Essays on Uncertainty and Business Cycle Fluctuations

by

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Declaration

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Tayushma Sewak 8/2/2023

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It is certainly with mixed emotions that I deal with the near ends and the submission of my PhD thesis. I chose to write a thesis on uncertainty. Little did I know that my whole PhD journey would be one where I personally juggle with the uncertainties involved in the life of a PhD student, especially with the realities of an unprecedented world health crisis that definitely impacted my education over the last years.

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Abstract

This thesis is a collection of three self-contained chapters that explore external vulnerability of different economies in terms of exposure to global uncertainty shocks and business cycle synchronisations.

The first chapter acts as background to Chapters 2 and 3, and provides a literature review of the main themes explored in this thesis. It explores the different types of uncertainty shocks, the different ways of measuring uncertainty and analyses the effects of uncertainty shocks, including their effects on trade flows. I further outline the business cycle synchronisation literature, highlighting the heterogeneity in different economies' exposure to global business cycle shocks, and exploring whether business cycles may be connected at a regional level or across economies sharing similar income levels.

Chapter 3 investigates how global economic, financial and trade policy uncertainty affect the trade flows of the seven largest emerging economies (EM-7) using a panel structural vector autoregressive model. Emerging economies are particularly exposed to uncertainty shocks, having mostly adopted export-led growth strategies and tending to specialise in a small subset of goods. Furthermore, they are relatively less financially integrated. We find that global economic uncertainty and trade policy uncertainty act as barriers to trade, leading to a protracted decline in EM-7's degree of openness and deteriorating their trade balance to GDP ratio. Global economic uncertainty shocks induce a 3–4% decline in imports and exports, and trade policy uncertainty shocks cause trade flows to contract by 4-5%. In contrast, financial uncertainty only has a short-lived impact on emerging economies' trade flows, triggering a 2% contemporaneous decline in imports and exports, with the impulse responses turning statistically insignificant shortly after. Trade policy uncertainty is the most important type of uncertainty affecting trade flows, explaining 11% of the variation in trade flows. 7-8% of the movement in imports and exports is explained by global economic uncertainty shocks, and less than 2% is explained by global financial uncertainty shocks.

Chapter 4 explores business cycle interdependence across economies. Using a Factor Augmented Vector Auto Regressive model, I estimate the impact of becoming more integrated with a global business cycle, a regional business cycle, as well as a business cycle common to economies having similar income levels on domestic business cycles. I find that business cycle fluctuations are driven primarily by external shocks rather than domestic shocks. The 2007/8 Global Financial Crisis stands out as the most synchronised recession over the 1995-2019 sample. Nonetheless, global shocks have waned over the latter part of the sample, and regional shocks have become more important. Emerging economies' business cycles are more volatile than advanced economies', and they are also more synchronised with each other. By estimating a group-specific factor that accounts for both income levels and region, I find that emerging economies are more vulnerable to regional shocks than advanced economies.

Chapter 1

Introduction

Emerging economies constitute a driving power in the global economy. Their share of global economic activity, measured in terms of PPP-adjusted GDP as a share of world total, has steadily increased from 36.7% in 1990 to 59.7% in 2019. China is the world's largest economy since 2016, and five of the largest economies of the world are emerging economies. Trade has been a key driver in their globalisation process, even leading to magnified trade linkages amongst emerging economies. Yet, their economic structures are different from those of developed economies. Their business cycles are more volatile than advanced economies', and their financial markets relatively underdeveloped, making them less prepared to face external shocks, see Koren and Tenreyro (2007) and Rose and Spiegel (2009). Kose et al. (2012) show that their business cycles are more integrated with each other than the rest of the world. Identifying the drivers of the business cycles in emerging economies is key to better understanding their growing role in the global economy.

This thesis explores the external vulnerability faced by different economies and their relative resilience to global shocks. As a prelude, Chapter 2 provides a comprehensive literature review on uncertainty and business cycle synchronisations. Chapter 2 features two sections: the first dedicated to defining and measuring uncertainty and its real economic effects; and the second focusing on output co-movement across economies and its implications for the domestic business cycle. In Chapter 3, together with coauthors, I investigate how different types of uncertainty shocks affect trade flows in emerging economies. In Chapter 4, I study the extent to which economies' business cycles are synchronised to a global business cycle. I also examine business cycle synchronisation amongst economies with similar income levels, as well as regional business cycle synchronisation.

Emerging economies are particularly vulnerable to uncertainty shocks. Chapter 3 investigates the effects of different types of uncertainty shocks, namely global economic uncertainty, global financial uncertainty and trade policy uncertainty, on the trade flows of the seven largest emerging economies, the EM-7 economies. We focus on trade flows as we expect trade flows to be sensitive to uncertainty shocks due to the sunk costs involved in exporting. In this sense, emerging economies would be more exposed to uncertainty shocks as they often adopt export-led growth strategies and tend to "hyper-specialize" in a small subset of goods, see Hanson (2012). We estimate a panel structural Vector Auto Regressive (VAR) model using monthly data from January 1999 to September 2019. We use Baker et al. (2016)'s global economic uncertainty measure to proxy for global economic uncertainty; we use Ludvigson et al. (2020)'s measure as a proxy for global financial uncertainty; and Caldara et al. (2020)'s trade policy uncertainty index is used as the measure of trade policy uncertainty in the respective VAR models.

Chapter 3 contributes to the literature in three ways. The existent uncertainty literature has extensively focused on the effects of uncertainty in advanced economies, see Castelnuovo (2019, 2022). We add to the literature by considering the seven largest emerging economies, the EM-7 economies, which provides a comparable sample to the G-7 economies. This paper is the first to provide a comparison of the effects of different types of uncertainty shocks on trade flows. Papers that study the effects of uncertainty on trade focus on particular types of uncertainty shocks in isolation, for example Novy and Taylor (2020) study the impact of stock market volatility shocks on imports. Handley (2014) and Handley and Limão (2015, 2017) examine the impacts of trade policy uncertainty. We examine whether the impacts of global economic, financial or trade policy uncertainty shocks on imports and exports are different across the three different uncertainty shocks. Uncertainty shocks are relatively under-explored in the trade literature, compared to aggregate expenditure shocks or changes in trade costs, see Arkolakis and Rodriguez-Clare (2012) and Head and Mayer (2014). Furthermore, these papers tend to focus on the contemporaneous impact of shocks perturbing trade flows. By using a panel VAR for our analysis, we not only cater for country-specific unobserved drivers of trade and uncertainty, but we are also able to showcase the dynamic impacts of the shocks on trade flows over a three-year horizon.

We find that global economic uncertainty and trade policy uncertainty act as barriers to trade, whereas financial uncertainty only has a short-lived impact on emerging economies' trade flows. Global economic uncertainty shocks induce a 3–4% decline in imports and exports, and trade policy uncertainty shocks cause imports to drop by 4.0% and exports by 4.8%. These effects are persistent, as indicated by impulse response functions that remain negative and statistically significant for over two years after the uncertainty shock. In contrast, global financial uncertainty shocks trigger a 2% contemporaneous decline in imports and exports, with the impulse responses turning statistically insignificant shortly after. About 11–12% of the movement in imports and exports in EM-7 economies is explained by trade policy uncertainty shocks, 7–8% is explained by global economic uncertainty shocks and less than 2% is explained by global financial uncertainty shocks. These results are important and showcase that uncertainty causes the degree of trade openness to shrink. It is therefore important to foster a more predictable economic environment, especially with regards to trade policy discussions, in order to allow the uninterrupted integration of emerging economies into the world economy.

Rising trade and financial integration imply that business cycle fluctuations stem increasingly from external spill-overs rather than from domestic sources. The external vulnerability of an economy may be broken down into two aspects: first, the external shocks that it faces; and second, into its ability to weather the external shock. External shocks tend to be common across economies. In particular, a global shock such as the 2007/8 Global Financial Crisis or the COVID-19 pandemic affects all economies. The extent to which these common shocks affect economies may vary across economies. For example, economies of similar income levels may be affected by these global shocks in a similar way. Kose et al. (2012) explore business cycle convergence amongst economies of similar income groups, and show that the business cycles of emerging economies have 'decoupled' from those of advanced economies. Levy Yeyati and Williams (2012) explain this decoupling through the rise of China. Economies within the same region may experience similar regional shocks. Regional centers of economic activity result from economies within the region tending to have similar economic structures or sharing common lenders, see Henderson et al. (2001). Economies have different levels of resilience to common external shocks. The literature has focused mainly on the impact of global shocks using a rather narrow selection of economies. Nonetheless, a wide range of empirical findings have been reported, with Stock and Watson (2005) estimating the share of G-7 output growth explained by a global factor to range between 1–88%, whereas the corresponding range observed by Mumtaz and Theodoridis (2017) for their sample of 11 OECD economies is 2–36%.

Chapter 4 explores business cycle interdependence amongst economies. It distinguishes between a global business cycle, a regional business cycle as well as a business cycle common to economies within the same income categories, and estimates their respective impacts on the domestic business cycle. In a first instance, the global and group-specific business cycles are estimated using a dynamic factor model. I estimate three dynamic factor models: the first one featuring a global factor and group-specific factors for advanced and emerging economies; the second one consisting of the global factor and a regional factor for Asia and Pacific economies, Western Hemisphere economies and European economies; and the third one including a group-specific factor that accounts for both income levels and regions. The group-specific factor accounting for both income and regions allows detecting whether the business cycles of advanced economies are more synchronised than that of emerging economies in any particular region. I then estimate country-by-country Factor Augmented Vector Auto Regressive

(FAVAR) models, *à* la Bernanke et al. (2005) using the estimated global and group-specific factor, and use the historical decompositions to identify the business cycle fluctuations resulting from structural global business cycle shocks.

I find that business cycle fluctuations are driven by external shocks rather than domestic shocks. The 2007/8 Global Financial Crisis stands out as the most synchronised recession for the sample period 1995-2019. Whilst the literature has tended to focus mainly on advanced economies, I include 14 emerging economies and find that emerging economies' business cycles behave differently from advanced economies'. They are more volatile, as indicated by the standard deviation of the emerging economies' group-specific factor being twice as large as that of advanced economies'. Emerging economies also have greater synchronicity than advanced economies. I find that emerging economies are more affected by external shocks than advanced economies. Global shocks have waned recently, and regional shocks have become more important. The results from the group-specific factor that accounts for both income levels and regions, in turn show that emerging economies are more affected by regional shocks than advanced economies. Overall, the results show that the contribution of external shocks as drivers of business cycle fluctuations is more sizeable than that of domestic shocks.

The remainder of the thesis is structured as follows. Chapter 2 provides an extensive literature review on external vulnerability resulting from uncertainty shocks or business cycle interdependence. Chapter 3 investigates the impacts of global economic uncertainty, global financial uncertainty and trade policy uncertainty shocks on the trade flows of emerging economies. Chapter 4 analyses business cycle synchronisation with the global business cycle, among economies with same income level, as well as regional business cycle. Chapter 5 concludes.

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Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author			
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Chapter 2

Implications for Open Economies of Global Uncertainty and Business Cycle Synchronisations: A Survey of the Literature

Abstract

This literature survey is organised into two sections. The first section provides an overview of the literature on uncertainty. It summarises the theoretical aspects, different methodologies and approaches used to measure uncertainty, and examines the macroeconomic effects as well as trade effects of uncertainty. The second section is concerned with the literature on business cycle synchronisation. It considers studies that evaluate output co-movement across economies as well studies considering alternative ways of measuring business cycle synchronisation. It also looks at the decouling-recoupling literature, and examines the case for business cycle synchronisation within subsets of economies, namely within economies sharing similar income levels or economies located within the same region.

JEL-Classification: C13, E30, E32, F13, F41, F43, F44, F62.

Keywords: uncertainty, international trade, trade policy, emerging economies, global business cycle synchronisation, regional business cycle.

2.1 Introduction

Global uncertainty has remained elevated over the recent years amidst a series of shocks ranging from Brexit, US-China trade tensions, the COVID-19 pandemic and lately, the war between Ukraine and Russia. As such, the literature on uncertainty has been expanding lately, offering new perspectives on different aspects of uncertainty. The nature of different uncertainty episodes is different. Accordingly, different measures of uncertainty have been developed, capturing different types of uncertainty, in addition to being measured using different methodologies.

Trade flows act as a possible channel for uncertainty to spill over across economies. Another strand of this literature which has been receiving unprecedented attention recently focuses on the relationship between trade and uncertainty. Prior to the heightened trade tensions between US and China in 2018/9, the global trade policy environment was rather tranquil, explaining the rather limited literature coverage on the subject in the past. However, following the trade tensions, the literature coverage has been increasing, catering to different aspects such as the development of different trade policy uncertainty measures or measuring the effects of trade policy uncertainty on investment and output.

Amidst higher trade and financial integration, economies' business cycles are increasingly influenced by global factors. Domestic business cycles may then be synchronising with a global business cycle. A particular section of the literature on business cycle synchronisation is also concerned with synchronisation within smaller subsets of economies. Countries with similar income levels may experience similar shocks or react similarly to external shocks, leading to higher business cycle synchronisation among these economies. Alternatively, economic and financial shocks spill over to economies within the same region, leading to business cycle synchronisation at a regional level.

The goal of this chapter is to review both the literature on trade and uncertainty and on global business cycles to provide a background for the analyses presented in chapters 3 and 4. This chapter is divided into two sections. Section 2.2 surveys the literature on uncertainty. I first consider what is meant by uncertainty and its expected effects on the economy. Then, I provide an overview of the different proxies used to measure uncertainty. I then summarise the different studies on the macroeconomic effects of uncertainty, and its interference with policy measures. This literature review also highlights how uncertainty has different implications for different economies. Finally, I review the literature on trade and uncertainty.

Section 2.3 reviews the literature on international business cycle synchronisation. I analyse different factors that lead to greater business cycle synchronisation and help explain the existence of a global business cycle. I then explore different ways of estimating business cycle synchronisation. I also review the literature that measures the extent to which economies are connected to the global business cycle, before looking at regional business cycle synchronisation and synchronisation among economies of similar income levels.

2.2 Uncertainty

2.2.1 What is Uncertainty and Why does it Matter?

Since the 2007/8 Global Financial Crisis, the global economic landscape is characterised by elevated uncertainty, as illustrated by different global uncertainty measures featured in Figure 2.1. Amidst heightened uncertainty, the literature has equally burgeoned on exploring different aspects of uncertainty.

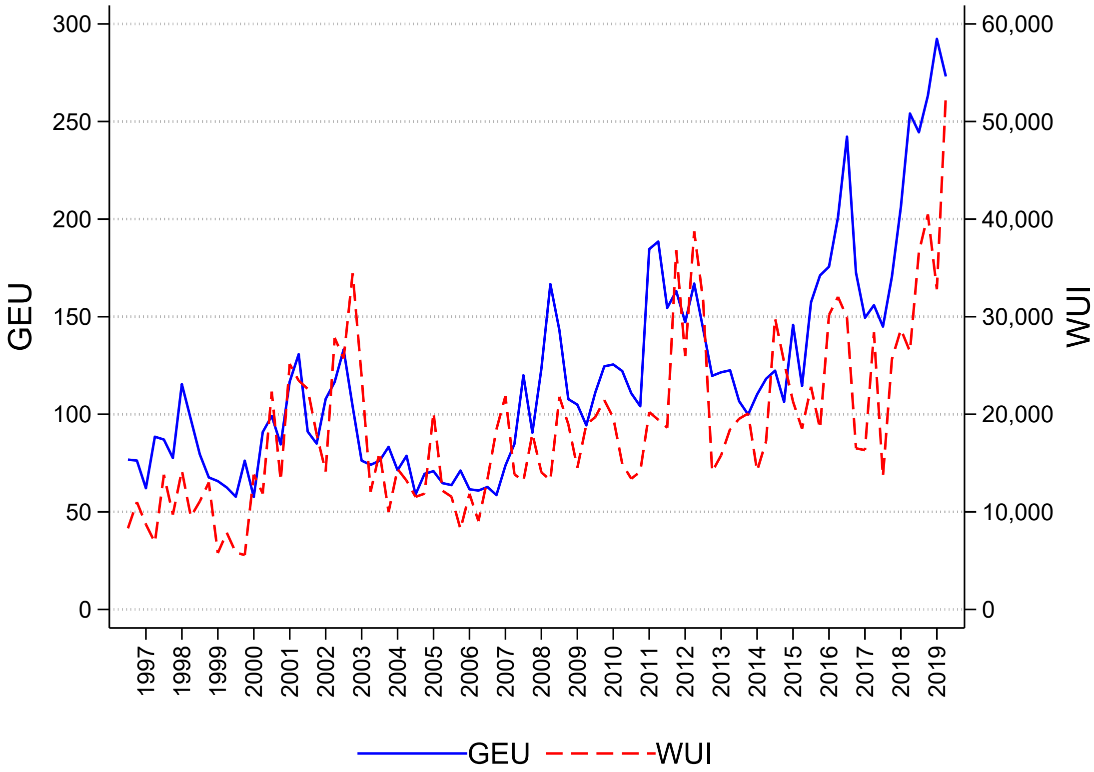
Uncertainty is different from risk. This distinction is spearheaded by Knight (1921) who defines risk as a known probability distribution over known possible outcomes, whereas uncertainty implies that economic agents are unable to predict the probability of future events happening. However, most papers cited throughout this literature review model uncertainty as a mean-preserving change in the volatility of the distribution. They assume that the underlying probability distribution is known; such that the equivalent as per Knight's definition would be tantamount to measuring risk.

Uncertainty impairs economic decision-making. In the presence of irreversible costs or sunk costs, uncertainty leads to an option value of waiting, see Bernanke (1983); Dixit (1989); Pindyck (1991); Abel and Eberly (1994). Firms faced with uncertainty adopt a "wait and see" approach, and postpone key investments or pause hiring until the uncertainty dissipates. Consumers adopt a more cautious stance when faced with uncertainty on their labour income streams. They tend to reduce consumption and increase precautionary savings (Caballero,1990). For this reason, uncertainty merits the attention of policy-makers. The effectiveness of counter-cyclical policy measures may be reduced as firms and consumers take more precautionary stances, therefore becoming less sensitive to monetary or fiscal policy actions.

2.2.2 Different Measures of Uncertainty

The development of different uncertainty measures has emerged as a key research area. The variety of uncertainty measures available stems from alternative approaches deployed by the authors. In particular, Kozeniauskas et al. (2018) differentiate between uncertainty measures that focus on firm-level shocks, aggregate macroeconomic shocks

Figure 2.1: Uncertainty in the Global Economy



Notes: *GEU* is available on a monthly basis, and has been averaged for each quarter. Data source: *GEU*: Global Economic Policy Uncertainty, Baker et al. (2016); *WUI*: World Uncertainty Index, Ahir et al. (2022).

or the dispersion in agents' beliefs and forecasts. Traditionally, the asset-market based Chicago Board Options Exchange's Volatility Index, the VIX, is a widely accepted proxy for uncertainty, see Bloom (2009); Carrière-Swallow and Céspedes (2013); Bhattarai et al. (2020); Cascaldi-Garcia et al. (2020); Novy and Taylor (2020); Caggiano et al. (2022). Studies that capture uncertainty using firm-level volatility look at sales revenue (Byun and Jo (2018)), stock returns (Bloom (2009); Christiano et al. (2014)) or TFP shocks (Bloom et al. (2018)). However, Jurado et al. (2015) point out that these firm-based measures of uncertainty may be misleadingly interpreted as a change in uncertainty, if the change in profits or sales are driven by company fundamentals or a change in investors' risk appetite.

News-based measures: Perhaps the most ground-breaking measure of news-based uncertainty is Baker et al. (2016)'s Economic Policy Uncertainty Index, paving the way for further research on similar news-based measures of uncertainty. It is constructed using a three-pronged approach. First, cases of economic policy uncertainty are identified by searching for uncertainty-related keywords in major newspapers. The number of articles containing these words are then normalised by the total number of articles having been sampled. Secondly, domestic economic policies that are set to be abolished over the next ten years are taken into consideration by using dollar-weighted numbers of such tax code provisions that are expected to lapse during that time period. Finally, the dispersion among different economic forecasters' predictions about the future levels of various macroeconomic variables is also considered. The strength of this widely-cited measure lies in the combination of different methodologies. The Economic Policy Uncertainty Index is not only news-based, but it also blends in the concept that uncertainty means that the economy becomes less predictable by considering policies that are expected to be abolished as well as the dispersion in macroeconomic forecasts. National Economic Policy Uncertainty Indices are available for 28 economies. The Global Economic Uncertainty Index is calculated as the GDP-weighted average of 21 selected National Economic Policy Uncertainty Indices. By dissecting US newspaper articles into different categories, categorical Economic Policy Indices such as Monetary Policy Uncertainty, Fiscal Policy Uncertainty, Health Care related Uncertainty or National Security Uncertainty are also available for the US.

Ahir et al. (2022) also use a text-search based approach to develop their World Uncertainty Index. They scrutinise the quarterly available Economist Intelligence Unit's country reports for 143 economies for uncertainty and uncertainty-related words, and normalise the number of occurrences by the total number of words. Given that the uncertainty measures for all economies are sourced from the Economist Intelligence reports, uncertainty indices across economies are more comparable, eliminating bias from different journalistic approaches.

Monetary policy, fiscal policy and geo-political uncertainty: Uncertainty measures can be developed to focus on particular aspects, such as financial, geo-political, monetary policy, fiscal policy, or trade policy uncertainty. On the monetary policy uncertainty realm, Husted et al. (2020) develop a Monetary Policy Uncertainty Index for the US using a news-based approach. They identify articles containing uncertainty, monetary policy and Federal Reserve related words. In addition, they scale the number of articles by those containing Federal Reserve related keywords to account for the change in the communication strategies adopted by the US Federal Reserve over time. They compare their Monetary Policy Uncertainty measure with the implied volatility on one-year swap rates and advocate for the relative strength of the news-based measure which successfully tracks uncertainty amidst unconventional monetary policy implementation. Caldara and Iacoviello (2022) also adopt a news-based approach for their proposed Geopolitical Risk Index. They categorise the risks in eight different categories from the threat, to escalation, or the realisation thereof, and accordingly look for keywords related to war, peace or terrorism in ten major newspapers in the US, UK and Canada. They estimate two different indices, namely, the Geopolitical Acts Index and the Geopolitical Threats Index. Hlatshwayo (2016) uses a search algorithm on the Dow Jones Factiva news aggregator that covers 36,000 news sources in different languages to develop country-specific generic, trade, fiscal and monetary policy uncertainty indices.

Trade policy uncertainty: Prior to the 2018 trade tensions between the US and China, trade policy uncertainty was relatively low, explaining the limited literature coverage on trade policy uncertainty. In the aftermath of the trade war, there has been renewed interest on trade policy uncertainty. Caldara et al. (2020) propose three different measures of trade policy uncertainty. The first measure is a time-varying firm-based measure whereby the quarterly earnings call reports of listed companies are analysed for words relating to trade and uncertainty. The second measure is a news-based aggregate measure, scanning seven US newspapers for articles containing words related to trade and uncertainty. The third measure is also an aggregate measure, that is estimated using a stochastic volatility model for import tariffs. Caldara et al. (2020) compare their two aggregate measures and note that the latter measure is unable to capture uncertainty episodes that do not result in a change in tariffs. Benguria et al. (2022) follow Caldara et al. (2020)'s approach to develop a firm-specific trade policy uncertainty using textual analysis on annual reports of Chinese firms listed on Shanghai and Shenzhen Stock Exchange.

Survey-based measures: Economic surveys are increasingly used as a source of information to assess the level of uncertainty. Professional forecasters make well-informed judgement about the course of the economy, as they hold real time information and possess expert knowledge on any structural changes. Jo and Sekkel (2019) use real GDP, unemployment, industrial production and building activity forecasts from the US survey of professional forecasters. They use a stochastic volatility factor model, that allows to differentiate between common uncertainty and variable-specific uncertainty, and the resulting macroeconomic uncertainty measure is the common factor of the forecast errors. Surveys offer a sure gateway to measuring inflation uncertainty or firms' uncertainty about future business conditions. Grishchenko et al. (2019) use a dynamic factor model for inflation expectations obtained from different surveys in the US and Europe, whereas Binder (2017) differentiates between survey respondents who provide round number forecasts and those who choose a larger set of outcomes to analyse inflation uncertainty in the US. Bachmann et al. (2013) use forecast errors from survey data for Germany and US in developing a business conditions uncertainty measure for each economy. Similarly, Arslan et al. (2015) use firms' survey data about production volumes to develop firm-level and aggregate measures of business uncertainty, whilst Morikawa (2016) do so for Japan based on forecast errors from the forecasts of the Short Term Economic Survey of Enterprises conducted by the Bank of Japan.

Econometric measures: A number of studies use econometric methodology to develop uncertainty indices. Jurado et al. (2015) use a large number of time series to develop an aggregate measure of macroeconomic uncertainty, as volatility of a single variable may indicate idiosyncratic uncertainty rather than an economy-wide shock. They estimate factors from a dataset of 132 macro series. They also differentiate between the predictable part of the series, i.e the conditional forecast, and the unpredictable component that they model using a stochastic volatility model. The resulting macroeconomic uncertainty index is an equal-weighted average of the uncertainty component of each individual series. Jurado et al. (2015)'s macroeconomic uncertainty measure comprises fewer large uncertainty shocks compared to Baker et al. (2016)'s Global Economic Policy Uncertainty measure. Ludvigson et al. (2020) employ the same strategy as Jurado et al. (2015) for 148 monthly financial indicators to develop a Financial Uncertainty indicator. Mumtaz and Musso (2021) use a dynamic factor model with time varying volatility for 22 OECD economies, that allows them to differentiate between global uncertainty, region-specific uncertainty and country-specific uncertainty. Carriero et al. (2020) estimate two measures of global uncertainty using a large scale heteroscedastic VAR model with errors embedded in a factor structure with time varying volatility. Their two measures reflect data limitations as country coverage improves: the first comprising real GDP series of 19 economies and the second consisting of 67 macroeconomic series for the UK, US and Euro area. Their global uncertainty measures are less correlated with Jurado et al. (2015)'s macroeconomic uncertainty measure than with Baker et al. (2016)'s Global Economic Policy Uncertainty. Caggiano and Castelnuovo (2021) use a dynamic hierarchical factor model on monthly volatility data on stock returns, exchange rate returns, government bond yields of 42 economies to estimate global financial uncertainty.

2.2.3 The Macroeconomic Effects of Uncertainty

Uncertainty, though a second-order variable, has first-order effects. Underlying the contractionary effects of uncertainty is a combination of the 'wait and see' response and the precautionary savings motive, leading to a fall in employment (Baker et al. (2016)), investment (Leahy and Whited (1996); Bloom et al. (2007); Gulen and Ion (2016); Baker et al. (2016), consumption (Kimball (1990); Romer (1990)) and output (Ramey and Ramey (1995); Baker et al. (2016)). Bloom et al. (2018) extends the 'wait and see' hypothesis, and show that uncertainty affects not only production but also productivity, as efficient plants delay expansions while unproductive ones halt their ongoing contractions.

The macroeconomic effect of uncertainty is ambiguous. Uncertainty raises financing costs due to a higher probability of default. Using the standard intertemporal capital asset pricing model, higher uncertainty leads to lower asset prices, reflecting a change in expected future cash flows or an increase in the discount rates, see Brogaard and Detzel (2015). Pástor and Veronesi (2013) use a general equilibrium model to analyse the impact of political uncertainty on stock prices. There is uncertainty about the overall impact of a policy change, and both the government and investors learn about the impact of a policy change on mean profitability in a Bayesian fashion. They show that when the government replaces less effective policies with counter-cyclical ones during economic downturns, investors are offered some sort of protection against losses, similar to a put option. However, the value of this protection is reduced by the resulting uncertainty about the selection of the policy enacted to replace the previous one

Uncertainty may also be viewed in terms of a widening of the range of possible outcomes, thereby triggering risk aversion and dampening business and consumer confidence (Nowzohour and Stracca (2020)). Economic agents then brace themselves for the materialisation of the worst possible outcomes. Basu and Bundick (2017) use a demand-driven model with nominal price rigidity to track the change in labour demand induced by uncertainty shocks. They show that following a reduction in consumption, output and labour input falls, reducing the demand for capital and investment. Due to the nominal rigidity assumption, adjustments occur through endogenous changes in the markups. In contrast, in competitive models, owing to the unchanged level of technology and capital stock, output remains unchanged after the uncertainty shock. A drop in consumption coupled with unchanged output implies a rise in investment. Meanwhile, labour supply may increase, assuming consumption and leisure are normal goods. Hence, in the competitive model, following uncertainty shocks, consumption falls, but output, hours worked and investment rises. One strand of the literature takes a so-called "growth options" approach, proposing that uncertainty may not be counter-cyclical. According to the so-called Oi-Hartman-Abel effect (Oi (1961); Hartman (1972); Abel (1983)), uncertainty may not constrain investment if the maximum possible loss is capped, for example through insurance contracts or the maximum loss is the sunk cost, whereas the upside potential is limitless. Furthermore, Bloom (2014) highlights that, in some scenarios, firms may not have the option to delay investment, for example, if they are in highly competitive industries where they need to be the first to develop the product.

According to Bloom et al. (2018), recessions are characterised by both negative first moment shocks and elevated uncertainty. Uncertainty has a contractionary economic impact whereas low economic growth periods are conducive to higher uncertainty, making it difficult to establish the direction of causality between growth and uncertainty. Ludvigson et al. (2020) highlight a few reasons through which recessions lead to higher uncertainty. First, recessions may trigger unprecedented policy measures, leading to higher policy uncertainty. Second, due to the higher costs of reversing investments, there is higher uncertainty in consumption growth. Third, as demonstrated by Fostel and Geanakoplos (2012), agents take greater risks during economic slowdowns. Finally, Fajgelbaum et al. (2017) evidence the presence of 'uncertainty traps' in the form of a high-uncertainty–low-growth spiral, due to slower information flow leading to lower investment during economic downturns. This spiral effect is further exemplified by Caggiano et al. (2022) who demonstrate larger contractionary effects of uncertainty shocks when the economy is in recession, compared to when the economy is performing well.

Uncertainty measures vary in terms of the methodology employed in their estimation or in different aspects of the economic risk or uncertainty that they aim to capture. The question therefore inevitably arises as to whether different types of uncertainty lead to different economic effects. Ludvigson et al. (2020) find that macroeconomic uncertainty leads to no significant long term real effects, contrasting the contractionary effects of financial uncertainty. Caldara and Iacoviello (2022) analyse the impact of geopolitical risk on both the macroeconomy and at firm level. They show a decline in investment and hours at the macro level, by estimating a structural VAR for the US. At the firm-level, they account for firm-specific exposure by first identifying the level of exposure of each firm in the sample by regressing their daily returns on the geopolitical risk measure, and using the median of the coefficients to separate low exposure firms from high exposure ones. They show that following a two standard deviation shock to the Geopolitical Risk Index, the drop in investment in high-exposure firms exceed the decline in low-investment ones by about 1%.

Uncertainty hinders the effectiveness of policy actions. The outcomes of various policy measures could be dependent on whether uncertainty is high or low. Aastveit et al. (2016) estimate a structural VAR model where they allow the interaction of the interest rate with the uncertainty index. For a comparison of monetary policy effects under high uncertainty versus low uncertainty periods, they illustrate the results for the 90^{th} and 10^{th} percentile of the historical distribution of the uncertainty measure. They consider three alternative measures of uncertainty, namely Bloom (2009)'s stock market volatility based measure, Ludvigson et al. (2020)'s macroeconomic uncertainty, and Baker et al. (2016)'s Economic Policy Uncertainty Index. Irrespective of the uncertainty measure being considered, monetary policy action is less effective when uncertainty is high.

Concomitantly, uncertainty about policy measures has real implications. This is particularly highlighted in the monetary policy strand of the literature. Basu and Bundick (2017) estimate that output declines by 0.2% following an uncertainty shock, and by 0.6% if monetary policy is constrained by the zero lower bound on interest rates[1]. Husted et al. (2020) use a VAR model to examine the effects of monetary policy uncertainty in the US. They highlight higher borrowing costs and a contraction

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[1]Basu and Bundick (2017) identify uncertainty shocks as an exogenous increase in the VIX

in output following monetary policy uncertainty shocks. Interestingly, they also use firm-level data to compare whether monetary policy uncertainty affects investment due to investment irreversibility or financial constraints. They proxy for investment irreversibility using the ratio of property, plant and equipment to total assets as well as sunk costs such as sale of investment, rent expenditure and depreciation. Higher uncertainty implies higher probability of default, leading to higher financing costs. They use several financial constraint proxies each focusing on size, age, cash flow or leverage of the firms. They conclude that monetary policy uncertainty acts through both the investment irreversibility and the financial constraints channels.

Separately, different economies experience different levels of uncertainty. Ahir et al. (2022) highlights the heterogeneity in individual economies' uncertainty. They explore the differences in uncertainty based on economies' income levels, and highlight that emerging and developing economies experience higher uncertainty compared to advanced economies. They suggest that this could stem from the poorer quality of institutions, more frequent natural disasters, as well as vulnerability to external shocks and a relatively restricted ability to fight these. They also present a measure of uncertainty synchronisation based on the absolute value of the difference between the uncertainty measures of two economies. They highlight that uncertainty is more synchronised across advanced economies. Furthermore, higher uncertainty synchronisation is associated with greater trade and financial linkages between economies. Examining spill-overs of economic policy uncertainty sourcing from the US, EU, and China, Biljanovska et al. (2021) show that uncertainty from the US has larger effects than that coming from EU or China. In addition, they also find that Chinese uncertainty shocks affect consumption and investment in Europe and the Western Hemisphere, whereas European uncertainty does not impact consumption and investment outside Europe.

Global uncertainty spill-overs are a cause for concern in emerging economies. Carrière-Swallow and Céspedes (2013) document that the impacts of a global uncertainty shock are more severe for emerging economies than advanced economies. They find that the average drop in investment in emerging economies is four times that of advanced economies. Furthermore, emerging economies also experience a more sizeable drop in consumption and slower recovery. The authors attribute the lack of resilience of emerging economies to the credit constraints affecting their financial markets. In the same vein, Bhattarai et al. (2020) illustrate that unanticipated US VIX shocks affect both real and financial variables in emerging economies; causing their currencies to depreciate, interest rate spreads vis-*à*-vis the US to widen, capital accounts to worsen, consumption and output to fall and net exports to the US to rise. They also highlight the heterogeneity in the response across economies in the sample, which they explain by the different monetary policy actions used by the economies. Apaitan et al. (2022) demonstrate that global uncertainty shocks have more sizeable effects on real variables in the Thai economy than domestic uncertainty shocks. The literature increasingly sheds light on global uncertainty as a driver of domestic business cycle shocks, see Berger et al. (2016); Mumtaz and Theodoridis (2017); Mumtaz and Musso (2021); Biljanovska et al. (2021). Whilst, Bloom (2009) show a swift recovery and an overshooting following uncertainty shocks in the US, Carrière-Swallow and Céspedes (2013); Apaitan et al. (2022) show that uncertainty has more persistent effects in emerging economies.

2.2.4 Trade and Uncertainty

Exporting is riskier than selling domestically. However, the literature on the effects of uncertainty and trade has started to gain momentum only recently, since the trade policy environment was particularly calm prior to Brexit or the US-China trade tensions. Typically, trade theories *à* la Melitz (2003) or Eaton et al. (2011) mostly abstract from uncertainty or assume that uncertainty is resolved before firms make decisions on domestic and export production and sales. Alternatively, rather than considering uncertainty effects, other types of shocks are explored in the trade literature, for example changes in trade costs or aggregate expenditure, see Arkolakis and Rodriguez-Clare (2012); Head and Mayer (2014).

Both the theoretical and empirical literature show that uncertainty hampers trade creation. If firms need to invest in sunk costs to enter an export market, uncertainty creates an option value of waiting, reducing entry into the export market, see Albornoz et al. (2012),Nguyen (2012), and Handley (2014). Baley et al. (2020) use a general equilibrium model with information frictions and show that higher uncertainty leads to less trade when domestic and foreign goods are easily substitutable.

Trade flows are even more responsive to uncertainty shocks than output, see Novy and Taylor (2020). Handley (2014) emphasizes that apart from sunk costs, trade uncertainty may also stem from lack of visibility on future tariffs. Under flexible trade regimes, there may prevail a gap between applied tariffs and maximum binding tariffs, leading to the risk that tariffs can be increased upto the maximum binding constraints. In contrast, bounded tariffs reduce uncertainty by narrowing the range of tariffs that can be applied, thereby reducing the maximum possible loss for exporters. In particular, Handley (2014) estimate that the number of varieties traded would increase by 4% if Australia only reduced tariffs to free trade levels, and by 17% if it both reduced tariffs as well as bound them through WTO commitments. Similarly, Handley and Limão (2015) show that Portugal's accession to the European Community (EC) reduced uncertainty about future EC policies towards Portugal (the risk that the EC would raise tariffs on Portuguese products disappeared when Portugal joined the EC), thereby boosting net entry as well as sales into EC markets. Furthermore, Handley and Limão (2017) estimate that China's accession to the WTO in 2001 explains over a third of the exports growth in 2001–2005 period. Douch and Edwards (2021) illustrate the negative impact of Brexit on exports, even prior to the 2016 referendum date due to uncertainty.

The effects of uncertainty shocks may take time to materialise. Meanwhile, most trade policy research tends to be examined in static frameworks. It is important to analyse the economic effects of a rise in trade policy uncertainty using a dynamic framework. Caldara et al. (2020) demonstrate for US firms that a trade policy uncertainty shock has an insignificant contemporaneous effect on firm's investment but investment declines gradually over four quarters following the shock. Benguria et al. (2022) use first-difference regressions on their firm-specific trade policy uncertainty measure to analyse the implications of the rise in trade policy uncertainty from 2017 to 2018 on Chinese firms. They estimate that a 10% increase in exposure to US tariffs increases firm's trade policy uncertainty by 0.07 standard deviation. The rise in uncertainty is more pronounced for smaller firms and firms with less diversified trading partner bases. They also demonstrate the negative and statistically significant effects of a rise in trade policy uncertainty on investment, R&D expenditure and profitability, with the effect increasing over time.

2.2.5 Takeaways from Uncertainty Literature

Several takeaways emerge from the summary of the literature on the macroeconomic effects and the trade effects of uncertainty. First, even though uncertainty shocks are second-moments shocks, they lead to first-order effects, affecting consumption, investment, employment and output. It is mostly documented that uncertainty shocks slow the economy, except for the case of investment projects where the losses are capped to a maximum or the upside profitability potential is limitless. Uncertainty is also cause for concern for policy-makers, rendering policy actions less effective. Secondly, different types of uncertainty shocks have different impacts on the economy. The literature coverage on different uncertainty measures is extensive, applying not only different methodologies, but also catering for the different nature of the shocks, ranging from macroeconomic, geopolitical, financial or trade policy uncertainty. Yet, there are only few studies that analyse the differential impacts of these different uncertainty measures on the economy. Third, emerging economies are more vulnerable to global uncertainty shocks than advanced economies. Finally, trade flows are more sensitive to uncertainty shocks due to the sunk costs involved in exporting as well as the lack of visibility on the trade policy front.

2.3 Business Cycle Synchronisation

2.3.1 Are Business Cycles Synchronised across Economies?: Some Theoretical Foundations

The synchronised decline in output observed during the COVID-19 pandemic illustrates contagion across the global economy. The pandemic is not a singular example. The 2007/8 Global Financial Crisis which hasd its roots in the US or the 2012 Eurozone Debt Crisis reverberated across the global economy as well. The events renewed interest into international business cycle transmission mechanisms. The second section of this literature review examines the literature on global business cycles. I also review the literature on regional spill-overs as well as business cycle transmissions across economies having similar income levels.

Greater trade and financial integration provide the premise for the existence of a global business cycle. Trade flows facilitate the spill-overs of demand and supply shocks across trading partners, leading to greater business cycle synchronisation, see Baxter and Kouparitsas (2005). Frankel and Rose (1998) suggest that this may not hold true if trade leads to higher specialisation and sector-specific shocks are more prominent. On the flip side, Caselli et al. (2020) argue that for economies with major domestic economic shocks, trade openness offers the opportunity to diversify demand and supply. In this case, business cycle synchronisation may actually reduce volatility as long as trading partners have less volatile business cycles. Regarding the financial integration channel, economic agents are able to participate in different financial markets and, arbitrage ensures that financial assets' prices become more synchronised, trickling down to business cycle synchronisation. However, Kalemli-Ozcan et al. (2003) highlight that in the long run capital reallocations are dictated by economies' comparative advantage, leading to specialisation and limiting the degree of business cycle synchronisation. Kose et al. (2003) link greater output comovement to greater trade and financial linkages, and Imbs (2004) additionally highlight the roles of sectoral similarity and intra-industry trade.

Eickmeier (2007) discuss the exchange rate and information transmission as two additional channels promulgating business cycle synchronisation. Positive income shocks abroad leads to a depreciation of the domestic currency, enhancing export competitiveness and similarly boosting aggregate demand domestically. However, it could also trigger higher import prices, leading to lower output correlation. The overall strength of the exchange rate channel is therefore ambiguous and additionally hinges on factors such as the size of the non-tradeables sector or pricing-to-market characteristics. The confidence channel pertains to the reaction of domestic agents to foreign news. On the one hand, they may have persistent expectations forming behaviour. On the other, during crisis times, they may over-react to foreign news. For example, Levchenko and Pandalai-Nayar (2020) show that a sentiment shock measured using US data on expectations explain a larger share of business cycle transmission between US and Canada than TFP shocks.

Globalisation is associated with greater business cycle synchronisation. Bordo et al. (1999) point out two waves of globalisation, namely the pre World War I and the post mid 1980's, and suggest that output is more synchronised during these two waves than during the Bretton Woods era. Nonetheless, Baldwin and Martin (1999) and Williamson (2002) highlight intrinsic differences across the two globalisation episodes, triggering greater business cycle synchronisation during the second wave (Artis and Okubo (2009)). Compared to the pre World War I era, the second globalisation wave featured more short-term cross-country financial flows conducive to technology spill-overs, greater intra-industry trade fuelled by economies of scale and product differentiation, intra-industry FDI compared to infrastructure investment, rapid economic progress in emerging economies, and the establishment of international policy organisations such as the IMF or the WTO.

The case for the existence of a global business cycle is supported by microeconomic foundations. In particular, Gabaix (2011) explain how shocks stemming from large firms spread economy-wide. Giroud and Mueller (2019) illustrates the impact of large firms' centralised decision-making, whereby establishments in non-tradeable sectors cut employment in response to a reduction in house prices in regions where the parent firm or its subsidiaries operate. Large firms are more likely to export or to be multinationals. A strand of the global business cycle literature inspects the role of MNCs in strengthening business cycle comovements across economies. Cravino and Levchenko (2017) find a positive relationship between headquarter sales growth and sales growth of the foreign affiliate. Di Giovanni et al. (2018) show that if the top 100 firms in France withdrew their trading relationships with a particular trading partner, the correlation between the firms' value added and the foreign economy's GDP would drop by 8%. Kleinert et al. (2015) also use French firms' data, and find that the presence of foreign affiliates boosts GDP correlation between France and the foreign economy by 16%. Bena et al. (2022), in turn use global data, and show that investment drops by around 18%–32% for firms having parents operating in countries experiencing economic downturns.

2.3.2 Measurement of Business Cycle Synchronisation

Pairwise correlations: The literature proposes different ways of estimating business cycle synchronisation. Some papers are based on pairwise correlations. Imbs (2004) isolate the cyclical component of GDP using the Band-pass filter and calculate the bilateral correlations for their sample of 24 economies, leading to 276 bilateral correlations. Similarly, Inklaar et al. (2008) and Dées and Zorell (2012) detrend GDP using the Hodrick-Prescott filter before calculating bilateral correlations. Kalemli-Ozcan et al. (2013) and Cesa-Bianchi et al. (2019) use the absolute value of the GDP growth difference between each economy pair.

Similar turning points in business cycles: A separate section of the literature adopts a different view. Harding and Pagan (2006) suggest that cycles are synchronised if individual cycles share the same turning points, local maximum or minimum. In similar spirit, Ductor and Leiva-Leon (2016) estimate business cycle dependence between two economies by allowing for a state variable governed by a Markov switching process. Two economies are co-dependent if they have a high probability of experiencing the same state of the economy.

Dynamic factor models: Dynamic factor models have emerged as an increasingly popular methodology to measure business cycle synchronisation, see Del Negro and Otrok (2008); Crucini et al. (2011); Mumtaz et al. (2011); Kose et al. (2012); Lee (2013). Kose et al. (2012) outline the superiority of dynamic factor models over measures of business cycle synchronisation that are based on pairwise correlations. First, pairwise correlations pertain to the correlation between only two economies. Taking the average across all pairs available ignores common business cycle fluctuations within subsets of economies, such as regional clusters. In addition, Georgiadis (2017) illustrates that estimates of spill-over effects from multilateral models are more accurate than those produced from bilateral models. With the dynamic factor model, the largest common dynamic component is extracted across the time series through the first principal component. Furthermore, it is effective at capturing dynamic properties of the data, such as autocorrelations and cross-correlations across variables. The extent to which each economy relates to the global business cycle is reflected in the factor loading: a positive factor loading indicates that the economy's business cycle has coupled with the global business cycle, whereas a negative factor loading signals decoupling from the global business cycle.

Factor Augmented VAR (FAVAR) models: Building on dynamic factor models, Factor Augmented VAR (FAVAR) models are used to quantify the effect of the global business cycle on different economies. Bernanke et al. (2005) initially developed the FAVAR model with a view to analysing the transmission of monetary policy. However, the FAVAR model has also been adopted in the international business cycle literature, see Boivin and Giannoni (2008); Mumtaz and Surico (2008); Vasishtha and Maier (2013). For smaller group of countries, Canova et al. (2007) uses VAR models to examine cross-country spill-overs. However, if the number of economies is increased, the degrees of freedom are constrained, leading to the 'curse of dimensionality'. In contrast, common factors summarise information across a large number of variables into a manageable number of factors. This methodology is especially relevant for a domestic economy where macroeconomic variables are characterised by a high degree of comovement, as highlighted by Stock and Watson (2016). However, this methodology is equally valid for the purpose of capturing comovement in real economic activity across economies. The FAVAR model is a two-step procedure: first using the dynamic factor model to obtain a measure of the global business cycle, and thereon estimating its effects on respective economies by including the estimated global business cycle measure as a regressor in a VAR equation in the second step. There are two ways of estimating the FAVAR model. The first constitutes of first estimating the factors using principal component analysis and estimating the Factor-augmented VAR separately. Alternatively, the factors and the VARs can be estimated in a single step using Bayesian likelihood methods and Gibbs sampling. However, Bernanke et al. (2005) highlights the computational complexity involved in the likelihood-based estimation procedure, as well as the disadvantage of using priors that penalise the original information content.

2.3.3 Business Cycle Synchronisation at a Global Level and Group-specific Levels

Global business cycle synchronisation: There is considerable heterogeneity in the way that the global business cycle transmits to domestic business cycle. External vulnerability can be decomposed into two aspects. The shocks, in the form of global business cycle shocks are common across economies. However, different economies respond differently to these shocks. In particular, different studies reach different conclusions regarding the impact of the global business cycle shocks. Using data from 1960 to 2002 for the G-7 economies, Stock and Watson (2005) find that the global factor accounts for a higher share of forecast variation in output in the 1984-2002 period, compared to the 1960-1983 period. Kose et al. (2003) use a larger sample of 76 economies, but present only the median findings. On average, they find that the global factor accounts for less than 10% of the forecast error variance in output. Nonetheless, they highlight that advanced economies are more affected by global factor shocks than developing economies. The difference is quite large, with 27% of the variance in advanced economies being explained by the global factor, and only 3% of the variance in developing economies being driven by global factor shocks.

Business cycle synchronisation amongst economies with similar income levels: Global business cycle fluctuations affect advanced economies and developing economies in different ways. Kose et al. (2012) shows that the importance of the global factor in driving business cycles across economies has been superseded by a group factor that accounts for differences in income levels. In particular, the share of the global factor in the variance decomposition of output has nearly halved from 15% in 1960–1984 to 8% in 1984–2008. They find that both advanced and emerging economies have decoupled from the global business cycle, and coupled with that of economies having similar income levels. In advanced economies, global business cycle shocks explain 14% of the variation in output whereas group-specific factor shocks explain 30%. Similarly, in emerging economies, the global factor explains less than 5% of the variation in output, compared to 7% explained by group-specific shocks. Meanwhile, Wälti (2012) calculates the Euclidean distance between 30 emerging market economies and growth rates of advanced economies, and reports that the business cycles of emerging economies and advanced economies have become more synchronised over time. Levy Yeyati and Williams (2012)'s findings are more in line with Kose et al. (2012). They especially emphasize that the relationship between advanced economies and emerging economies changes with time; emerging economies' business cycles were synchronised with that of G7 economies in 1993–2003, but decoupled in the 2000–2010 period on the back of the growing importance of China.

It is important to account for two distinct factors capturing co-movement across advanced economies and emerging economies separately, since the literature highlights intrinsic differences in the economic structures of advanced and emerging economies. Emerging economies tend to 'hyper-specialise' and rely on a restricted number of trading partners (Hanson (2012)). They also have weaker institutions and less efficient financial markets, see Calderón and Fuentes (2010). Their mmacroeconomic policies are less stable and transparent as policy-makers are likely to reverse fiscal, monetary, or trade policies more frequently than in developed economies. They are also more vulnerable to financial shocks, and the flight-to-safety options exercised by foreign investors trigger exchange rate depreciation and volatility. Crucini (1997) points out that the effect of external shocks are exacerbated in smaller economies. Business cycles of emerging economies are more volatile, and they face deeper recessions than industrial economies, see Calderón and Fuentes (2014). Aguiar and Gopinath (2007) suggest that the business cycle shocks in emerging economies are dominated by shocks to the trend growth rather than transitory shocks, such that consumption is more volatile than output.

Regional business cycle synchronisation: A separate strand of the literature compares synchronisation with the global business cycle with regional business cycle synchronisation. A regional factor explains a higher share of business cycle fluctuations over time. Mumtaz et al. (2011) shows that the global factor explains less than 20% of output growth variance whereas the regional factor explains over 50% across different regions. Considering four different time periods from 1860–2007, they show that with the exception of North America, the regional factor's contribution ranks highest in the most recent 1985–2007 sub-sample period. Gomez et al. (2013) use the correlation and distance matrices of 103 economies to build nested hierarchical structures of interaction to analyse growth clusters between 1950–1980 and 1981–2009. They find that in the latter period growth clusters tend to be more regional, and propose that business cycle synchronisation is taking place at a regional rather than global level. Nonetheless, Gomez et al. (2013), Matesanz and Ortega (2016) and Matesanz Gomez et al. (2017) suggest that global business cycle synchronisation strengthens during economic crises.

Apart from a global business cycle, business cycles of economies may integrate with that of other economies in the region. Henderson et al. (2001) put emphasis on regional centers of activity. Countries within the same region import from and export more extensively with each other. di Giovanni and Levchenko (2010), Ng (2010) and Johnson (2014) associate higher trade in intermediate goods with greater output comovement, and document that countries that trade in intermediate goods are concentrated within particular regional clusters. This is further substantiated by Kose and Yi (2006) who show that countries with lower transport costs have higher output comovement. Regional business cycle synchronisation may also be explained by the fact that countries within the same region have similar economic structures and common bank lenders (Van Rijckeghem and Weder (2001)) as well as portfolio lenders. Cai et al. (2008) further highlights informational linkages that lead to volatility spill-overs in exchange rate markets within regions.

2.3.4 Takeaways from Business Cycle Synchronisation Literature

As economies become increasingly integrated into global trade and financial networks, their business cycles become, in principle, more synchronised. The literature proposes trade, financial flows, exchange rates, the transmission of news across borders as well as the presence of MNCs as possible reasons underlying greater business cycle comovement across economies. The empirical literature, on its part, highlights considerable heterogeneity in the way that domestic business cycles are impacted by global business cycle shocks. More generally, the importance of the global business cycle has waned over time. Group-specific factors for income levels and regional factors are emerging as drivers of domestic business cycle fluctuations, instead.

2.4 Conclusion

This literature survey details the theoretical insights on how uncertainty affects the economy, the variety of different uncertainty measures, as well as the different impact of uncertainty in emerging economies. Still, not much is known about how trade flows are affected by different types of uncertainty shocks. This is particularly because the trade literature tends to use static frameworks, whereas uncertainty shocks affects the dynamics of trade. Therefore, in Chapter 3, we explore empirically how different types of uncertainty, namely global economic uncertainty, financial uncertainty and trade policy uncertainty, affect trade flows in emerging economies. This empirical exercise adds to the literature on trade and uncertainty by focusing on emerging economies, as well as comparing the different effects triggered from different uncertainty shocks.

The second section of this survey is geared towards summarising the literature on business cycle synchronisation across economies. In particular, we learn that business cycle synchronisation evolves over time. In addition, studies examining business cycle synchronisation focus exclusively either on global business cycle synchronisation, regional business cycle synchronisation or synchronisation amongst economies with similar income levels. In Chapter 4, I adopt a more holistic approach. I use a Factor Augmented VAR model to examine the contribution of a global business cycle, a regional business cycle, as well as a business cycle shared by economies having same income levels as drivers of domestic business cycles across economies. I consider a mix of advanced and emerging economies which provides a more parsimonious measure of the global business cycle. Furthermore, using data till 2019, we are able to gather a more updated view on how business cycle co-movement has evolved recently.

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Contribution to the Paper	Contributed to the initial research idea, planning, reviewing the literature, collecting data and analysing the results, wrote a substantial part of the manuscript
Overall percentage (%)	80%
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.
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Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

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Chapter 3

Does Uncertainty Matter for Trade Flows of Emerging Economies?

[1]

Abstract

Uncertainty shocks have been shown to affect the real economy, but uncertainty remains about their trade effects and whether effects are similar across different types of uncertainty. We investigate how global economic, financial, and trade policy uncertainty affect the trade flows of the seven largest emerging economies (EM-7) using a panel structural vector autoregressive model. We find that: (1) Global economic and trade policy uncertainty shocks induce a protracted decline of about 4 to 5% in EM-7's imports and exports. (2) Global economic and trade policy uncertainty act as trade barriers, reducing the EM-7's degree of openness and deteriorating their trade balance to GDP ratio. (3) Financial uncertainty only has a short-term impact on EM-7's trade flows. (4) Trade policy uncertainty is the most important type of uncertainty affecting trade flows, explaining 11% of the variation in trade flows.
JEL-Classification: F13, F41, F62.

Keywords: international trade, trade policy, uncertainty, emerging economies, panel VAR.

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3.1 Introduction

Heightened uncertainty about the future affects decisions by firms, workers, and consumers. Trade flows are particularly vulnerable to uncertainty shocks as establishing relationships with foreign businesses and consumers implies considerable sunk costs.[2] Apart from pointing out highly prominent events, such as the supply chain disruptions in the wake of Covid-19 lockdowns or the war between Russia and Ukraine, systematically measuring uncertainty shocks is difficult, as uncertainty is a latent variable. Creating different uncertainty indices has recently developed into an active research area, with authors mostly studying the macroeconomic impact of their uncertainty measure in isolation, mostly abstracting from its trade effects, and mostly focusing on advanced economies (see Castelnuovo, 2019 for a review of the literature).

In this paper, we provide the first comparison of the effects on emerging economies' trade of three main facets of uncertainty: global economic, financial, and trade policy related uncertainty. Understanding the impact of uncertainty shocks is particularly important for emerging economies as they are especially exposed to uncertainty: Their output growth is more volatile compared to developed economies, and their financial markets are less developed or too remote from financial centers to hedge against these fluctuations, see the evidence presented in Koren and Tenreyro (2007) and Rose and Spiegel (2009). Emerging economies are also particularly exposed to uncertainty shocks as they often adopt export-led growth strategies and, according to Hanson (2012), tend to "hyper-specialize" in producing and exporting only a small subset of goods, making them potentially more vulnerable to external shocks.

Identifying which type of uncertainty is most detrimental to emerging economies' trade flows is crucial, as Ludvigson et al. (2020) document that different types of uncertainty have different macroeconomic effects. Cascaldi-Garcia et al. (2020) review the plethora of uncertainty measures used in the literature. Besides measuring different types of uncertainty, different measures are based on different methodologies, from news and survey-based measures, to asset market-based volatility measures, to indicators of Knightian uncertainty. Importantly, Liu and Sheng (2019) document the low correlation between different uncertainty measures.[3] To credibly guide trade policy decisions, a better understanding of whether different types of uncertainty have different trade effects, and whether trade policy uncertainty is particularly damaging to emerging

[2] The empirical relevance of sunk costs for international trade has been documented by, inter alia, Roberts and Tybout (1997), Das et al. (2007), Handley and Limão (2015), and Meinen (2015).

[3] Estimated macroeconomic effects partly differ even for one type of uncertainty when changing the measurement methodology, as demonstrated by Alexopoulos and Cohen (2015) who find a difference in the magnitude of estimated macroeconomic effects of economic uncertainty when their text-based uncertainty indicator is measured using more general words.

economies' trade flows, is needed.

To compare the trade effects of different types of uncertainty, we consider three alternative measures of uncertainty: We use Baker et al. (2016)'s global economic policy uncertainty index to proxy for the overall level of global economic uncertainty (GEU). We use Ludvigson et al. (2020)'s index based on volatility forecast errors as our measure of exogenous global financial uncertainty (GFU). Finally, given our interest in trade flows, we also consider Caldara et al. (2020)'s trade policy uncertainty index (TPU). In the literature, these measures are typically used in isolation across separate studies, making a direct comparison of their implications difficult. To facilitate this comparison, we will estimate the exact same empirical models, only swapping the used uncertainty indicators.[4]

For our comparison exercise, we use a panel data set for the seven largest emerging economies, the EM-7: Brazil, China, India, Indonesia, Mexico, Russia, and Turkey. The EM-7 economies are similarly important in the group of emerging economies as the G-7 economies are for developed economies, with the EM-7 accounting for 80% of the aggregate output of emerging economies. We use monthly data from January 1997 to September 2019 to estimate a panel structural Vector Auto Regression (VAR) model. Panel VAR models have several advantages for our purposes: Contrary to standard VARs, panel VARs allow us to disentangle the effects of uncertainty shocks on trade flows, while controlling for country-specific unobserved drivers of both uncertainty and trade. For example, geographically remote countries face higher trade costs, as documented by the gravity literature (see for an overview Head and Mayer, 2014). At the same time, di Giovanni and Levchenko (2009) document that more geographically remote countries exhibit lower annual output volatility. Similarly, Martin and Rey (2006) show in a theoretical model that lower trade costs make financial crashes less likely. Our panel VAR approach controls for these long-run differences in countries' average remoteness via the inclusion of country-specific fixed effects. Our empirical approach is flexible and complements more structural studies that rely on particular functional form assumptions for consumer or firm behaviour concerning the relationship between trade and uncertainty such as Handley and Limão (2017).

We find that global economic and trade policy uncertainty shocks reduce the degree of openness of EM-7 economies, whereas financial uncertainty has a relatively negligible impact on their trade flows. These results are robust to using alternative measures of uncertainty and across a battery of different specifications. In our baseline results, imports and exports drop on impact following a GEU and TPU shock, reaching a trough after a few months. GEU shocks trigger a 3–4% decline in imports and exports,

[4] Our interest lies in comparing the trade effects of these different uncertainty measures. We do not pursue the issue of whether one type of uncertainty "causes" another type of uncertainty.

while a deeper deterioration is noted following the TPU shock, which causes imports to drop by 4.0% and exports by 4.8%. Our results suggest a persistent effect from the global economic and trade policy uncertainty shocks, as the impulse responses remain significant for over two years after the uncertainty shocks. On the flip side, a financial uncertainty shock triggers a contemporaneous decline of around 2% in imports and exports, with the impulse responses turning statistically insignificant shortly after. We also find that global economic and trade policy uncertainty shocks trigger a mild deterioration of the trade balance to GDP ratio in emerging economies. The forecast error variance decomposition exercise exposes the extent to which uncertainty shocks matter for EM-7 trade flows at the three-year forecast horizon. About 7 to 8% of the movement in imports and exports is explained by the global economic uncertainty shocks, and a higher proportion, 11–12% pertain to trade policy uncertainty shocks. Meanwhile, GFU shocks account for less than 2% of the variation in imports and exports, indicating that emerging economies' trade is insulated from global financial uncertainty disturbances. This seems consistent with the decoupling phenomenon between EM-7 and advanced economies' business cycles, see Kose et al. (2003, 2012).

Our results have important policy implications. Lower openness implies lower gains from trade, as demonstrated by Arkolakis and Rodriguez-Clare (2012). Our finding that global economic and trade policy uncertainty shocks lead emerging economies' openness to shrink may reflect that trade liberalization efforts lately have encountered more resistance in an environment of higher uncertainty. Avoiding a downward spiral between higher uncertainty and demands for trade restrictiveness which in turn leads to higher trade policy uncertainty has clear economic benefits. Our results highlight the benefits of a calmer, more predictable economic environment, particularly with respect to trade policy discussions.

We are not the first to study the relationship between trade and uncertainty. The theoretical literature has established a clear link between trade flows and uncertainty. If firms have to invest into sunk costs to enter an export market, uncertainty leads to an option value of waiting for the firm, reducing entry into export markets, see Albornoz et al. (2012) and Nguyen (2012).[5] Handley (2014) shows that uncertainty due to a lack of credibility of trade policy causes firms to delay investment, reducing trade creation. Relatedly, Handley and Limão (2015) and Handley and Limão (2017) show that reduced uncertainty due to WTO membership and trade agreements increases firm entry into export markets and hence trade flows. Baley et al. (2020) demonstrate in a two goods, two countries general equilibrium model that higher uncertainty leads to less trade,

[5]Defever et al. (2015) present empirical evidence for this mechanism using Chinese firm-level data. Lou et al. (2022) find that higher uncertainty reduces innovation of firms using data on Chinese firms' patent applications, consistent with firms preferring not to invest into R&D when uncertainty is high.

unless the elasticity of substitution between domestic and foreign goods is low.[6]

On the empirical side, Novy and Taylor (2020) use a structural VAR to compare the impacts of uncertainty shocks on trade and domestic activity in the US, using the uncertainty measure by Baker et al. (2016). In contrast, we shed light on the EM-7's dynamic response of trade flows to different types of uncertainty shocks. We quantify the different impact of uncertainty on imports, exports, and the trade balance, a key macroeconomic indicator for policymakers.[7]

More generally, we contribute to the literature which studies the macroeconomic effects of uncertainty shocks. This literature has focused primarily on advanced economies, see Castelnuovo (2019) for an overview. Carrière-Swallow and Céspedes (2013) is a notable exception. Using standard VARs estimated country by country, they show that the repercussions of an uncertainty shock are more severe for emerging economies than developed economies; in comparison, our panel VAR approach allows us to control for unobserved time-invariant country-specific determinants of trade. Bhattarai et al. (2020) documents the heterogeneous impact of US uncertainty on emerging economies, attributing the differential impacts to the differences in the monetary policy responses. These papers focus on the impact of uncertainty on aggregate consumption and investment, but abstract from the effects of uncertainty on international trade, which are our primary concern. Bonciani and Ricci (2020) study the impact of financial uncertainty on a large set of countries and document that its effects differ for emerging economies. Biljanovska et al. (2021) study the impact of economic policy uncertainty in a panel of developed and emerging economies using quarterly data, not monthly, as we do, and again abstract from its trade effects. A common feature of these studies is that they consider the impact of a single uncertainty measure, whereas our focus lies on a comparison of different uncertainty measures. Similarly, a strand of the literature considers the effect of uncertainty shocks for emerging markets in country-specific case studies using simple VARs, e.g., Cerda et al. (2018) for Chile, but abstracting from trade effects, and Apaitan et al. (2022) for Thailand. Choi and Shim (2019) compare the effects of financial uncertainty, as measured by the VIX index, versus economic policy uncertainty on six emerging economies estimating country by country VAR models, while again abstracting from the trade effects of uncertainty.

The remainder of the paper is structured into four sections. Section 3.2 presents descriptive evidence on the relationship between different uncertainty measures and

[6]Fernández-Villaverde and Guerrón-Quintana (2020) provide a review of the macroeconomic theoretical literature which links uncertainty to the real economy, but they abstract from its trade effects.

[7]The empirical literature has tended to focus exclusively on imports or exports in isolation, see Novy and Taylor (2020) on imports, and Handley (2014), Lewis (2014), Handley and Limão (2015), Feng et al. (2017), and De Sousa et al. (2020) on exports.

trade. Section 4.2 presents our empirical strategy. Section 4.3 illustrates the dynamics of EM-7's trade flows in response to the selected measures of uncertainty shocks via impulse responses. Section 4.3 also investigates how much of the variation in trade flows can be explained by uncertainty shocks using forecast error variance decompositions. Section 4.4 concludes.

3.2 Descriptive Evidence

Our goal is to compare the international trade effects of three uncertainty measures widely used in the literature. We describe these measures in the following before presenting some descriptive evidence on the relationship between these measures and international trade.

Global economic uncertainty (GEU): We use the global economic policy uncertainty index developed by Baker et al. (2016). The news-based index is constructed using a three-pronged approach. The same methodology is applied to compute a national economic policy index for each country. First, cases of economic policy uncertainty are identified by scanning articles from major local newspapers, normalised by the total number of articles in the sample of newspapers. Secondly, domestic economic policies that are set to extinguish over the next ten years are taken into consideration. Finally, dispersion among different forecasters predictions about the future levels of key macroeconomic variables is considered. Once the national economic policy indices are computed, the Global Economic Policy Uncertainty Index is constructed, based on the GDP weights of each country.

Global financial uncertainty (GFU): We use Ludvigson et al. (2020)'s financial uncertainty measure as a representative of global financial uncertainty, which builds on the approach by Jurado et al. (2015). Jurado et al. (2015) argue that movements in stock-based measures of uncertainty such as the Chicago Board Options Exchange's Volatility Index, the VIX, may be misleadingly interpreted as uncertainty, when the underlying cause could be unrelated, for example a change in investors' risk appetite. Building on the premise that uncertainty reflects greater unpredictability of the state of the economy, Ludvigson et al. (2020) use a time-varying volatility model and calculate uncertainty as being the common component of the three month ahead forecast errors. They use diffusion indices on 147 financial variables to compute the conditional forecasts. Our relevant GFU measure is the quarter-ahead forecast error.

Trade policy uncertainty (TPU): We use Caldara et al. (2020)'s news-based trade policy uncertainty. The TPU index is computed by scouring over seven major US newspapers for articles containing both uncertainty and trade related keywords. The resulting index reflects the share of articles discussing trade policy uncertainty.

Table 3.1: Contemporaneous and Lagged Cross-Correlation between Uncertainty and Trade

Uncertainty Measures	Exports	Imports	Total Trade
GEU_t	-0.377***	-0.402***	-0.391***
GEU_{t-1}	-0.392***	-0.413***	-0.406***
GFU_t	-0.175***	-0.157***	-0.163***
GFU_{t-1}	-0.194***	-0.174***	-0.181***
TPU_t	-0.623***	-0.613***	-0.622***
TPU_{t-1}	-0.612***	-0.602***	-0.610***

Notes: Exports and imports are calculated as the first principal component of the exports and imports, respectively, of the seven countries included in the sample. Total trade calculated as the sum of exports and imports, is also derived as the first principal component of the total trade in the selected countries. Trade variables for each country, are deseasonalised and detrended using a log linear trend, prior to extracting the principal component. *** significant at 1%. Data source: Trade flows, IMF Direction of Trade Statistics; GEU: Global Economic Uncertainty, Baker et al. (2016); GFU: Global Financial Uncertainty, Ludvigson et al. (2020); TPU: Trade Policy Uncertainty, Caldara et al. (2020).

Having described the uncertainty measures we use throughout this study, we can have a look at some descriptive evidence. Simple correlations between the three measures and trade flows give some first indication about the importance of uncertainty shocks for international trade. Table 3.1 presents contemporaneous and lagged cross-correlations between trade flows and GEU, GFU, and TPU. Both exports and imports are negatively correlated with uncertainty, no matter which uncertainty measure is used. Yet, the table also indicates that correlations differ, depending on the type of uncertainty measure. Judging by these simple correlations, trade policy uncertainty seems to have the greatest negative impact on trade flows.

Figure 3.1 corroborates the differences in the relationship between trade flows and the different uncertainty measures. It simultaneously plots the year on year growth rate of total trade (the sum of exports and imports) for the seven largest emerging economies as well as the three uncertainty measures.[8] Clearly, spikes of the different types of uncertainty do not necessarily coincide. A synchronised spike in GEU and GFU signals the inherent global economic and financial uncertainty prevalent during the 2007/8 Global Financial Crisis (GFC). GFU has since stabilised. On the other hand, GEU which encompasses wider-ranging sources of uncertainty, has remained

[8]Note that while Figure 3.1 presents the year on year trade growth rate and the uncertainty indices in levels for illustrative purposes, we transform our data before estimating the panel VAR model (3.1), see Section 3.3.1 for details.

elevated, exacerbated by Brexit, the impositions of sanctions on Iran as well as trade tensions between the US and China. The trade policy environment has historically been relatively stable, as indicated by the TPU index which had been fairly tame over the sample period. However, TPU witnessed a noticeable rise as from 2017, reflecting heightened trade policy uncertainty during the Trump presidency.

The graphs also indicate the negative relationship between uncertainty and trade growth. In particular, amidst the rising global economic and financial uncertainty spurred during the GFC, there was a steep contraction of emerging economies' trade flows. Meanwhile, the dip in trade flows in 2018/9 coincides with the heightened trade policy uncertainty, but is less pronounced than the GFC-induced drop.

While the descriptive evidence may be suggestive, unobserved differences across countries in the relationship between uncertainty and trade flows may lead to biased conclusions. We therefore estimate the trade effects of uncertainty in a rigorous way while controlling for unobserved country-specific time-invariant heterogeneity in the next section.

3.3 Empirical Strategy

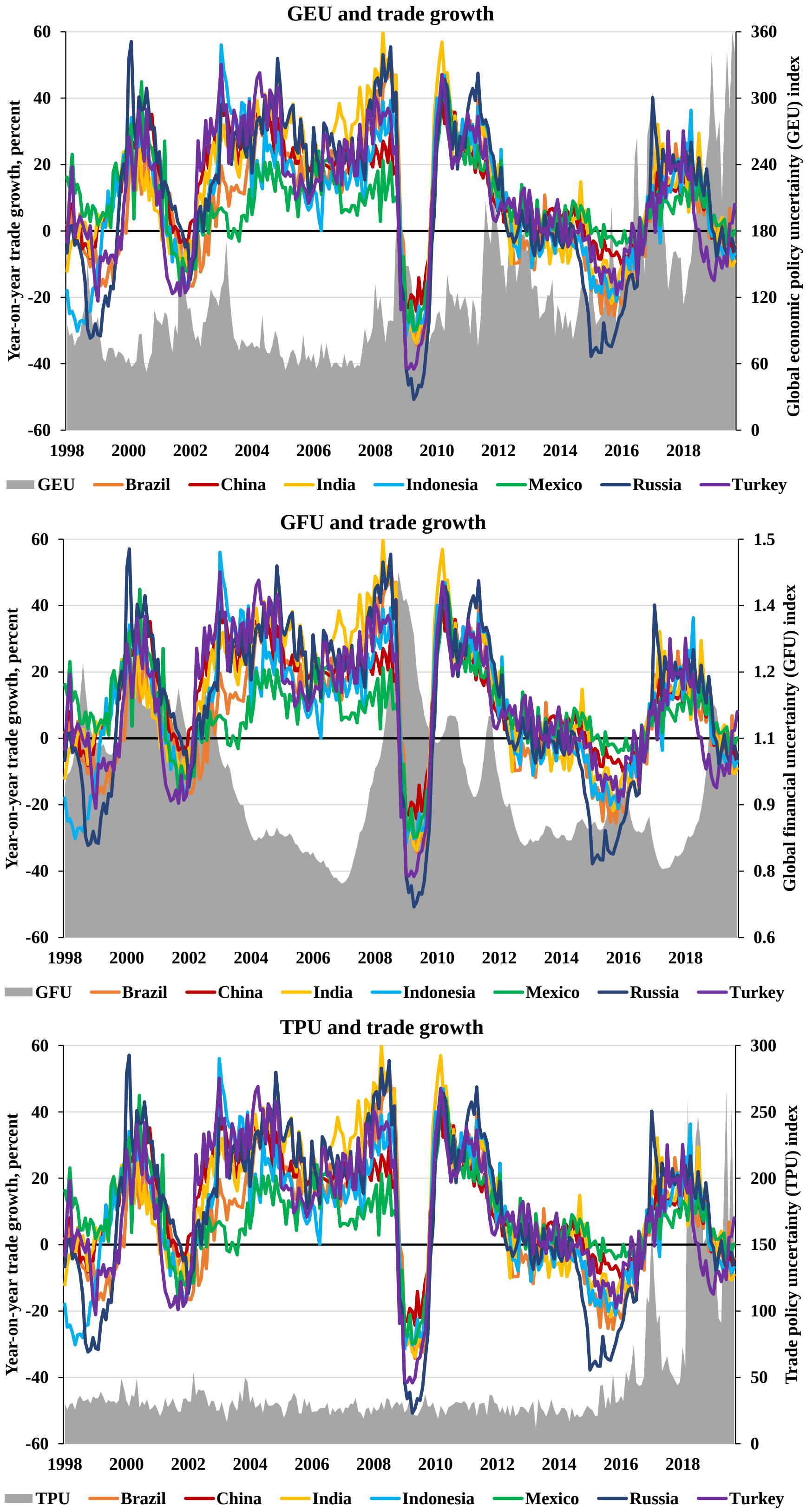
The aim of our empirical analysis is to measure the impacts of different types of global uncertainty shocks on trade flows of emerging economies. We estimate a structural panel VAR using monthly data from seven large emerging economies.

3.3.1 Data

Sample selection: Our sample comprises the seven largest emerging economies of the world, namely, Brazil, China, India, Indonesia, Mexico, Russia and Turkey, dubbed as the EM-7 by the World Bank (Huidrom et al., 2017). Our focus on the EM-7 economies is motivated by the economic importance of these countries: The EM-7 make up about 80% of aggregate output of emerging economies, similar to the G-7 who represent about 80% of aggregate output of advanced economies. In addition, EM-7 economies are important trading partners of emerging and developing economies, accounting for more than half of their total exports. Our monthly data run from January 1997 (the first year GEU is available) to September 2019 (purely due to data availability).

Uncertainty measures: In Section 3.2, we have already described the data sources of the three uncertainty measures (GEU, GFU, TPU) we use in this study. Table 3.1 and Figure 3.1 report the raw data, i.e., the index values of these measures. A drawback of these index values is that their levels may not be immediately comparable. To make these different measures of uncertainty comparable, we create indicators for

Figure 3.1: Uncertainty and Trade Growth in Emerging Economies



Notes: Trade flows are computed as the sum of imports and exports. Data source: Trade flows, IMF Direction of Trade Statistics; *GEU*: Global Economic Uncertainty, Baker et al. (2016); *GFU*: Global Financial Uncertainty, Ludvigson et al. (2020); *TPU*: Trade Policy Uncertainty, Caldara et al. (2020).

high uncertainty episodes using the same definition across all three measures. It is these indicators, not the raw index values, that we will use in our panel VAR regressions. We describe how we construct these indicators in the following paragraph.

Indicators for high uncertainty episodes: We follow Bloom (2009) and identify high uncertainty episodes as periods where each uncertainty index exceeds its respective mean by more than 1.28 standard deviations, based on the 10% level of significance for an upper-tailed test.[9] We use these binary indicators of uncertainty for estimating our panel VAR model.

Using these indicator variables instead of the underlying indices themselves has three advantages: 1.) As we use the same definition of high uncertainty episodes, the high uncertainty episode indicators are readily comparable amongst each other. 2.) Firms may adjust their behavior if uncertainty increases beyond a certain level, irrespective of the specific value of the uncertainty indices. Using the indicator variables reflects this reasoning. 3.) The indicators are arguably more exogenous than the respective uncertainty index itself.

We illustrate the high uncertainty episodes identified by each indicator for each uncertainty index in Figure 3.2 as shaded areas. The identified episodes highlight the heterogeneity amongst the uncertainty indices. GEU shocks tend to be more frequent and encompass uncertainty linked to the 2007/8 GFC, the Eurozone debt crisis, the Brexit referendum, Trump's election as US president and the trade tensions between US and China. Heightened TPU uncertainty is only a recent phenomenon: The 2017 episode captures the threat of a trade war between the US and China, and the 2019 episode its actual materialization. In contrast, GFU shocks were more frequent in the earlier part of the sample, including the Russian Financial Crisis, the dot-com bubble, the 9/11 terrorist attack and the GFC, having tamed down since. Compared to the GEU, the GFU shock during the GFC is of a longer duration.

Trade data and other variables: Imports and exports are obtained from the IMF Direction of Trade Statistics Database. The financial market variable is the local stock price index sourced from the OECD. Domestic activity is proxied by local Industrial Production (IP) whereas global demand is captured by global IP, both from Bloomberg.[10] To control for changes in trade flows due to changes in relative prices,

[9] Bloom (2009) actually identifies high uncertainty episodes as periods based on the 5% level of significance for an upper-tailed test, in a sample ending in 2009. Using this definition in our sample would imply classifying the 2007/8 Global Financial Crisis as well as the European sovereign debt crisis from 2009 to 2012 as episodes of low uncertainty. Nevertheless, we check the robustness of our results to this alternative threshold in Section 3.4.2.

[10] Local IP has been rebased to a single base period (January 2005) for all countries, first to ensure comparability across countries, and second, owing to the fact that some countries' data were in levels whereas others' were only available as percentage changes.

we control for the real exchange rate ($REER$), calculated by using nominal bilateral exchange rates against the US Dollar, adjusting for the consumer price indices in the US and each emerging economy. Table 3.2 summarizes the data used and their respective sources.

Seasonality and data transformations: As monthly data are affected by pronounced seasonality, we deseasonalize the series, separately for each country (except global IP, as it is already available deseasonalized from Bloomberg). We then take logs and detrend using a linear trend. All the series in the panel data set, except the uncertainty indices, are deseasonalized and detrended. We do not detrend the uncertainty indices as there is no a priori reason to expect a secular trend in uncertainty.[11] We also compute the trade balance to GDP ratio, using seasonally adjusted real GDP in local currency units for each EM-7 country from the St Louis Federal Reserve Economic Data. We convert to US Dollars using the quarterly exchange rate extracted from the same source. As GDP data are only available at quarterly frequency, we convert to monthly frequency by linear interpolation. We follow Schmitt-Grohé and Uribe (2018)'s approach to scale the trade balance by the secular component of GDP and detrend the resulting trade balance to GDP ratio.

3.3.2 The Empirical Model

The aim of the empirical model is to identify the different uncertainty shocks, and to compare their respective impacts on trade flows of EM-7 economies. The empirical model is the following first-order panel VAR system:

$$A \begin{bmatrix} U_t \\ Glo_t \\ Stk_{i,t} \\ Dom_{i,t} \\ M_{i,t} \\ X_{i,t} \\ REER_{i,t} \end{bmatrix} = \eta_i + B \begin{bmatrix} U_{t-1} \\ Glo_{t-1} \\ Stk_{i,t-1} \\ Dom_{i,t-1} \\ M_{i,t-1} \\ X_{i,t-1} \\ REER_{i,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_t^U \\ \epsilon_t^{Glo} \\ \epsilon_{i,t}^{Stk} \\ \epsilon_{i,t}^{Dom} \\ \epsilon_{i,t}^{M} \\ \epsilon_{i,t}^{X} \\ \epsilon_{i,t}^{REER} \end{bmatrix}, \tag{3.1}$$

where η_i is a (7×1) vector of country-specific fixed effects, following a wealth of studies using panels of emerging economies, e.g., Uribe and Yue (2006), Akinci (2013), Pasricha et al. (2018), Caballero et al. (2019), and Bhattarai et al. (2020).

U_t represents any of the three indicators for high uncertainty episodes.[12] We estimate three separate VARs: A first one where U_t represents the high uncertainty indicator

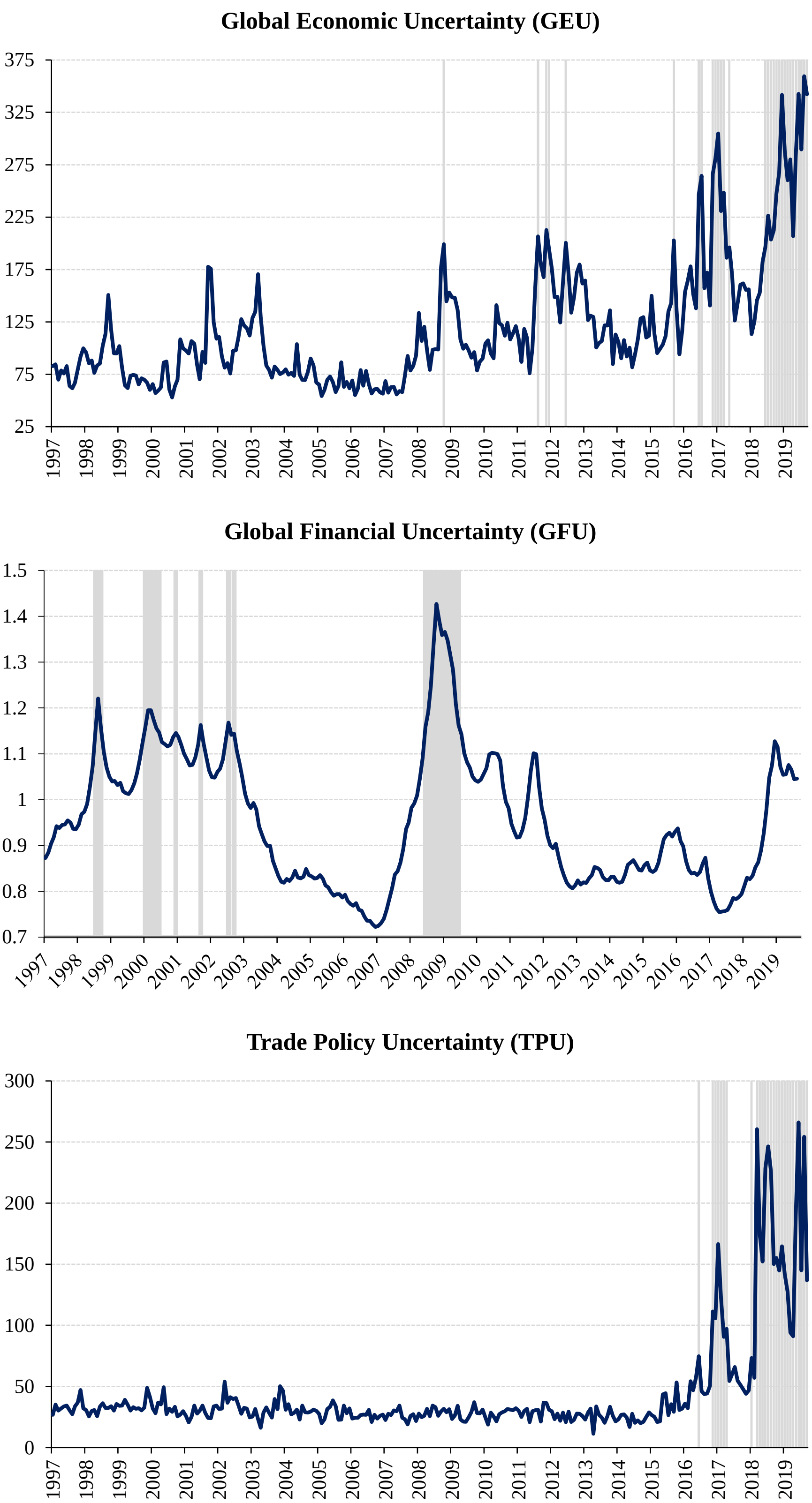
[11] We check the robustness to this in Section 3.4.2.

[12] To choose the optimal lag length, we use the model selection procedures suitable for dynamic

Table 3.2: Data and Data Sources

Variable	**Unit of measurement**	**Source**
GEU_t: Global Economic Policy Uncertainty	Index (raw data); indicator for high uncertainty episodes (panel VAR)	Baker et al. (2016) (raw data)
GFU_t: Financial Uncertainty	Index (raw data); indicator for high uncertainty episodes (panel VAR)	Ludvigson et al. (2020) (raw data)
TPU_t: Trade Policy Uncertainty	Index (raw data); indicator for high uncertainty episodes (panel VAR)	Caldara et al. (2020) (raw data)
Glo_t: Global IP	Index	Bloomberg
$X_{i,t}$: Exports	$ million	IMF Direction of Trade Statistics
$M_{i,t}$: Imports	$ million	IMF Direction of Trade Statistics
$Stk_{i,t}$: Stock Market Index	Share Price Index (Base Year=2010)	OECD Database
$Dom_{i,t}$: Local IP	Index (Jan 2005=100)	Bloomberg
Nominal bilateral exchange rate	Price of 1 US Dollar in local currency units	Federal Reserve Bank of St. Louis
Consumer Price Index (CPI)	Index	OECD Database
$REER_{i,t}$: Real exchange rate	Price of 1 US Dollar in local currency units, adjusted for differences in CPIs	Constructed by the authors

Figure 3.2: High Uncertainty Episodes



Notes: Shaded areas highlight high uncertainty episodes which we define as periods wherein the underlying uncertainty index exceeds its mean by 1.28 standard deviations. Data source: *GEU*: Baker et al. (2016); *GFU*: Ludvigson et al. (2020); *TPU*: Caldara et al. (2020).

for GEU; a second one where U_t represents the high uncertainty indicator for GFU; and a third one where U_t represents the high uncertainty indicator for TPU. All other variables are defined as given in Table 3.2. Our specification follows standard specifications used in the uncertainty literature, adjusted to our purposes in terms of data availability for EM-7 countries. We use $Dom_{i,t}$, Glo_t and $Stk_{i,t}$ to proxy for domestic activity, external demand conditions and domestic financial conditions, respectively.[13]

Structural identification of the empirical model is obtained by imposing restrictions that turn matrix A in Equation (3.1) into a lower triangular matrix with unit diagonal elements. We recover structural shocks from the VAR innovations by using a Cholesky decomposition identification strategy. Our ordering of variables is standard and follows Baker et al. (2016) and Caggiano et al. (2014). Importantly, as we are interested in the impact of uncertainty shocks, we put the uncertainty measure at the top, assuming that no other variable can affect the uncertainty indicator contemporaneously but only with a lag. Given that we use monthly data, this assumption seems plausible and is standard in the uncertainty literature. Nevertheless, it is debatable. Therefore, in our robustness checks (see Section 3.4.2), we follow Caggiano et al. (2014) and allow all other variables to influence the uncertainty indicator contemporaneously by ordering it last. Our results are robust to this alternative ordering. Concerning the other variables, we create a global block containing the uncertainty index and the global IP at the top, followed by a domestic block. This implies that EM-7 economies react contemporaneously to global shocks, while changes in EM-7 economies only affect global indicators with a lag. The economic interpretation of our structural identification strategy is that we treat each individual EM-7 economy as a small open economy in the short-run, i.e., contemporaneously, and as a large open economy in the long-run, i.e., we allow for each EM-7 economy to impact the global block, albeit with a lag. This is akin to modelling large open economy or general equilibrium effects as "second round" effects. Our ordering therefore goes from the uncertainty index, global IP, the domestic stock market, local IP, imports, exports, and finally, the real exchange rate.

Panel VARs are an example of dynamic panel models, i.e., panel models with lagged variables. In such models, the presence of fixed effects renders OLS parameter estimates biased, see Nickell (1981). We therefore estimate parameters using a generalized method

panel models with unobserved individual effects developed by Andrews and Lu (2001). These model selection criteria are similar to likelihood-based information criteria and model the trade-off between the value of the J-statistic and the number of parameters and moments included. We report model selection criteria in Table A.1 in the Appendix. Irrespective of the uncertainty measure, they unanimously favour one lag.

[13] Novy and Taylor (2020) use monthly employment as their measure for domestic activity, but monthly employment data are not available for EM-7 countries.

of moments estimator by Holtz-Eakin et al. (1988) using forward-orthogonalized variables as suggested by Arellano and Bover (1995).[14] We instrument transformed variables by the first lag of their respective untransformed counterparts in levels.[15]

We present impulse response functions of our estimated models which describe the reaction of all the variables in the model following a one standard deviation shock to each uncertainty variable GEU, GFU and TPU, for up to 36 months after the shock. The impulse response confidence intervals are based on 500 Monte Carlo simulations. The 68% and 95% confidence intervals are derived from the resulting distributions.

3.4 Results

3.4.1 Uncertainty Shocks and Trade Flows

Exports and imports. To compare the trade effects of the different uncertainty measures, we estimate three panel VARs using Equation (3.1), each featuring a different uncertainty indicator and including both exports and imports as separate variables. We present impulse response functions following a one standard deviation shock to each of the uncertainty indicators in Figure 3.3. Results are to be read row-wise. The first row shows the impulse responses in a model where Baker et al. (2016)'s global economic uncertainty index (GEU) is used. Similarly, the second row depicts the impulse responses to a standard deviation uncertainty shock in the model where uncertainty is captured by Ludvigson et al. (2020)'s financial uncertainty index (GFU). Finally, the third row's set of impulse responses reflect the dynamics following a shock to Caldara et al. (2020)'s trade policy uncertainty index (TPU).

The results accentuate how different uncertainty measures impact imports and exports in emerging economies heterogeneously. In particular, GEU and TPU shocks lead to a protracted decline in trade flows, while financial uncertainty shocks, captured by GFU, have a short-lived impact on trade.

Our results suggest that all types of uncertainty act as a barrier to trade. However, the extent and duration of the decline in trade flows depend on the nature of the shock. Global economic uncertainty and trade policy uncertainty shocks lead to a persistent

[14] Monte Carlo simulations by Hayakawa (2009) suggest the superiority of forward-orthogonal deviations over first-differencing. The forward-orthogonal transformation consists of subtracting the mean of future observations at each period t from each variable to eliminate the country fixed effects.

[15] We use Stata 16 and the package `pvar` by Abrigo and Love (2016). Similar panel VAR procedures are adopted in cross-country panels in related contexts, e.g., by Balcilar et al. (2021) who investigate the effect of uncertainty on housing prices and Adarov (2021) who investigates the effect of financial cycles on the current account and other macroeconomic variables.

decline in trade. GEU and TPU shocks occasion a contemporaneous drop in trade flows, but this deteriorates further after a quarter. Following a GEU shock, imports contract by 1.7% on impact, and drop further by 3.2% after two months. Similarly, exports fall by 1.7% contemporaneously and by 3.8% thereafter. A similar dynamic is noted for TPU shocks, whereby imports and exports drop by 1.3% on impact, and by 4.0% and 4.8%, respectively by the sixth month. Our results complement existing evidence on the trade-reducing impact of uncertainty covering developed economies, see Handley (2014), Handley and Limão (2015), Handley and Limão (2017), De Sousa et al. (2020), and Novy and Taylor (2020).

In contrast to the enduring decline in trade flows triggered by global economic uncertainty and trade policy uncertainty shocks, financial uncertainty shocks only have a transitory impact on trade flows. Admittedly, the contemporaneous impact of GFU shocks to the tune of 1.7% for imports and 2.2% for exports exceed the contemporaneous impacts observed for GEU and TPU shocks. However, in the case of GFU shocks, trade flows return to positive trajectory by the third month. In contrast, impulse responses of imports and exports remain negative and statistically significant for 2.5 years in the case of GEU and TPU shocks. Focusing only on global financial uncertainty shocks, Bonciani and Ricci (2020) also document its short term impact on trade flows in emerging economies, contrasting the longer-lasting contraction in advanced economies. Similarly, Novy and Taylor (2020) find larger negative effects of financial uncertainty on U.S. imports. Hence, our results for GFU shocks lend support to the evidence on the decoupling between emerging economies and advanced economies' business cycles, see Kose et al. (2003, 2012).

Turning to the other variables, we find that across the three models, uncertainty shocks trigger a depreciation of EM-7 currencies as well as a deterioration of stock market performance, reflecting 'flight-to-safety' adjustments of international investors. This resonates with evidence of perceived riskiness of emerging economies in times of uncertainty, see Uribe and Yue (2006) and Akinci (2013). Global economic uncertainty and trade policy uncertainty engender long-lasting depreciation of EM-7 currencies, as indicated by impulse responses that persist in the positive region for several months after the shock. Meanwhile, GFU shocks have the largest impact on global IP among all the uncertainty measures we consider. In contrast, except for the contemporaneous drop, their impact on EM-7's real activity is rather short-lived. This is again in line with the decoupling literature, highlighting how the business cycles of emerging economies have diverged from advanced economies'. Following a GFU shock, EM-7's stock market prices plunge by nearly 10%, followed by an immediate recovery. In contrast, following a GEU or a TPU shock, stock market prices drop by around 4.0% initially and remain rather lethargic afterwards, failing to recover within three years. Overall, the results also draw a clear demarcation line between how uncertainty affects financial markets versus real activity, with stock markets reacting more aggressively to uncertainty shocks than local IP.

Our results highlight the sensitiveness of emerging economies' trade flows to different types of external uncertainty shocks. Trade flows react even stronger to uncertainty shocks than domestic activity. In other words, the damages caused by uncertainty shocks are most visible in the impulse responses of trade flows. Heightened trade policy uncertainty is the most detrimental source of uncertainty.

The impulse response functions indicate that exports undergo a marginally deeper contraction than imports, following uncertainty shocks. This corresponds with the intuition that investment dips more significantly than consumption following uncertainty episodes (Caballero, 1990). Carrière-Swallow and Céspedes (2013) highlight that this also holds in the context of emerging economies. Consumption expenditure and hence imports are particularly impacted by precautionary savings by private households. Concomitantly, investment's sensitiveness to uncertainty stems from the option value of waiting, delaying firms' decision to export (Handley and Limão, 2015). Accordingly, exporters are therefore less likely to enter new export markets, when the prevalent level of uncertainty is high. Consistent with this, we find that uncertainty shocks cause emerging economies' local IP to deteriorate less than their trade.

Trade balance. Amidst the rising popularity of protectionist policies across major economies, policymakers have shown increased interest in measures of macroeconomic imbalances, in particular, large and persistent trade surpluses and deficits. If emerging economies' trade balance worsens in response to external uncertainty shocks, these protectionist tendencies may be exacerbated in times of heightened uncertainty. To this end, we investigate the impact of uncertainty on the trade balance to GDP ratio, $TB/Y_{i,t}$, by replacing the latter as the trade variable in our panel VAR in Equation (3.1). The resulting empirical model is the following panel VAR model with order 1:

$$M \begin{bmatrix} U_{i,t} \\ Glo_t \\ Stk_{i,t} \\ Dom_{i,t} \\ TB/Y_{i,t} \\ REER_{i,t} \end{bmatrix} = \eta_i + \Gamma \begin{bmatrix} U_{t-1} \\ Glo_{t-1} \\ Stk_{i,t-1} \\ Dom_{i,t-1} \\ TB/Y_{i,t-1} \\ REER_{i,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_t^{U} \\ \epsilon_t^{Glo} \\ \epsilon_{i,t}^{Stk} \\ \epsilon_{i,t}^{Dom} \\ \epsilon_{i,t}^{TB/Y} \\ \epsilon_{i,t}^{REER} \end{bmatrix}. \tag{3.2}$$

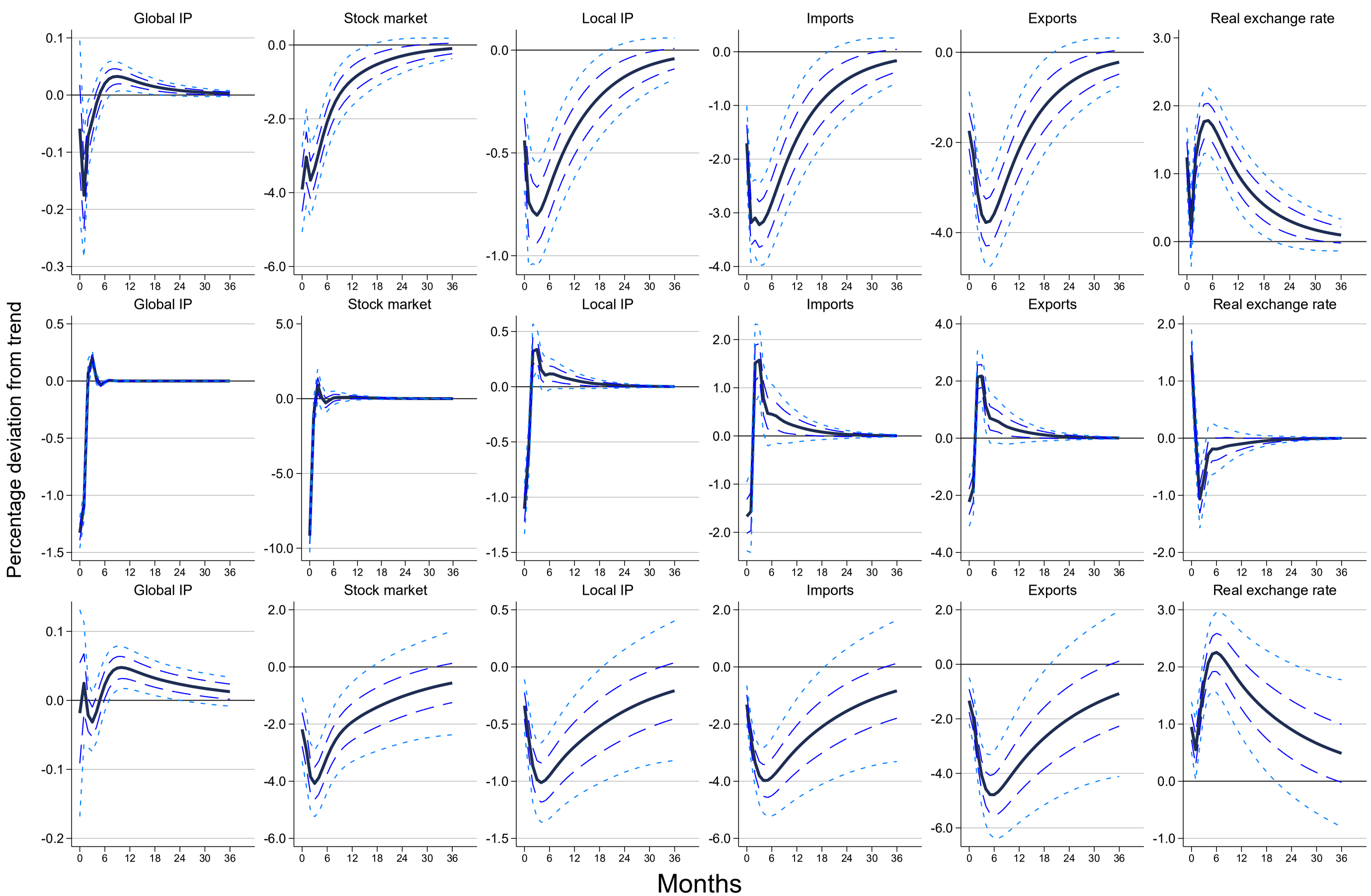
Figure 3.4 illustrates the impact of external uncertainty on the EM-7's trade balance to GDP ratio. Figure 3.4 is organized in the same way as Figure 3.3, i.e., the first row shows the impulse response functions to a one standard deviation shock in the high uncertainty episodes indicator created from the GEU index, the second row tracks a GFU shock, and finally the third row depicts the impulse response functions to a TPU shock. The results broadly echo the results presented in Figure 3.3. Impulse responses

Figure 3.3: Impulse Responses to a Standard Deviation Shock to Different Uncertainty Measures

(1) Model featuring Baker et al. (2016) Global Economic Uncertainty (GEU) Index

(2) Model featuring Ludvigson et al. (2020)'s Financial Uncertainty (GFU) Index

(3) Model using Caldara et al. (2020)'s Trade Policy Uncertainty (TPU) Index



Notes: Solid lines show point estimates of impulse responses. The dashed and dotted lines depict the 68% and 95% confidence bands, based on 500 Monte Carlo simulations, respectively.

for global IP, local IP, the stock price index and the real exchange rate are qualitatively in line with the findings presented earlier, except for the fact that the impulse responses turn statistically insignificant at a slightly earlier stage when $TB/Y_{i,t}$ is used.

Trade policy uncertainty comprises the greatest risk to the trade balance to GDP ratio in emerging economies. $TB/Y_{i,t}$ drops by about 0.34 percentage points following a TPU shock, and its impulse response remains negative and statistically significant for 18 months. $TB/Y_{i,t}$'s response to a GEU shock is quite similar, dropping by 0.32 percentage points on impact but turning statistically insignificant rather quicker, by the seventh month after the shock. Meanwhile, $TB/Y_{i,t}$ does not respond contemporaneously to a GFU shock. Although the response is positive and signficant for about six months, the magnitude stays close to zero.

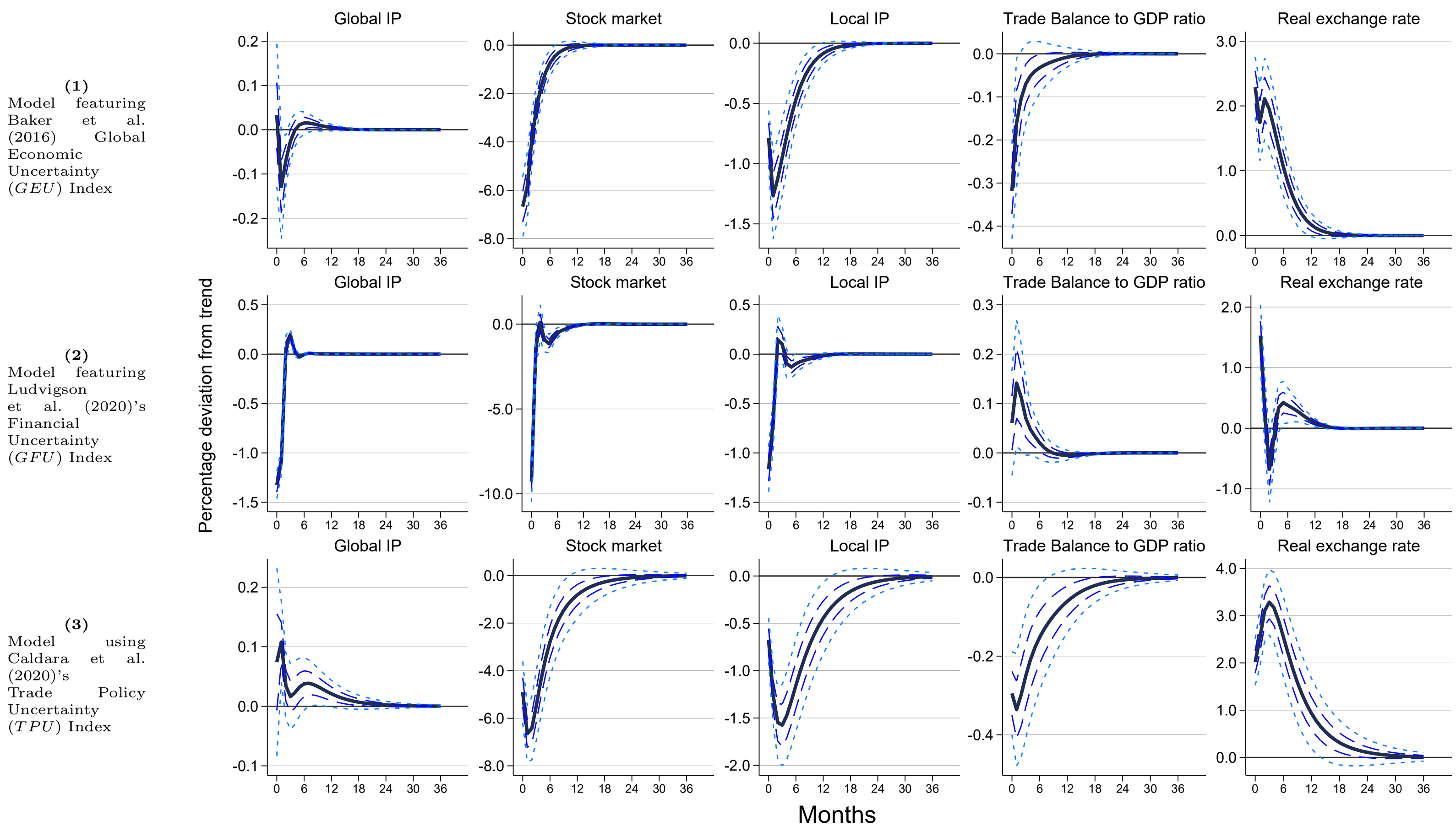
Overall, our results highlight that uncertainty matters for trade flows of emerging economies. However, the source of uncertainty matters. The effects of financial uncertainty shocks on openness are not large, as the impulse responses of imports and exports quickly revert to near-zero. On the contrary, global economic uncertainty and trade policy uncertainty pose a prolonged challenge to nurturing the degree of openness in EM-7 economies, as indicated by the simultaneous contraction of imports and exports, even more than a year after the uncertainty shock has subsided. Global economic uncertainty and trade policy uncertainty also contribute to a worsening of the trade balance.

3.4.2 Robustness Checks

Different uncertainty measures. Our baseline results show how EM-7 trade flows vary with spikes in global economic, global financial and trade policy uncertainty, using the GEU, GFU and TPU indices as the respective measures of uncertainty. Different uncertainty measures of a specific type of uncertainty should correlate. However, differences may exist due to the particular methodologies used in computing the different indices. In the first series of robustness tests, we check whether alternative proxies for financial and trade policy uncertainty corroborate our baseline results. Note that we create the respective indicators for high uncertainty episodes for all the alternative uncertainty proxies, as we did for our baseline results. As in our baseline, all panel VARs use these indicator variables, not the underlying raw index data, so that we can directly compare the results across the different uncertainty proxies.

In the first robustness check, we explore the consequences of using alternative financial uncertainty shocks. Particularly, we use Caggiano and Castelnuovo (2021)'s global financial uncertainty index as well as the Chicago Board Options Exchange's Volatility Index, VIX. Caggiano and Castelnuovo (2021) derive a global financial uncertainty measure using a large-scale dynamic factor model on financial markets

Figure 3.4: Uncertainty Shocks in a Model with Trade Balance to GDP Ratio



Notes: Solid lines show point estimates of impulse responses. The dashed and dotted lines depict the 68% and 95% confidence bands, based on 500 Monte Carlo simulations, respectively.

data for 42 countries. The VIX, on its part, commonly referred to as a 'fear gauge', tracks stock market jitters from the implied volatility of the S&P500 index over a 30-day window. It is a widely used financial uncertainty measure (see, e.g., Caggiano et al., 2014; Baker et al., 2016). Figure A.1 in the Appendix shows that the results with Caggiano and Castelnuovo (2021)'s global financial uncertainty measure and the VIX are both similar to our baseline.

Next, we compare Caldara et al. (2020)'s measure of TPU (our baseline) with Baker et al. (2016)'s trade policy uncertainty measure. As illustrated in Figure A.2 in the Appendix, the shape of the impulse response functions are preserved, albeit we find a marginally milder contraction of trade flows when we use Baker et al. (2016)'s trade policy uncertainty measure.

Using alternative data transformations. To rule out the possibility that our results may be artefacts of our chosen data transformations, we try out a battery of sensible alternatives. Bloom (2009) and Carrière-Swallow and Céspedes (2013) identify uncertainty periods over the sample by considering months where the *detrended* uncertainty index exceeds its mean by a certain threshold. In our baseline, we chose to identify uncertainty episodes based on the original values rather than the detrended ones. The TPU has only started to increase recently, and log-linear detrending, as we did for other variables in the VAR, would create spurious negative shocks in the early period, and underestimate the magnitude of disturbances in recent times. A deterministic log-linear trend may not be flexible enough. We therefore use the filter recently proposed by Hamilton (2018) to detrend the uncertainty indices before identifying episodes where the detrended values exceed the mean by 1.28 standard deviation. The shape of the impulse responses are maintained, as shown in Figure A.3 in the Appendix.

Some uncertainty episodes may be more important than others; and assigning a value of 1 for all uncertainty shocks may not appropriately portray the intensity of the uncertainty episode. We therefore also check whether results differ, when instead of just using a dummy equalling 1 when the index exceeds the mean$+1.28\sigma$, we set the uncertainty indicator equal to its log-linear detrended value during high-uncertainty episodes, and 0 otherwise, similar to Bloom (2009). Results, as pictured in Figure A.3 in the Appendix, still corroborate our main findings.

Alternative ordering. Our baseline ordering of variables assumes a global block, with the uncertainty index being the most exogenous followed by global IP, and a domestic block with the stock market, local IP, imports, exports and the real exchange rate. Following Caggiano et al. (2014), we try an alternative ordering where we still include the uncertainty index in the foreign block, but order it after global IP, assuming that no emerging economies' shock is able to impact global uncertainty contemporaneously. In another robustness check, we consider an alternative scenario where the EM-7 are large open economies in terms of their effect on global uncertainty even in the short-run, i.e., we allow their domestic shocks to lead to contemporaneous spill-overs on the global uncertainty indices. For this scenario, we order the different uncertainty measures last in the Structural Panel VAR. This means that global IP and EM-7's macroeconomic variables do not react on impact to uncertainty shocks. We show results in Figure A.4 in the Appendix. Despite an expansionary blip in imports and exports following a *GFU* shock when uncertainty is ordered last, results echo the baseline findings of long-term contractionary effects of economic and trade policy uncertainty, albeit at lower levels.

Different high uncertainty episodes. As the data coverage extends to recent years, some high uncertainty episodes previously identified in the literature get weeded out if a high threshold is used as cut-off, as pointed out by Carrière-Swallow and Céspedes (2013). For example, Bloom (2009) identifies high uncertainty episodes as periods where his HP-filtered uncertainty measure exceeds its mean by 1.65 standard deviations, based on the 5% level of significance for an upper-tailed test, in a sample ending in 2009. Using this cut-off in our sample ending in 2019, for example, the European sovereign debt crisis would no longer be categorized as a high uncertainty episode of the *GEU* index. To avoid this, we chose a lower cut-off of 1.28σ for our main specifications for all indices. As a robustness check, we follow Bloom (2009) and identify high uncertainty episodes as periods where the underlying indices exceed their respective mean by 1.65 standard deviations. We illustrate the high uncertainty episodes using this definition as shaded areas in Figure A.5 in the Appendix. For the impulse response functions, these differences in cut-offs still lead to results qualitatively similar to the baseline, as pictured in A.6 in the Appendix.

3.4.3 How Much of the Variation in Trade Flows Can Be Explained by Uncertainty Shocks?

Sections 3.4.1 and 3.4.2 document the dynamic adjustment of trade flows and the trade balance in the aftermath of a given exogenous shock to global economic, financial, and trade policy uncertainty. It is still unclear, however, to what extent uncertainty shocks explain the observed variation in trade flows and the trade balance, compared to other shocks. In other words, we would like to know whether uncertainty shocks are a major driver of trade flows. To answer this question, we conduct a variance decomposition to ascertain the degree to which the various uncertainty shocks contribute to explaining the movements in variables in the VAR models given by Equations (3.1) and (3.2). Figure 3.5 presents the variance decompositions of the model including imports and exports, whilst Figure 3.6 shows the variance decompositions when the trade balance to GDP ratio is used instead. In each of the figures, the first row illustrates the variance decomposition of the *GEU* shock, the second portrays the *GFU*'s shock variance decomposition and the third row depicts the variance decomposition of the TPU shock.

Figure 3.5 suggests that the contribution of uncertainty shocks to fluctuations in imports and exports of EM-7 economies differs, depending on the type of uncertainty being considered. Global economic uncertainty shocks explain 7 to 8% of the variation in imports and exports. Trade policy uncertainty shocks explain more than 11%, the highest proportion of the variation in imports and exports of all uncertainty measures we consider. These figures are non-negligible, as we are talking about second-moment shocks (i.e., mean-preserving increases in variance), as opposed to realised first-moment shocks. In comparison, financial uncertainty shocks do not seem to matter much, and explain less than 2% of the variation in imports and exports at the three-year horizon. Once again, EM-7 trade flows appear to be insulated from GFU shocks.

It also becomes clear that global economic uncertainty shocks and trade policy uncertainty shocks explain the largest amount of variation in exports and imports among all the variables considered in our panel VAR. This highlights the importance of uncertainty shocks for trade and trade policy discussions. Trade flows of emerging economies are particularly vulnerable to uncertainty shocks, more so than, e.g., local IP or the domestic stock market.

Turning to Figure 3.6, we find that global economic uncertainty and particularly financial uncertainty shocks do not help much in explaining the movement in the trade balance in emerging economies. Instead, trade policy uncertainty explains more than 5% of the variation in the trade balance to GDP ratio. The corresponding proportion explained by GEU shock is only 1.6%, whereas the contribution of GFU shocks is close to zero.

Summing up, our results quantify the importance of uncertainty shocks for trade flows in emerging economies and call for a consideration of trade effects in studies on the macroeconomic effects of uncertainty. Particularly trade policy uncertainty shocks explain a sizeable share of the variance of imports and exports, illustrating their importance in an absolute sense. Trade policy uncertainty shocks are also more important in a relative sense, as their contribution in explaining the variation in trade flows is higher than the contribution of global economic and financial uncertainty shocks.

3.5 Conclusion

Uncertainty has become a major concern around the globe. While financial uncertainty was at the forefront of policymakers' minds during the Global Financial Crisis, trade policy uncertainty surged during the Trump presidency, and global economic uncertainty has increased, not least during the ongoing pandemic. While the

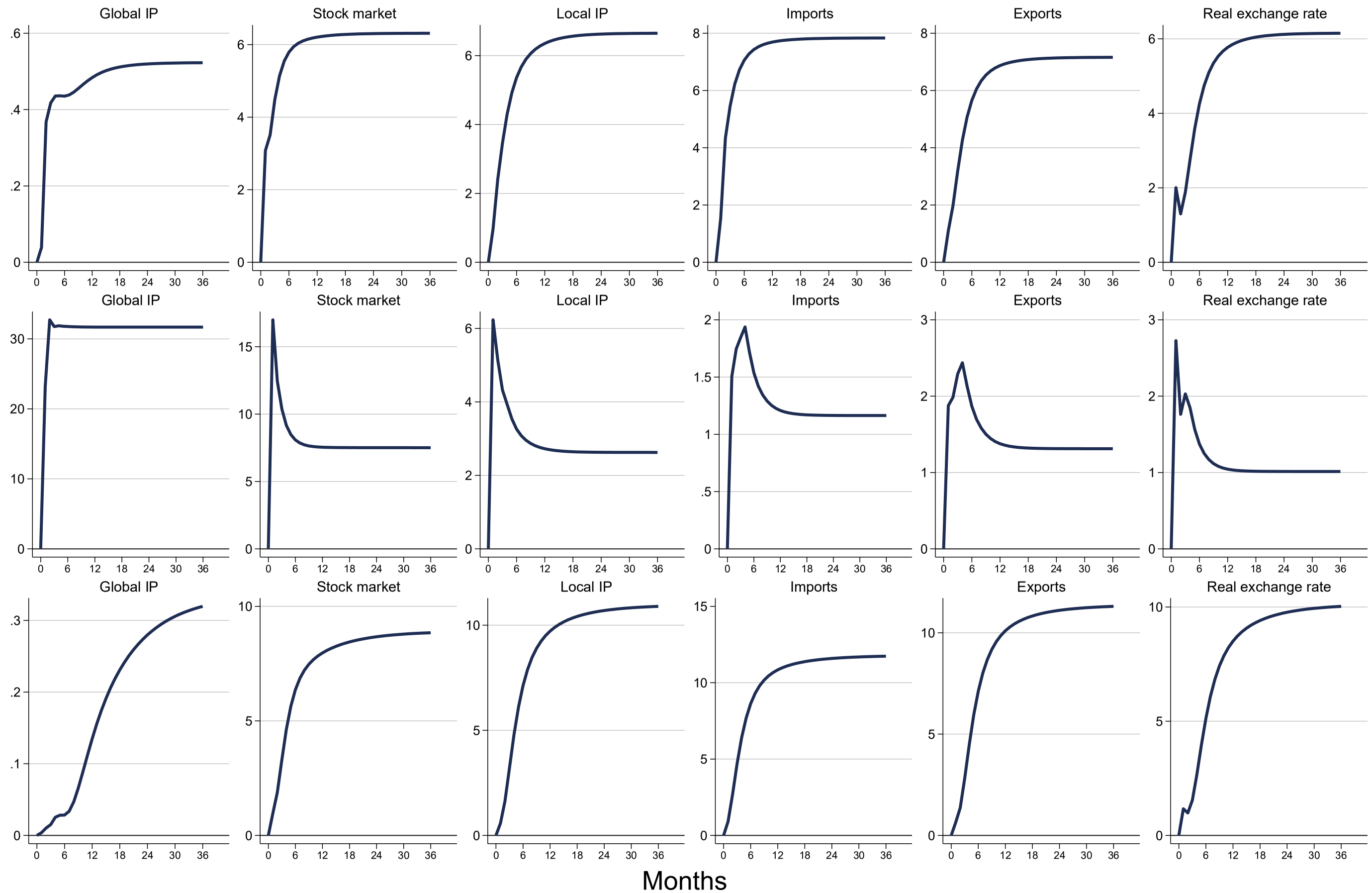
Figure 3.5: Forecast Error Variance Decomposition

Percentage Variation Explained by an Uncertainty Shock

(1) Model featuring Baker et al. (2016) Global Economic Uncertainty (GEU) Index

(3) Model featuring Ludvigson et al. (2020)'s Financial Uncertainty (GFU) Index

(3) Model using Caldara et al. (2020)'s Trade Policy Uncertainty (TPU) Index



Notes: The graphs show the percentage variation in the respective variable explained by the respective uncertainty shock.

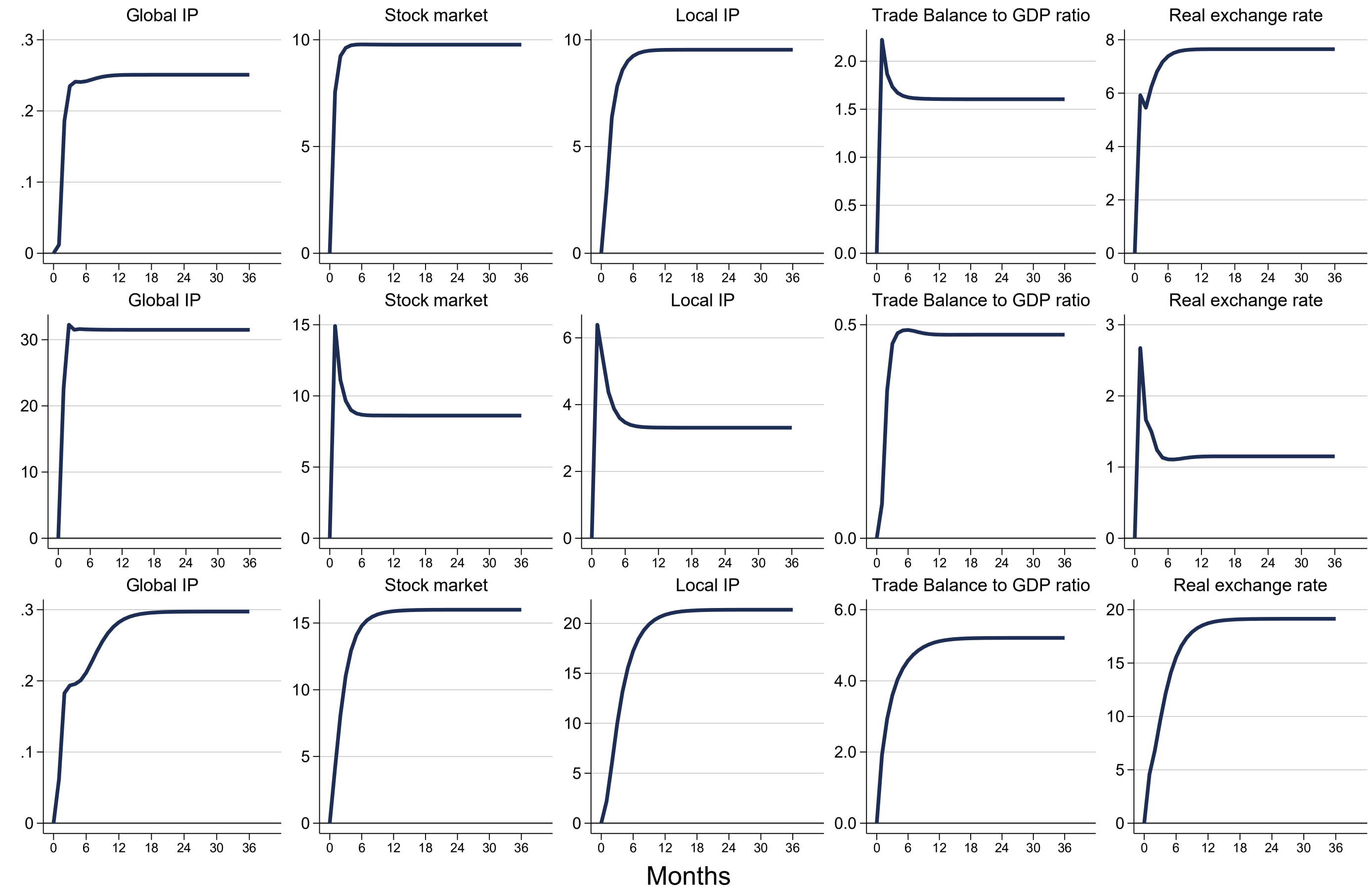
Figure 3.6: Forecast Error Variance Decomposition in a Model with Trade Balance to GDP Ratio

Percentage Variation Explained by an Uncertainty Shock

(1) Model featuring Baker et al. (2016) Global Economic Uncertainty (*GEU*) Index

(3) Model featuring Ludvigson et al. (2020)'s Financial Uncertainty (*GFU*) Index

(3) Model using Caldara et al. (2020)'s Trade Policy Uncertainty (*TPU*) Index



Notes: The graphs show the percentage variation in the respective variable explained by the respective uncertainty shock.

macroeconomic effects of these different dimensions of uncertainty have been studied in detail, less is known about their effects on international trade.

Our paper illustrates the detrimental impact of global economic, financial, and trade policy uncertainty on the trade flows of the seven largest emerging economies. Using a panel VAR model, we find that global economic and trade policy uncertainty shocks induce a protracted decline in emerging economies' imports and exports. We find that trade policy uncertainty is important in an absolute sense: It explains more than 10% of the variation in imports and exports. Trade policy uncertainty is also important in a relative sense: It explains a larger share of the variation in emerging economies' trade flows than global economic uncertainty or financial uncertainty. Hence, macroeconomic studies on the effect of uncertainty should consider its impact on trade flows, and trade studies should investigate the trade effects of uncertainty, particularly if their interest lies on short-run adjustment dynamics in the wake of major increases in uncertainty. This has implications, e.g., for analyses of the trade effects of the heightened uncertainty due to the current invasion of Ukraine by Russia.

More generally, our results provide evidence for the concern of policymakers about the return of more volatile trade policy discussions in the wake of the Trump era and the ongoing pandemic. Heightened trade policy uncertainty not only fills newspaper columns and twitter feeds, but has real consequences for emerging economies' integration into the world economy.

Statement of Authorship

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Principal Author

Name of Principal Author (Candidate)	Tayushma Sewak		
Contribution to the Paper	This is a sole-authored paper.		
Overall percentage (%)	100%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	11 November 2022

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Contribution to the Paper			
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Chapter 4

External Shocks and Business Cycle Fluctuations

Abstract

Business cycle volatility is detrimental to growth and welfare, and it is important to gauge the different sources of business cycle fluctuations for the design of sound macroeconomic policies. This paper investigates the impacts of becoming more synchronised to a global business cycle, a regional business cycle, or a business cycle shared by economies within the same income group by using a Factor Augmented Vector Auto Regressive model. I find that these external sources of vulnerability explain a greater share of economies' business cycle fluctuations than domestic shocks. Emerging economies' business cycles are more volatile than advanced economies, and they also tend to be more synchronised with each other. Global shocks have waned over the latter part of the sample period 1995–2019. In turn, regional shocks explain a greater share of volatility than global shocks. Emerging economies are also more affected by regional shocks than advanced economies. Overall, the estimated global and group-specific factors account for a greater share of deviations from trend output than domestically-sourced shocks, highlighting that external spill-overs need to be monitored.

JEL-Classification: C13, E30, E32,F41, F43, F44, F62.

Keywords: Global business cycle synchronisation, Regional business cycle, Emerging economies, FAVAR.

4.1 Introduction

Rising trade and financial integration herald a greater possibility for economies' business cycles to be exposed to international business cycle comovements. This means that curbing volatility and nurturing a stable macroeconomic environment may not entirely rest within the control of domestic macroeconomic policies. With countries, especially emerging economies, becoming increasingly connected through trade and financial linkages, part of business cycle fluctuations may in fact be imported. In particular, the worldwide economic contraction induced by the Covid-19 pandemic is a telltale sign of business cycle synchronisation across economies. This raises concerns over the existence of a common global business cycle that may influence domestic business cycles. In addition to global linkages, business cycles of economies within a region may converge as trade and financial integration may also be localised within regions. This may take the form of regional trade agreements such as EU, NAFTA, ASEAN, COMESA, or the consolidation of efforts to facilitate investment within regions. This implies that, in addition to a global business cycle, domestic economic performance may also be affected by regional business cycles. Identifying and understanding the sources of business cycle movements is key to designing suitable policies for macroeconomic stability.

Exposure to common external shocks contributes to business cycle interdependence amongst economies. It is important to identify the sources of these common shocks. On a global scale, global economic shocks may manifest themselves through synchronised recessions such as the 2007/8 Global Financial Crisis or the economic downturns observed during the most recent COVID-19 episode. Concomitantly, the business cycles of countries with similar economic structures may converge. Advanced economies are more financially integrated than emerging economies, and are therefore better able to use international financial markets for risk sharing. This suggests the prevalence of common cyclical fluctuations among advanced economies, and among emerging economies, separately. Kose et al. (2012) even highlight that group-specific factors for advanced versus emerging economies are more significant in explaining cyclical fluctuations than a global factor. Levy Yeyati and Williams (2012) shows that emerging economies' business cycles have decoupled from those of advanced economies, on the back of the growing importance of China. Frankel and Rose (1998) establishes the cornerstone relationship between trade and output comovement, laying the premise for global cyclical interdependence. Building on this, di Giovanni and Levchenko (2010), Ng (2010) and Johnson (2014) emphasize that countries with higher trade in intermediate goods would have greater output comovement. Countries that trade in intermediate goods tend to be concentrated within particular geographic regions, suggesting the prevalence of a regional business cycle. Kose and Yi (2006) lend support to this, by demonstrating that countries with lower transport costs exhibit greater output comovement.

This paper distinguishes between a global business cycle, a regional business cycle as well as a business cycle shared by economies within the same income categories (advanced and emerging economies), and analyses their repercussions on domestic business cycle movements. There are two aspects to external vulnerability. On the one hand, the size and frequency of external shocks are common across economies or economies of particular categories. On a global scale, the common external shock could take the form of a global recession; on an income group level, examples include the 2013 taper tantrum episode that triggered synchronised uncertainty in emerging markets; and finally, on a regional scale, examples include the 1997 Asian Financial Crisis or the 2010 Eurozone Debt Crisis. On the other hand, different economies may react differently to the same external shocks. For example, even within the limited G7 sample in Stock and Watson (2005), France's share of variance explained by a global factor shock is 88%, compared to only 1% for Japan. Similarly, Mumtaz and Theodoridis (2017) compute the variance of output growth explained by the global factor for 11 OECD economies, and the corresponding range is wide at 2–36%. This paper caters for the twin aspects of vulnerability: the common external shocks and the reaction of different economies to the external shock. Estimated global and group-specific factors represent the common external shocks, and the historical error decomposition identifies the real net exposure of different economies to these shocks.

This paper makes three principal contributions to the literature on international business cycle synchronisation. Research on global spill-overs has primarily focused on advanced economies so far. I go beyond this by adding 14 emerging economies to the analysis. Emerging economies have gained importance on the global landscape. China is the largest economy since 2016 (using GDP measured at purchasing power parity). Five of the largest economies in the world are emerging economies. Emerging economies have become an integral part of global value chains, and are also financially integrated. Hanson (2012) highlights the central role of emerging economies in international trade, with North-South trade and South-South trade overtaking the share of North-North trade. In contrast, studies on global cyclical interdependence focus on a restricted set of economies: Stock and Watson (2005)'s analysis of the global business cycle include only the G7 economies, Del Negro and Otrok (2008) select 19 developed economies, Mumtaz and Theodoridis (2017) use 11 OECD economies, Carriero et al. (2020) consider 19 developed economies, and Mumtaz and Musso (2021) 22 OECD economies. Kose et al. (2003, 2012) are notable exceptions, focusing on a broad selection of economies. In comparison, I use quarterly data, and provide an updated measure that includes the dynamics in the aftermath of the 2007/8 Global Financial Crisis. The second contribution therefore lies in providing an updated view on whether the real business cycles of emerging economies have decoupled from those of advanced economies. Kose et al. (2003) show that the correlation of emerging economies' output with G7 economies' output turns negative in the 1990's, compared to positive correlation in previous years. Meanwhile, Levy Yeyati and Williams (2012) show that emerging economies' real business cycles decoupled from G7 economies in 2000-2010 period whereas there was convergence in the 1993-2000 period. The literature clearly establishes that the degree of synchronisation between advanced economies' and emerging economies' business cycles evolves over time. Whilst most related studies date to the last decade, this paper provides fresh perspectives using updated data till 2019 for a broader sample.

The third contribution of this paper consists of providing an empirical comparison of regional spill-overs to global linkages. Henderson et al. (2001) highlights the prominence of regional centers of economic activity. Countries within the same region tend to share similar economic structures, have common lenders as well as similar portfolio lenders, leading to regional gravitational forces. Whilst studies on regional spill-overs abound in the financial literature, the real economic implications have been under-explored.[1] This paper fills the gap by analysing the impact of regional spill-overs on real GDP. The 1994/5 Tequila Crisis, the 1997 Asian Financial Crisis or the 2010 Eurozone Debt Crisis are significant reminders of the repercussions of regional spill-overs. On the one hand, intra-regional trade and financial flows may seem less risky than fully opening up the economy, where the balance of payments remains at the mercy of fluctuations in international prices. In particular, there is the case that regional trade agreements are even more advantageous as they allow for greater bargaining power, and enables better cooperation amongst participating economies (Kose and Rebucci (2005)). However, this may mean that economies within particular regions become inter-dependent, leading to regional clusters of volatility. This paper not only compares regional business cycle synchronisation with global business cycle synchronisation, but also analyses whether emerging economies in a region are more vulnerable to either source of vulnerability, compared to advanced economies.

I estimate the external vulnerability of 45 advanced and emerging economies using a two-step procedure. The first step consists of estimating the global business cycle, the group-specific business cycle for advanced and emerging economies respectively, as well as the regional business cycle. The second step aims at measuring the importance of these external drivers for the domestic business cycle. In the first step, three dynamic factor models are estimated. The first model consists of a global factor together with group-specific factors for advanced economies and emerging economies, separately. The second model consists of the global factor and region-specific factors

[1] See Kaminsky and Reinhart (2000); Kodres and Pritsker (2002); Pericoli and Sbracia (2003) for a discussion on financial contagion within regions. In particular, Kaminsky and Reinhart (2000)'s measure of crisis mainly focuses on exchange rate whereas Kodres and Pritsker (2002) and Pericoli and Sbracia (2003) consider asset prices.

that measure synchronisation in business cycles amongst Asia and Pacific economies, Western Hemsiphere economies and European economies, respectively. In order to investigate whether business cycles of advanced economies in a particular region are more synchronised than those of emerging economies in that region, the third model includes a group-specific factor that accounts for both countries' income levels and regions. Having extracted the dynamic global and group-specific factors, I implement the second step of my procedure by estimating three Factor augmented Vector Auto Regressive (FAVAR) models for each country in the sample. I then compute historical decompositions to track down the contribution of the global business cycle shock over time. This exercise also helps pin down the extent to which different economies are sensitive to regional economic shocks or shocks pertaining to economies within the same income categories.

I find that external shocks explain a greater share of business cycle fluctuations than domestic shocks. The estimated global factor suggests that the 2007/8 Global Financial Crisis constitutes the most synchronised recession for the sample period 1995–2019. There is considerable heterogeneity in the way economies react to external vulnerability, as also observed by Stock and Watson (2005),Kose et al. (2012) and Mumtaz and Theodoridis (2017). This can be explained by differences in economies' income levels and regional factors. The business cycles of emerging economies behave differently from that of advanced economies. Emerging economies' business cycles are more synchronised with each other than those of advanced economies. Emerging economies also face greater volatility; the standard deviation of the emerging economies' factor is almost twice that of advanced economies' factor's. Combining the effects of the global factor and the group factor for income levels, I find that external factors trigger greater deviation from trend output in emerging economies compared to advanced economies. Regional factors have become more important over time. Volatility in the global factor has waned since 2012, and economies are since more affected by regional shocks compared to global shocks. Using the group-specific factor that accounts for both income levels and regions, I find that emerging economies are more exposed to regional shocks than advanced economies. Overall, the share of global shocks and group-specific shocks exceed the size of domestic shocks, showing that the considerable share of business cycle fluctuations stems from outside the respective economies.

The literature on measuring the synchronisation of business cycles is large and uses complementary approaches. I use a FAVAR model following Bernanke et al. (2005)'s seminal paper. While the FAVAR model was initially developed to analyse monetary policy shocks, it has also been applied to analyse spill-overs from international shocks, see Boivin and Giannoni (2008), Mumtaz and Surico (2008) and Vasishtha and Maier (2013). Imbs (2004), Imbs (2006), Inklaar et al. (2008) and Dées and Zorell (2012) consider pairwise correlations in the cyclical component of real GDP. Similarly, Kalemli-Ozcan et al. (2013) and Cesa-Bianchi et al. (2019) look at the difference in the absolute value between any country pair's real GDP growth. Kose et al. (2003) investigates each economy's real GDP correlation with a measure of world GDP that has been constructed using G-7 economies' GDP. Under these approaches, synchronisation is measured as the average of the estimated bivarite correlations. The issue with pairwise correlations lies in that it tends to overlook comovement prevailing within subsets of countries within the sample. An alternative approach to correct for this is to identify a numeraire country as a reference for assigning weights to the correlations. However, this leads to the possibility of bias as the reference economy dominates the business cycle. Unlike static correlation measures, the dynamic factor model employed in this paper is able to capture the dynamic properties of the data. It identifies the largest common dynamic component without the need to average across variables or assign a numeraire economy. Furthermore, it is used to identify comovement across economies within the same income group or within the same region. Another approach commonly adopted is to classify economies' business cycles as being synchronised if they simultaneously experience turning points in their business cycles, see Harding and Pagan (2006) and Ductor and Leiva-Leon (2016). Nevertheless, negative global shocks may just prolong the trough for an economy that was already on a contractionary phase. In relatively smaller samples as in Canova et al. (2007), VAR models help to account for cross-country spill-overs. However, However, as the number of countries increases, VAR models are quickly constrained by the lack of degrees of freedom. Conversely, the factor-based model used in this paper is not subject to the 'curse of dimensionality', being able to summarise the large amount of information in a small number of factors for the large set of countries I use.

More broadly, this study relates to the literature on macroeconomic volatility. Ramey and Ramey (1995) have established a negative relationship between growth and volatility. Koren and Tenreyro (2007) connects this negative relationship with the sectoral composition of national output, highlighting that developing economies' business cycles are more volatile as they are less diversified compared to advanced peers, and tend to specialise in volatile sectors. While Koren and Tenreyro (2007) and Carvalho and Gabaix (2013) focus on the sectoral composition, this paper distinguishes between business cycle fluctuations stemming from domestic drivers versus business cycle fluctuations derived from external sources. Studies on macroeconomic volatility are supported by microeconomic foundations. Gabaix (2011) emphasizes that owing to the fat-tailed distribution of firms, shocks to large firms reverberate across the economy. Di Giovanni et al. (2018) extends this reasoning to international firms and their role in strengthening business cycle comovements between economies, especially as larger firms are more likely to export or to be multinationals. Using French firm-level data, they illustrate that if the top 100 firms withdrew their trading relationships with a particular trading partner, the correlation between the firms' value added and the foreign economy's GDP would drop by 8%. This paper complements this strand of the literature by considering the macroeconomic side of external sources of volatility. I use the factor augmented model developed by Bernanke et al. (2005). Boivin and Giannoni (2008), Mumtaz and Surico (2008) and Vasishtha and Maier (2013) also use FAVAR models to analyse spill-overs from international shocks. This paper adds to this literature by extending the sample to include emerging economies. Furthermore, I consider regional shocks as well as business cycle synchronisation amongst economies of similar income levels.

The remainder of the paper is structured into three sections. Section 4.2 presents the empirical strategy. Section 4.3 shows the estimated global factor, group factor for income levels, the regional factor as well as the group-specific factor that takes into account both income levels and regions. Section 4.3 also investigates the extent to which each type of external shock matters for overall macroeconomic volatility using a historical decomposition. Section 4.4 concludes.

4.2 Empirical Strategy

The aim of the empirical model is to identify the external business cycle shocks, and analyse their repercussions on the respective economies. To this end, I use a two-step approach. The first step consists of estimating the global business cycle, by harnessing the information available in a number of variables across countries. This is achieved by estimating a standard dynamic factor model, as in Stock and Watson (2016). I estimate three dynamic factor models: the first model includes a group-specific factor for advanced and emerging economies, the second model includes a region-specific factor; and the third model incorporates a group-specific factor that considers both countries' income levels and regions. The second step involves measuring the historical contribution of external shocks on each domestic economy. Therefore, I estimate country-by-country VARs using the global and group-specific factors estimated in the first step, together with the real GDP for each economy, resulting in a small open-economy factor augmented vector auto regressive (FAVAR) model. The empirical strategy for the FAVAR model's estimation follows Bernanke et al. (2005). While Bernanke et al. (2005) initially developed the FAVAR model with a view to analyse the transmission of monetary policy shocks, FAVAR models have also been used to analyse spill-overs from international shocks, see Boivin and Giannoni (2008), Mumtaz and Surico (2008) and Vasishtha and Maier (2013).

4.2.1 Data and Data Transformations

Country-level data: I use quarterly real GDP data for 45 advanced and emerging economies available from the OECD quarterly national accounts dataset. Table 4.1

displays the list of economies included in the analysis. Real GDP is measured in US Dollars, at fixed Purchasing Power Parities (PPPs) with 2015 as the reference year. Exceptionally, for China, data was only available measured at current prices and in Yuans. In order for data to be at par for country-by-country comparisons, Chinese GDP was converted using the PPPs available from the OECD database. The data is available at quarterly frequency for the period 1995 to 2019. I deseasonalise all real GDP data.

International commodity Prices: In addition to individual countries' real GDP data, the global factor estimate is rendered more robust through the incorporation of key international commodity prices that are quick to track global fluctuations. Estimates of global factors, whether for stock asset prices (Forbes and Chinn (2016)) or for global uncertainty (Mumtaz and Musso (2021)), routinely include major commodity prices. I use monthly data from 1995 onwards for NYMEX Light Sweet Crude Oil (WTI), the US Brent Crude Oil and gold prices to capture for those additional global ramifications. Monthly data is converted to quarterly frequency through simple averaging and, each series is transformed into growth rates to induce stationarity. Following Stock and Watson (2016), the long term trend of each differenced series is estimated using a biweight low pass filter, with a bandwidth of 100 quarters. Furthermore, each data series is standardised to ensure comparability across shocks.

4.2.2 Step 1: Estimating the Global Factor and Group-specific Factors

First, I estimate the global factor using a dynamic factor model.

Dynamic factor models have emerged as the standard way to estimate global business cycles, see Stock and Watson (2005), Crucini et al. (2011), Kose et al. (2012), Mumtaz and Theodoridis (2017) and Mumtaz and Musso (2021). Unlike VAR models where the shock needs to be identified, dynamic factor models do not require any restrictive assumptions about the nature of the shock, capturing a broader spectrum of shocks. The factor loadings allow for a differential impact of the global factor on each economy. Furthermore, factor-based models obviate the problem of the 'curse of dimensionality' by summarising information contained in a series of variables into factors that capture common fluctuations.

Dynamic factor model with a global factor and group-specific factors for advanced economies and emerging economies

The dynamic factor model is used to estimate a global business cycle. Additionally, in a similar spirit to the estimation of the global business cycle, it is possible to extract group factors to quantify the extent of synchronisation amongst particular economies. Kose et al. (2012) highlight some degree of synchronicity in business cycles amongst advanced economies and emerging economies, separately, amidst the waning importance of the global factor. I therefore estimate a group-specific factor common to either advanced or emerging economies. The global factor captures comovement in all the variables whereas the group-specific factor reflects fluctuations that are common to either advanced or emerging economies. The dynamic factor model representation used to estimate the global business cycle is given in Equations (4.1)-(4.3): [2]

$$X_t^{i,g} = \lambda(L)_{Glo}^{i,g} f_t^{Glo} + \lambda(L)_g^{i,g} f_t^g + e_t^{i,g} \qquad \text{for g=(ADV,EME)}, \tag{4.1}$$

$$f_t^{Glo} = \psi(L)_{Glo} f_{t-1}^{Glo} + \eta_t^{Glo}, \tag{4.2}$$

$$f_t^g = \psi(L)_g f_{t-1}^g + \eta_t^g, \tag{4.3}$$

where $X_t^{i,g}$ is the (48×1) vector of time series used to extract the common global factor, and $e_t^{i,group}$ is the idiosyncratic error term. $X_t^{i,g}$ includes the real GDP growth data for 45 economies together with global oil and gold prices. Focusing on real GDP growth, $X_t^{i,g}$ represents the real GDP growth of country i whose economic development type is g, where g indicates whether the economy is an advanced economy or an emerging economy. The latent global factor is given by f_t^{Glo}, which follows a VAR(4) process. $\lambda(L)_{Glo}^{i,g}$ represent the dynamic factor loading of the i^{th} series in $X_t^{i,g}$, with respect to the global factor. I restrict the lag polynomials to be AR(4), such that the lag polynomial matrices $\lambda(L)_{Glo}$ and $\psi(L)_{Glo}$ are (48×4) and (4×4), respectively. Stock and Watson (2016) propose to express the dynamic factor model in a static form in order to be able to estimate the global factor using principal component analysis.

The global factor, f_t^{Glo} is estimated first. The equations involved in estimating the global factor is displayed in equations (4.4)-(4.5)

$$X_t^i = \kappa \mathbf{F}_t^{Glo} + e_t^i, \tag{4.4}$$

$$\mathbf{F}_t^{Glo} = \phi(L)\mathbf{F}_{t-1}^{Glo} + \omega\eta_t \tag{4.5}$$

where $\mathbf{F}_t^{Glo} = (f_t^{Glo\prime}, f_{t-1}^{Glo\prime}, ..., f_{t-4}^{Glo\prime})'$ is a (5×1) vector, constituting the current and lagged values of f_t^{Glo}. The i^{th} row in λ_{Glo} in equation (4.1) translates to $\kappa =$

[2]I use the package available from Stock and Watson (2016) to estimate the dynamic factor model.

$(\lambda^{i1}_{Glo}, \lambda^{i2}_{Glo}, ..., \lambda^{i4}_{Glo})$ in the static form. $\phi(L)$ is a matrix containing the VAR coefficients in $\psi(L)_{Glo}$ and 1s and 0s, while $\omega = \begin{bmatrix} I_5 & 0_{(5\times1)} \end{bmatrix}'$.

Writing down the model in static form illustrates that the common space spanned by the static factors can be estimated by principal components. The principal component analysis aims at producing principal components or factors that retain a maximum of the variation in the original data, and which are uncorrelated with each other. The data is standardised by subtracting the mean and dividing by the respective standard deviations, prior to the principal component analysis. Furthermore, following Stock and Watson (2016), the columns in κ are orthogonal and are scaled to have unit norm. κ and $\mathbf{F}^{Glo}_t$ in equation (4.4) are then treated as unknown parameters in a least squares problem.[3]

We use the Bai and Ng (2002)'s criterion and the Marginal R^2 to determine the number of global factors in equation (4.2). Similar to the Akaike Information Criterion, Bai and Ng (2002)'s measure includes a penalty term to the least squares minimising function in equation (4.5) for the additional factor. The Marginal R^2 calculates the contribution of the additional factor in the regressions of X_t against the factors. The selection criteria, displayed in Table A.1 in the Appendix, unanimously favour 1 global factor, as portrayed by the minimum Bai and Ng (2002)'s measure for the first 5 factors, and the corresponding maximum marginal R^2.

The group-specific factors for advanced and emerging economies, f^g_t are then estimated separately, using a procedure similar to that used for estimating the global factor. The group-specific factors capture business cycle convergence amongst advanced economies and emerging economies, respectively, as presented in Equations (4.6)–(4.7):

$$X^g_t = \lambda(L)_g \hat{f}^g_t + e^g_t \qquad \text{for g=(ADV,EME)}, \tag{4.6}$$

$$\hat{f}^g_t = \psi(L)_g \hat{f}^g_{t-1} + \eta^g_t, \tag{4.7}$$

The advanced economies' factor, $\hat{f}^{ADV}_t$, is estimated using real GDP series for 31 advanced economies, such that X^{ADV}_t is a (31×1) vector, and similarly $\hat{f}^{EME}_t$ is estimated using the real GDP data for the remaining 14 emerging economies. The estimation strategy for the group-specific factors follow closely the estimation of

[3]Given our sample has different starting dates for the data series, the least squares problem is $\min\left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} S_{it}(X^{i,g}_t - \zeta\mathbf{F}^{Glo}_t)^2\right)$, where $S_{it} = 1$ if the observation is available, and 0 otherwise. The objective function is then minimised through iterations for κ, assuming $\mathbf{F}^{Glo}_t$ is given, alternating with iterations for $\mathbf{F}^{Glo}_t$, given ζ. The least-squares principal components estimator of the factors is $\hat{\mathbf{F}}^{Glo}_t = N^{-1}\hat{\zeta}' X_t$, where $\hat{\zeta}$ is the sample estimator of the covariance matrix of X_t.

the global factor, implying lag polynomials of order 4 and estimation by principal components for each group's equations. An additional step is further undertaken to render the group-specific factors orthogonal to the global factor. In order to impose orthogonality, I follow Kose et al. (2006)'s approach whereby each group-specific factor, $\hat{f}_t^{ADV}$ and $\hat{f}_t^{EME}$, estimated in equations (4.6)–(4.7) is regressed on the global factor, and substituted with the resulting residual, as depicted in Equations (4.8) and (4.9):

$$f_t^{ADV} = \hat{f}_t^{ADV} - \alpha_{ADV} - \beta_{ADV} f_t^{Glo}, \tag{4.8}$$

$$f_t^{EME} = \hat{f}_t^{EME} - \alpha_{EME} - \beta_{EME} f_t^{Glo}, \tag{4.9}$$

Dynamic factor model with a global factor and region-specific factors

Countries with geographical proximity are more likely to trade with each other. Kose et al. (2003) and Imbs (2004) show how trade acts as a conduit for greater synchronicity in economies' business cycles. Ignoring the regional factor might therefore lead to uninformed judgement on the real external exposure of economies. Even without the inclusion of a regional factor, Kose et al. (2012) demonstrate that economies across different regions are affected by the global business cycle heterogenously. Meanwhile, Mumtaz and Musso (2021) and Gong and Kim (2018) showcase the statistical significance of the regional factor. Similar to the dynamic factor model with the global factor and the group-specific factors for advanced and emerging economies in the previous section, I estimate a dynamic factor model with the global factor and region-specific factors in Equations (4.10)-(4.17):

$$X_t^{i,r} = \lambda(L)_{Glo}^{i,r} f_t^{Glo} + \lambda(L)_r^{i,r} \hat{f}_t^r + e_t^{i,r} \qquad \text{for r=(AP,EU,WH)}, \tag{4.10}$$

$$f_t^{Glo} = \psi(L)_{Glo} f_{t-1}^{Glo} + \eta_t^{Glo}, \tag{4.11}$$

$$\hat{f}_t^r = \psi(L)_r \hat{f}_{t-1}^r + \eta_t^r, \tag{4.12}$$

where $X_t^{i,r}$ is the (48×1) vector of all time series included in the estimation of the common global factor, and $e_t^{i,r}$ is the idiosyncratic error term. $X_t^{i,r}$ represents the real GDP growth of country i located in region r, where r denotes any of the three regions: Asia and Pacific (AP), Western Hemisphere (WH) and Europe (EU).[4]

[4]African economies were left out from this study due to data limitations.

Each regional factor reflects the degree of synchronicity in the business cycles of economies located within the region. The Asian Pacific factor, $\hat{f}_t^{AP}$, is derived using real GDP series for 6 Asian Pacific economies economies; the European factor $\hat{f}_t^{EU}$, is estimated using real GDP series for 30 economies clubbed as the European region, and the remaining 7 economies' real GDP data is used to estimate $\hat{f}_t^{WH}$,the Western Hemisphere factor. Similar to the estimation of group specific factors based on income levels, regional factors are orthogonal to the global factor. Each regional factor, $\hat{f}_t^{AP}$, $\hat{f}_t^{EU}$, and $\hat{f}_t^{WH}$ is regressed on the global factor, and substituted with the resulting residual, as shown in Equations (4.13)-(4.15):

$$f_t^{AP} = \hat{f}_t^{AP} - \alpha_{AP} - \beta_{AP} f_t^{Glo}, \tag{4.13}$$

$$f_t^{EU} = \hat{f}_t^{EU} - \alpha_{EU} - \beta_{EU} f_t^{Glo}, \tag{4.14}$$

$$f_t^{WH} = \hat{f}_t^{WH} - \alpha_{WH} - \beta_{WH} f_t^{Glo}, \tag{4.15}$$

Dynamic factor model with a global factor and a group factor for countries' income levels and regions

Finally, I also explore whether the business cycles of advanced economies in a particular region are more synchronised than the business cycles of emerging economies in the region. This is catered for by including a group-specific factor that accounts for both income levels and regions. This therefore leads to 6 categories, namely: advanced Asia Pacific economies, emerging Asia Pacific economies, advanced European economies, emerging European economies, advanced economies in the Western Hemisphere as well as emerging economies in the Western Hemisphere. The resulting dynamic factor model is laid out in Equations (4.16)-(4.18):

$$X_t^{i,gr} = \lambda(L)_{Glo}^{i,gr} f_t^{Glo} + \lambda(L)_r^{i,gr} \hat{f}_t^{gr} + e_t^{i,gr} \tag{4.16}$$

for gr=$(AP_{ADV}, AP_{EME}, EU_{ADV}, EU_{EME}, WH_{ADV}, WH_{EME})$,

$$f_t^{Glo} = \psi(L)_{Glo} f_{t-1}^{Glo} + \eta_t^{Glo}, \tag{4.17}$$

$$\hat{f}_t^{gr} = \psi(L)_{gr} \hat{f}_{t-1}^{gr} + \eta_t^{gr}, \tag{4.18}$$

$X_t^{i,gr}$ represents the real GDP growth of country i, and gr denotes each of the six groups: advanced Asia Pacific economies (AP_{ADV}), emerging Asia Pacific economies

(AP_{EME}), advanced European economies (EU_{ADV}), emerging European economies (EU_{EME}), advanced Western Hemisphere economies (WH_{ADV}), and emerging Western Hemisphere economies (WH_{EME}). $e_t^{i,gr}$ is the idiosyncratic error term.

The group factor for advanced Asia Pacific economies, $\hat{f}_t^{AP_{ADV}}$, captures the degree of synchronicity in the business cycles of 3 advanced Asian Pacific economies included in our sample. The corresponding group factor for emerging economies in the Asia Pacific region, $\hat{f}_t^{AP_{EME}}$ includes 4 economies in the category. The group factor for advanced European economies, $\hat{f}_t^{EU_{ADV}}$ reflects the business cycles synchronisation in 25 advanced European economies, and the emerging European economies' factor, $\hat{f}_t^{EU_{EME}}$ is estimated with real GDP data for 6 economies ranking in the sub-sample. Only Canadian and US real GDP features in the estimation of advanced Western Hemisphere factor, $\hat{f}_t^{WH_{ADV}}$; whereas the emerging Western Hemisphere factor, $\hat{f}_t^{WH_{EME}}$, includes 5 economies. Finally, the group-specific factors for income levels and regions is made orthogonal to the global factor, by regressing each of the 6 factors on the global factor, and replacing them by the residuals, as shown in Equation (4.19) below:

$$f_t^{gr} = \hat{f}_t^{gr} - \alpha_{gr} - \beta_{gr} f_t^{Glo}, \tag{4.19}$$

for gr=$(AP_{ADV}, AP_{EME}, EU_{ADV}, EU_{EME}, WH_{ADV}, WH_{EME})$,

Having estimated the global factor and group factors accounting for countries' income levels as well as regional factors, the next step involves investigating the impact of these external factors on each economy's volatility. In the next Section 4.2.3, this is accomplished through country-by-country VARs.

4.2.3 Step 2: Country VARs

I estimate country-by-country VARs with a view to investigate whether economies have synchronised with or decoupled from the global business cycle. The global business cycle is proxied by the global factor, $f_{i,t}^{Glo}$ estimated in Step 1. We are also interested in analysing how other external influences, whether it be through business cycle fluctuations that are shared with economies within a similar income group or region, affect the economy's business cycle. Therefore, the group-specific factors estimated using the three dynamic factor models in step 1 are used to proxy for business cycle synchronisation among particular category of economies. As such, a VAR is estimated using the global factor as a predictor variable, tantamount to a Factor Augmented VAR, FAVAR model, as in Bernanke et al. (2005). The global factor as well as the group factors estimated in Equations (4.1)–(4.19) are used as inputs in the VAR models.

Three VAR(4) models are estimated for each of the 45 economies in the sample, using the group-specific factors estimated in the previous section. The VAR models are laid out in Equations (4.20)–(4.22):

$$A_{1i}\begin{bmatrix} f^{Glo}_{i,t} \\ f^{g}_{i,t} \\ GDP_{i,t}\end{bmatrix} = \eta_{1i} + \beta_{1i}(L)\begin{bmatrix} f^{Glo}_{i,t-1} \\ f^{g}_{i,t-1} \\ GDP_{i,t-1}\end{bmatrix} + \begin{bmatrix} \epsilon^{f^{Glo}}_{i,t} \\ \epsilon^{f^{g}}_{i,t} \\ \epsilon^{GDP}_{i,t}\end{bmatrix} \quad \text{for g=(Adv,Eme)}, \tag{4.20}$$

$$A_{2i}\begin{bmatrix} f^{Glo}_{i,t} \\ f^{r}_{i,t} \\ GDP_{i,t}\end{bmatrix} = \eta_{2i} + \beta_{2i}(L)\begin{bmatrix} f^{Glo}_{i,t-1} \\ f^{r}_{i,t-1} \\ GDP_{i,t-1}\end{bmatrix} + \begin{bmatrix} \epsilon^{f^{Glo}}_{i,t} \\ \epsilon^{f^{r}}_{i,t} \\ \epsilon^{GDP}_{i,t}\end{bmatrix} \quad \text{for r=(AP,EU,WH)}, \tag{4.21}$$

$$A_{3i}\begin{bmatrix} f^{Glo}_{i,t} \\ f^{gr}_{i,t} \\ GDP_{i,t}\end{bmatrix} = \eta_{3i} + \beta_{3i}(L)\begin{bmatrix} f^{Glo}_{i,t-1} \\ f^{gr}_{i,t-1} \\ GDP_{i,t-1}\end{bmatrix} + \begin{bmatrix} \epsilon^{f^{Glo}}_{i,t} \\ \epsilon^{f^{gr}}_{i,t} \\ \epsilon^{GDP}_{i,t}\end{bmatrix} \tag{4.22}$$

for gr=$(AP_{ADV}, AP_{EME}, EU_{ADV}, EU_{EME}, WH_{ADV}, WH_{EME})$,

where $GDP_{i,t}$ represents the growth rate of real GDP of the particular country and $f^{Glo}_{i,t}$ refers to the estimated global factor. In Equation (4.20), the estimated advanced economy factor, $f^{ADV}_{i,t}$ is used in the VARs for advanced economies, and the emerging economies' group factor, $f^{Eme}_{i,t}$ is used for emerging economies' VARs. Similarly, in Equation (4.21), the contribution of the regional factor is compared to that of the global factor. Asia Pacific economies' VAR models is estimated using their factor, $f^{AP}_{i,t}$, European economies' VARs using $f^{EU}_{i,t}$, and the Western Hemisphere VARs using their corresponding factor, $f^{WH}_{i,t}$. In Equation (4.22), $f^{AP_{ADV}}_{t}$ is used to estimate the VAR models for advanced Asia Pacific economies, $f^{AP_{EME}}_{t}$ for emerging Asia Pacific economies, $f^{EU_{ADV}}_{t}$ for advanced European economies, $f^{EU_{EME}}_{t}$ for emerging economies in Europe, $f^{WH_{ADV}}_{t}$ for Canada and the US, and finally $f^{WH_{EME}}_{t}$ for emerging Western Hemisphere economies.

Having already estimated the global and group factors in the dynamic factor model laid out in equations (4.1)–(4.19), the VAR models just include the estimated global factor and the orthogonalised group factors as regressors and are estimated in the standard way. Another way of estimating the model is by jointly estimating the respective dynamic factor models and the corresponding VAR model by maximum likelihood. Bernanke et al. (2005) estimate a FAVAR using both methods, and highlight that the computational complexity of the likelihood-based estimates are not justified because the results are broadly similar to the ones under the two-step procedure where factors are estimated using principle components analysis and the VAR is estimated separately using the estimated factors. Furthermore, the use of priors in likelihood based estimates penalises the information content, whereas the approach I choose for this paper is more data-driven and agnostic.

Structural identification of the global business cycle shock is obtained by using the Cholesky decomposition identification strategy. As standard in the literature, see Mumtaz and Surico (2008) and Vasishtha and Maier (2013), I assume that domestic economies react contemporaneously to global business cycle shocks while, the repercussions of domestic shocks only carry through to the global economy with a lag. In the recursive structure adopted, the global factor is placed at the top of the VAR, followed by the group-specific factors and finally the real GDP. This implies that each economy is treated as a small open economy in the short run. Domestic economic performance is affected by ongoing global economic developments, whereas domestic economic shocks do not contribute to any contemporaneous impact on their respective groups or the global business cycle. However, the spill-overs of domestic economic shocks transmit to the particular group or the global economy with a lag. In other words, domestic economic shocks spill over to other economies with a lag.

The historical decomposition helps identify the extent to which domestic business cycle fluctuations are explained by external influences. The results may be interpreted as each economy's exposure to global business cycle shocks or group-specific business cycle shocks. The historical decomposition breaks down the value of any of the variables in VAR (4.20)–(4.22) in any particular period of time into: 1.) its initial value; 2.) the contribution of the global business cycle shock; 3.) the share of the group factor; as well as 4.) the contribution of its own shock. To exemplify, starting by re-writing VAR (4.20) in its structural form as shown in Equation (4.23) below: [5]

$$\mathbf{Y_{i,t}} = \gamma + \beta_i(L)\mathbf{Y_{i,t-1}} + \theta\varepsilon_{\mathbf{i,t}}, \tag{4.23}$$

where $\mathbf{Y_{i,t}} = \begin{bmatrix} f^{Glo}_{i,t} \\ f^{g}_{i,t} \\ GDP_{i,t} \end{bmatrix}$ and $\varepsilon_{\mathbf{i,t}} = \begin{bmatrix} \epsilon^{f^{Glo}}_{i,t} \\ \epsilon^{f^{g}}_{i,t} \\ \epsilon^{GDP}_{i,t} \end{bmatrix}$.

The historical decomposition stems from re-writing the VAR using the Wold representation. Replacing $\mathbf{Y_{i,t-1}} = \gamma + \beta_i(L)\mathbf{Y_{i,t-2}} + \theta\varepsilon_{\mathbf{i,t-1}}$ in Equation (4.23) yields:

[5]See Cesa-Bianchi (2015) for a detailed discussion on historical decomposition.

$$\mathbf{Y_{i,t}} = \gamma + \beta_i(L)^t \mathbf{Y_{i,0}} + \sum_{j=0}^{t-1} \beta_i(L)^j \theta \varepsilon_{\mathbf{i,t-j}}, \tag{4.24}$$

Equation (4.24) illustrates how each economy's GDP can be broken down into a sequence of shocks, allowing us to quantify the extent to which the domestic business cycle fluctuations can be accounted for by external shocks versus domestic shocks. Expanding Equation (4.24) for $t = 2$ and replacing $\gamma + \beta_i(L)^t Y_{i,0}$ by Y_{init}, and replacing the coefficient matrices with $\beta_i(L)\theta = \begin{bmatrix} \beta^I_{11} & \beta^I_{12} & \beta^I_{13} \\ \beta^I_{21} & \beta^I_{22} & \beta^I_{23} \\ \beta^I_{31} & \beta^I_{32} & \beta^I_{33} \end{bmatrix}$, and $\theta = \begin{bmatrix} \beta^{II}_{11} & \beta^{II}_{12} & \beta^{II}_{13} \\ \beta^{II}_{21} & \beta^{II}_{22} & \beta^{II}_{23} \\ \beta^{II}_{31} & \beta^{II}_{32} & \beta^{II}_{33} \end{bmatrix}$ leads to the following representation for country i:

$$\begin{bmatrix} f^{Glo}_{i,2} \\ f^{Group}_{i,2} \\ GDP_{i,2} \end{bmatrix} = \begin{bmatrix} f^{Glo}_{i,init} \\ f^{Group}_{i,init} \\ GDP_{i,init} \end{bmatrix} + \begin{bmatrix} \beta^I_{11} & \beta^I_{12} & \beta^I_{13} \\ \beta^I_{21} & \beta^I_{22} & \beta^I_{23} \\ \beta^I_{31} & \beta^I_{32} & \beta^I_{33} \end{bmatrix} \begin{bmatrix} \epsilon^{f^{Glo}}_{i,1} \\ \epsilon^{f^{Group}}_{i,1} \\ \epsilon^{GDP}_{i,1} \end{bmatrix} + \begin{bmatrix} \beta^{II}_{11} & \beta^{II}_{12} & \beta^{II}_{13} \\ \beta^{II}_{21} & \beta^{II}_{22} & \beta^{II}_{23} \\ \beta^{II}_{31} & \beta^{II}_{32} & \beta^{II}_{33} \end{bmatrix} \begin{bmatrix} \epsilon^{f^{Glo}}_{i,2} \\ \epsilon^{f^{Group}}_{i,2} \\ \epsilon^{GDP}_{i,2} \end{bmatrix} \tag{4.25}$$

It can be gathered from equation (4.25) that the contribution of the global business cycle shock at $t = 2$ to country i domestic business cycle is given by $\beta^I_{31}\epsilon^{f^{Glo}}_{i,1} + \beta^{II}_{31}\epsilon^{f^{Glo}}_{i,2}$. The contribution of the group factor is given by $\beta^I_{32}\epsilon^{f^g}_{i,1} + \beta^{II}_{32}\epsilon^{f^g}_{i,2}$ and the contribution of own domestic macroeconomic shocks is measured as $\beta^I_{33}\epsilon^{GDP}_{i,1} + \beta^{II}_{33}\epsilon^{GDP}_{i,1}$. This historical decomposition is carried out iteratively for each time period.

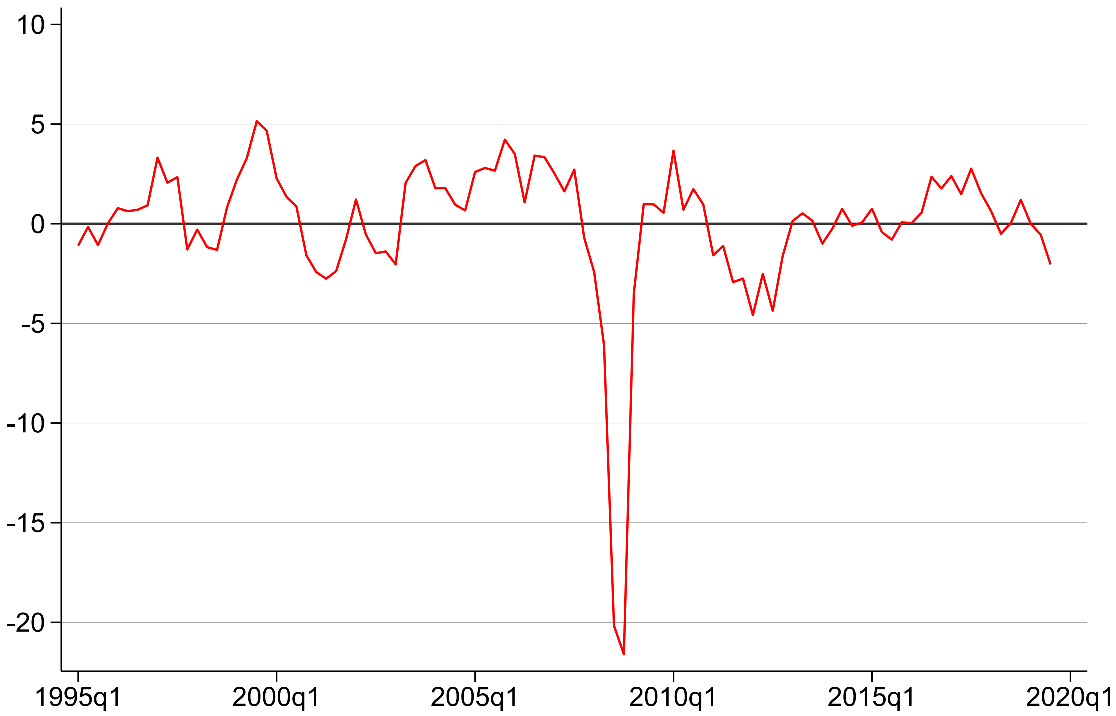
The second step from the VAR models enables a break-down of each economy's historical business cycle fluctuations into domestic factors versus external factors. External factors comprise both the global factor as well as group-specific factors. The results are presented in Section 4.3.

4.3 Results

4.3.1 Global Factor and Group-specific Factors for Income Levels and their Impacts on Business Cycle Fluctuations

I start by showing the results from Step 1. Figure 4.1 presents the global factor obtained from estimating Equation (4.2). Similar to Kose et al. (2012) and Mumtaz and Theodoridis (2017), the estimated global factor coincides with major global economic events. The 2007/8 Global Financial Crisis (GFC) constitutes the biggest shock to the global economy for the sample period. Movements in the global factor from 1999 to 2002 are probably linked to the developments in the Eurozone. The global factor is propelled to the positive territory in 1999, reaching a peak, reflecting the introduction and acceptance of the Euro. The global factor weakens in 2000, highlighting the depreciating EUR/USD exchange rate and the dot com bubble crash. This is further exacerbated by the 9/11 terrorist attacks and the Afghanistan war in 2001. The global factor continued to remain negative till early 2003 due to the second Persian Gulf War. Thereon, the global factor lingered in positive zone from 2003 to 2007, spurred by the strong performance of emerging economies. Amidst the 2007/8 Global Financial Crisis, the global factor dropped drastically, by over seven times in 2007/8, reaching its minimum for the sample period. The Eurozone debt crisis also constituted a negative shock to the global factor. The global factor has since then been relatively less volatile.

Figure 4.1: Global Factor



Notes: The solid red line depicts the common global factor estimated in Equation (4.2), extracted from real GDP data on 45 economies, global oil prices and the international gold price.

There is a disconnect between the business cycles of advanced economies and emerging economies. Emerging economies' business cycles are more volatile than that of advanced economies. Figure 4.2 compares the advanced economies' group factor that has been estimated using real GDP data for advanced economies in the sample, with the group factor for emerging economies that is, in turn, estimated with only emerging economies' real GDP data. The standard deviation of the emerging economies' factor (1.1) is almost twice the standard deviation of the advanced economies' (0.6). The advanced economies' factor has remained relatively range-bound over the sample period. Meanwhile, the group factor for emerging economies highlight alternating periods of economic expansions and contractions in emerging economies. In particular, emerging economies' was rather subdued till 2001. This is then followed by a sustained growth streak, with the emerging economies' factor remaining in the positive zone till 2013. In 2013, financial markets in emerging economies plunged due to expectations of the withdrawal of quantitative easing measures by the US Federal Reserve. Emerging economies' performance has been rather muted since. Interestingly, emerging economies' growth dynamics diverge from advanced economies'. The correlation between the two factors is -0.9. Whenever the emerging economies' factor is negative, the corresponding group factor for advanced economies appears in the positive territory, and vice versa.

Advanced economies and emerging economies react to global economic shocks in a similar way. Figure 4.3 decomposes the cyclical GDP of each economy into domestic factors, the global factor and the group-specific factor for advanced and emerging economies, as derived from Equation (4.20) in Step 2. I calculate the average of these historical decompositions for advanced economies and emerging economies, separately. Figure 4.4 presents the average business cycle fluctuations triggered by the global factor, the group-specific factor and domestic factors, respectively, for advanced and emerging economies. As pictured in the top panel of Figure 4.4, the percentage deviation from trend growth attributed to global shocks is similar for advanced and emerging economies. Considering the case of the 2007/8 GFC, all economies were faced with the same problem of worsening global economic conditions, which is captured by the contraction in the global factor in Figure 4.1. The resulting recession is the most synchronised recession over the sample period. The country-by-country historical breakdown in Figure 4.3 allows to identify the heterogeneous external vulnerability that is possibly masked by averages. Estonia, Latvia, Lithuania and Argentina's economies were hit most severely by the 2007/8 GFC, with the global factor shock causing their cyclical GDP growth rates to fall by about 5%–7%. As a comparison, on average, global factor shocks triggered a 2.7% and 3.2% drop in advanced economies' and emerging economies' cyclical GDP growth rates, respectively.

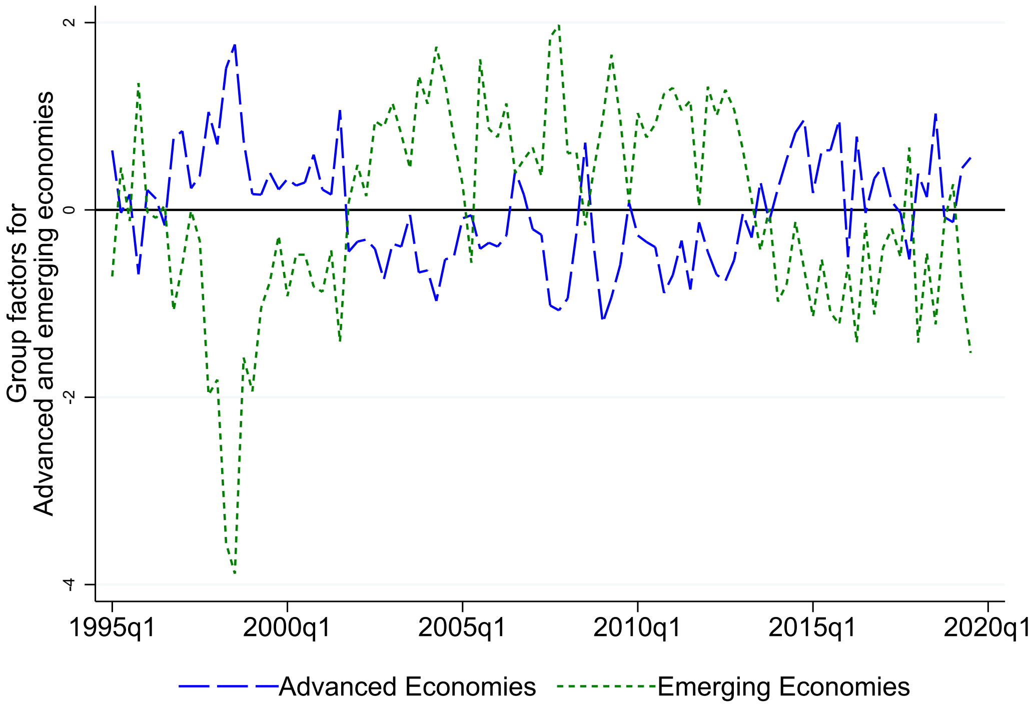
Business cycles of emerging economies are more synchronised with each other. The historical decomposition averages illustrated in the middle panel of Figure 4.4 shows that the emerging group factor's average impact on cyclical GDP growth in emerging economies is within the range of -1.1%–0.7%. Meanwhile, the corresponding average impact of the advanced group factor on developed economies' cyclical GDP growth rate is between -0.6%–0.5%. Emerging economies' business cycles exhibited significant volatility prior to the 2000's. This is explained by domestically sourced vulnerabilities, as illustrated in the bottom panel of Figure 4.4. However, intrinsic vulnerability in emerging economies has decreased recently. Since 2012, domestic shocks cause deviations from trend output to the tune of -0.2%–0.2% in emerging economies, compared to -0.4%–0.5% for advanced economies. Global economic shocks also explain a lower share of the variation in output since 2012. Prior to the 2007/8 GFC, the percentage deviation from trend output triggered by global shocks ranged from -0.5% to 0.8%. This range has narrowed to -0.5%–0.3% after 2012. The decline reflects primarily the stabilisation of global economic conditions, with the absence of major fluctuations in the global factor in the latter segment of the sample. Therefore, the drop in business cycle fluctuations caused by global factors may be interpreted as the absence of global shocks rather than the economies' increased ability to cope with international economic shocks.

Overall, timing seems to be of essence in the analysis of sources of business cycle fluctuations. Findings from this paper resonates with Kose et al. (2012); Levy Yeyati and Williams (2012) in terms of the decoupling of emerging economies' business cycles from advanced economies'. This holds especially true for the 1995-2006 period where, similar to Kose et al. (2012), I find that emerging economies' business cycles are more affected by the group factor than the global factor. In particular, in emerging economies, the group-specific factor shocks trigger deviation from trend output in the range of -1.1%–0.6%, whereas global factor shocks' impacts' range is about -0.4%–0.8%. However, by using updated data, I am able to highlight the importance of the global factor during the 2007/8 GFC, and its continuing declining importance post 2012.

External shocks explain a sizeable share of a country's business cycles. External shocks, if interpreted as shocks outside the domestic realm, can be considered as the combination of global shocks and the group factor for countries' income levels. External shocks are more more important in emerging economies, compared to advanced economies. External shocks cause output to deviate from trend by around -1.6%–1.4% in emerging economies, and by -0.9%–1.2% in advanced economies[6]. As a comparison, domestic shocks cause deviations from trend output in the range of -0.9%–0.5% in emerging economies, and of -0.4%–0.5% in advanced economies. External shocks have even greater repercussions in terms of business cycle fluctuations than domestic shocks.

[6]These calculations excludes the climax years of the 2007/8 GFC, namely 2008-2009.

Figure 4.2: Group-specific factors for Countries' Income Levels



Notes: The dashed blue line shows the group factor estimated using real GDP data for 31 advanced economies, whereas the dashed green line shows the group factor for the 14 emerging economies in the sample.

4.3.2 Regional Factors and their Impacts on Business Cycle Fluctuations

Business cycles across different geographical regions are different, indicating the existence of different centers of gravities of macroeconomic performance based on regions. Figure 4.5 illustrates the regional factors estimated using real GDP of economies within each respective region, using Equations (4.10)-(4.17) from Step 1. The business cycles of Asia Pacific and Western Hemisphere economies are more volatile, compared to the business cycles of European economies. The standard deviation of the Asia Pacific group factor is 1.2, that of the Western Hemisphere factor is 1.0, whereas Europe's factor's is 0.6. Major economic crises affecting each region can be discerned from the regional factors pictured in Figure 4.5. The dip of the Asia Pacific group factor in 1997 pertains to the Asian Financial Crisis. The Western Hemisphere group factor traces the Mexican tequila crisis, the dot-com bubble, the Argentinian debt default, the uncertainty from NAFTA negotiations and the recession in Brazil. European economies' business cycles are relatively less volatile, suggesting less contagion between European economies, compared to other regions. However, the European group factor still indicates a protracted decline after the 2007/8 GFC till the end of woes from the European debt crisis.

Regional factors trigger greater fluctuations from trend output, compared to the global factor. Regional factors and global factors also affect different regions in heterogeneous ways. Figure 4.6 decomposes the cyclical GDP of each economy into domestic factors, the global factor and the regional factors, resulting from Equation (4.21) in Step 2. Figure 4.7 illustrates the averages of these historical decomposition values for each region. On a country-by-country basis, Figure 4.6 shows that different economies are affected by regional factors and the global factor differently. Figure 4.7 sheds more clarity, and shows that regional factors tend to be more important in Asia Pacific and Western Hemisphere economies. With the exception of the major impact of the 2007/8 GFC related global factor shock, business cycle fluctuations associated with the global factor appear to have tamed at the end of the sample period. For Asia Pacific economies, since 2012, the percentage deviation from trend stemming from global shocks ranges -0.3%–0.2% and deviations from regional shocks lie in the range -0.3%–0.4%. Similarly, for Western Hemisphere economies, since 2012, the deviations from trend output coming from global shocks is around -0.5%–0.5%, compared to the wider range of -0.8%–0.5% resulting from regional shocks. On the flip side, European economies are more impacted by global shocks than regional shocks. Since 2012, global shocks trigger deviations of -0.5%–0.4% from trend output, and regional shocks only lead to a -0.3%–0.3% deviation from trend output, in European economies. To a certain extent, this makes sense given the less volatile regional factor for European economies, their external shocks seem to emanate from other global shocks instead.

Regional factors and global factors account for the major share of business cycle fluctuations, compared to domestic factors. Deviations from trend output caused by domestic shocks range -0.2%–0.1% for Asia Pacific economies, -0.3%–0.3% in Western Hemisphere economies, and -0.4%–0.5% in Europe, 2012 onwards. In contrast, summing across the deviations from trend output stemming from global factor shocks and the regional factor shocks, the resulting business cycle fluctuations triggered in Asia Pacific economies ranges -0.6%–0.6%, -1.3%–1.0% in Western Hemisphere economies and -0.8%–0.7% in European economies, respectively, in the post 2012 sample.

4.3.3 Group Factors for Both Income Levels and Regions and their Impacts on Business Cycle Fluctuations

The business cycles of emerging economies have decoupled from advanced economies'. Figure A.1 illustrates the group-specific factor that takes into consideration both the income levels and regions, estimated using Equations (4.16)-(4.18) in Step 1. In particular, as pictured in Figure A.1, in the 2000's economic performances in emerging economies in Asia Pacific, Europe and the Western Hemisphere were mostly stable, contrasting uneven performances in advanced economies counterparts. In particular, the mean average values of the emerging factors for each region are positive, whereas the mean value for the advanced Western Hemisphere economies is -0.1, that of advanced European economies -0.1, and zero for advanced Asia Pacific economies.

Regional shocks affect advanced economies and emerging economies differently. On a country-by-country basis, Figure A.2 decomposes the cyclical GDP of each economy into domestic factors, the global factor and the group-specific factor for income levels and regions, estimated using Equation (4.22) in Step 2. Figure A.3 shows the averages of these historical error decomposition values for each group of economies within the region and having the same income levels. Emerging economies are more affected by regional shocks than advanced economies. Since 2012, the group-specific shock triggers percentage deviation from trend output of about -0.6%–0.9% in emerging Asia Pacific economies, and -0.4%–0.6% in the region's advanced economies. A similar story prevails for Western Hemisphere economies where the group-specific factor causes deviations from trend output to the tune of -1.3%–0.7% in emerging economies, compared to -0.7%–0.7% in advanced Western Hemisphere economies. In Europe as well, deviations from trend output triggered by the group-specific shock ranges -1.0%–0.7% in emerging economies, and -0.4%–0.4% in advanced economies.These results highlight the importance of differentiating between advanced and emerging economies when analysing the regional spill-overs.

4.3.4 Robustness Checks

Alternative real GDP measures. The baseline results are calculated using real GDP that adjusts for the differences in the price levels across economies. The real GDP measure is crucial in estimating the global, group-specific factors for advanced and emerging economies and the regional factors. The objective of the paper remains focused on business cycle synchronisation amongst economies. Adjusting real GDP measures for the changes in CPI leads to the possibility of swings in CPI masking the underlying change in real GDP, leading to erroneous conclusions on the level of business cycle synchronisation. I test for the sensitivity to the choice of the real GDP measure by replacing the PPP-based real GDP with real GDP measured in US Dollars, this time purely based on the bilateral exchange rate vis-à-vis the US Dollar. Figure A.4 in the Appendix shows the global factor, the group specific factors for income levels and the regional factors, when the alternative exchange rate-based real measure is used.

The global factor as well as group factors produced when the exchange rate based real GDP is used are slightly more volatile than the baseline measures. However, the global factor using the alternative GDP measure still corroborate the baseline finding that the 2007/8 GFC constituted the deepest synchronised contraction for the sample period. The group factors thus produced are positively correlated to the baseline global factor and group factors. As pictured in Figure A.4, this robustness check portrays somewhat greater volatility in emerging economies, compared to the baseline. In addition, on a regional basis, the Western Hemisphere factor correlates lowest with the corresponding baseline factor, suggesting that fluctuations under the alternative may really be driven by the exchange rate.

Alternative detrending method. The second robustness check serves to ascertain the sensitivity of findings to the choice of the data transformation methodology. The baseline follows Stock and Watson (2016), such that the real GDP series are detrended using a biweight low-pass filter with a bandwidth of 100 quarters. Stock and Watson (2016) justifies the use of the low-pass filter due to the slowdown in growth noted over their 1959–2014 sample period, as well as in the literature. Meanwhile, the sample period in this paper is considerably shorter. In order to eliminate the possibility that the countries' business cycles are mismeasured, I apply the Hodrick and Prescott (1997) to detrend the real GDP series in the second robustness check. The results are presented in Figure A.5 in the Appendix. The results corroborate the baseline findings.

4.4 Conclusion

Macroeconomic volatility hampers growth and welfare. As countries become increasingly inter-connected through global trade and financial networks, business cycle fluctuations may not only source domestically, but also globally or regionally, or simply comove with countries' having similar economic structures.

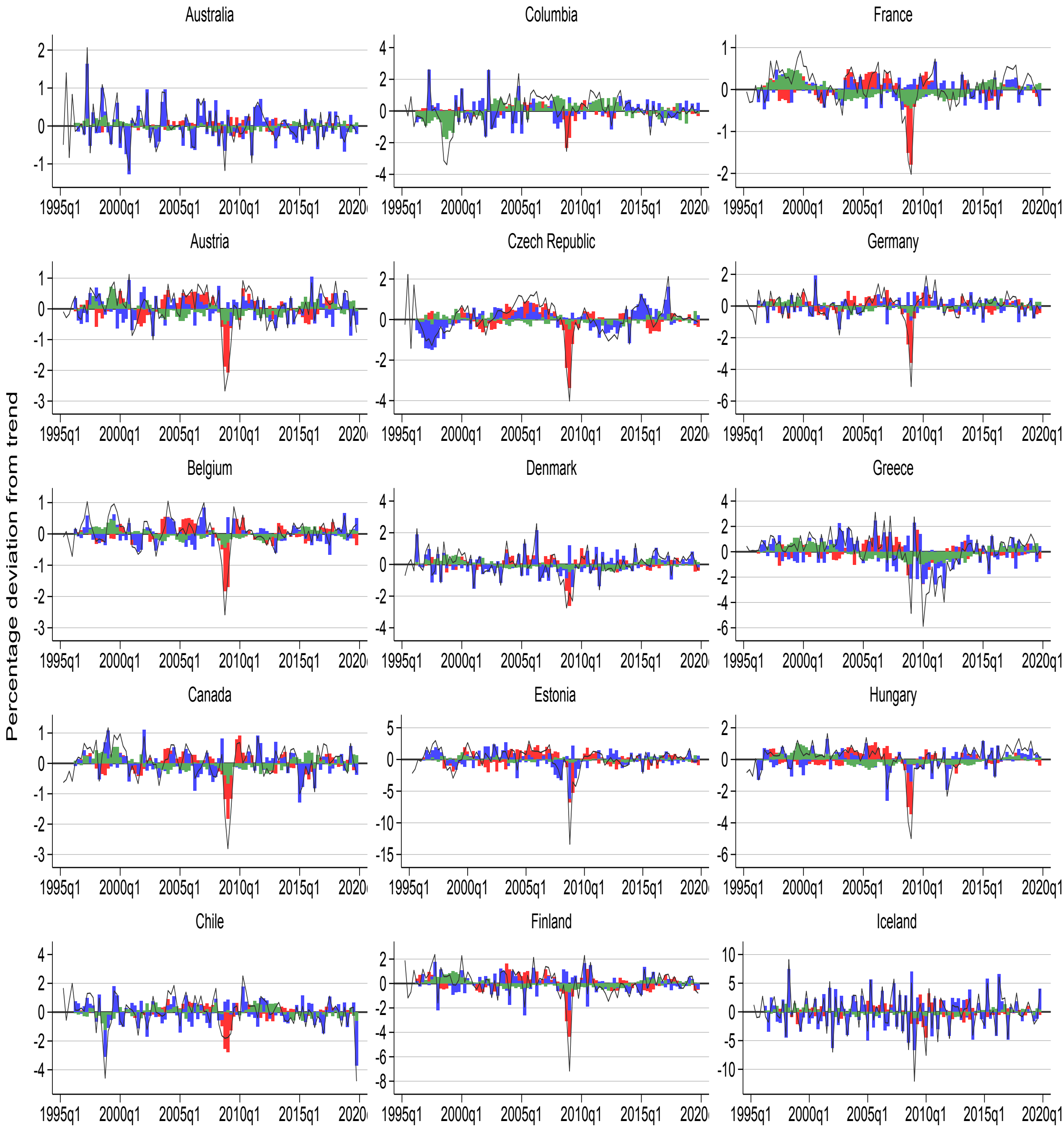
This paper shows that external sources of vulnerability is a cause for concern. Different economies are impacted by external shocks in heterogenous ways. The paper investigates business cycle comovoments between economies of similar income levels, as well as countries within the same region. Using a FAVAR model, this paper illustrates that emerging economies' business cycles are more volatile than advanced economies'. Emerging economies' business cycles are also more synchronised with each other, than advanced economies'. However, both advanced and emerging economies react in a similar way to global shocks. Global shocks have waned over the sample period, and a greater share of volatility stems from regional shocks. The regional shocks are more prominent in Asia Pacific and Western Hemisphere economies. Using a group-specific factor that accounts for both income levels and regions, I find that regional shocks are more important for emerging economies than advanced economies.

The impact of external shocks, whether global, region-specific or income level-specific, exceeds the impact of domestic shocks. Amidst elevated global uncertainty, these transmission channels for business cycle fluctuations are accentuated. Policy-makers aiming at reducing overall macroeconomic uncertainty can no longer undermine global or regional spill-overs.

Table 4.1: List of Economies

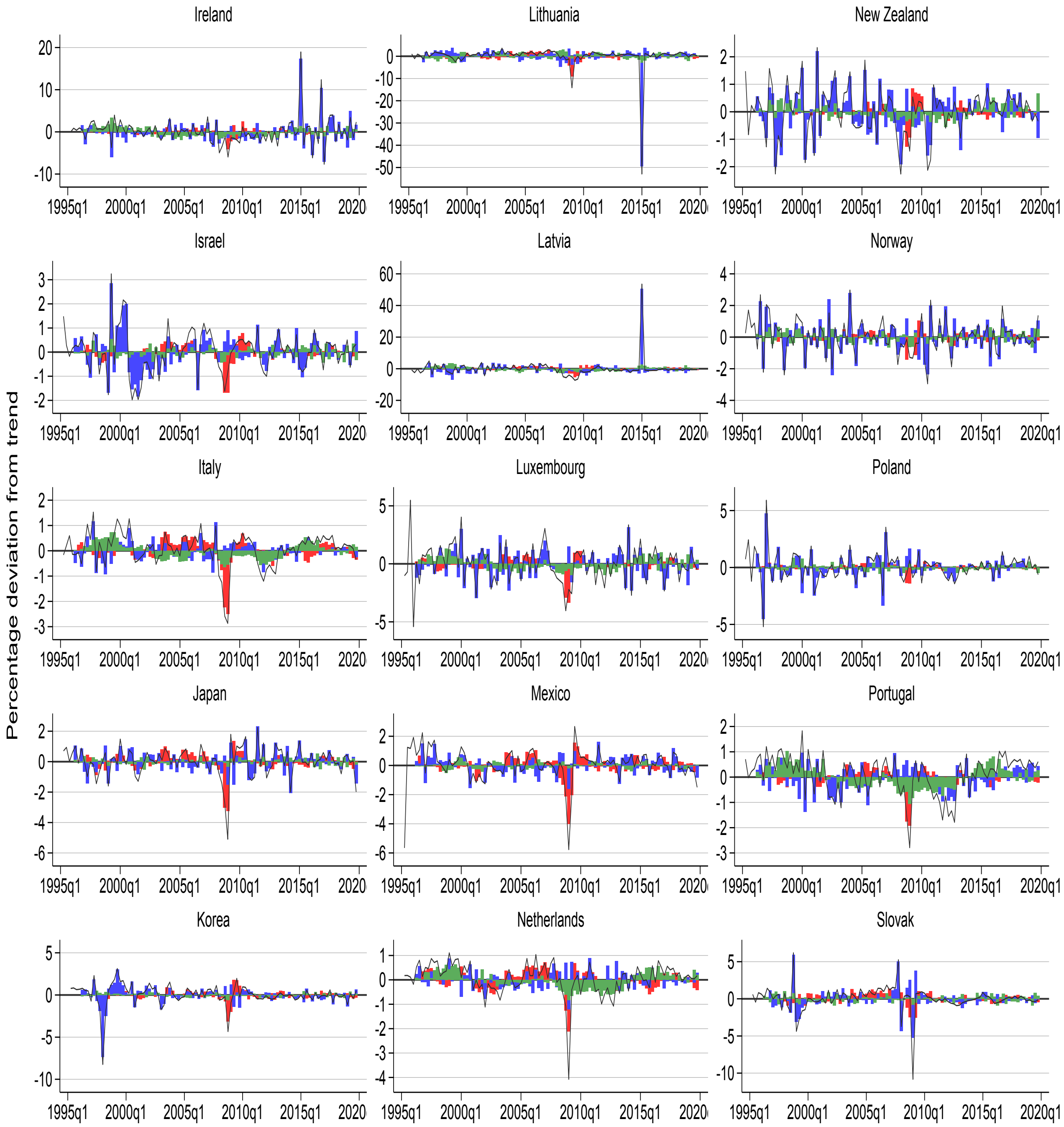
Advanced		**Emerging**
Asia Pacific		
Australia		China
Japan		India
Korea		Indonesia
New Zealand		
Europe		
Austria	Latvia	Bulgaria
Belgium	Lithuania	Hungary
Czech Republic	Luxembourg	Poland
Denmark	Netherlands	Romania
Estonia	Norway	Russia
Finland	Portugal	Turkey
France	Slovakia	
Germany	Slovenia	
Greece	Spain	
Iceland	Sweden	
Ireland	Switzerland	
Israel	United Kingdom	
Italy		
Western Hemisphere		
Canada		Argentina
United States		Brazil
		Chile
		Colombia
		Mexico

Figure 4.3: Historical Error Decomposition into Domestic Factors, the Global Factor and Group-specific Factors for Countries' Income levels (1/3)



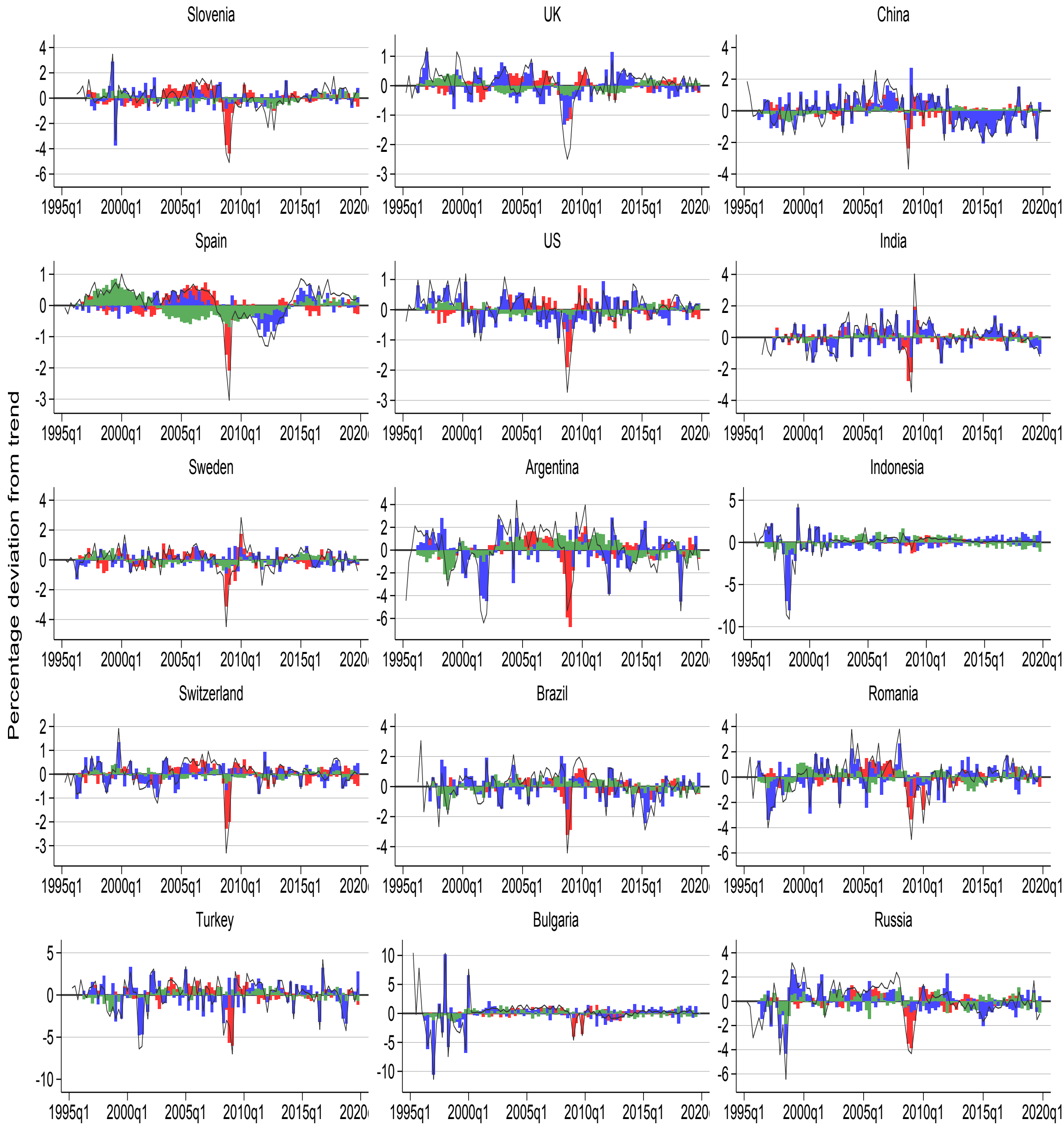
Notes: The solid black line plots the cyclical GDP of each country. Red bars show the percentage deviation from trend output that can be explained by global shocks. Blue bars depict the proportion of deviation from trend output explained by domestic shocks, whereas the proportion pertaining to the group-specific factor for advanced or emerging economies are illustrated by the green bars.

Historical Error Decomposition into Domestic Factors, the Global Factor and Group-specific Factors for Countries' Income levels (2/3)



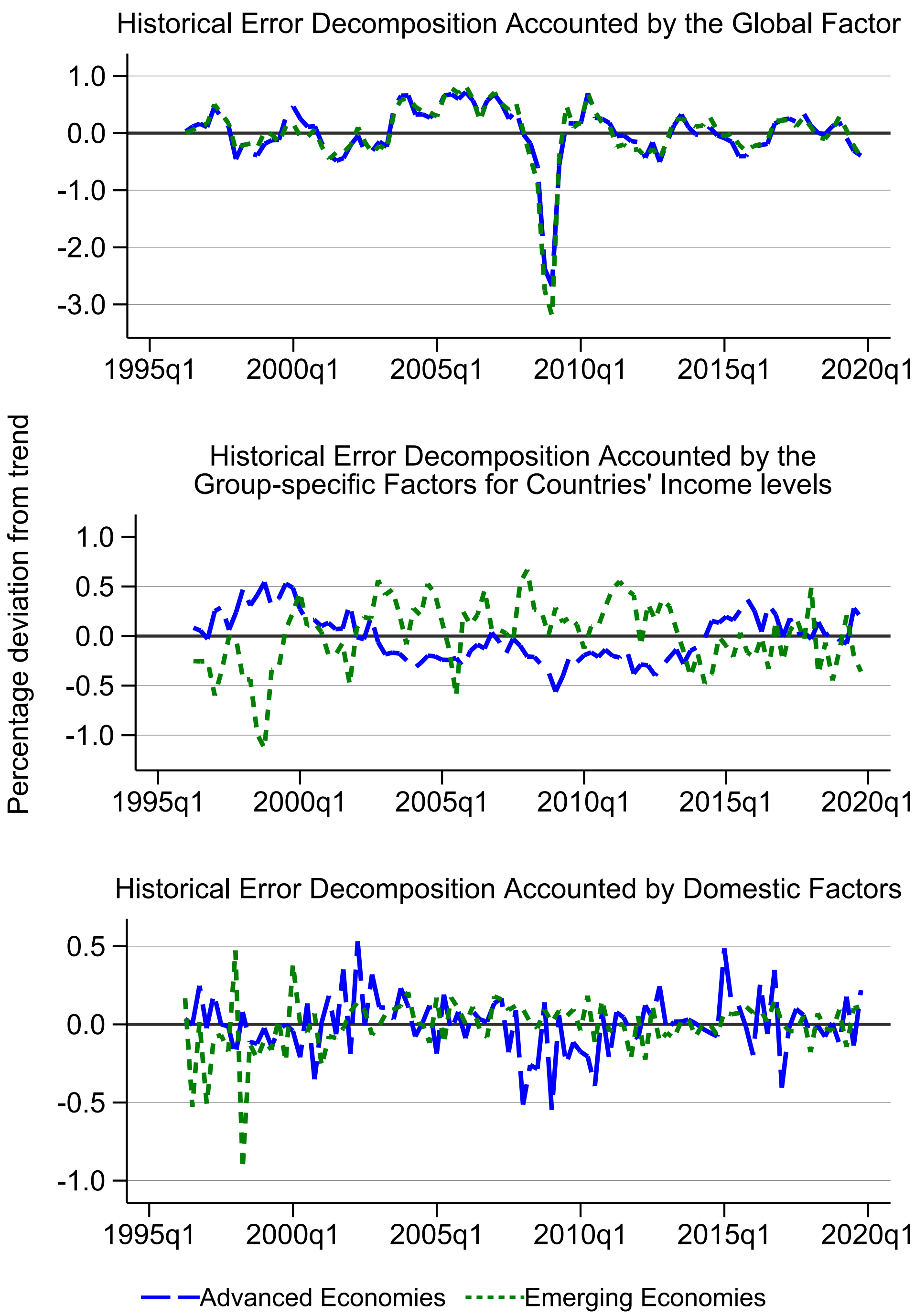
Notes: The solid black line plots the cyclical GDP of each country. Red bars show the percentage deviation from trend output that can be explained by global shocks. Blue bars depict the proportion of deviation from trend output explained by domestic shocks, whereas the proportion pertaining to the group-specific factor for advanced or emerging economies are illustrated by the green bars.

Historical Error Decomposition into Domestic Factors, the Global Factor and Group-specific Factors for Countries' Income levels (3/3)



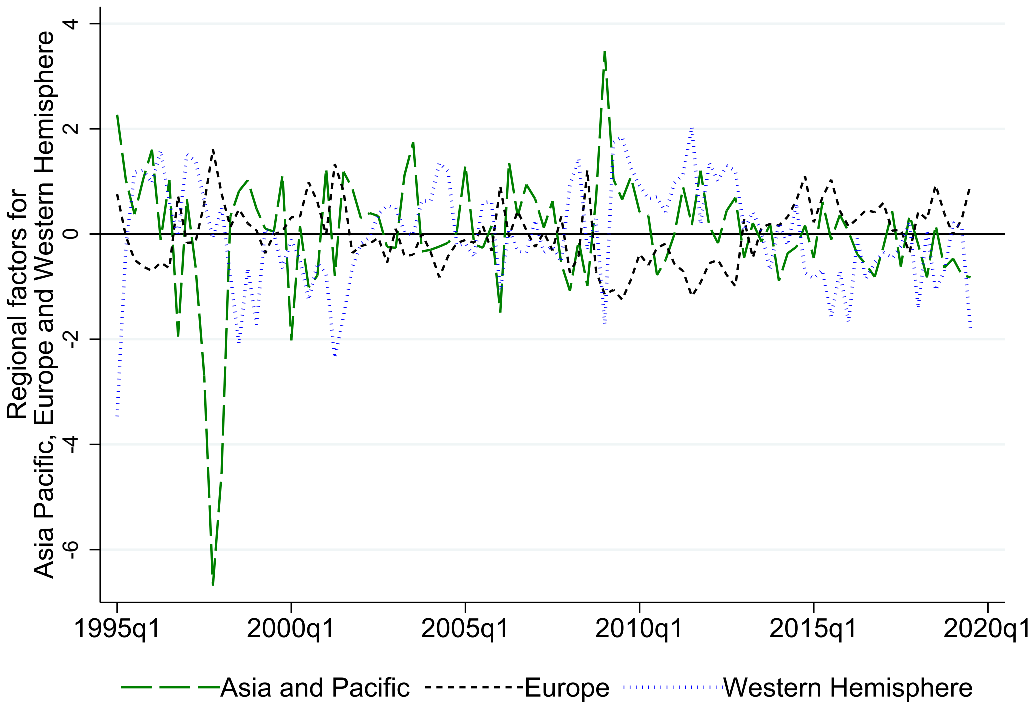
Notes: The solid black line plots the cyclical GDP of each country. Red bars show the percentage deviation from trend output that can be explained by global shocks. Blue bars depict the proportion of deviation from trend output explained by domestic shocks, whereas the proportion pertaining to the group-specific factor for advanced or emerging economies are illustrated by the green bars.

Figure 4.4: Proportion of Deviations from Trend Output Accounted by Global Factors, Group-specific Factors for Countries' Income Levels and Domestic Factors



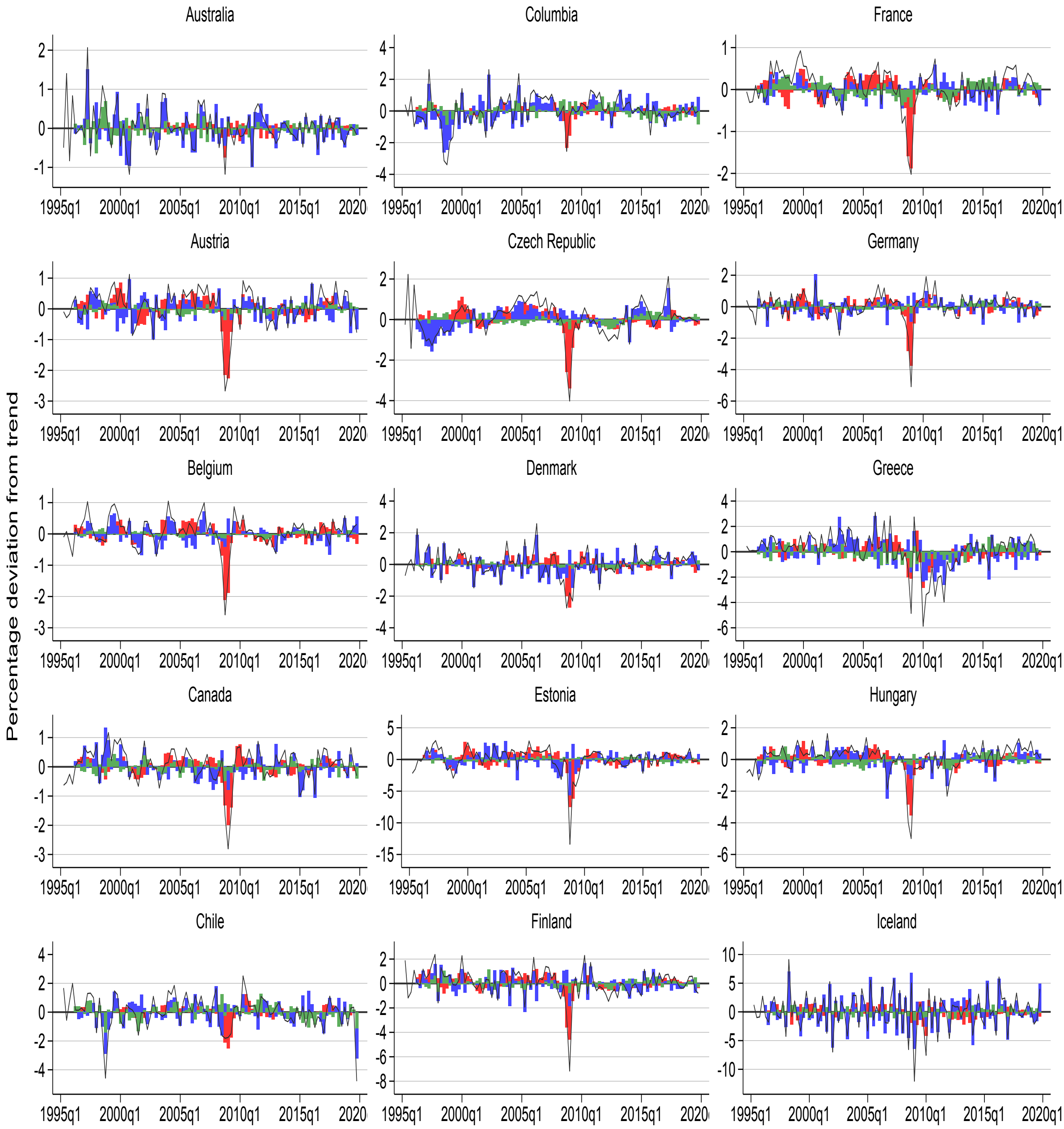
Notes: This figure calculates the average of the historical decomposition, separately, for advanced economies and emerging economies in the sample. Blue long dashed lines denote the average for advanced economies only, and green short dashed lines represent the corresponding average for emerging economies. In the top panel, the average percentage deviation from trend caused by global factors are illustrated for advanced economies and emerging economies, respectively. In the middle panel, the percentage deviation from trend output triggered by the group-specific factor for advanced economies and emerging economies are presented, and in the bottom panel the percentage deviation from trend output caused by domestic factors are shown.

Figure 4.5: Regional Factors



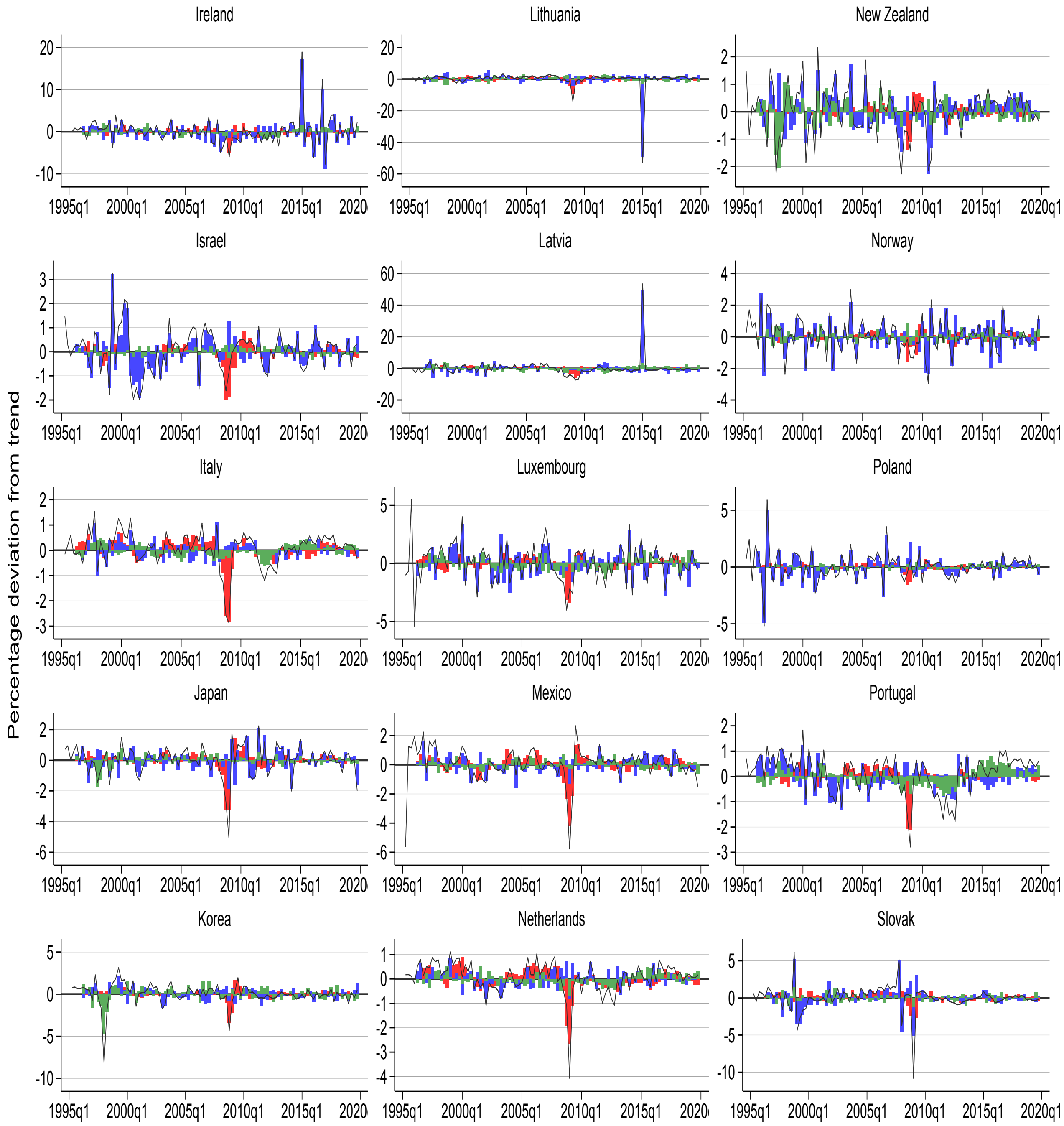
Notes: The long dashed green line shows the group factor estimated using real GDP data for Asia Pacific economies. The short dashed black line shows the group factor for European economies in the sample, and the blue dotted line depicts the group factor for Western Hemisphere economies.

Figure 4.6: Historical Error Decomposition Accounted into Domestic Factors, the Global Factor and Regional Factors (1/3)



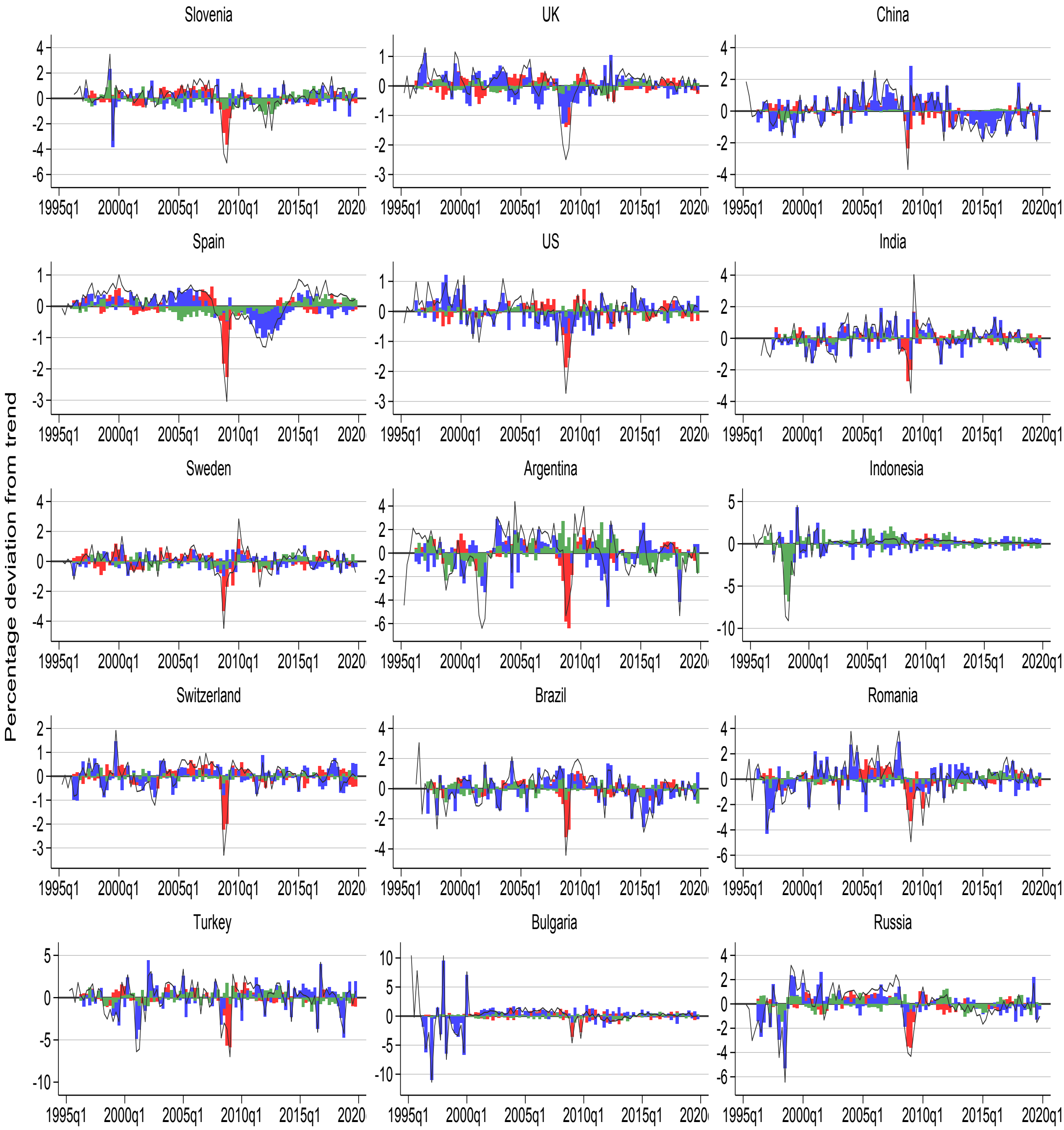
Notes: The solid black line plots the cyclical GDP of each country. Blue bars depict the proportion of deviation from trend output explained by domestic shocks. Red bars indicate the percentage deviation from trend output explained by global factor shocks, and green bars the percentage deviation from trend output explained by regional shocks.

Historical Error Decomposition Accounted into Domestic Factors, the Global Factor and Regional Factors (2/3)



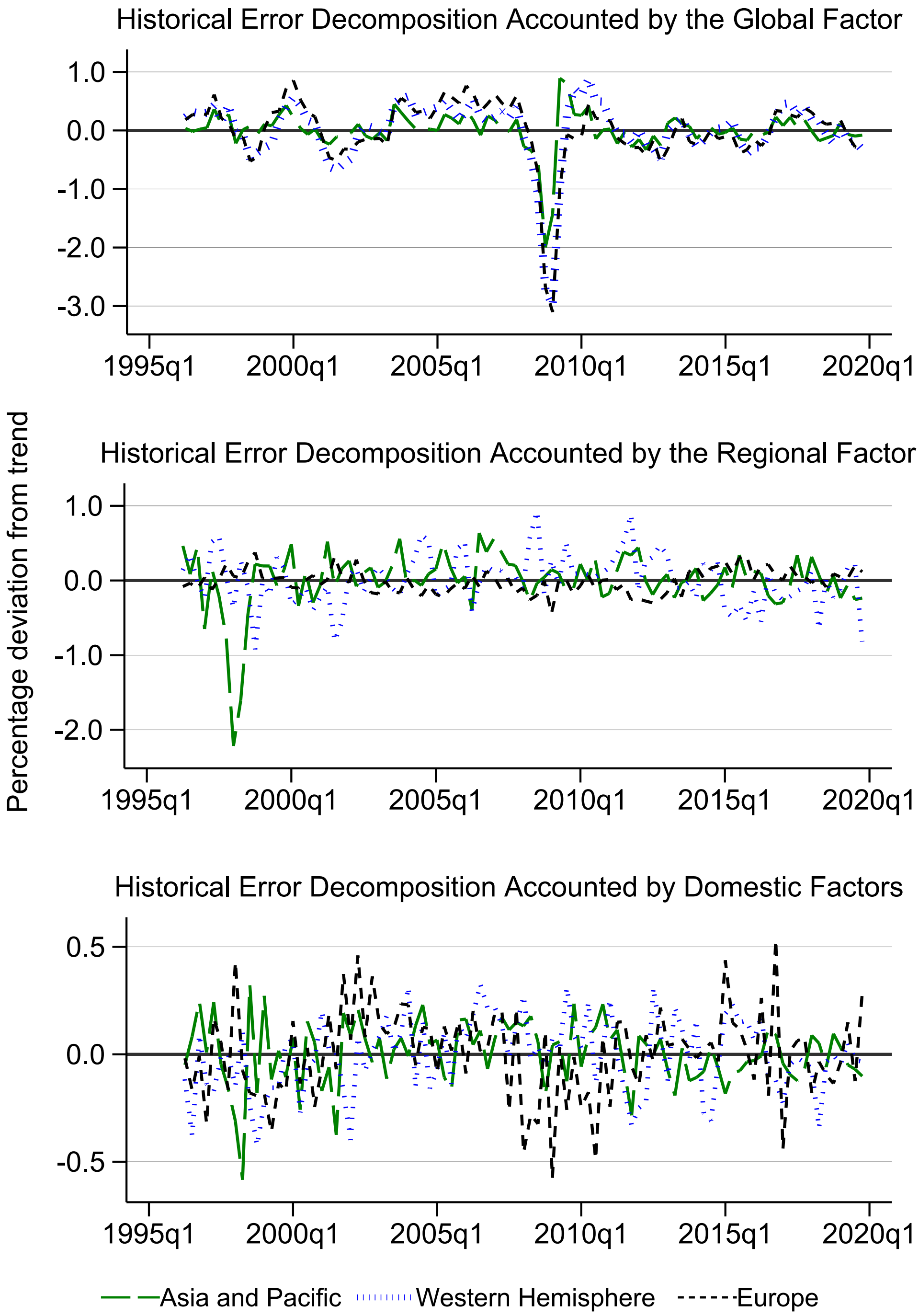
Notes: The solid black line plots the cyclical GDP of each country. Blue bars depict the proportion of deviation from trend output explained by domestic shocks. Red bars indicate the percentage deviation from trend output explained by global factor shocks, and green bars the percentage deviation from trend output explained by regional shocks.

Historical Error Decomposition Accounted into Domestic Factors, the Global Factor and Regional Factors (3/3)



Notes: The solid black line plots the cyclical GDP of each country. Blue bars depict the proportion of deviation from trend output explained by domestic shocks. Red bars indicate the percentage deviation from trend output explained by global factor shocks, and green bars the percentage deviation from trend output explained by regional shocks.

Figure 4.7: Proportion of Deviations from Trend Output Accounted by Global Factors, Region-specific Factors and Domestic Factors



Notes: This figure calculates the average of the historical decomposition, separately, for Asian Pacific economies, European economies and Western Hemisphere economies. Green long dashed lines denote the average for Asian Pacific economies only, short dashed black lines for European economies exclusively, and blue dotted lines represent the corresponding average for Western Hemisphere economies. In the top panel, the average percentage deviation from trend caused by global factors are illustrated for Asia Pacific, European and Western Hemisphere, respectively. In the middle panel, the percentage deviation from trend output triggered by the region-specific factors are presented, and in the bottom panel the percentage deviation from trend output caused by domestic factors are shown for Asia Pacific economies, European economies and Western Hemisphere economies, respectively.

Chapter 5

Conclusions

This thesis explores external vulnerability from two different lenses. In a first instance, we consider different types of uncertainty shocks and how they affect the trade flows in emerging economies. The global economy is characterised by elevated uncertainty. The nature of uncertainty shocks has evolved over time. Global financial shocks were at the forefront during the 2007/8 Global Financial Crisis. Trade policy uncertainty which was previously relatively under control, skyrocketed following the 2018 trade tensions between US and China, and has remained high since in the wake of global supply shortages in the wake of the COVID-19 pandemic and the Ukraine-Russia war. We document that different uncertainty shocks herald different implications for the trade flows in emerging economies. We find that global economic and trade policy uncertainty shocks reduce emerging economies' openness, and trigger a deterioration of their trade balance to GDP ratio. Global economic and trade policy uncertainty shocks induce a protracted decline of about 4 to 5 % in emerging economies' imports and exports. The effects are statistically significant for over two years after the shock. In contrast, global financial uncertainty shocks only have a mild short-lived impact on trade.

Uncertainty shocks act as barriers to trade. Trade policy uncertainty explains 10% of the variation in imports and exports, and global economic uncertainty around 7–8%. Emerging economies tend to adopt export-led growth strategies, and our findings suggest that uncertainty shocks effectively prevent them from reaping the gains from trade, and threaten their integration into the global economy. Our results provide evidence for the benefits of greater transparency and credibility in trade policy discussions. The effects of uncertainty shocks on trade flows are persistent. We make a contribution in understanding the linkages between uncertainty and trade flows. Results imply that macroeconomic studies on the effects of uncertainty should not abstract from its long run impact on trade flows. Similarly, trade studies should consider the dynamic effects of uncertainty on trade flows. I leave for future work, extensions including a comparison with advanced economies' trade effects of uncertainty using a similar framework, and the use of granular trade data to better understand the types of goods more vulnerable to uncertainty shocks.

The second aspect of external vulnerability considered in this thesis pertains to business cycle interdependence. External vulnerability in this context is broken down into two aspects. On the one hand, economies face similar global shocks. On the other hand, these global shocks affect different economies differently. By using three dynamic factor models, I first estimate a global business cycle; a regional business cycle for Asia and Pacific economies, Western Hemisphere economies and European economies, respectively; and finally a business cycle common to advanced economies and emerging economies, respectively. I then use a FAVAR model for each economy to compare the historical contribution of these estimated external business cycle shocks with domestic business cycle shocks. I find that that external business cycle shocks explain a greater share of economies' business cycle fluctuations than domestic shocks. In particular, the global factor and the group factor for income levels trigger deviations from trend output in the range of -0.9–1.2% in advanced economies, and -1.6–1.4% in emerging economies. Summing the contributions of the global shock and the regional shock, external shocks' impact on cyclical GDP growth rates in Asia Pacific economies ranges about -0.6–0.6%, -1.3–1.0% in Western Hemisphere economies, and -0.8–0.7% in European economies. This compares with significantly narrower ranges for the corresponding deviation from trend output stemming from domestic shocks: -0.2–0.1% for Asia Pacific economies, -0.3–0.3% for Western Hemisphere economies, and -0.4–0.5% for European economies.

The thesis additionally documents how business cycle synchronisations have changed over time. The majority of the literature studying business cycles consider samples that end before 2010. I document how global business cycle shocks are relatively tame in my post 2012 sample, whilst regional business cycle shocks explain a greater share of business cycle fluctuations. Further research along this avenue could assess linkages between intra-regional trade and financial flows and regional output co-movement. The findings also call for more research on regional spill-overs, especially on how crises may potentially spread within regions. In a sense, the findings also support for regional co-operation on policy-making, especially with a view to curb volatility from regional spill-overs.

I also show how emerging economies' business cycles behave differently from advanced economies'. Their business cycles are almost twice as volatile, and they also tend to be more synchronised amongst themselves. Whilst the literature has heavily focused on advanced economies, the inclusion of emerging economies not only leads to a more truly global estimate of the global business cycle, not one that is identified from a handful of developed economies, but also helps understand business cycle fluctuations in emerging economies.

Policy-makers concerned with creating and nurturing a stable macroeconomic environment should aim for policies that address their vulnerability to shocks external to their economies, be they level shocks like global business cycle shocks or second moment shocks like uncertainty shocks.

Appendix

A.1 Lag Selection Criteria

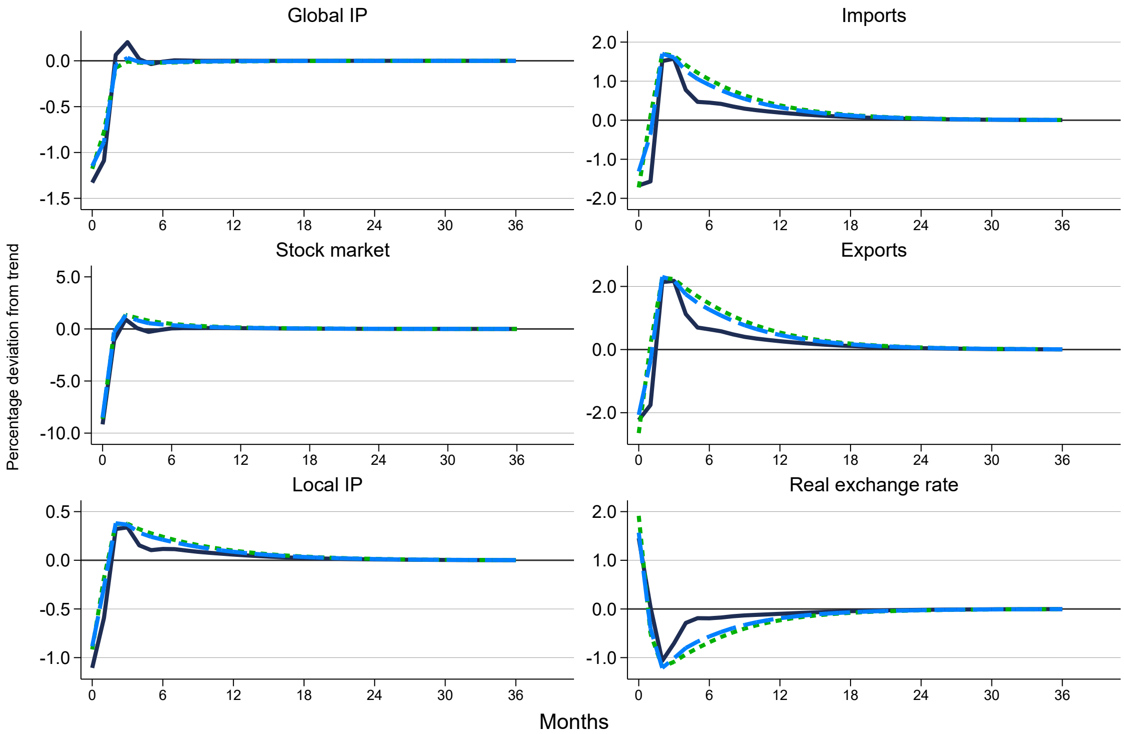
Table A.1: VAR Order Selection Criteria

	Andrews and Lu (2001)'s model selection criteria		
Lag length	**BIC**	**AIC**	**QIC**
Global Economic Uncertainty (GEU)			
1	-2456.159*	-431.950*	-1224.648*
2	-2170.937	-355.541	-1066.466
3	-1874.371	-271.789	-900.941
Global Financial Uncertainty (GFU)			
1	-2457.093*	-432.885*	-1225.582*
2	-2168.619	-353.223	-1064.148
3	-1800.619	-266.4827	-867.264
Trade Policy Uncertainty (TPU)			
1	-2454.042*	-429.834*	-1222.531*
2	-2166.950	-351.554	-1062.479
3	-1872.255	-265.672	-894.824

Notes: Table presents three moment model selection criteria developed by Andrews and Lu (2001) for the panel VAR presented in Equation (3.1) in the main text for different lag lengths: Bayesian Information Criterion (BIC), the Akaike Information Criterion (AIC), and the Hannan-Quinn Information Criterion (QIC). * indicates the minimum of the respective criterion.

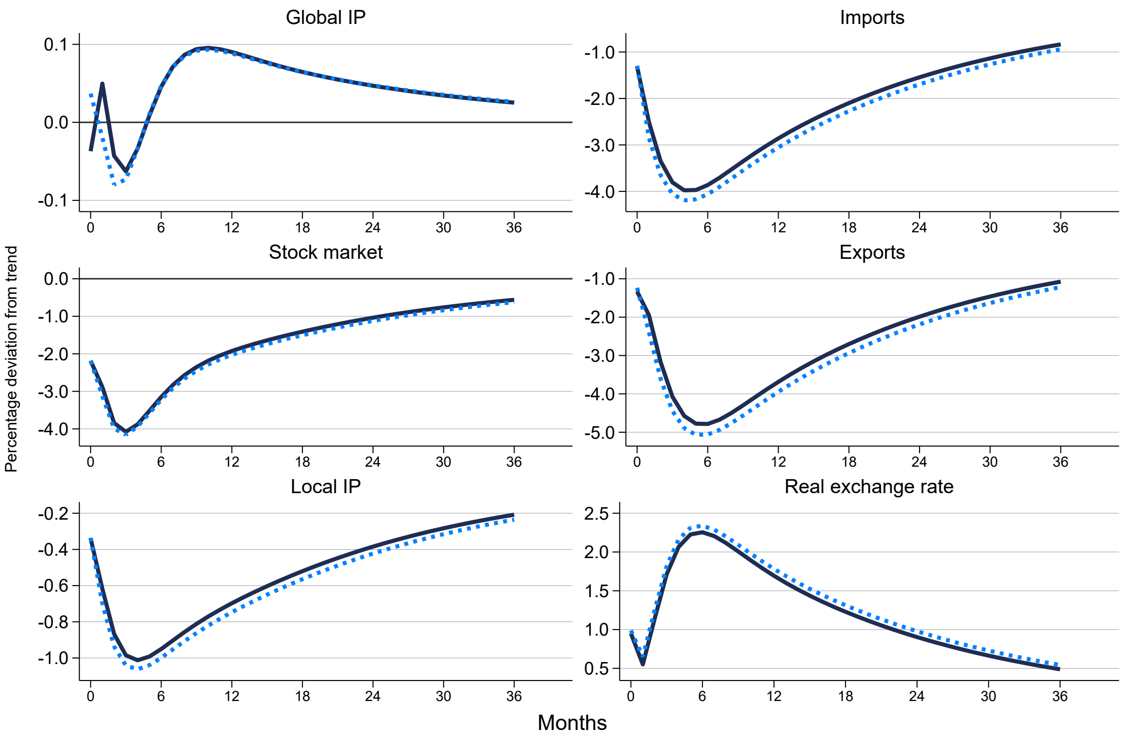
A.2 Robustness Checks

Figure A.1: Impulse Responses to a Standard Deviation Shock to Different Global Financial Uncertainty Measures



Notes: The green dotted line depicts the results when Caggiano and Castelnuovo (2021)'s measure is used as an alternative global financial uncertainty indicator. The bright blue dashed line depicts the impulse responses to a VIX shock. The solid blue line shows the baseline estimates from Figure 3.3 using the Ludvigson et al. (2020)'s global financial uncertainty index (GFU) for comparison.

Figure A.2: Impulse Responses to a Standard Deviation Shock to Different Trade Policy Uncertainty Measures



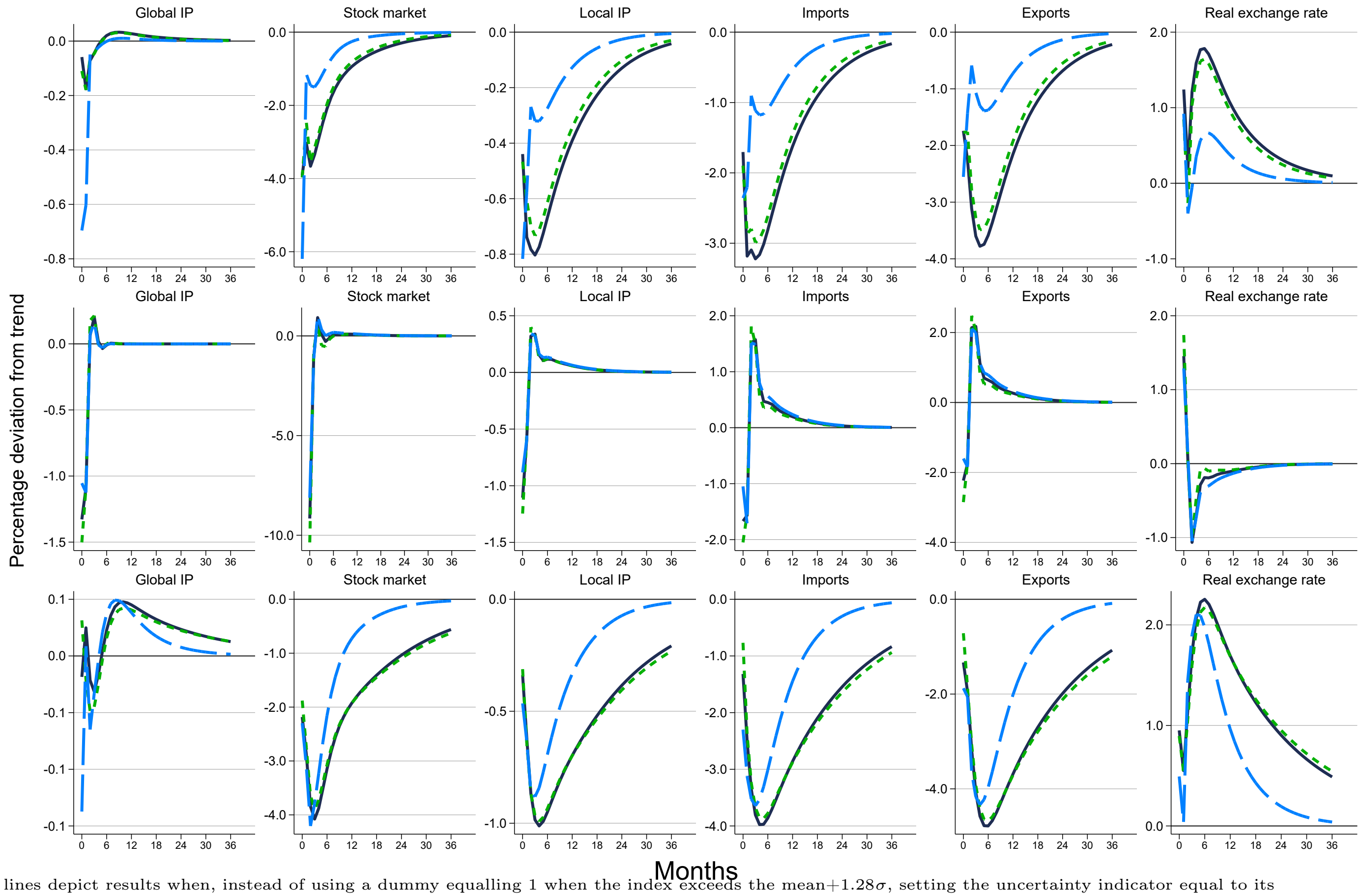
Notes: The dashed line depicts the impulse responses using Baker et al. (2016)'s measure of Trade Policy Uncertainty. The solid blue line shows the baseline estimates from Figure 3.3 using the Caldara et al. (2020)'s Trade Policy Uncertainty index (TPU) for comparison.

Figure A.3: Impulse Responses to a Standard Deviation Shock to Different Uncertainty Measures Using Alternative Data Transformations

(1) Model featuring Baker et al. (2016) Global Economic Uncertainty (GEU) Index

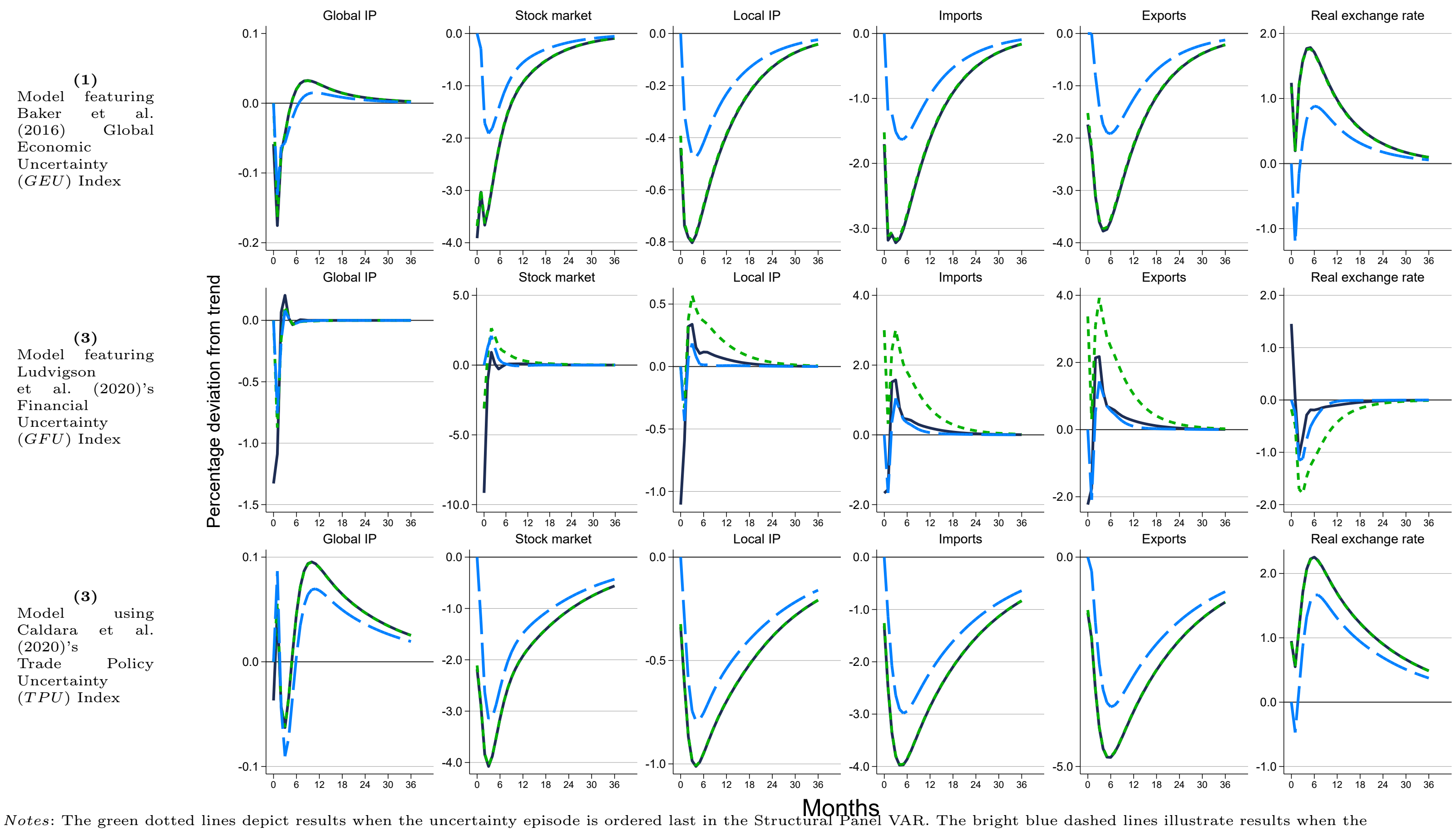
(3) Model featuring Ludvigson et al. (2020)'s Financial Uncertainty (GFU) Index

(3) Model using Caldara et al. (2020)'s Trade Policy Uncertainty (TPU) Index



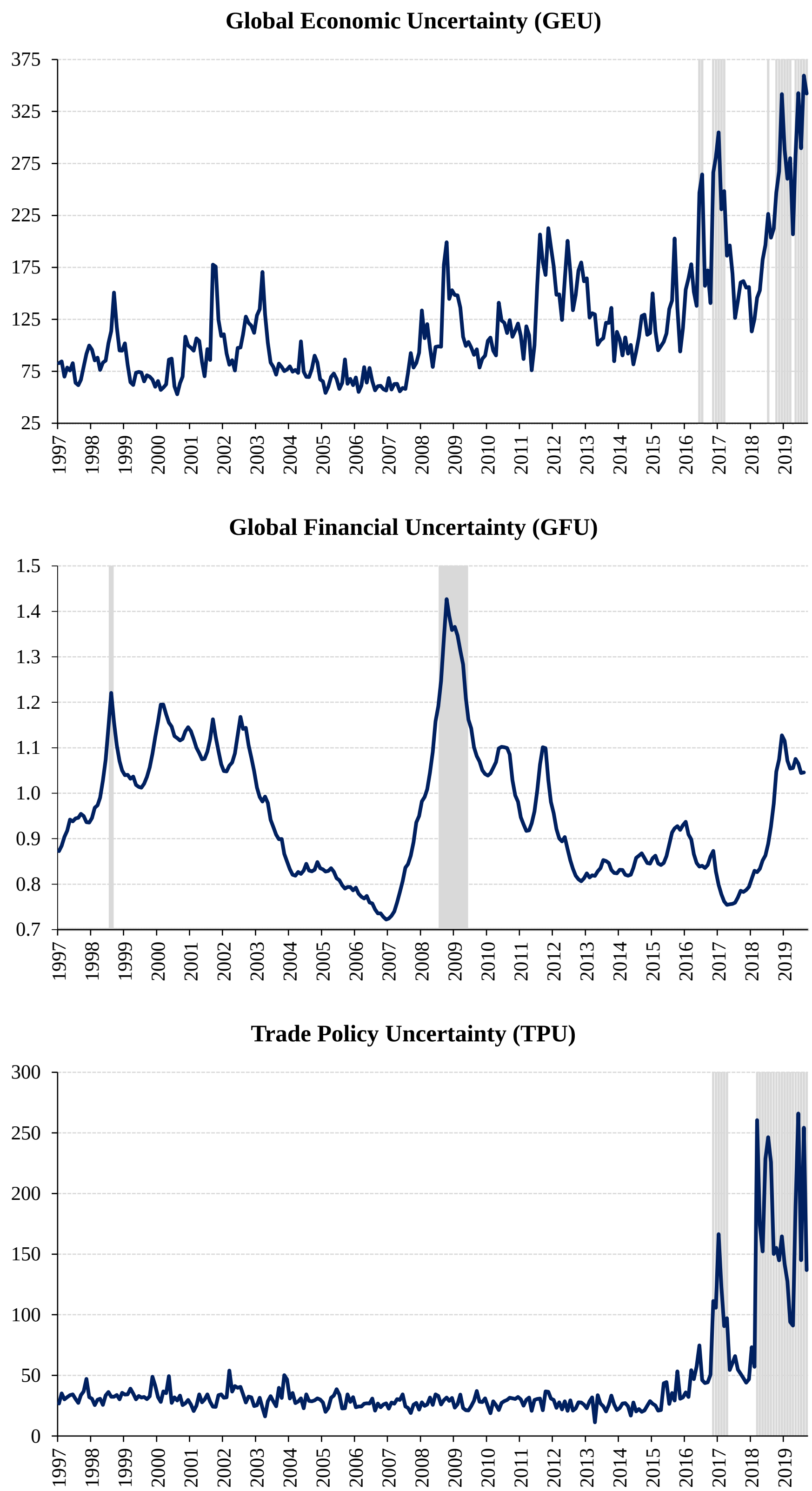
Notes: The green dotted lines depict results when, instead of using a dummy equalling 1 when the index exceeds the mean+1.28σ, setting the uncertainty indicator equal to its log-linear detrended value during high-uncertainty episodes, and 0 otherwise. The bright blue dashed lines illustrate results when the uncertainty index is detrended using the Hamilton (2018) Filter before identifying high-uncertainty episodes. Solid dark blue lines show the baseline results from Figure 3.3 for comparison.

Figure A.4: Impulse Responses to a Standard Deviation Shock to Different Uncertainty Measures with Alternative Ordering



Notes: The green dotted lines depict results when the uncertainty episode is ordered last in the Structural Panel VAR. The bright blue dashed lines illustrate results when the uncertainty index is still within the foreign block, but is ordered after global IP. Solid dark blue lines show the baseline results from Figure 3.3 for comparison.

Figure A.5: High Uncertainty Episodes Defined Using a Different Cut-off



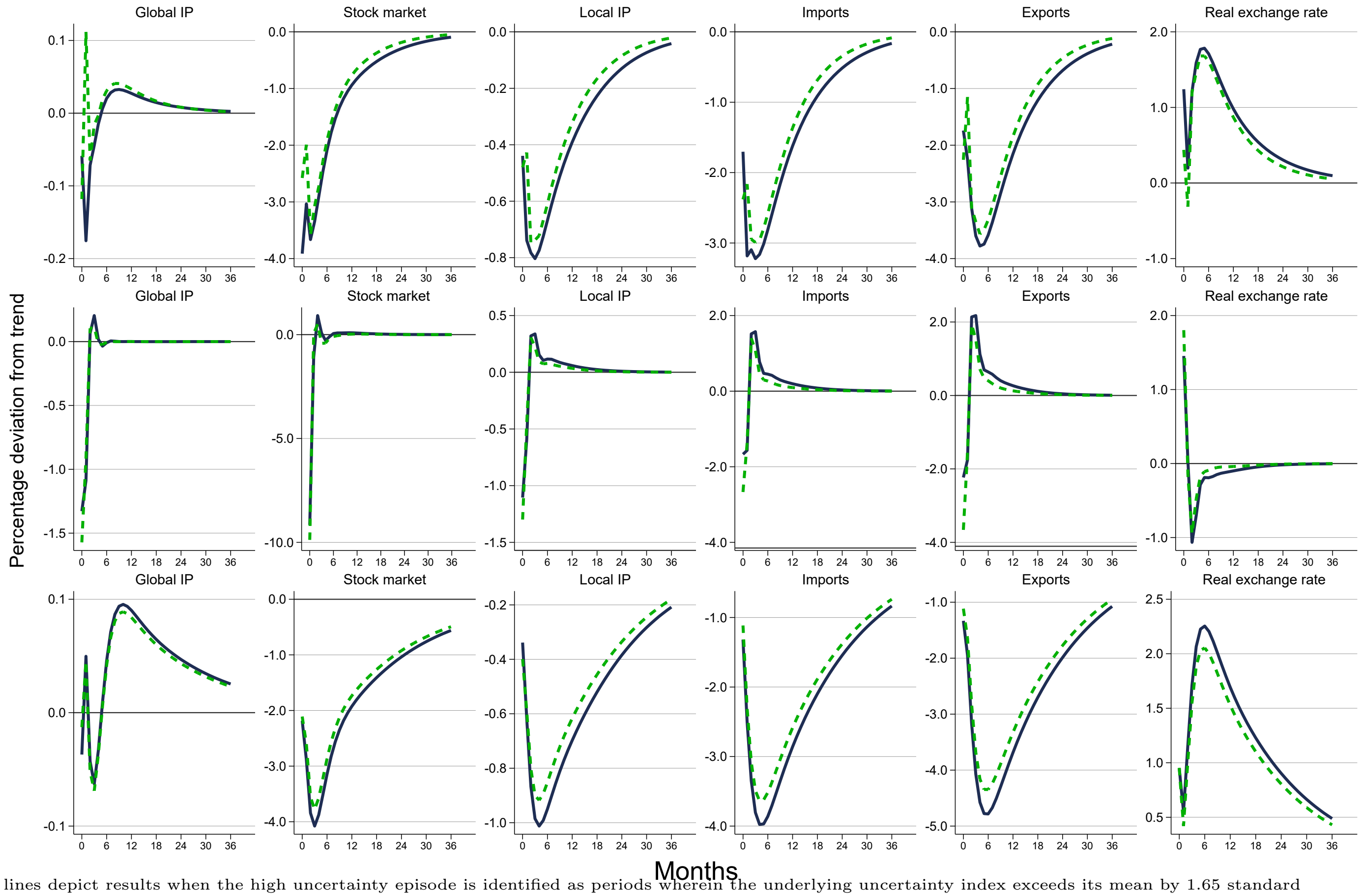
Notes: Shaded areas highlight high uncertainty episodes which we define as periods wherein the underlying uncertainty index exceeds its mean by 1.65 standard deviations. Data source: *GEU*: Baker et al. (2016); *GFU*: Ludvigson et al. (2020); *TPU*: Caldara et al. (2020).

Figure A.6: Impulse Responses to a Standard Deviation Shock to Different Uncertainty Measures with Different Threshold for High Uncertainty Episodes

(1)
Model featuring Baker et al. (2016) Global Economic Uncertainty (GEU) Index

(3)
Model featuring Ludvigson et al. (2020)'s Financial Uncertainty (GFU) Index

(3)
Model using Caldara et al. (2020)'s Trade Policy Uncertainty (TPU) Index



Notes: The green dotted lines depict results when the high uncertainty episode is identified as periods wherein the underlying uncertainty index exceeds its mean by 1.65 standard deviations. Solid dark blue lines show the baseline results from Figure 3.3 for comparison.

Appendix

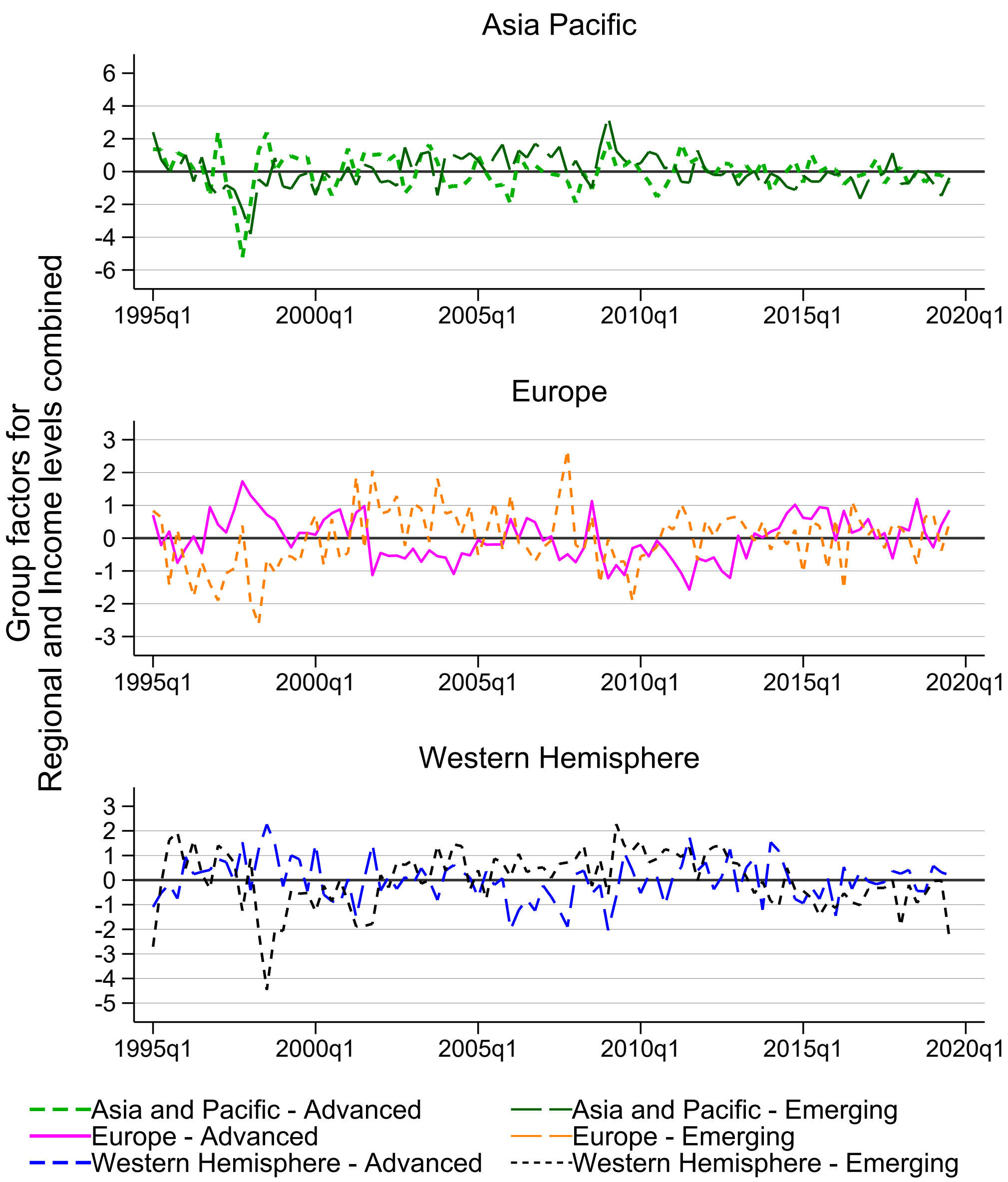
A.1 Selection Criteria for the Number of Factors

Table A.1: Statistics for Selecting the Number of Global Factors

Number of factors	**Bai and Ng (2002)'s Information Criteria**	**Marginal R^2**
1	-0.2043	0.2270
2	-0.1913	0.0733
3	-0.1617	0.0562
4	-0.1235	0.0466
5	-0.0830	0.0418

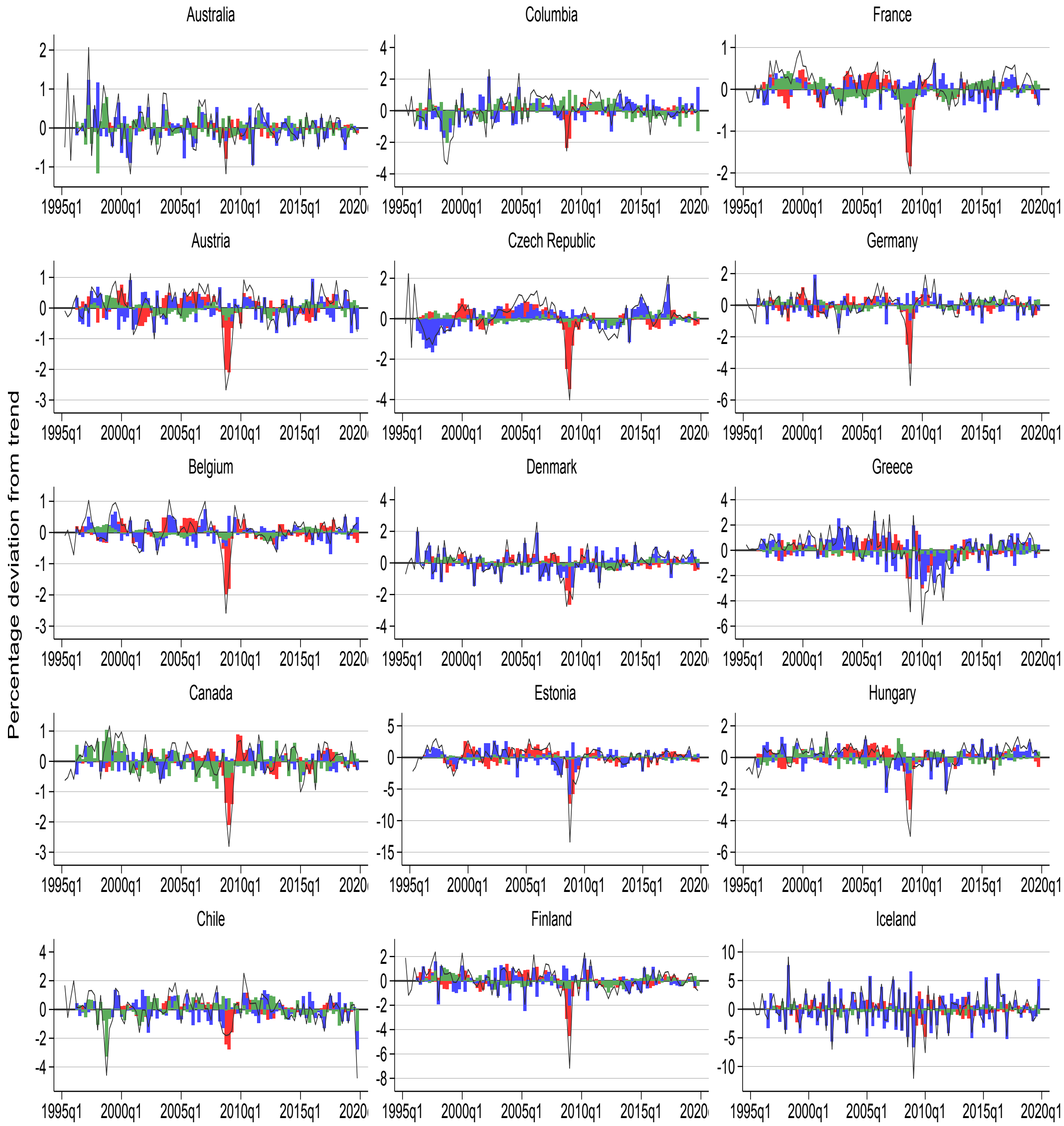
Notes: Table presents the Bai and Ng (2002)'s Information Criterion and the Marginal R^2, that have been used to choose the number of factors in equation (4.2) in the main text.

Figure A.1: Group Factors Categorised by Income Levels and Regions



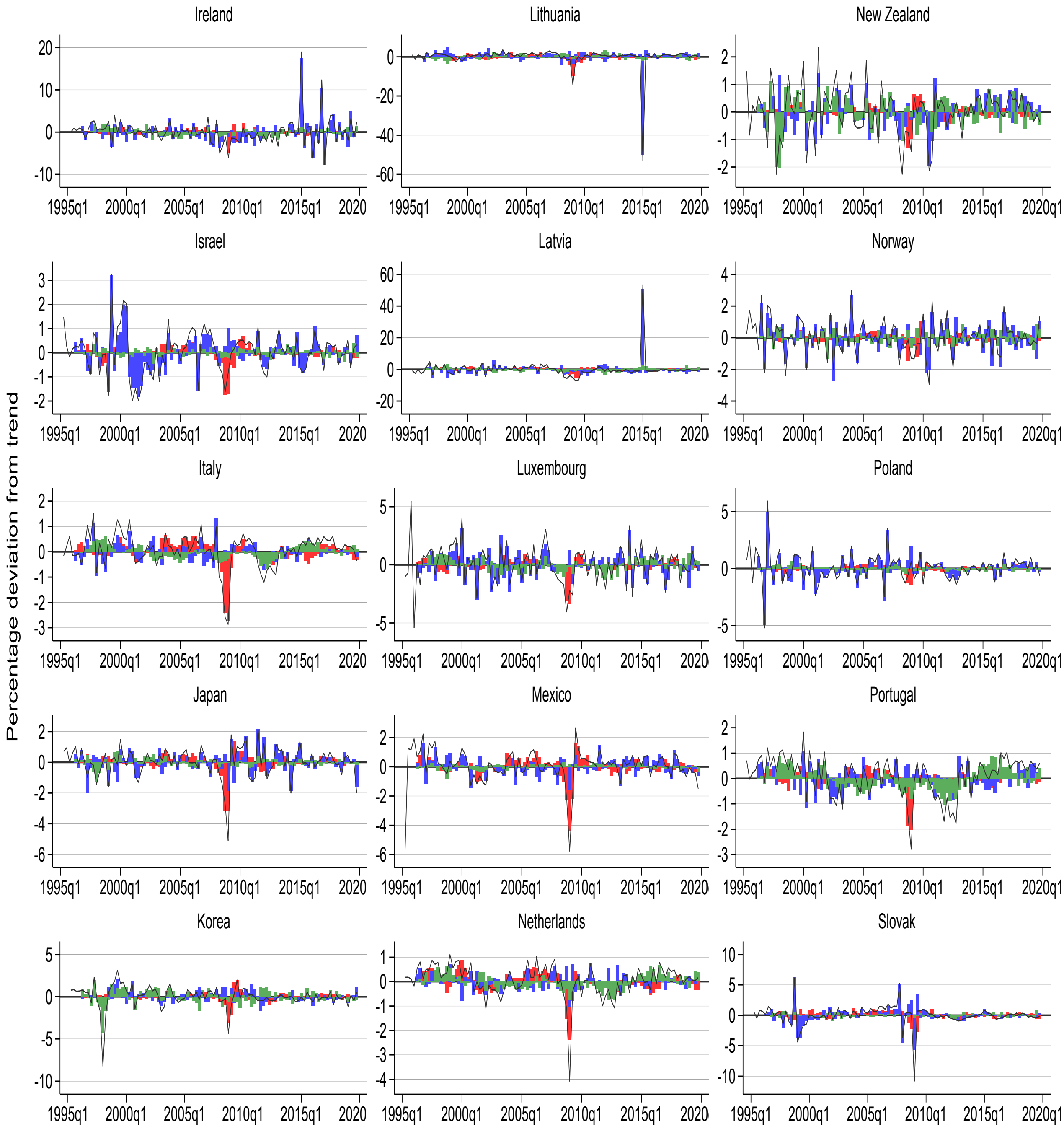
Notes: In the topmost panel, the group factor for advanced Asia Pacific economies, illustrated by the short dashed green line is compared to the group factor for emerging Asia Pacific economies, shown by long dashed dark green line. In the middle panel, the common factor for advanced European economies depicted by the solid pink line is shown alongside the common factor for emerging European economies represented by the short dashed orange line. In the bottom panel, the long dashed blue line represents the common factor for advanced Western Hemisphere economies, and the short dashed black line for emerging Western Hemisphere economies.

Figure A.2: Historical Error Decomposition Accounted into Domestic Factors, the Global Factor and a Group Factor Categorised by Income Levels and Regions (1/3)



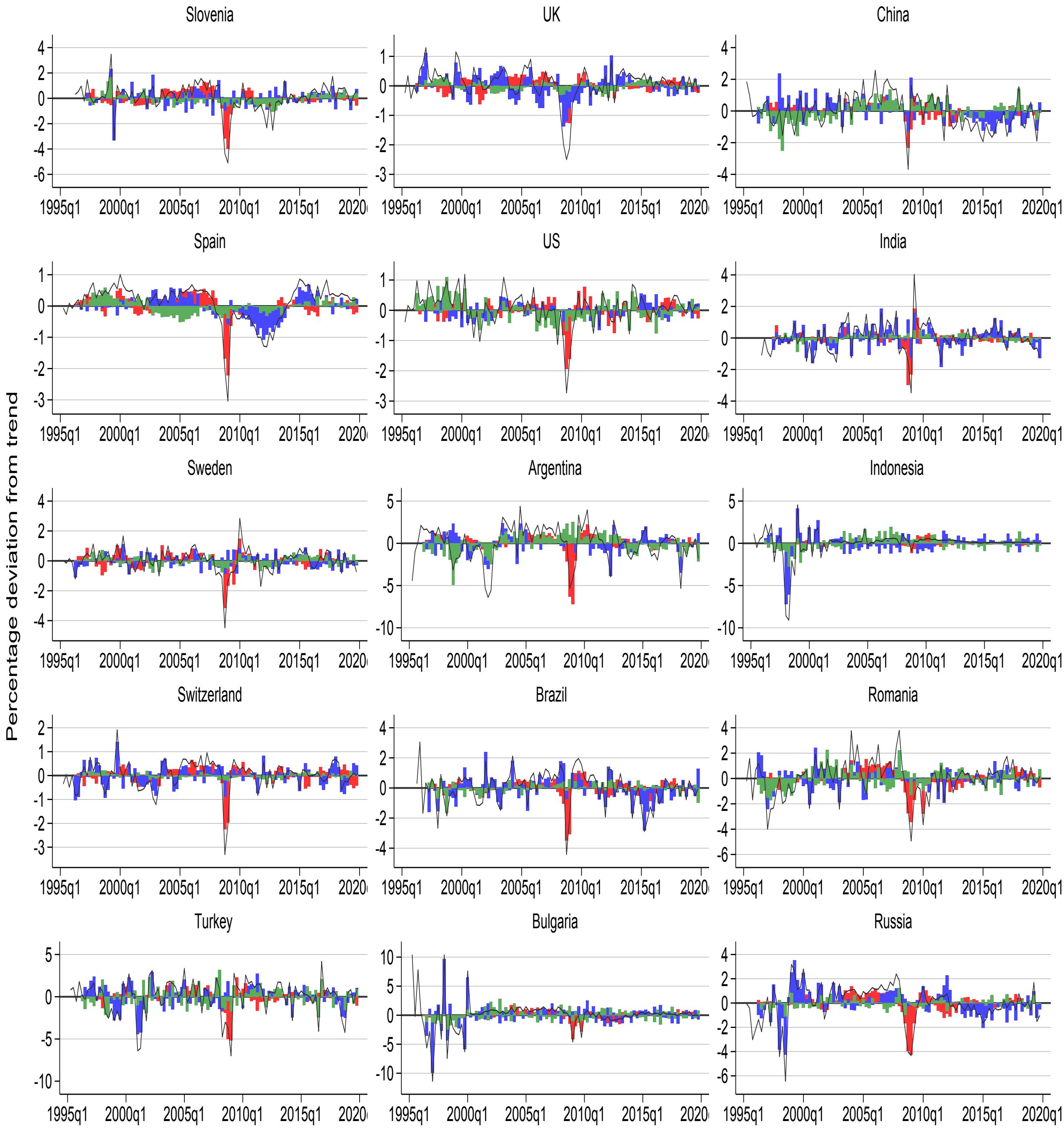
Notes: The solid black line plots the cyclical GDP of each country. Blue bars depict the proportion of deviation from trend output explained by domestic shocks. Red bars indicate the percentage deviation from trend output explained by global factor shocks. Green bars represent the percentage deviation from trend output explained by group-specific shocks, calculated for groups within the same geographical region and income level within that region.

Historical Error Decomposition Accounted into Domestic Factors, the Global Factor and a Group Factor Categorised by Income Levels and Regions (2/3)

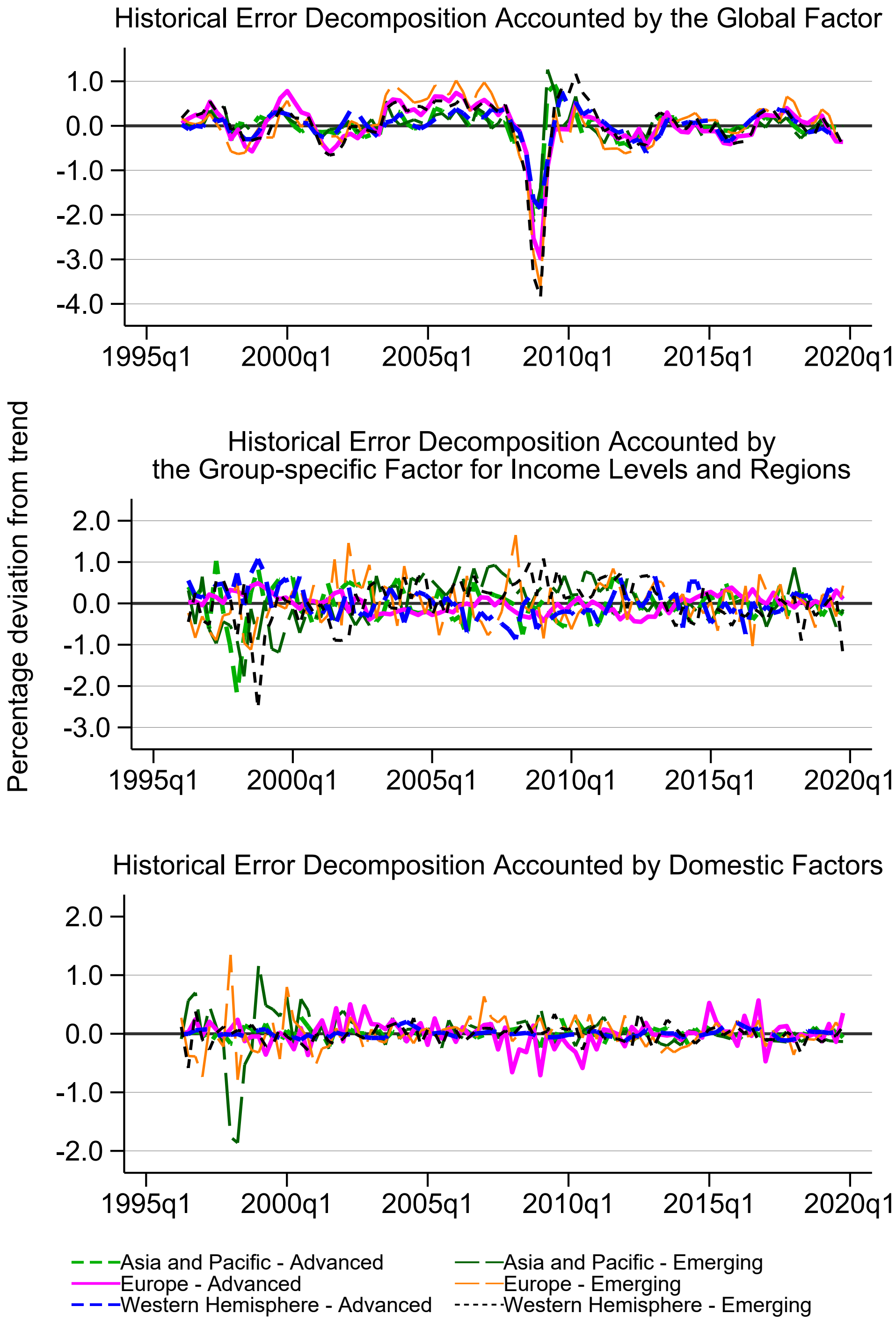


Notes: The solid black line plots the cyclical GDP of each country. Blue bars depict the proportion of deviation from trend output explained by domestic shocks. Red bars indicate the percentage deviation from trend output explained by global factor shocks. Green bars represent the percentage deviation from trend output explained by group-specific shocks, calculated for groups within the same geographical region and income level within that region.

Historical Error Decomposition Accounted into Domestic Factors, the Global Factor and a Group Factor Categorised by Income Levels and Regions (3/3)

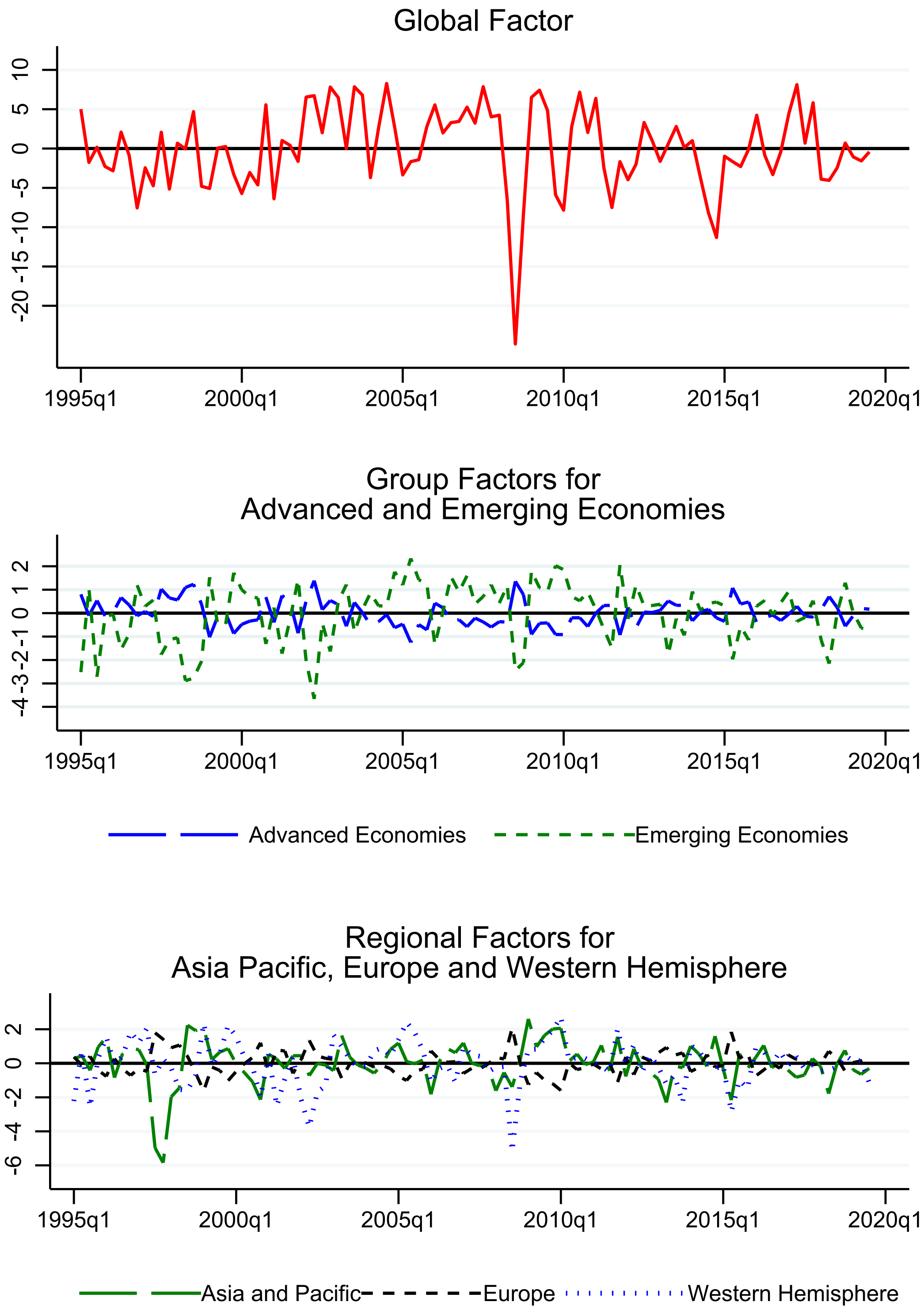


Notes: The solid black line plots the cyclical GDP of each country. Blue bars depict the proportion of deviation from trend output explained by domestic shocks. Red bars indicate the percentage deviation from trend output explained by global factor shocks. Green bars represent the percentage deviation from trend output explained by group-specific shocks, calculated for groups within the same geographical region and income level within that region.



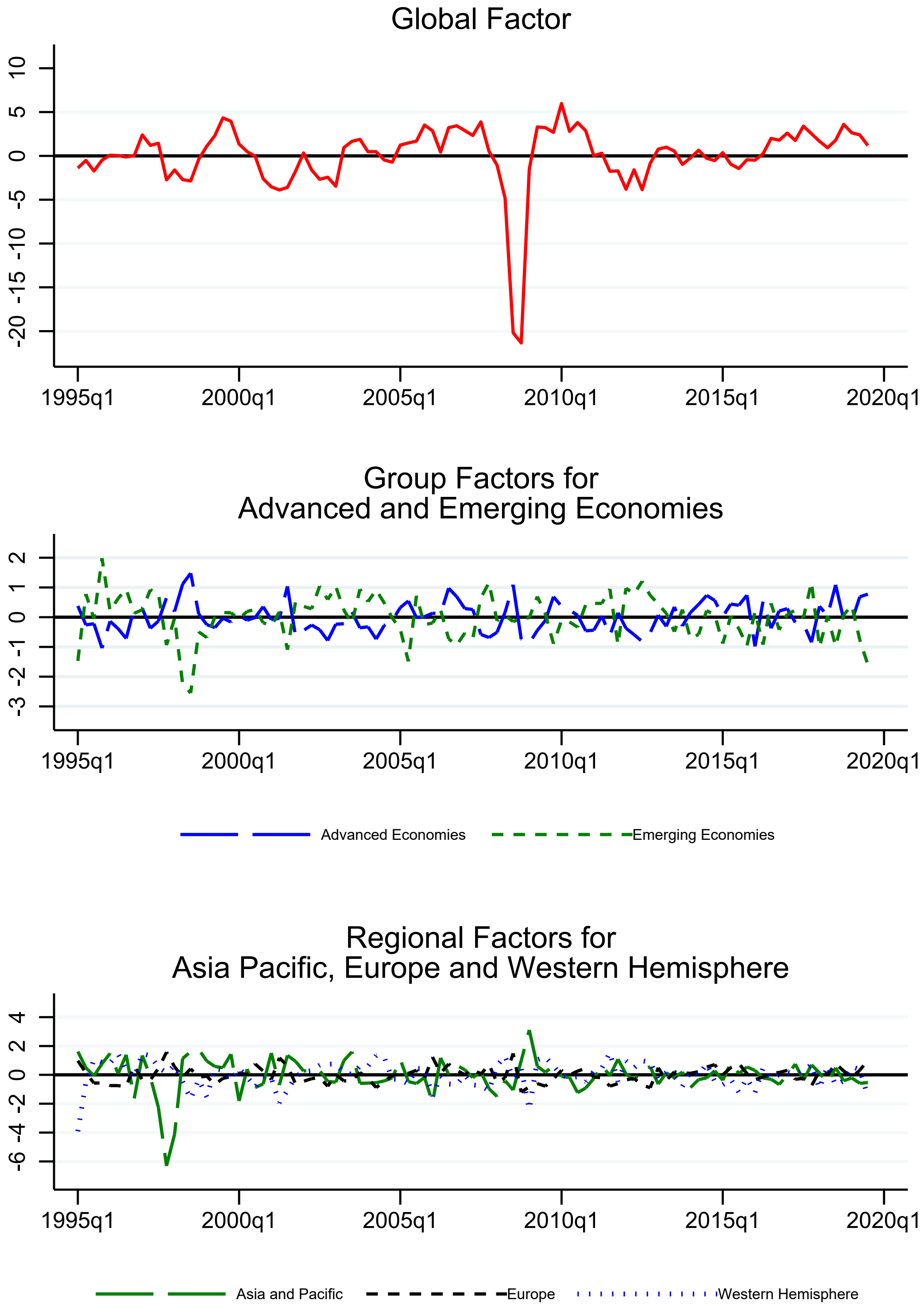
Notes: This figure calculates the average of the historical decomposition, separately, for (1) advanced Asian Pacific economies, (2) emerging Asian Pacific economies, (3) advanced European economies, (4) emerging European economies, (5) advanced Western Hemisphere economies, and (6) emerging Western Hemisphere economies.
Green dashed lines lines denote the average for advanced Asian Pacific economies only, long dashed dark green lines for emerging Asian Pacific economies, the solid pink line for advanced European economies, the long dashed orange line for emerging European economies,the dashed blue line for advanced Western Hemisphere economies and the dashed black line for emerging Western Hemisphere economies only.
In the top panel, the average percentage deviation from trend caused by global factors are illustrated for the different categories of economies. In the middle panel, the percentage deviation from trend output triggered by the group-specific factors are presented. The group-specific factors are computed based on the countries' classification both by income levels and regions. In the bottom panel, the percentage deviation from trend output caused by domestic factors are shown.

Figure A.4: Global Factor, Group-specific Factors for Countries' Income Levels and Regional Factors Estimated using Exchange Rate Based Measures of Real GDP



Notes: This figure presents the global factor, the group factors based on income levels, and the regional factors, estimated using real GDP measured the bilateral USD exchange rate for each economy in the sample.
The top panel presents the global factor using exchange rate based measures of real GDP for 45 economies. In the middle panel, the dashed blue line shows the group factor for advanced economies and the dashed green line the corresponding factor for emerging economies. In the bottom panel, the long dashed green line shows the group factor for Asia Pacific economies, the short dashed black line shows the group factor for European economies, and the blue dotted line depicts the group factor for Western Hemisphere economies.

Figure A.5: Global Factor, Group-specific Factors for Countries' Income Levels and Regional Factors Estimated Using Alternative Detrending Method



Notes: This figure presents the global factor, the group factors based on income levels, and the regional factors, estimated when real GDP is detrended using the HP Filter.
The top panel presents the global factor using exchange rate based measures of real GDP for 45 economies. In the middle panel, the dashed blue line shows the group factor for advanced economies and the dashed green line the corresponding factor for emerging economies. In the bottom panel, the long dashed green line shows the group factor for Asia Pacific economies, the short dashed black line shows the group factor for European economies, and the blue dotted line depicts the group factor for Western Hemisphere economies.

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