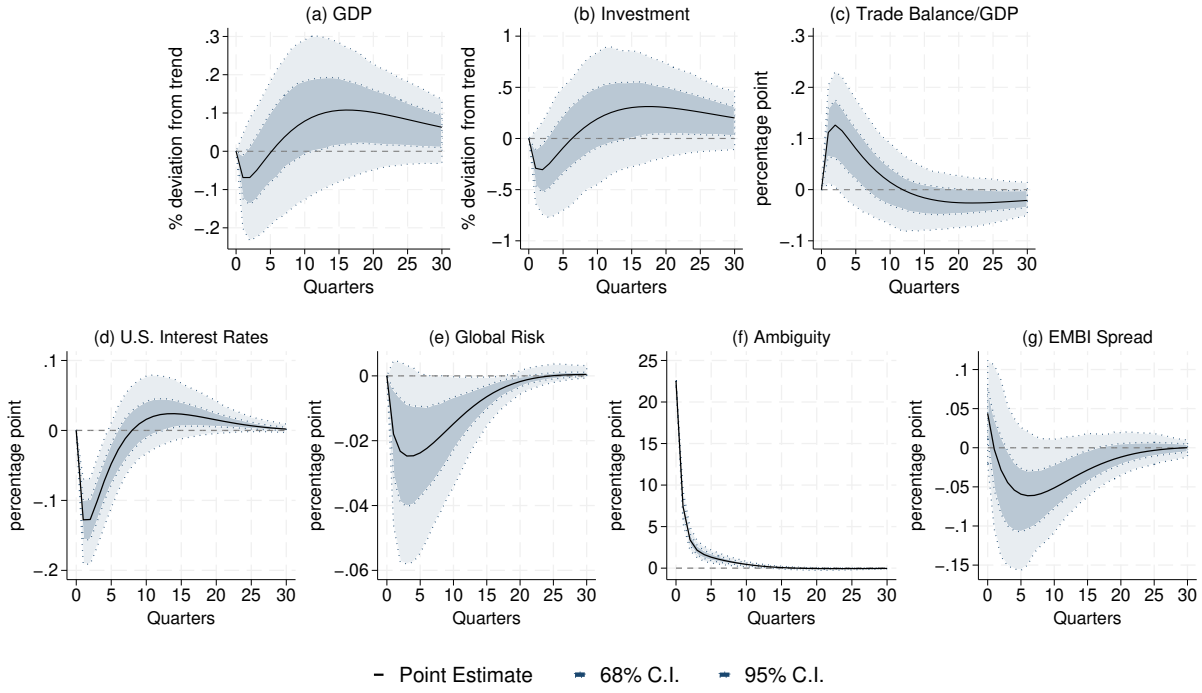


Figure C.14: IRFs to one std. dev. shock to ambiguity

Note: Panel SVAR with lag length = 1.

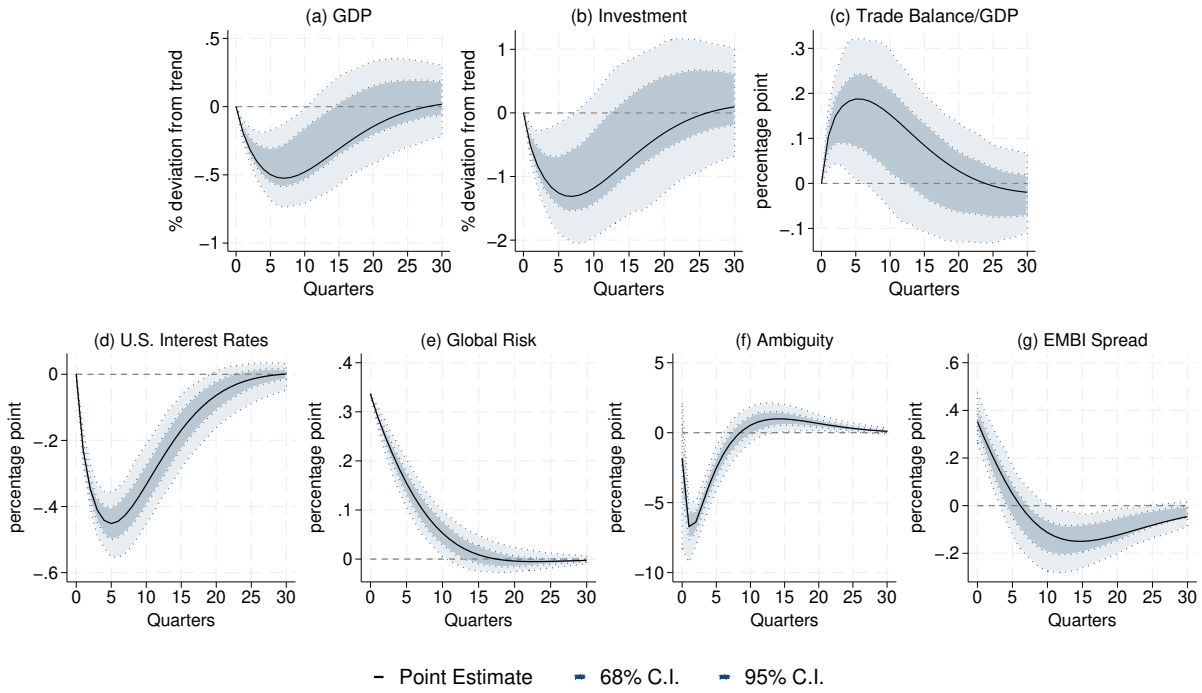


Figure C.15: IRFs to one std. dev. shock to BAA spread

Note: Panel SVAR with lag length = 1.

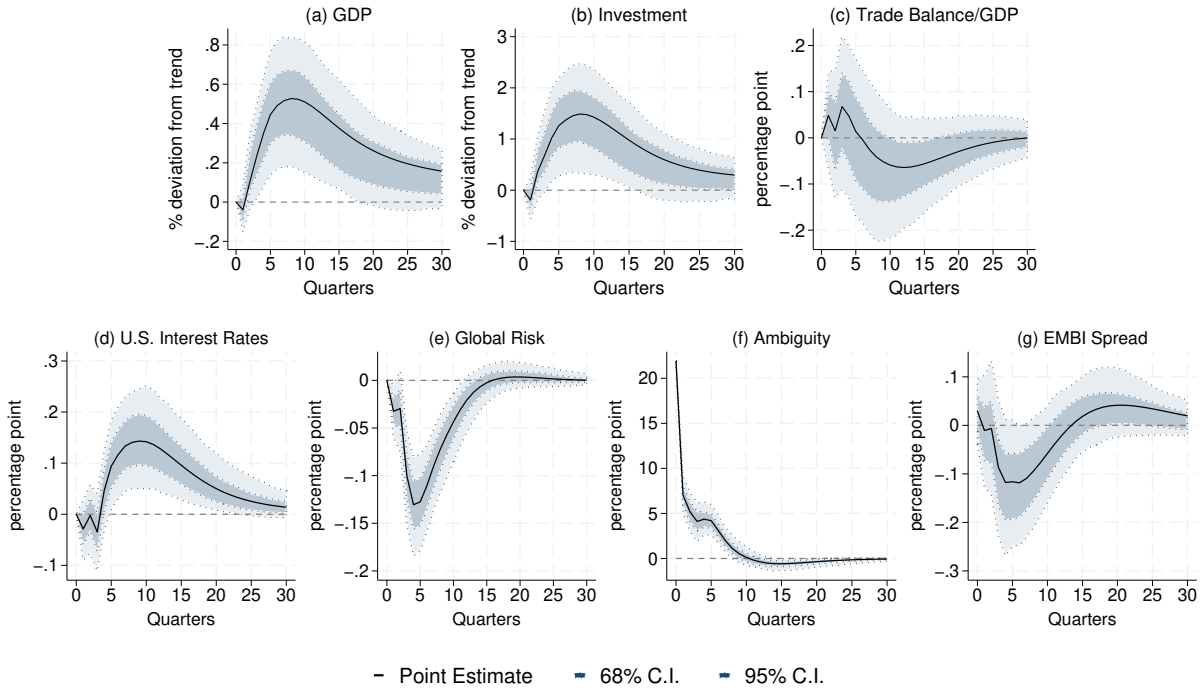


Figure C.16: IRFs to one std. dev. shock to ambiguity

Note: Panel SVAR with lag length = 3.

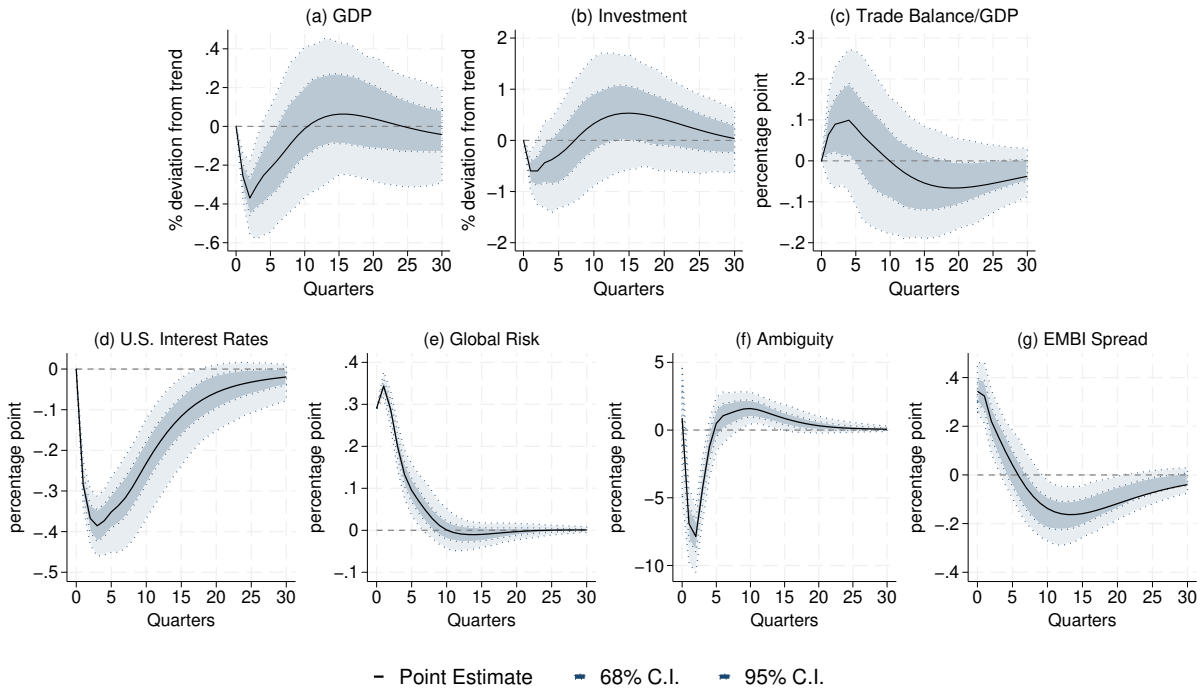


Figure C.17: IRFs to one std. dev. shock to BAA spread

Note: Panel SVAR with lag length = 3.

C.5 Alternative specifications

The figures below show the results (i) when we allow for all variables to depend on all other variables in the model, including the U.S. interest rate, the Baa spread, and ambiguity, (ii) when there are no spillovers between the variables in the shock block, (iii) when there are no spillovers from country spread to real variables, and (iv) when we change the orderings of the shock block variables.

C.5.1 All shock variables feed each other

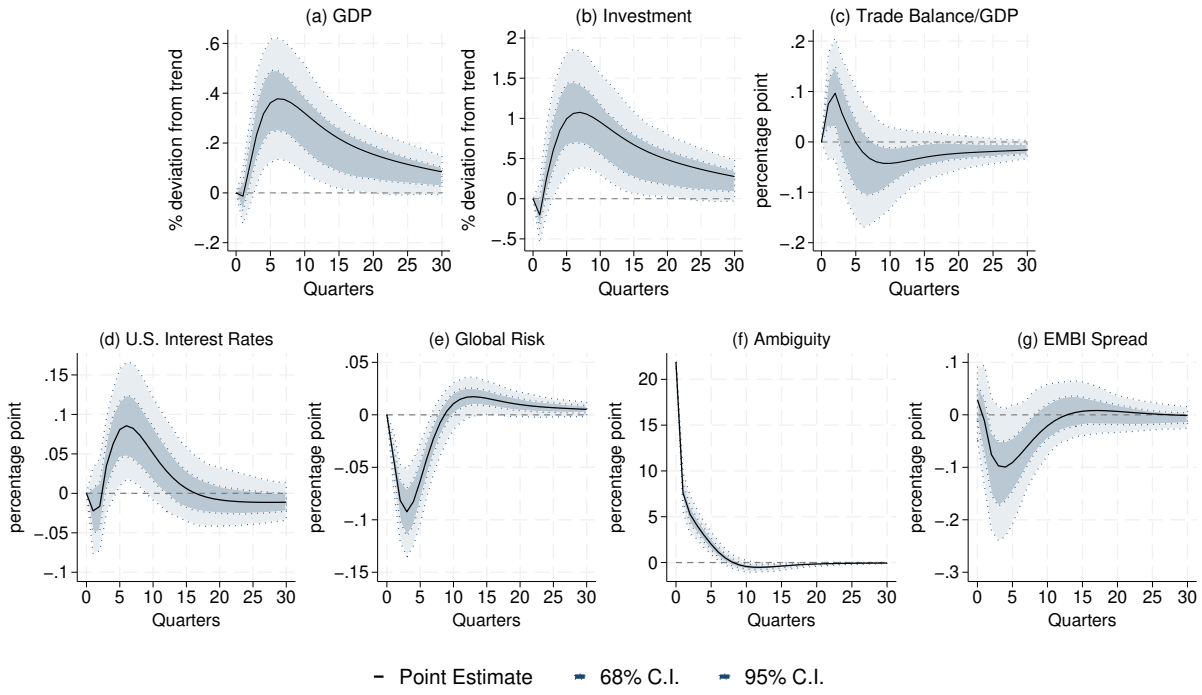


Figure C.18: IRFs to one std. dev. shock to ambiguity when all variables feed each other

Note: Panel SVAR when all variables are allowed to depend on all other variables in the model.

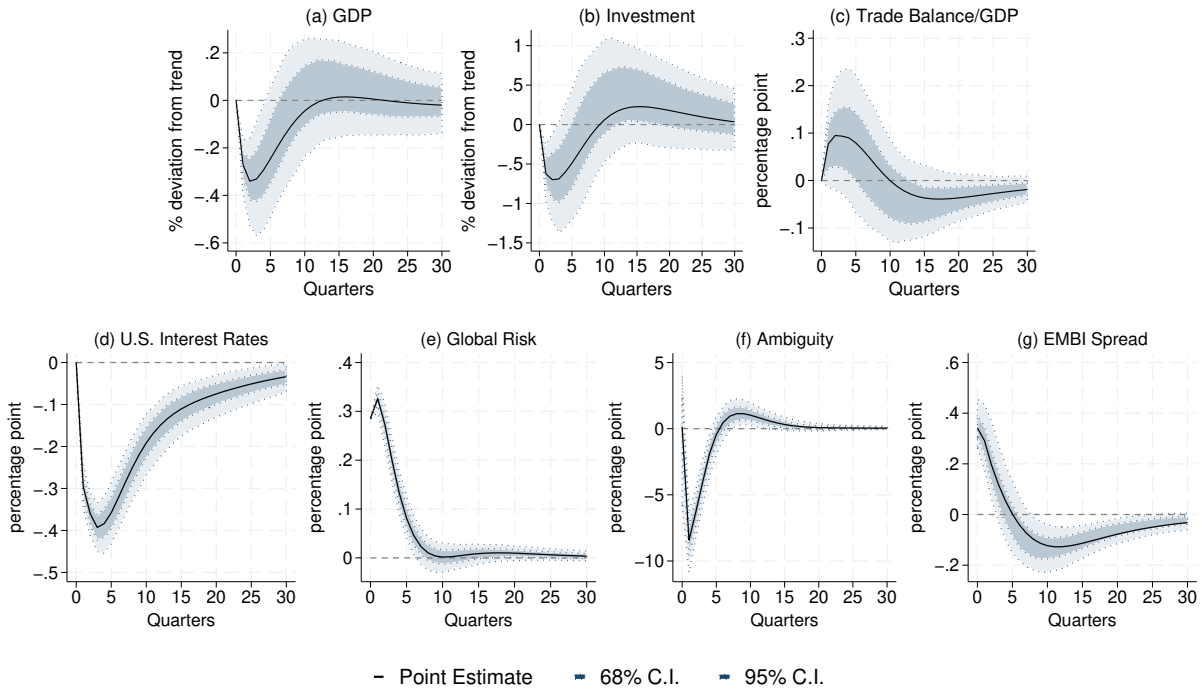


Figure C.19: IRFs to one std. dev. shock to BAA spread when all variables feed each other

Note: Panel SVAR when all variables are allowed to depend on all other variables in the model.

C.5.2 No shock block spillovers

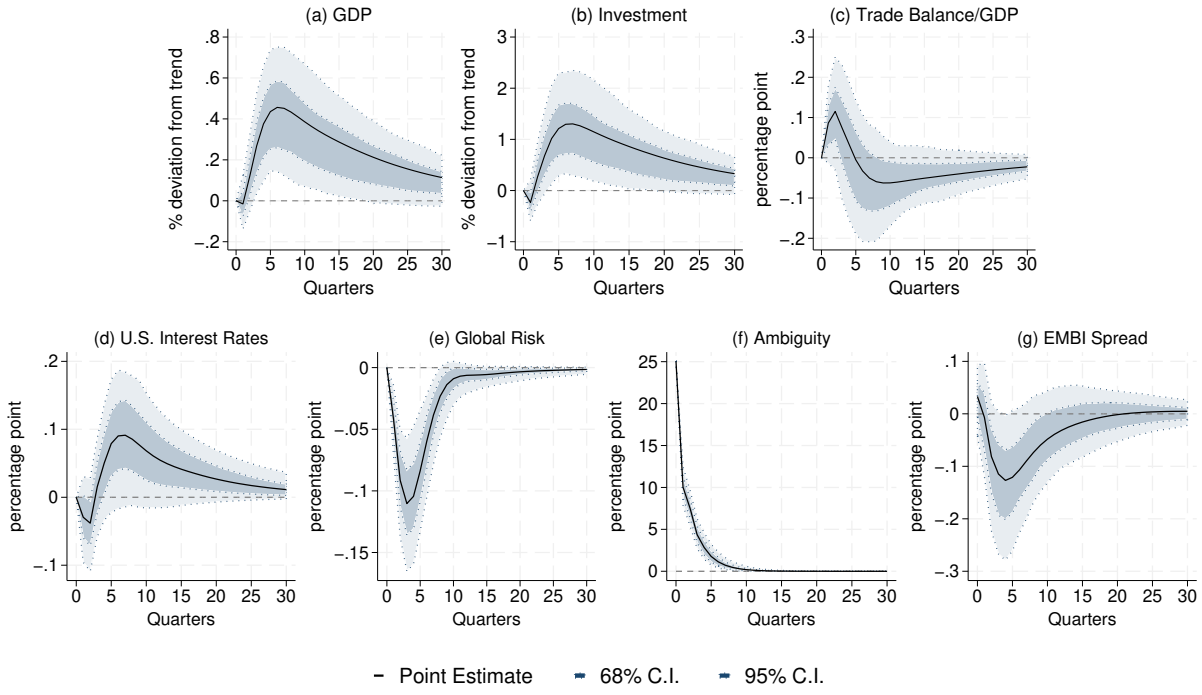


Figure C.20: IRFs to one std. dev. shock to ambiguity when ambiguity is VAR(2)

Note: Panel SVAR when there are no spillovers between ambiguity and other shock variables.

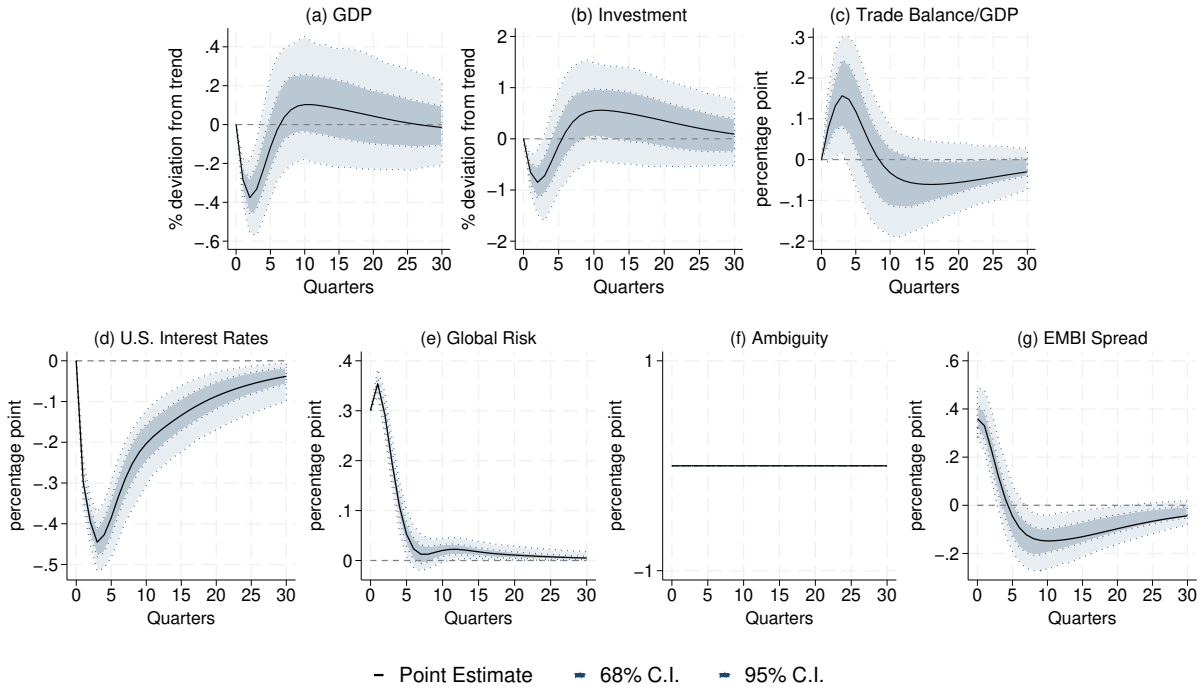


Figure C.21: IRFs to one std. dev. shock to BAA spread when ambiguity is VAR(2)

Note: Panel SVAR when we there are no spillovers between ambiguity and other shock variables.

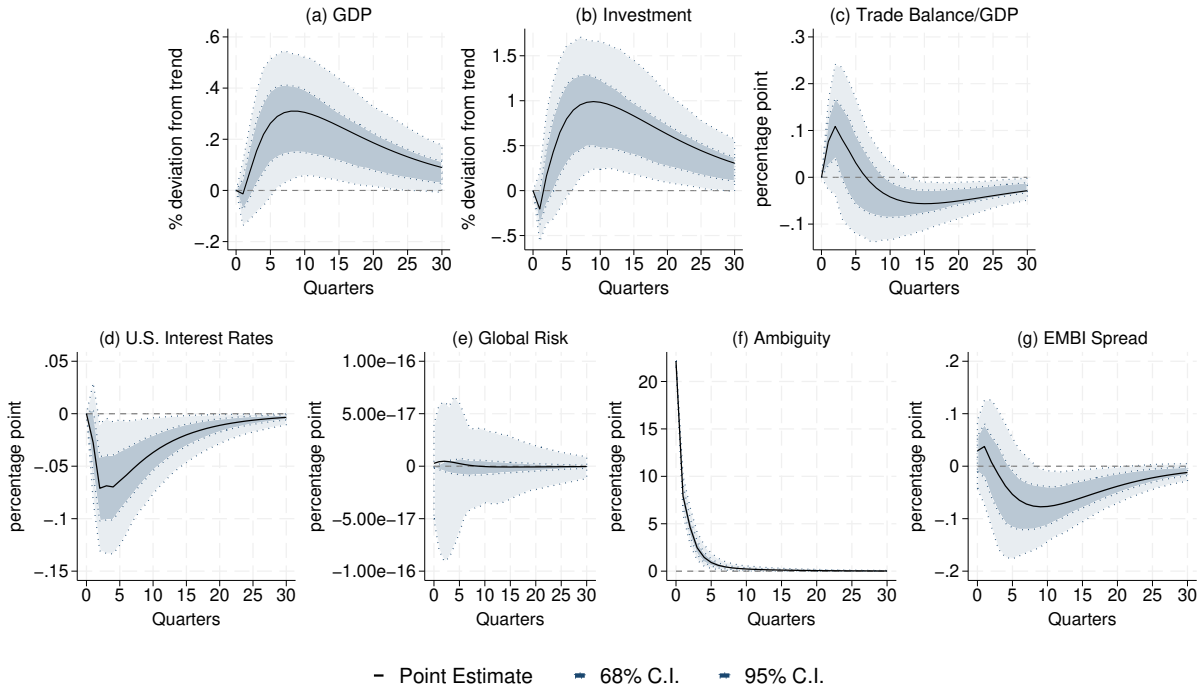


Figure C.22: IRFs to one std. dev. shock to ambiguity when BAA spread is VAR(2)

Note: Panel SVAR when we there are no spillovers between BAA spread and other shock variables.

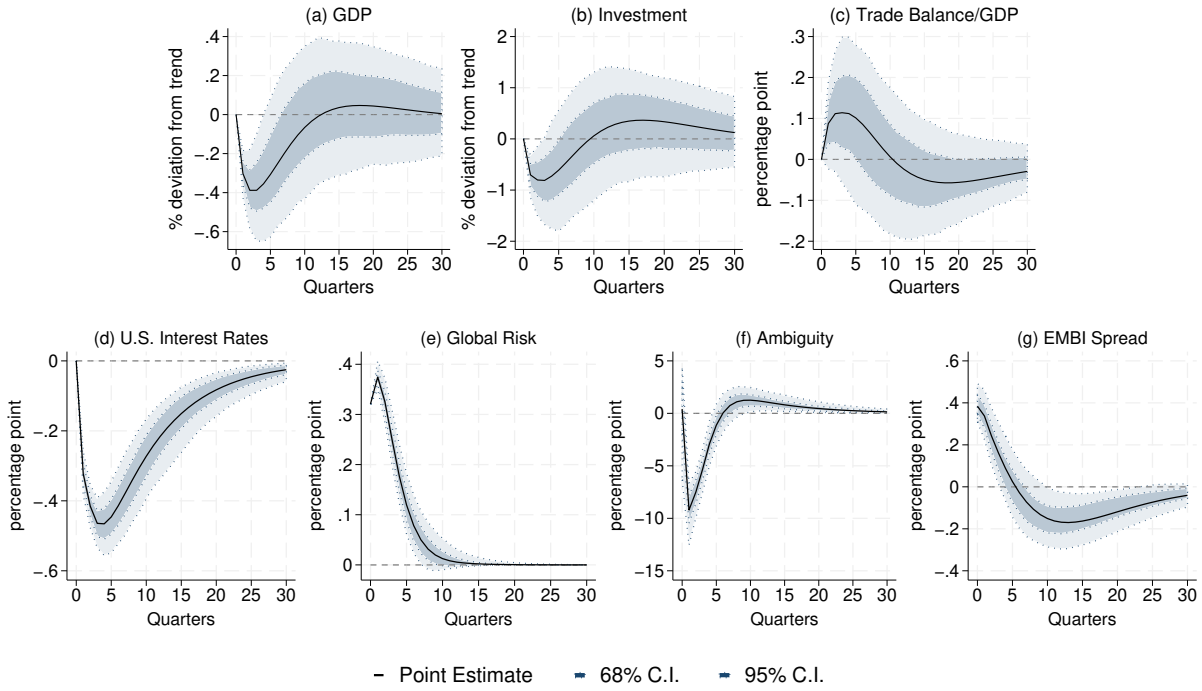


Figure C.23: IRFs to one std. dev. shock to BAA spread when BAA spread is VAR(2)

Note: Panel SVAR when there are no spillovers between BAA spread and other shock variables.

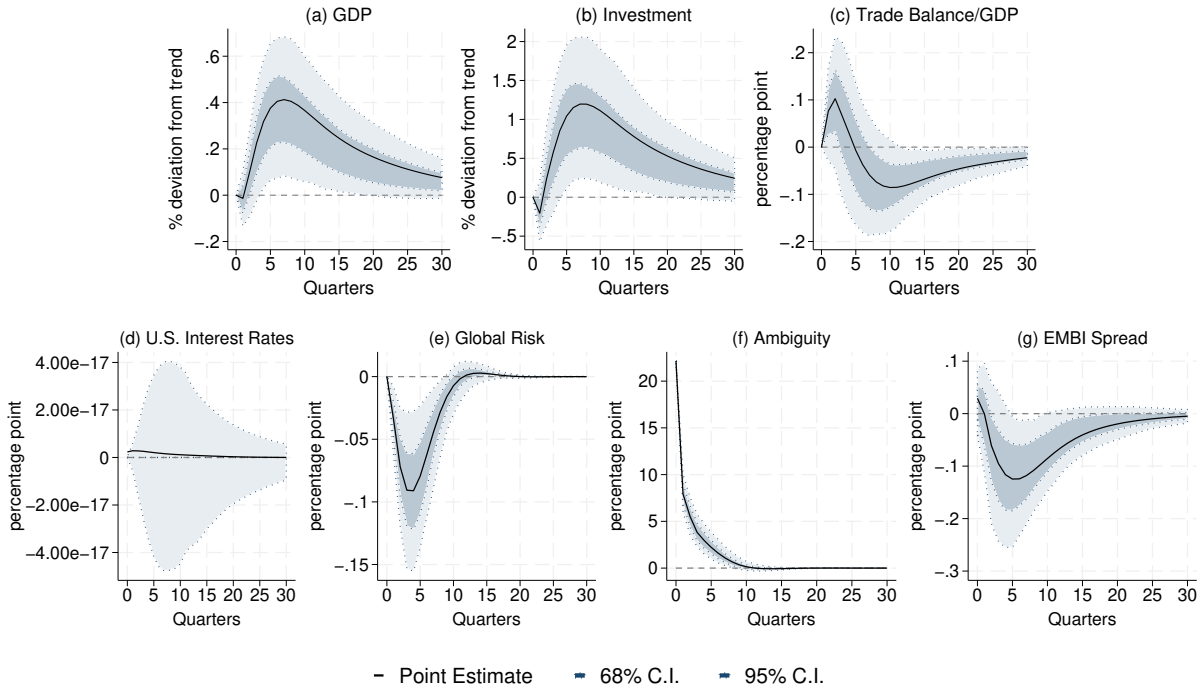


Figure C.24: IRFs to one std. dev. shock to ambiguity when U.S. interest rate is VAR(2)

Note: Panel SVAR when there are no spillovers between U.S. interest rate and other shock variables.

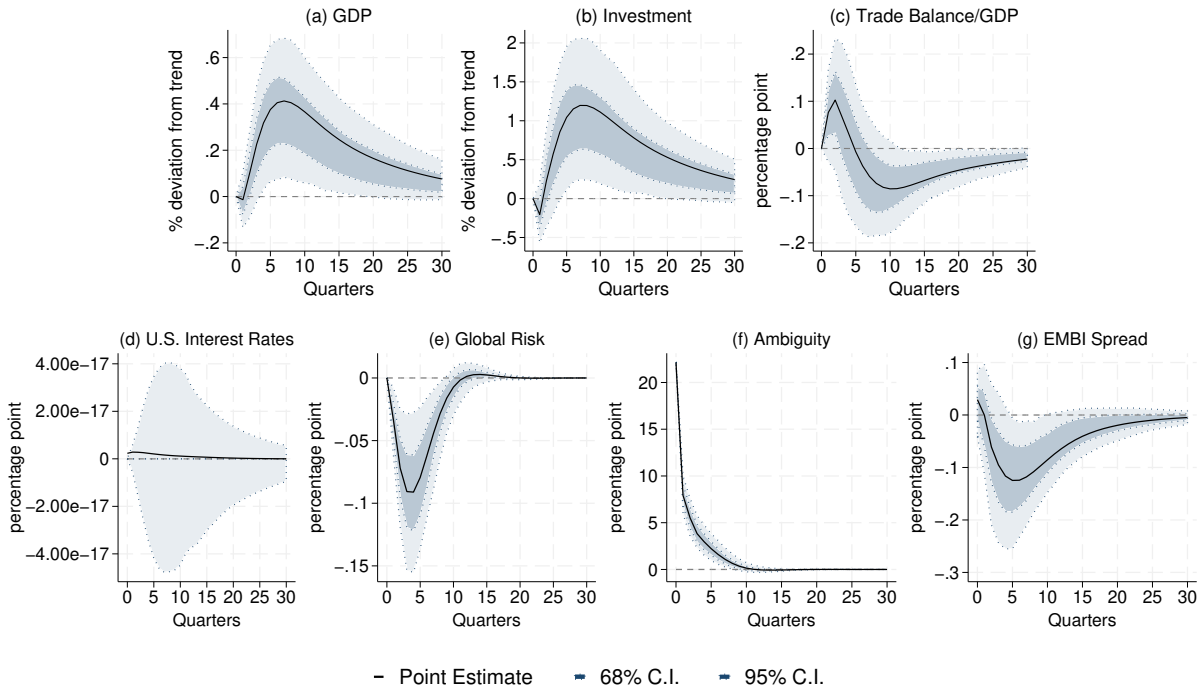


Figure C.25: IRFs to one std. dev. shock to BAA spread when U.S. interest rate is VAR(2)

Note: Panel SVAR when there are no spillovers between U.S. interest rate and other shock variables.

C.5.3 Country spread does not depend on shock variables

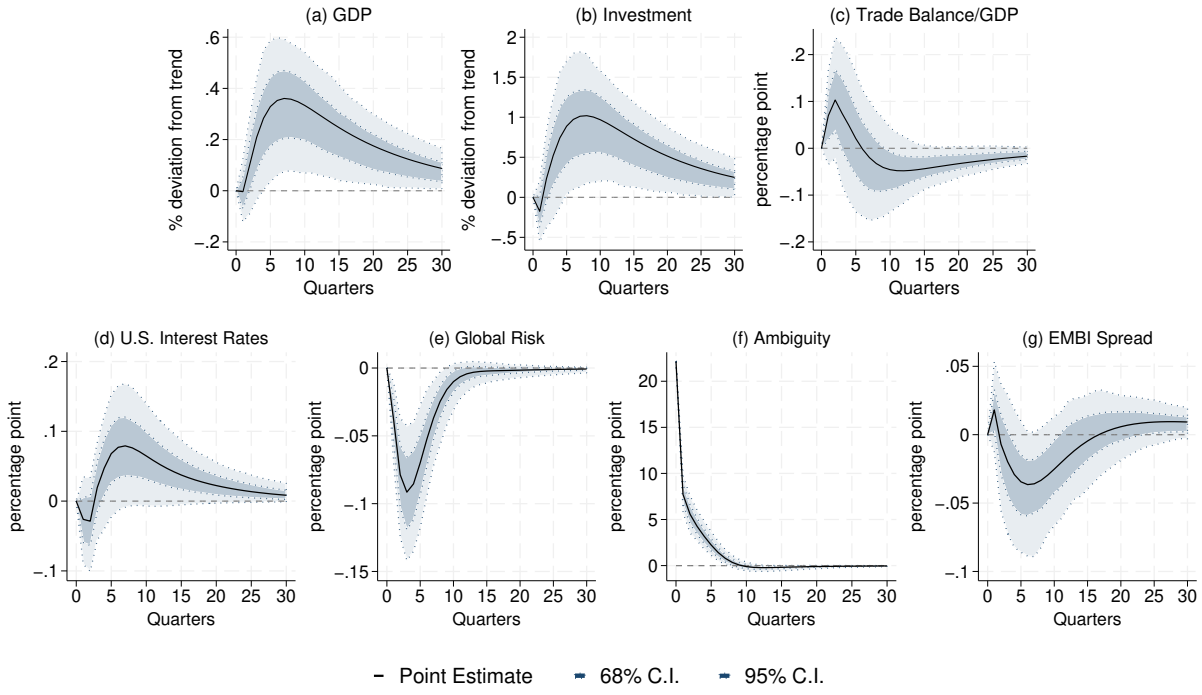


Figure C.26: IRFs to one std. dev. shock to ambiguity when country spread does not depend on shock block variables

Note: Panel SVAR when we assume country spread does not depend on shock block variables.

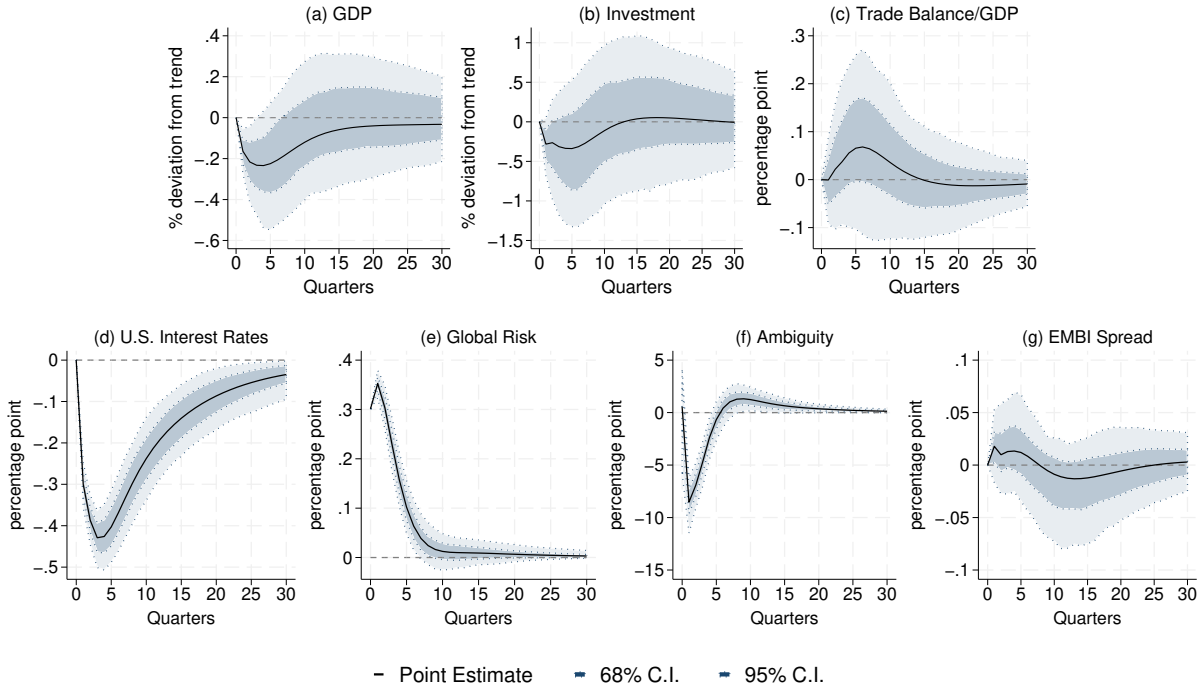


Figure C.27: IRFs to one std. dev. shock to BAA spread when country spread does not depend on shock block variables

Note: Panel SVAR when we assume country spread does not depend on shock block variables.

C.5.4 No spread between country spread and real variables

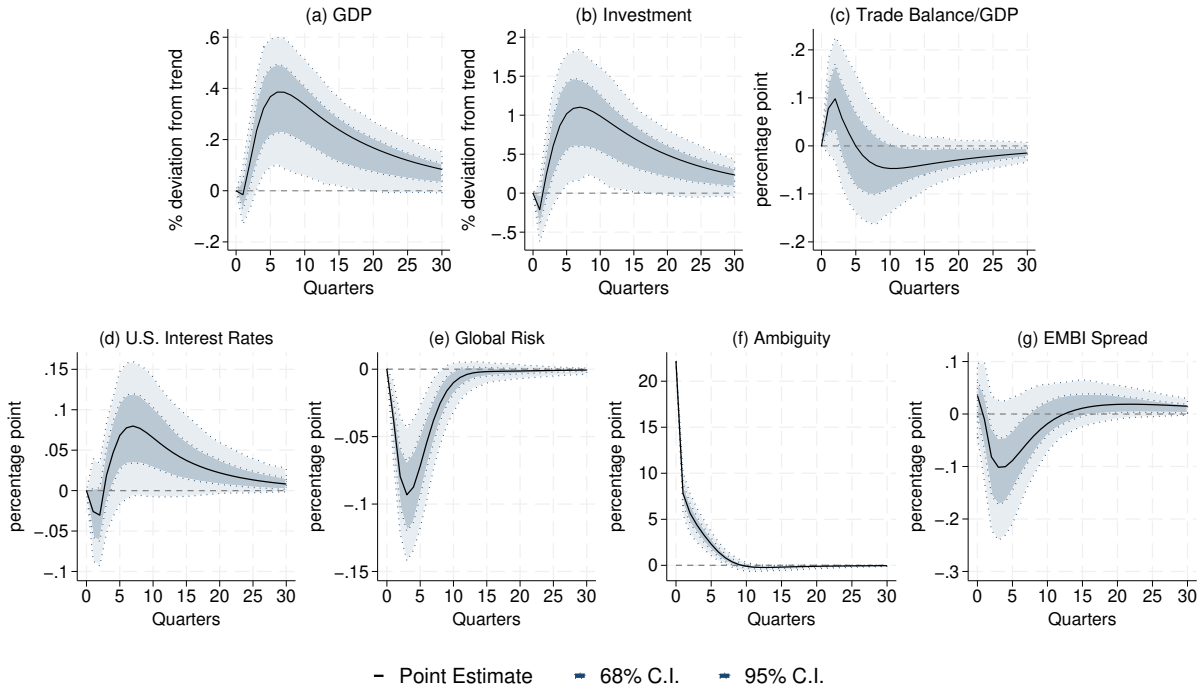


Figure C.28: IRFs to one std. dev. shock to ambiguity when no spillovers between country spread and real variables

Note: Panel SVAR when we assume country spread does not depend on real variables.

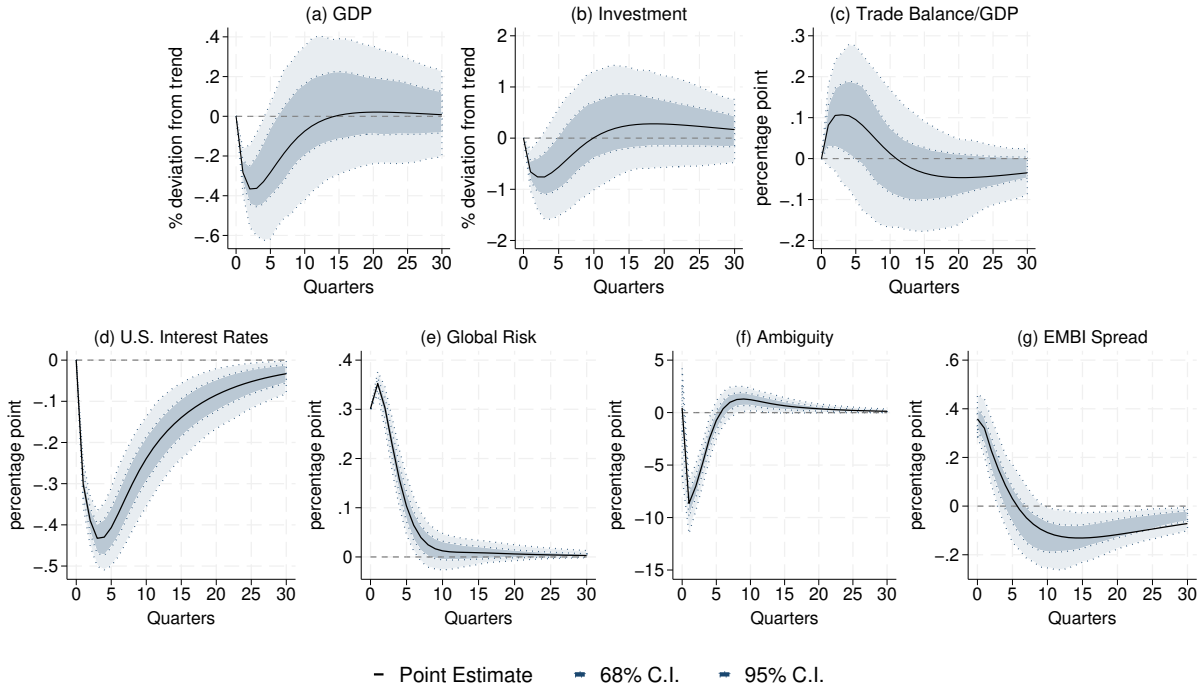


Figure C.29: IRFs to one std. dev. shock to BAA spread when no spillovers between country spread and real variables

Note: Panel SVAR when we assume country spread does not depend on real variables.

C.5.5 Alternative shock block orderings

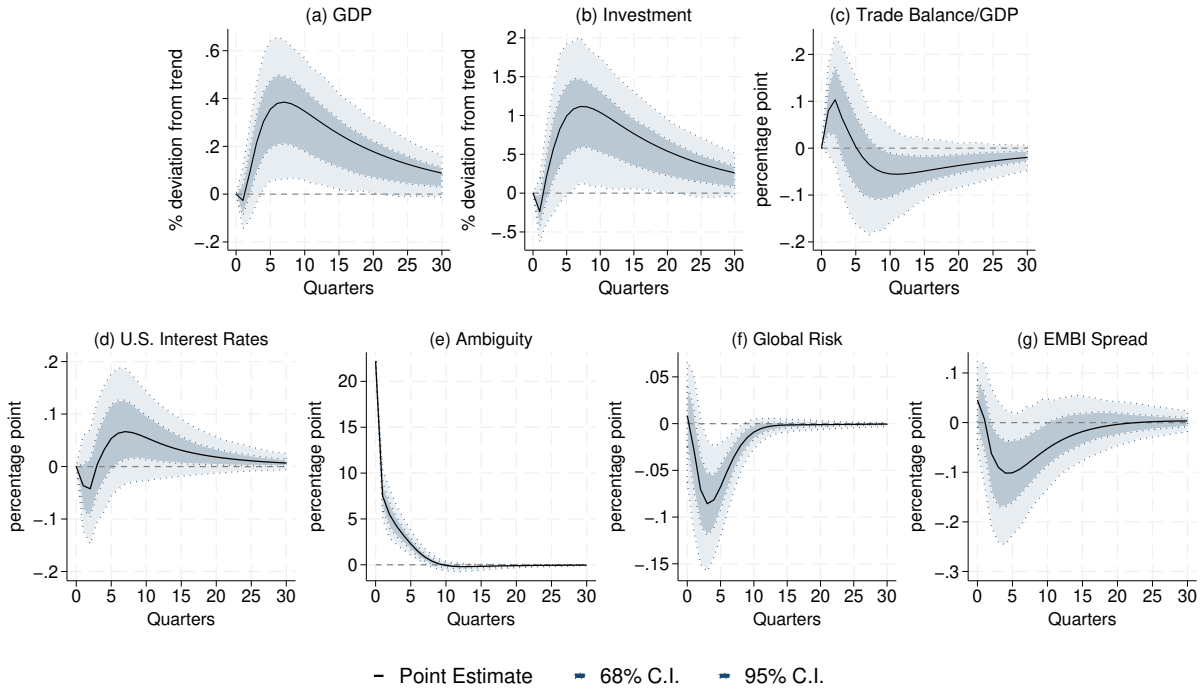


Figure C.30: IRFs to one std. dev. shock to ambiguity with alternative ordering

Note: Panel SVAR when we order the shock block as: R_t^{US}, $ambig_t$, and GR_t.

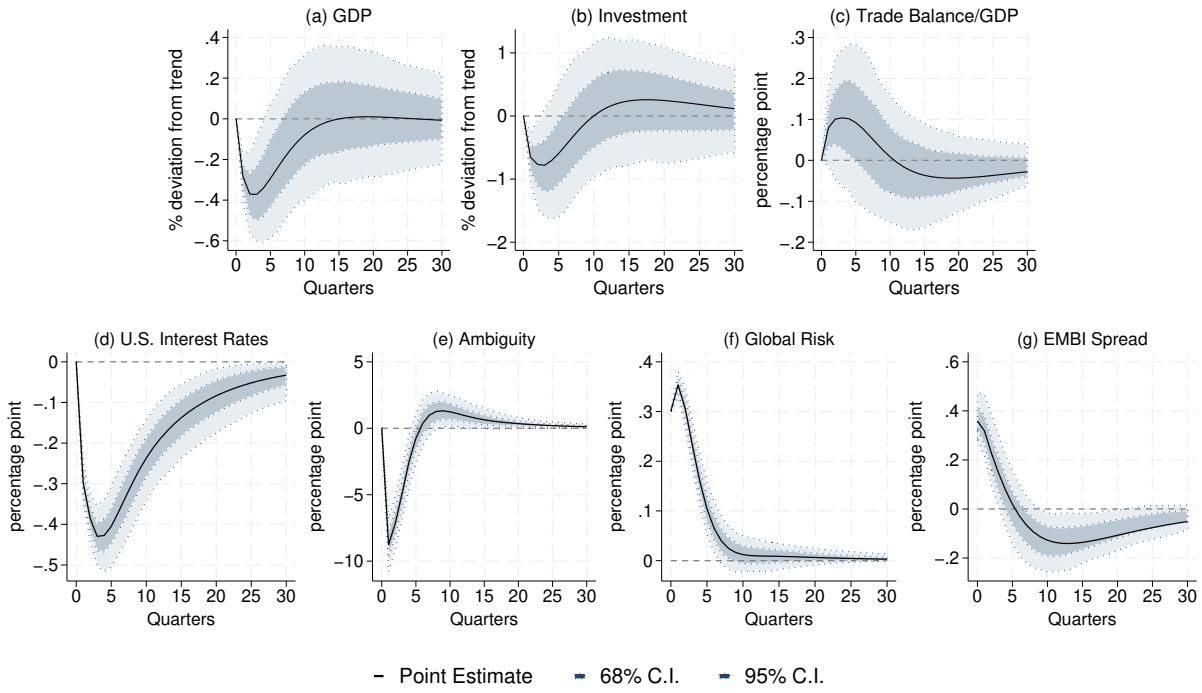


Figure C.31: IRFs to one std. dev. shock to BAA spread with alternative ordering

Note: Panel SVAR when we order the shock block as: R_t^{US}, $ambig_t$, and GR_t.

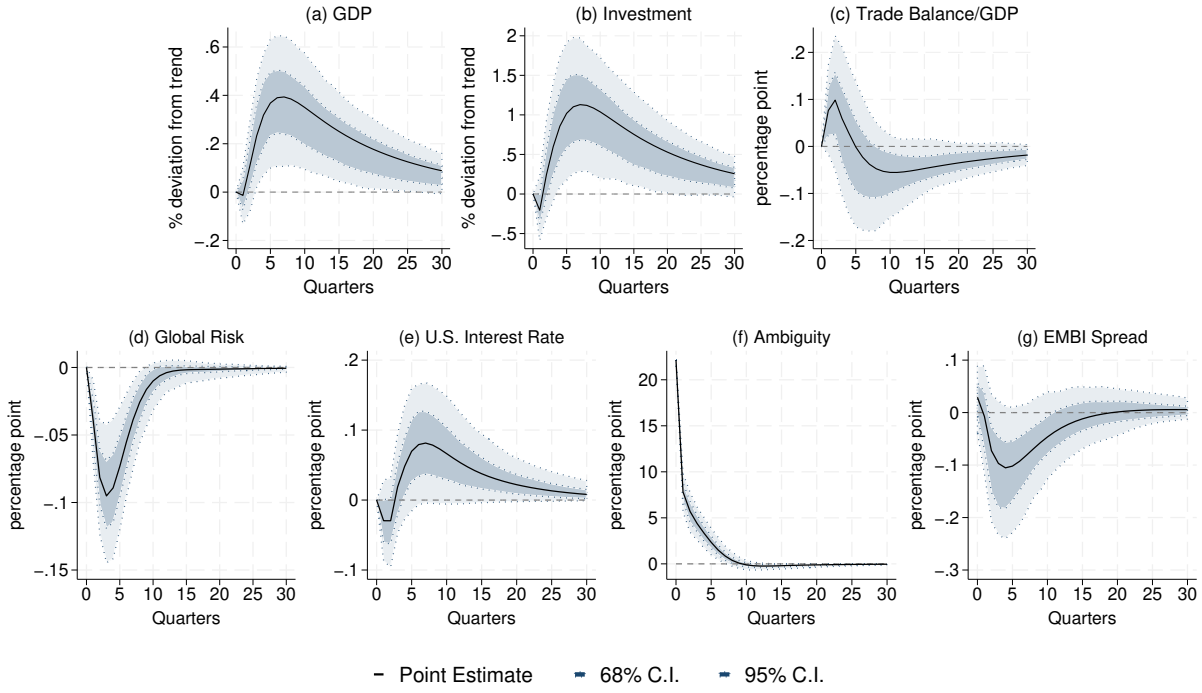


Figure C.32: IRFs to one std. dev. shock to ambiguity with alternative ordering

Note: Panel SVAR when we order the shock block as: GR_t, R_t^{US}, and $ambig_t$.

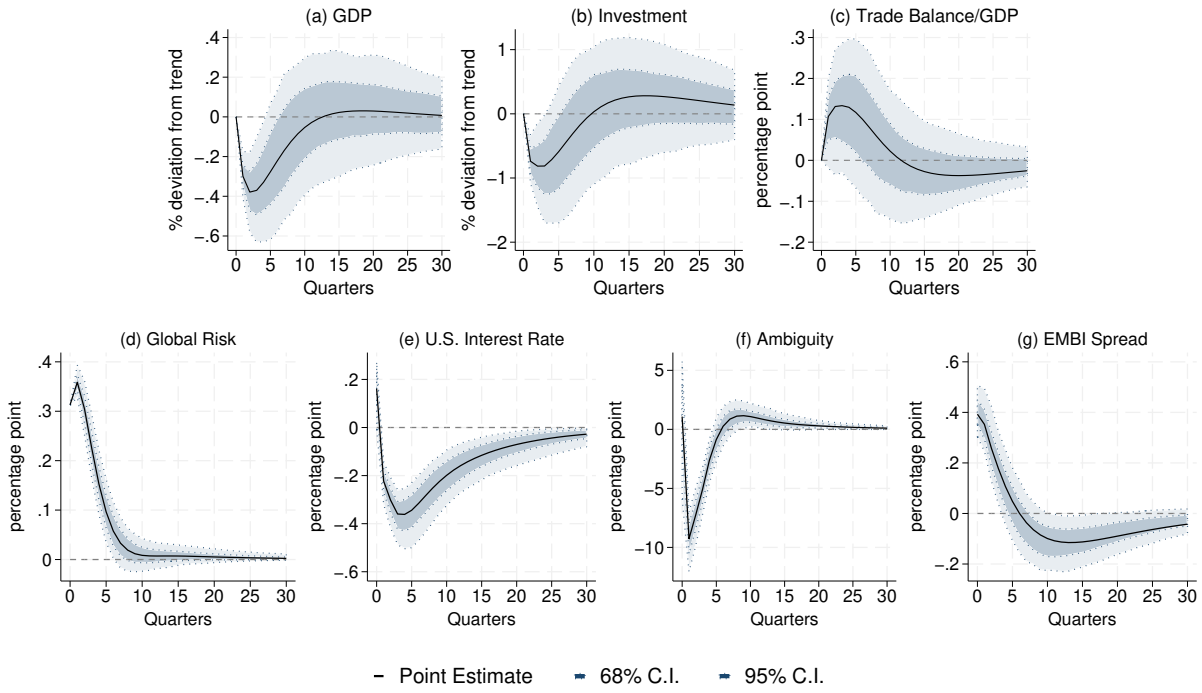


Figure C.33: IRFs to one std. dev. shock to BAA spread with alternative ordering

Note: Panel SVAR when we order the shock block as: GR_t, R_t^{US}, and $ambig_t$.

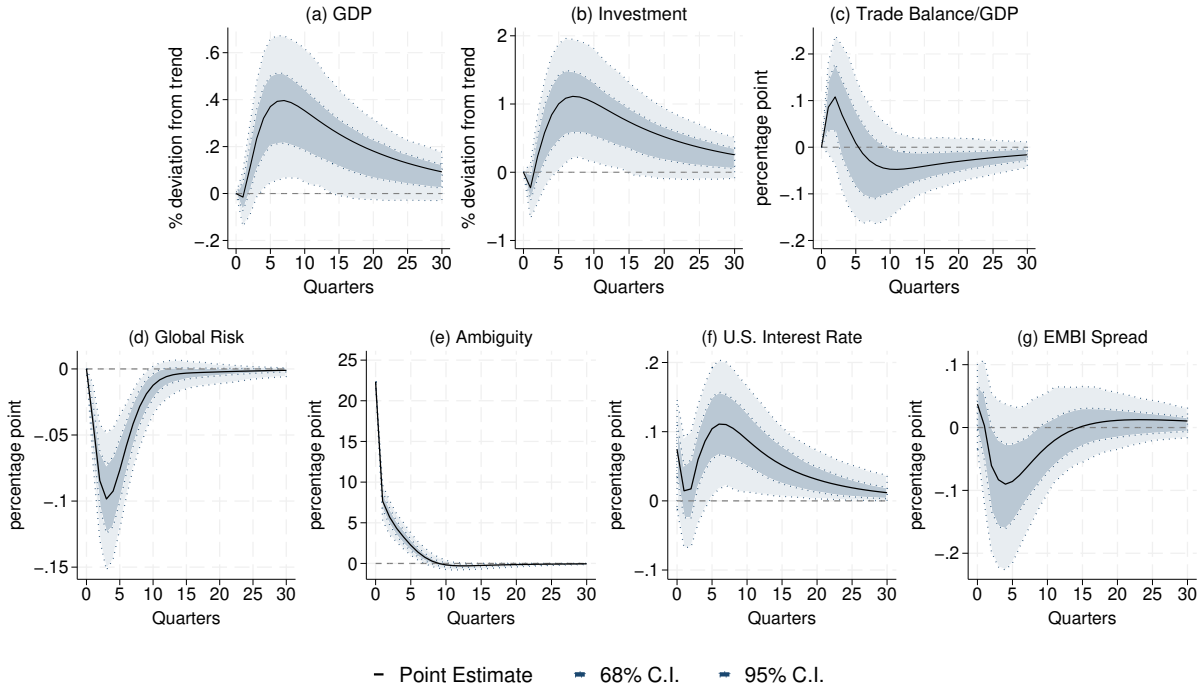


Figure C.34: IRFs to one std. dev. shock to ambiguity with alternative ordering

Note: Panel SVAR when we order the shock block as: GR_t, $ambig_t$, and R_t^{US}.

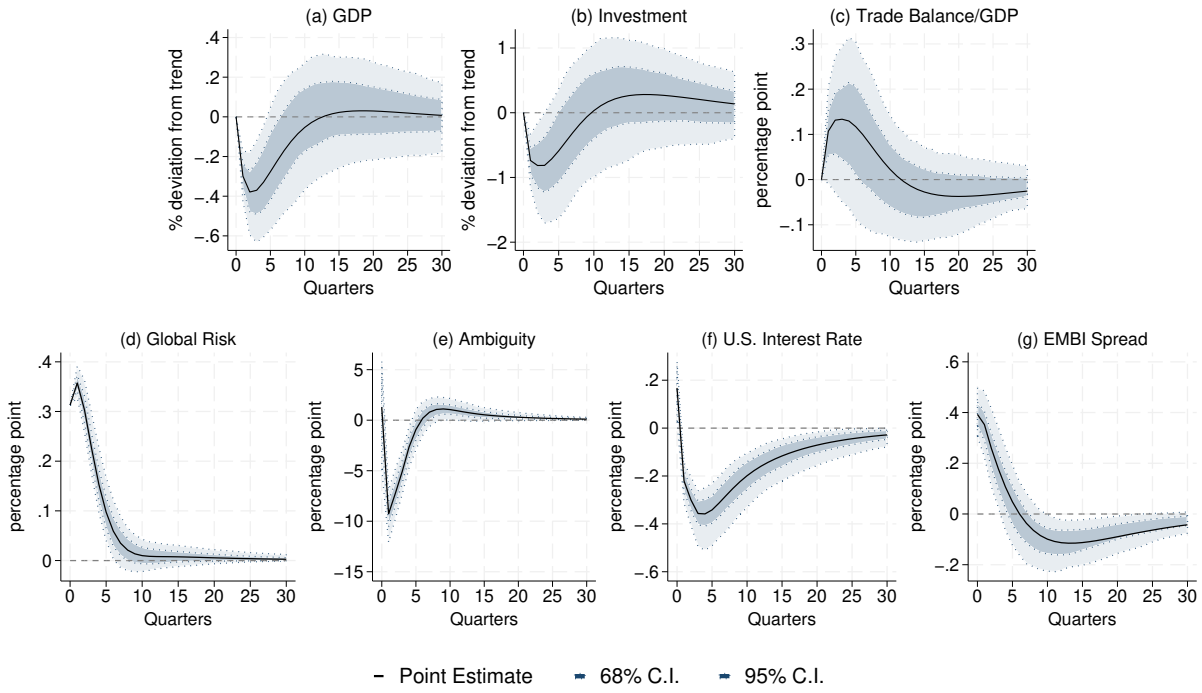


Figure C.35: IRFs to one std. dev. shock to BAA spread with alternative ordering

Note: Panel SVAR when we order the shock block as: GR_t, $ambig_t$, and R_t^{US}.

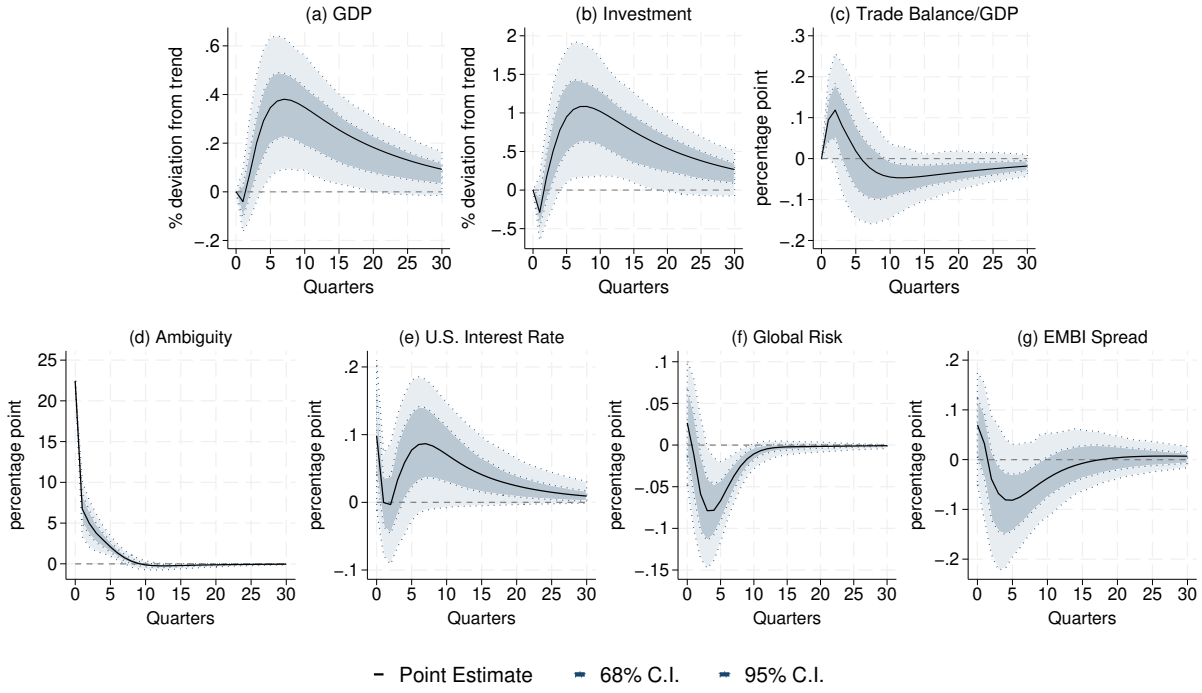


Figure C.36: IRFs to one std. dev. shock to ambiguity with alternative ordering

Note: Panel SVAR when we order the shock block as: $ambig_t$, R_t^{US}, and GR_t.

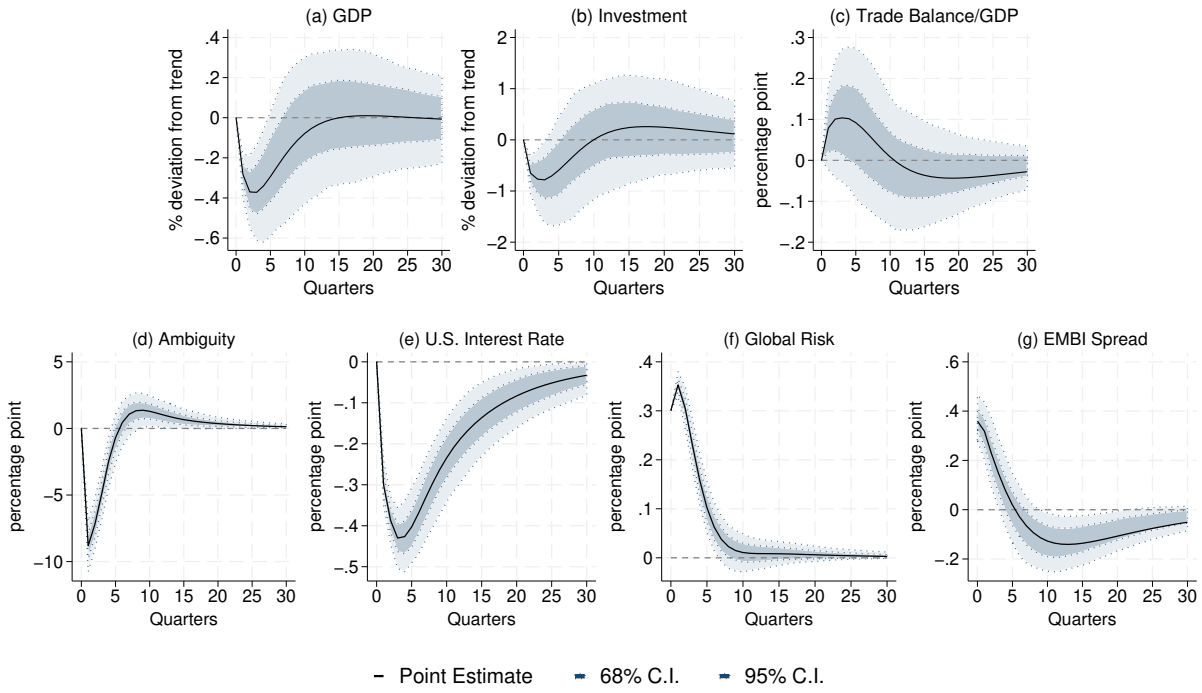


Figure C.37: IRFs to one std. dev. shock to BAA spread with alternative ordering

Note: Panel SVAR when we order the shock block as: $ambig_t$, R_t^{US}, and GR_t.

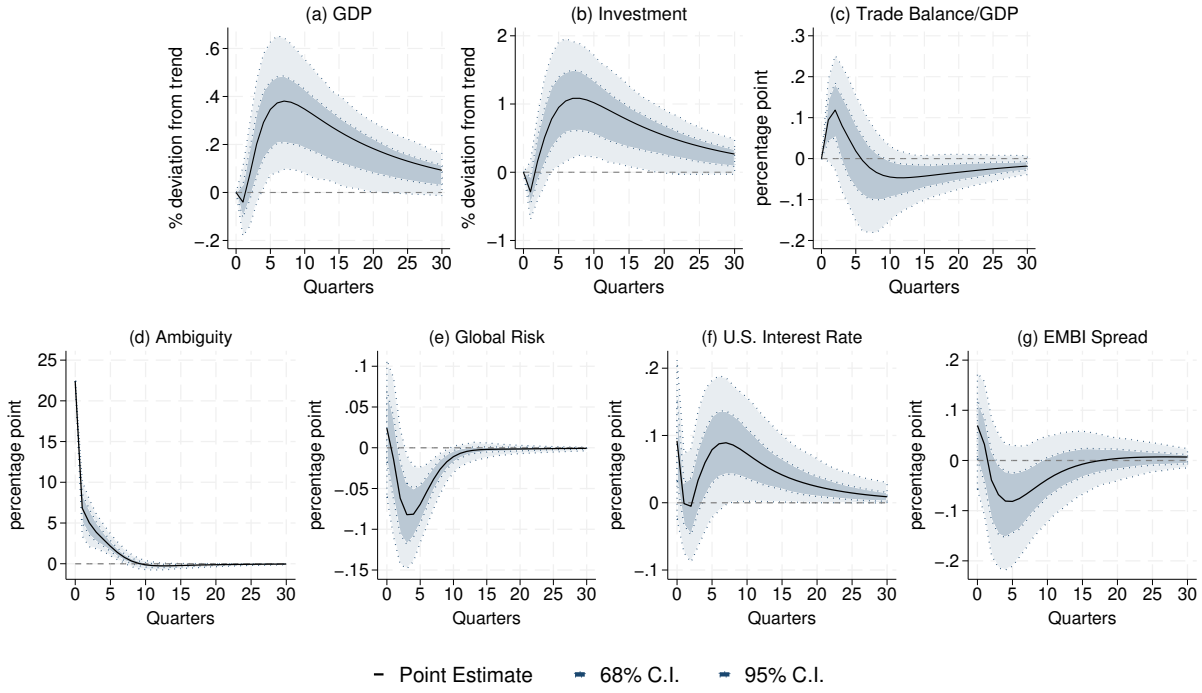


Figure C.38: IRFs to one std. dev. shock to ambiguity with alternative ordering

Note: Panel SVAR when we order the shock block as: $ambig_t$, GR_t, and R_t^{US}.

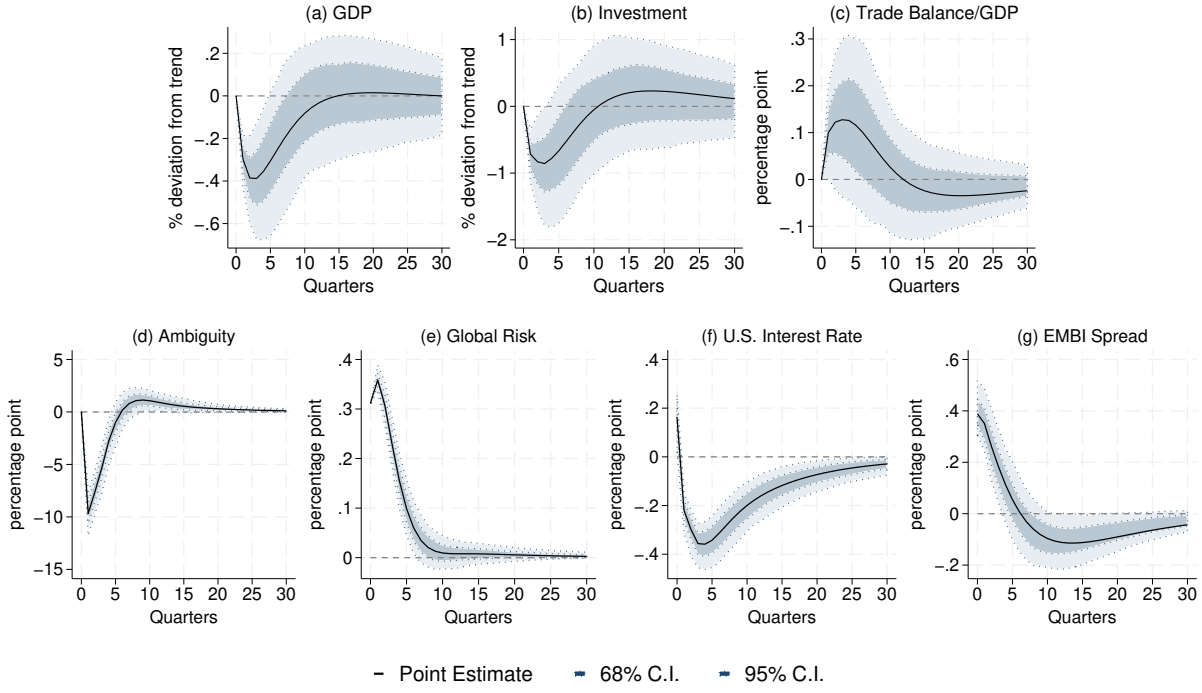


Figure C.39: IRFs to one std. dev. shock to BAA spread with alternative ordering

Note: Panel SVAR when we order the shock block as: $ambig_t$, GR_t, and R_t^{US}.

C.6 Larger sample of countries

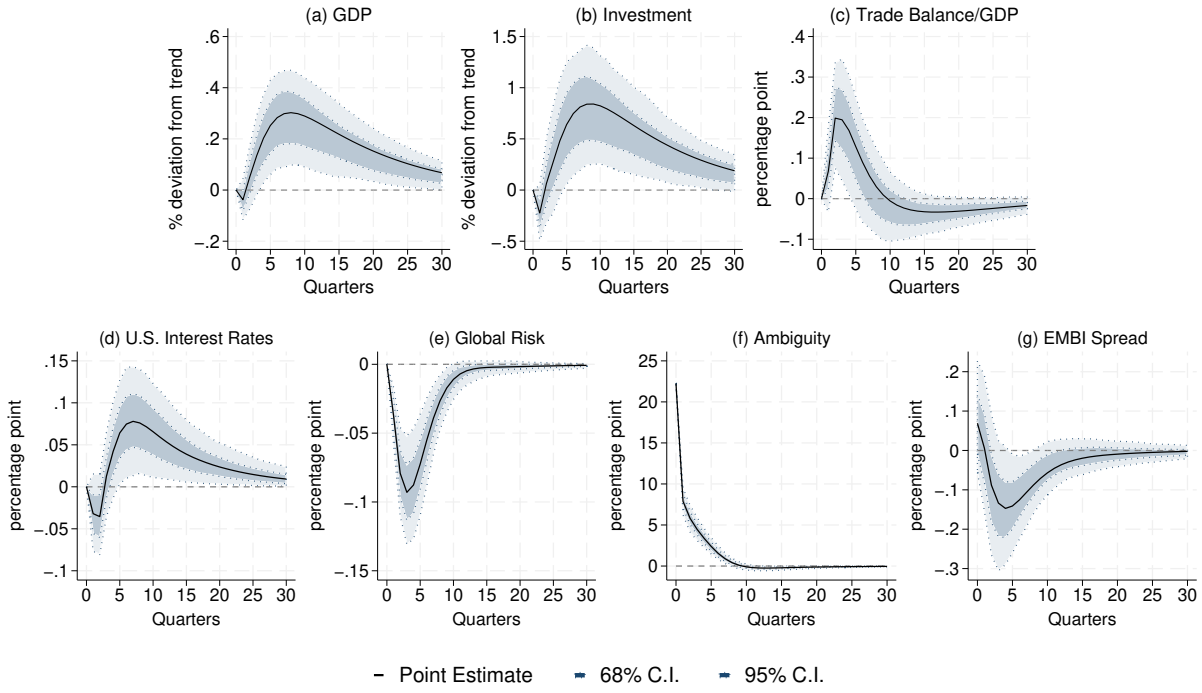


Figure C.40: IRFs to one std. dev. shock to ambiguity with larger sample

Note: Panel SVAR when the sample of countries expands to include Argentina, Brazil, Chile, Colombia, Ecuador, Malaysia, Mexico, Peru, Philippines, South Africa, Thailand, and Turkey.

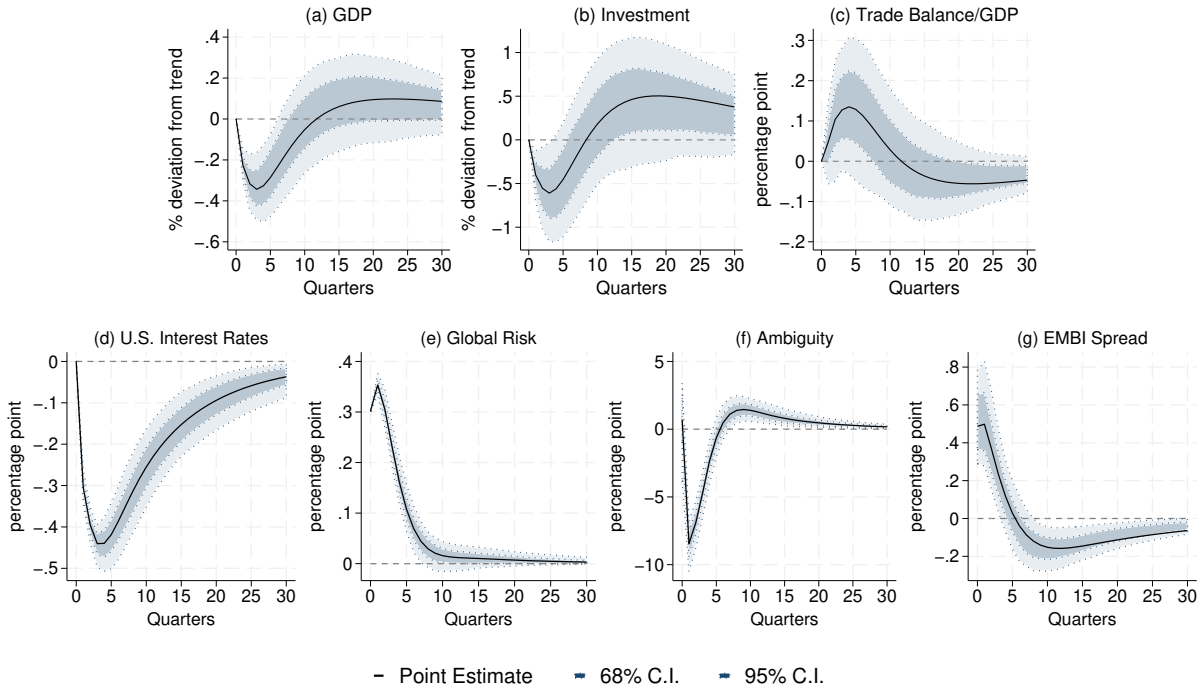


Figure C.41: IRFs to one std. dev. shock to BAA spread with larger sample

Note: Panel SVAR when the sample of countries expands to include Argentina, Brazil, Chile, Colombia, Ecuador, Malaysia, Mexico, Peru, Philippines, South Africa, Thailand, and Turkey.