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Business Cycles, Exchange Rates, and Commodity Prices in Transition Economies

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by

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ABSTRACT

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Salome Giorgadze

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Under the Supervision of Professor Kundan Kishor

My dissertation studies macroeconomic connectedness in the transition economies through the business cycle and exchange rate channels and the downside risk relationship between commodity prices and exchange rates of developing economies. My first two chapters focus on the transition economies of the Commonwealth of Independent States, the CIS, a group of former Soviet republics, and my third chapter considers other developing countries too. The first chapter examines macroeconomic connectedness in the CIS region through business cycle synchronization. I investigate the role of the global factor and the CIS factor in evolution of business cycles in the CIS countries by applying a dynamic factor model. In addition I also examine whether the role of these two factors has changed over time. Results indicate that overall business cycle synchronization of these countries within the region and globally is low. Russia is the most globally integrated CIS country and Belarus displays the highest degree of comovement with the CIS factor. The results show that 2014 Russo-Ukrainian conflict and subsequent Russian sanctions had a profound effect on the region leading to an increase in synchronization within the CIS and decline in the role of the global factor.

The second chapter estimates macroeconomic connectedness in the CIS countries through risk spillovers via the exchange rates. I collect high frequency daily data on exchange rates from January 2006 to July 2020 and use the Diebold-Yilmaz method of variance decomposition, as well as the Barunik-Krehlik method of frequency variance decomposition, for the analysis. I find that macroeconomic risk in the region has

maintained a higher average level since 2015, a difficult year full of regional and global challenges. Currencies managed by more flexible exchange rate regimes (the Euro, Russian ruble, Armenian dram, Georgian lari, Ukranian hryvnia) on average transmit risk in the region. Time-frequency decomposition signifies that while the majority of risk transmission is smaller-scale and short-lived, spillovers from main regional and global crises are bigger and more persistent.

The third chapter evaluates the impact of commodity price changes on the exchange rate changes for developing countries that are major exporters of selected globally important commodities. In particular, I focus on the tail behavior of this relationship since extreme events often have undesirable macroeconomic consequences such as inflationary pressure. I achieve this by estimating quantile regressions and subsequently using them to calculate tail risk measures of expected shortfall and longrise. My findings show that commodity price changes are negatively impactful on the exchange rate changes during depreciation episodes. Moreover, tail risk magnitudes have increased since the Great Recession. The results obtained in this chapter show that commodity dependent economies have been exposed to more macroeconomic risk through the exchange rate channel and that commodity price changes could be an associated signal of downside risk to exchange rate changes.

To

my mother,

my brother,

and my host family

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LIST OF ABBREVIATIONS

AR - Autoregressive

BK - Barunik-Krehlik

CIS - Commonwealth of Independent States

DFM - Dynamic Factor Model

DY - Diebold-Yilmaz

EAEU - Eurasian Economic Union

ECU - Eurasian Customs Union

EM - Emerging Market

EME - Emerging Market Economies

EU - European Union

FEVD - Forecast Error Variance Decomposition

GDP - Gross Domestic Product

HP - Hodrick and Prescott Filter

IFS - International Financial Statistics

IMF - International Monetary Fund

KPPS - Koop-Pesaran-Potter-Shin

MLE - Maximum Likelihood Method

OEC - Observatory of Economic Complexity

OECD - Organization for Economic Cooperation and Development

OLS - Ordinary Least Squares

PCA - Principal Component Analysis

PVAR - Panel Vector Autoregression

VAR - Vector Autoregression

UNCTAD - United Nations Conference on Trade and Development

WB - World Bank

WTI - West Texas Intermediate

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Chapter 1

Introduction

The Commonwealth of Independent States, the CIS, is one of the youngest transition economy regions in the world. Given their relatively small economic sizes and only recent openness to the global economy, their economic progression has received fairly narrow research attention, with the exception of Russia, the region's most influential economy. My first two chapters are dedicated to adding to the economic literature on these economies as these countries are furthering their integration into the world economy and are gaining more consideration in the light of ongoing geopolitical situations. I employ both low frequency quarterly RGDP data and high frequency daily exchange rate data, and utilize characteristic time series econometrics methods to offer a comprehensive analysis.

In my first two chapters I take the broad macroeconomic view of the connectedness of the CIS region within itself and globally. One of the main research questions in related literature with regard to this region is whether a monetary or a more involved economic union is a beneficial option for these economies. The findings of my first two chapters suggest that due to the low levels of regional and global connectedness and the prevalent role of the idiosyncratic component in the real and financial economic aspects of these countries, they are not yet in a position to form such a union. My findings also show that the regional exchange rate connectivity has increased since 2015 and that real and financial linkages are highly sensitive to regional and global shocks. I also discover that countries with less flexible exchange rates are more susceptible to risk spillovers from other currencies, and that oil prices on average transmit shocks to currencies. The ensuing policy implications include that local policymakers need to be aware of the increasing exposure to macroeconomic risk spillovers from the rest of the region, and that maintaining less flexible exchange rates regimes puts them on a receiving end of the spillover shocks. Moreover, understanding the shock transmission role of the oil prices may help policymakers be better prepared for the turbulence in that commodity market.

These findings motivated me to think further on the role of commodity prices as macroeconomic risk transmitters, given how reliant transition and developing economies are on commodity exports. More developing economies are moving towards flexible exchange rate regimes - and as we see from my aforementioned results, on one hand it may help them be less susceptible to spillovers from regional currencies, as well as allowing for more potential monetary policy options. However, having flexible exchange rates for commodity export-dependent economies may make them more vulnerable to changes in commodity prices. This possible vulnerability may add another obstacle for policymakers in meeting their goals of maintaining monetary stability, to which exchange rate stability is a critical component for these economies.

Current literature on the commodity price - exchange rate relationship has noted the existence of nonlinearity there, and in my third chapter I build on that and look into the downside risk of this relationship. I consider the downside risk as the risk of a big depreciation in particular due to the inflationary consequences of prolonged depreciation. Although prominent theoretical assumptions highlight the positive aspects of depreciation, in reality the consequences of depreciation for developing countries involved in commodity trade are largely undesirable. In my sample I keep several CIS countries due to their commodity export dependent status, flexible exchange rate regime, and data availability, and add other commodity dependent economies and commodities besides oil. I apply the vulnerable growth approach by Adrian et al. (2019) to carry out my analysis, which allows me not only to see that commodity price changes could be a signal of downside risk to exchange rate changes but also to trace that this risk has increased in the recent years. Policy implications include building more resilience toward commodity export dependence, such as more efforts into export diversification, and developing more precautionary and stabilizing tools.

Chapter 2

Business Cycle Synchronization in the CIS region

2.1 Introduction

The Commonwealth of Independent States, CIS, was formed by a number of ex-USSR countries in early 1990s. Currently the CIS member states are Armenia, Azerbaijan, Belarus, Kazakhstan, Kyrgyzstan, Moldova, Russia, Tajikistan, and Uzbekistan. Turkmenistan and Ukraine, while not being official member states, are allowed to participate in CIS. Georgia withdrew from CIS following the Russo-Georgian war that took place in August 2008. The Eurasian Economic Union (EAEU) started functioning in 2015 after a series of futile attempts of the CIS states to assemble a formal regional economic institution. The EAEU is comprised of Belarus, Kazakhstan, Russia, Armenia, and Kyrgyzstan. It was preceded by the Eurasian Customs Union established in 2010 between Russia, Belarus, and Kazakhstan. Russia's role as the anchoring economic and political center of the CIS region carried over from the Soviet past, in which the CIS countries were tied by the central government based in Moscow. However, in the meantime of the almost thirty years which have passed since the dissolution of the USSR, China has emerged as an important economic power, the EU was forged, and the scales of international trade and financial markets have multiplied. Table 1 demonstrates that today not only Russia but also China, EU, and UK are important trade partners for the region's selected countries.

Country	Top Export Partners	Top Import Partners
Armenia	Russia 24.2%	Russia 28%
	Bulgaria 12.8%	China 11.5%
	Switzerland 12%	Turkey 5.5%
	Georgia 6.9%	Germany 4.9%
	Germany 5.9%	Iran 4.3%
Azerbaijan	Italy 23.2%	Russia 17.7%
	Turkey 13.6%	Turkey 14.8%
	Israel 6.1%	China 9.9%
	Russia 5.4%	US 8.3%
	Germany 5%	Ukraine 5.3%
Belarus	Russia 43.9%	Russia 57.2%
	Ukraine 11.5%	China 8%
	UK 8.2%	Germany 5.1%
Georgia	Russia 14.5%	Turkey 17.2%
	Azerbaijan 10%	Russia 9.9%
	Turkey 7.9%	China 9.2%
	Armenia 7.7%	Azerbaijan 7.6%
	China 7.6%	Ukraine 5.6%
Kazakhstan	Italy 17.9%	Russia 38.9%
	China 11.9%	China 16.1%
	Netherlands 9.8%	Germany 5.1%
	Russia 9.3%	US 4.3%
	Switzerland 6.4%	
Kyrgyzstan	Switzerland 59.1%	China 32.6%
	Uzbekistan 9.4%	Russia 24.8%
	Kazakhstan 5.1%	Kazakhstan 16.4%
	Russia 4.9%	Turkey 4.8%
	UK 4%	US 4.2%
Moldova	Romania 24.6%	Romania 15.5%
	Russia 13.7%	Ukraine 11.4%
	Italy 9.1%	Russia 10.6%
	Germany 6.2%	China 10.4%
	Ukraine 5.3%	Germany 8.9%
Russia	China 10.9%	China 21.2%
	Netherlands 10%	Germany 10.7%
	Germany 7.1%	US 5.6%
	Belarus 5.1%	Belarus 5%
	Turkey 4.9%	Italy 4.5%
Ukraine	Russia 9.2%	Russia 14.5%
	Poland 6.5%	China 11.3%
	Turkey 5.6%	Germany 11.2%
	India 5.5%	Poland 7%
	Italy 5.2%	Belarus 6.7%

Table 1: Trade Partnership (2017 data from the CIA World Factbook)

The CIS countries, including Russia itself, have become more attuned to the global business cycle throughout their transition processes. The work done by the IMF (November 2012 Regional Economic Outlook[1] and October 2013 World Economic Outlook[2]) suggests that the weakening of the ties within the CIS region and with Russia specifically was on the flip side of this development. The IMF's analysis shows that bolstering of the region's exports to Europe in the 2000s came at the expense of exports to Russia. Moreover, the IMF finds that the correlations of the annual output growth rates between the region and the rest of the world went up in 2003-12 as compared to the earlier decade. They assign this development to improvements in trade openness, larger labor migration and remittance flows, and big common shocks. They

[1]International Monetary Fund. (2012). Regional Economic Outlook: Middle East and Central Asia. Washington, DC, November.

[2]International Monetary Fund. (2013). World Economic Outlook: Transitions and Tensions. Washington, DC, October.

highlight that the output correlations of the region with the US, Europe, and China increased in 2003-12, with the increase in correlations with China being the largest. The IMF deems that the economies diverted some of the trade channels from Russia to China, as reflected by the still high but diminished over the decade correlations with Russia. They also explain that, as compared to the decade after the collapse of USSR, in 2003-12 the intraregional correlations dropped while the linkages with other countries, especially China, ascended.

The IMF's findings give an insight into how the region started to interact more with countries beyond Russia in the first decade of 2000s. Although pairwise correlation of business cycle indicators is informative, it does not measure the relative role of global and the CIS factor in evolution of business cycles in CIS countries, and how the role of these factors have changed over time. This is especially important in our context since we seek to assess the degree to which the CIS countries' business cycles are synchronized with each other and also examine the effects of the Russo-Ukrainian conflict that commenced in 2014 and of the sanctions imposed on Russia by the West on the business cycle alignments of the CIS countries. To understand the importance and evolution of these different components, we apply a dynamic factor model (DFM hereafter) as in Stock and Watson (1991). DFM models have been widely applied in macroeconomics and finance, and are a typical workhorse model to understand business cycle synchronization across different regions or countries. The proposed dynamic factor model decomposes real GDP growth of the countries in our sample into three unobserved factors: global factor, CIS factor, and idiosyncratic factor. The relative importance of these factors enables us to examine the roles of CIS and global factors in these countries' business cycle stances. An extension of the model - a rolling dynamic factor model - allows us to examine the time-variation of the importance of different factors in the business cycle evolution.

Our research adds to the literature showing that the levels of business cycle correlation within the CIS region and with the rest of the world is low. Armenia, Belarus, Russia, and Ukraine display the most synchronization within the CIS. These countries have historically closer ties (especially cultural) to Russia. Among the CIS countries Kazakhstan, Russia, and Ukraine have the highest levels of synchronization with the global economy as measured by the common component in the dynamic factor model. These countries have the biggest economies among the sample countries, which can explain their relatively better global connectedness. We also find that 2015 was a critical year in our analysis that changed the dynamics of business cycle synchronization within the region. Synchronization with the CIS factor spiked while the comovement with the global factor dropped for all the countries in our sample during that period. We attribute this to the regional spillover effects from the Russo-Ukrainian conflict and the subsequent Russian sanctions and the impact of the global economic slowdown led by the decrease in Chinese economic activity in 2015. This result implies that in that time period the CIS countries were more interconnected and influenced by events related to Russia.

The results presented in this paper have interesting policy implications. The finding that there is significant degree of heterogeneity among the CIS countries in terms of their business cycle synchronization with Russia and the rest of the world suggests that a common macroprudential policy may not be an effective tool. This also poses a question mark on the feasibility of forming some form of currency union as has been stipulated in the past. The results from rolling dynamic factor model provide evidence on unintended consequences of sanctions with regional factor compensating for the decline in the role of global factor in business cycle synchronization.

The organization of the paper is the following: Section 2 gives a brief literature review, Section 3 presents data description, Section 4 contains model specification, Section 5 discusses the empirical results, and Section 6 concludes.

2.2 Literature Review

Mundell's establishment of the concept of the optimal currency area (OCA) in 1961 has inspired an extensive volume of research in international economics literature. As Frankel and Rose (1998) summarize, a lot of the literature has focused on regional integration and on conditions required for an OCA to be successful. Frankel and Rose explain that one of such conditions is positive correlation in business cycle synchronization of candidate countries. Much work has been dedicated to the evaluation of business cycles of EMU and Euro, the largest-scale experiment in OCA and regional integration in modern history. For instance, Artis and Zhang (1995) have shown that the business cycles of countries participating in the Exchange Rate Mechanism (ERM) part of the EMS (European Monetary System) became more synchronized with Germany than the US upon entering the ERM. Forni et al. (2000) develop a generalized dynamic factor model, which they use to construct an index parsing the macroeconomic state in the EURO area. Employing a Markov-switching regime process and MS-VAR modeling, Artis et al. (2004) identify a common European business cycle. Applying wavelet analysis to European data, Aguiar-Conraria and Soares (2011) find that there is a high correlation between business cycle synchronization and physical proximity.

Significant amount of work has been done to examine the business cycle synchronization in developing countries as well. For instance, Calderon et al. (2007) analyze a large sample of 147 industrial and developing countries and find that on average more trade integration is related to more business cycle synchronization. They also discover that this integration effect is more prominent for industrial countries than for developing countries. Calderon et al. also detect that when countries have comparable production structures, the effect of trade intensity on business cycle synchronization is larger, and that more intra-industry trade is associated with higher business cycle correlation.

Business cycle synchronization studies are central to the between-regional comparison discourse. Caetano and Caleiro (2018) examined evolution of business cycle synchronization in the Eurasian region, consisting of European and CIS countries, over the 1990-2016 period. Their findings suggest that belonging to an economic union increases business cycle synchronization within the union. Benczur and Ratfai (2014) find that the highest output volatility in their sample of a mix of G7, EU, DE, CEE, LA, OE, and CIS countries belongs to the CIS countries. This work supports previous findings of Benzcur et al. (2007) where they discover that the fluctuations in the business cycles of the group of CIS countries in their sample are more volatile and less persistent than elsewhere. Within their group of CIS countries (Armenia, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Russia, and Ukraine) they establish that Russia, Belarus, Ukraine, and to a lesser degree Kazakhstan and Moldova have similarities in GDP components (relative volatility, cyclicality and persistence), in industrial production (relative volatility and persistence), and in the behavior of prices and interest rates. In their examination of 62 countries of various income levels, Altug et al. (2012) find that the transition and CIS countries have severe contractions in their business cycles similar to those of the Latin American countries. Unlike the Latin American region, however, these countries have longer business cycle expansions. The authors determine that improved governance and higher income levels are related to longer expansions and that more central bank independence relates to lesser severity of contractions. Moreover, they estimate that similarity in governance indices and labor and capital development are better determinants of business cycle synchronization than monetary factors, such as central bank independence or membership in a currency union.

Russia's influence on the CIS region has also been empirically studied. Alturki et al. (2009) take a sample spanning 1997-2008 data for 12 countries in the CIS region and build a VAR model determining the spillover effects of changes in Russian and European growth rates on the growth rates of the CIS countries. They detect that GDP growth rates of Belarus, Kazakhstan, Tajikistan, and to some degree of Georgia and Kyrgyzstan are significantly affected by a shock to Russian growth. Only Georgian GDP growth rate appears to be impacted by a European growth rate shock. Furthermore, Alturki et al. perform variance decomposition that evaluates how the variances in growth rates in Russia and Europe affect variation in growth rates of the CIS countries. Among the CIS countries, the variation in the Russian growth rate is more impactful for the growth rates of Kazakhstan, Kyrgyzstan, and Belarus. The variation in the European growth rate is more important for the growth rates of Georgia, Kyrgyzstan, and Belarus among the CIS countries. Finally, Bayramov et al. (2020) use a VAR model to identify that the accumulated impact coefficient of shocks to the Russian economy on CIS countries is 0.72. They find that the main spillover venues from Russia to CIS are trade, FDI, and remittances. The authors also conclude that oil and gas exporting countries in the region (Azerbaijan, Kazakhstan and Turkmenistan) are highly dependent on commodity prices, bringing about comovement among them.

As far as a focused analysis of the CIS regional union feasibility, the book by Vymyatnina and Antonova (2014) provides a comprehensive summary of the issues involved in the formation of the union. The authors use various techniques (cointegration analysis, correlation and volatility measuring, VAR modeling) to assess the co-movements of the business cycle synchronization within the aforementioned Eurasian Customs Union (ECU) between Russia, Belarus, and Kazakhstan. Their analysis determines that there is more correlation between Russia and Kazakhstan bilaterally and with the ECU mean than with Belarus. Vymyatnina and Antonova conclude that the synchronization of business cycles of the three countries is not as sizable as desired, with the key concern being the development of regional integration. The authors believe that although the economic co-dependence and spillovers exist, expansion of integration is crucial for a successful economic union to emerge. Blockmans et al. (2012) echoed these concerns when they adopted Haas and Schmitter's (1964) conditions for successful implementation of economic unions to compare the EAEU and the European Economic Community's positionings. The comparison is not in the EAEU's favor. Blockmans et al. designate the relative sizes of the economies, distances between economic centers, unbalanced patterns of regional trade integration, and slow dynamics in capital and labor flows as the stumbling blocks towards development of a well-functioning economic union in the EAEU region.

2.3 Data Description

The countries in our sample include Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Russia, and Ukraine. Although Georgia withdrew from CIS in 2009 and Ukraine has been inactive since 2015, it is important to include them due to their close affiliation to the region. The quarterly RGDP data runs from 2001 to 2016. The time span is limited due to restricted data availability. Data was obtained from the IMF International Financial Statistics (IFS) database and the OECD Stat website.

Principal component analysis (PCA), illustrated in Figure 1, shows that there are two principle factors explaining variation in growth rates in our sample: the first one led by EU and the second one led by China. Kazakhstan and Georgia gravitate towards the first "Western" factor while majority of the CIS countries, including Russia, are clustered in between the two. Moldova and Kyrgyzstan seem to be outliers and are located closer to the second factor led by China.

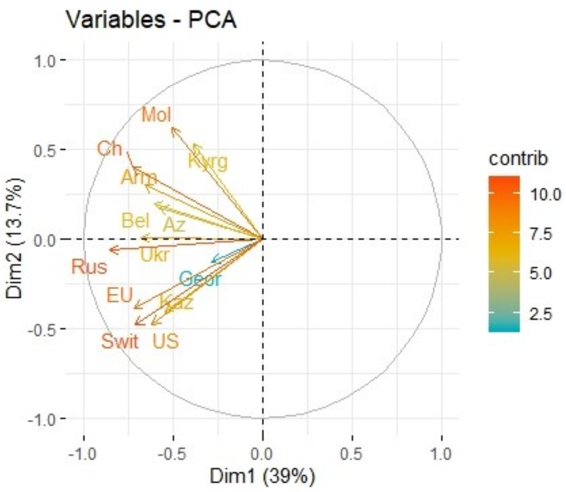


Figure 1: Principle Component Analysis

Below is a correlation table of the cyclical parts of the RGDP fluctuations, which were extracted through HP filtering.[3] The table (Figure 2) is organized according to hierarchical clustering:

[3]We used the standard for quarterly data frequency of 1600 for filtering.

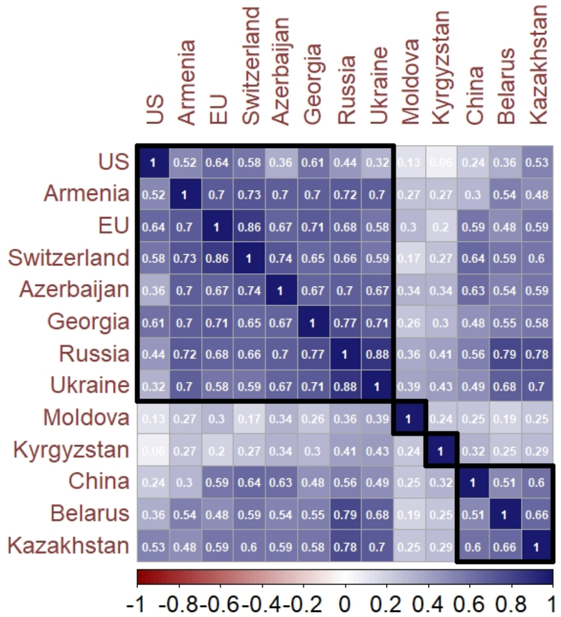


Figure 2: HP cycles correlations: Higher values imply more correlation

There is some evidence of synchronization within the CIS region as measured by simple correlation. Armenia, Azerbaijan, Georgia, Kazakhstan, and Ukraine display a significant degree of correlation with one another. All of the CIS countries exhibit notable correlation with Russia. Kyrgyzstan and Moldova stand out as they have low correlation overall with every country in the sampl, with their highest correlation being with Russia and Ukraine. Apart from a high correlation with other CIS countries, Russia has distinct correlation with China, EU, and Switzerland. Importantly, 6 out of 9 CIS countries (including Russia) are markedly correlated with EU, and 7 out of 9 CIS countries are correlated with Switzerland.[4] The hierarchical clustering[5] hints at two general groupings: the bigger one with the Western countries, the Caucasus, Russia, and Ukraine, and the smaller one with China, Belarus, and Kazakhstan; and Moldova and Kyrgyzstan are on

[4]The results from rolling OLS regressions (window size=5 years) for the cycles of the CIS countries on the cycles of Russia, China, EU, and US show that the R-squared values of the regressions fluctuate over time. For instance, adjusted R-sqared values drop during the Great Recession. This suggests that the CIS countries were less connected to Russia, China, the EU, and the US then. Thus, the variation in adjusted R-squared values throughout time for all CIS countries is reflective of the corresponding changes in macroeconomic environment.

[5]We use the complete-linkage hierarchical clustering, the default and one of the most widely-used methods of the 'corrplot' package in R.

their own. The clustering exercise in part corroborates the PCA results.

Since one of the primary goals of this work is to surmise Russia's impact on the CIS region, in this part we examine cross-correlation of Russian cycle obtained by HP filtering with the CIS countries' cycles. Table 2 demonstrates the results: t-3 through t-1 stand for the third, second, and first lag[6], t indicates the contemporaneous value, and t+1 through t+3 are the first, second, and third lead. The Russian cycle exhibits overwhelmingly positive correlation with all countries except for Moldova in second and third leads. Kyrgyzstan and Moldova feature the lowest overall correlations while Belarus, Kazakhstan, and Ukraine - the highest. The largest correlation falls for the concurrent lag for all countries - besides Kazakhstan who has the highest one in the first lag - followed by the first lag and the first lead. This implies that the relationship is at its strongest contemporaneously, and weakens the further we are into future or past.

	t-3	t-2	t-1	t	t+1	t+2	t+3
Armenia	0.11	0.36	0.60	**0.72**	0.70	0.60	0.45
Azerbaijan	0.21	0.49	0.65	**0.70**	0.58	0.39	0.26
Belarus	0.22	0.42	0.65	**0.79**	0.78	0.62	0.47
Georgia	0.35	0.64	0.76	**0.77**	0.74	0.52	0.30
Kazakhstan	0.51	0.66	**0.80**	0.78	0.57	0.34	0.15
Kyrgyzstan	0.13	0.19	0.29	**0.41**	0.31	0.20	0.12
Moldova	0.24	0.26	0.31	**0.36**	0.27	-0.02	-0.24
Ukraine	0.39	0.62	0.81	**0.88**	0.77	0.55	0.34

Table 2: HP cycles cross-correlations with the Russian cycle

2.4 Model Specification

As shown in the previous section, there is significant heterogeneity across countries and time in how synchronized the region is to the major economies. Since PCA and correlation tables do not provide information about time variation in synchronization, a model that could capture underlying trends dynamically while allowing for country-specific variation is needed. Dynamic factor models (DFM), one of the applications of the state-space models, fit these specifications. Factor models were originally devised for cross-sectional

[6] Lags represent quarters.

data until Geweke extended their application to time series in 1977 (Stock and Watson, 2010.) Early works using DFMs inferred that a sizeable part of the observed variation in macroeconomic variables could be attributed to just a handful of factors. DFM's advantage is that it gives an adaptable structure for modeling a large time series by having a small number of unobserved variables explain the comovement between a large amount of observed variables (Watson et al, 2012.) This makes DFM a great fit for estimating business cycle synchronization among numerous countries. For instance, Del Negro and Otrok (2008) use DFM with time-varying parameters to outline the evolution of international business cycle for a sample of 19 countries from 1970-2005.

Our dynamic factor model involves two common factors - a CIS factor and a global factor. In addition to the EU, we add Switzerland, UK, US, and China to the nine CIS countries for a better measurement of the common global factor.[7] One of the recurrent issues in the synchronization literature is how to transform the variable of interest: should it be the growth rate of the variable or a trend-cycle decomposition model based cycle. In order to avoid the complications associated with model based cycles, we use a model-free approach and use annualized growth rate of real GDP from equation (1). This approach is also consistent with the existing work in the literature. For example, see Hirata et al. (2012) and Kose et al. (2003), among others.

State-Space Representation:

$$\triangle y_{it} = \gamma_i c_{1t} + \delta_i c_{2t} + \eta_{it}, \ (1)$$

where $\triangle y_{it}$ is growth rate of RGDP of country i[8], c_{1t} is the CIS common component, c_{2t} is the global common component, and η_{it} is the idiosyncratic component;

$$c_{it} = \beta_i c_{it-1} + v_{it}, \ v_{it} \quad \sim i.i.d. \, \mathcal{N}(0, \sigma^2_{v_i}), \ (2)$$

as the common components are assumed to follow an AR(1) model, i=1 (CIS), 2 (global);

[7] We first built a model with only the CIS and idiosyncratic components and it was dominated by the main model in terms of significantly higher likelihood values with the CIS, global, and idiosyncratic components.

[8] One issue that may arise in the use of growth rate as the left hand side variable is that we may lose valuable information in the level of real GDP. Existence of cointegration in the level of real GDP among these countries would necessitate the use of levels of real GDP. However, we do not find any evidence of cointegration in the level of real GDP for all the countries in our sample.

$$\eta_{it} = \phi_i \eta_{it-1} + e_{it}, \ \ e_{it} \ \ \sim i.i.d. \, \mathcal{N}(0, \sigma^2_{e_i}), \ \ (3)$$

since the idiosyncratic component is also assumed to be described by an AR(1) model.

The CIS factor is proxied by Russia due to its de facto status of the regional leader. The global factor is represented by the EU. Thus, we are assuming the γ value for Russia and the δ value for EU to be 1. Making the EU the proxy for the global component is sensible in the current context given its relatively central geographical location among the countries in the sample.

Dynamic factor models, being state-space models, require two equations for estimation: a measurement equation and a transition equation. Measurement equation gives the relationship between the observed variables (the growth rates) and the unobserved state variables (the idiosyncratic cycles and common factors), estimating equation (1). Transition equation gives the assumed dynamics of the unobserved state variables, estimating quations (2) and (3). Please see Appendix A for the state-space representation of the model.

Variance Decomposition

Recall equation (1):

$$\triangle y_{it} = \gamma_i c_{1t} + \delta_i c_{2t} + \eta_{it}, \ \ (1)$$

Let us consider the variance of the left-hand side variable, a country i's growth rate. Seeing that it is a sum of three orthogonal components, we can write it the following way:

$$var(\triangle y_{it}) = \gamma_i^2 var(c_{1t}) + \delta_i^2 var(c_{2t}) + var(\eta_{it}),$$

Or

$$var(\triangle y_{it}) = \gamma_i^2 \sigma^2_{c_1} + \delta_i^2 \sigma^2_{c_2} + \sigma^2_{\eta_i}, \ \ (4)$$

Since the common and idiosyncratic components are assumed to be described by AR(1) as in equations (2) and (3), we can estimate the unconditional variances $\sigma^2_{c_i}$ and

$\sigma^2_{\eta_i}$ by:

$$\sigma^2_{c_i} = \frac{\sigma^2_{v_i}}{1-\beta^2_i},$$

where i=1 (CIS), 2 (global); and

$$\sigma^2_{\eta_i} = \frac{\sigma^2_{e_i}}{1-\phi^2_i},$$

where i is a country in our sample.

One of the benefits of using DFMs is that it allows us to calculate how much variation across countries is in common, or how much of the total variation in a country's growth is driven by common components.

$$Share\ of\ the\ CIS\ component = \frac{\gamma^2_i\sigma^2_{c_1}}{\gamma^2_i\sigma^2_{c_1} + \delta^2_i\sigma^2_{c_2} + \sigma^2_{\eta_i}} \quad (5)$$

and

$$Share\ of\ the\ global\ component = \frac{\delta^2_i\sigma^2_{c_2}}{\gamma^2_i\sigma^2_{c_1} + \delta^2_i\sigma^2_{c_2} + \sigma^2_{\eta_i}} \quad (6)$$

2.5 Empirical Results

We estimate the DFM presented in the above section using maximum likelihood via the Kalman filter.[9] Tables 3 and 4 display the estimates of the main parameters of interest in our model - the loadings on the common factors - which provides some information on the level of comovement with the common cycles[10]:

[9]For estimation details, see Kim and Nelson (1999).

[10]The estimates of the remaining parameters are reported in Appendix A.

Country	Estimate	Standard Error
Armenia	1.173	0.316
Azerbaijan	0.743	0.227
Belarus	1.298	0.301
Georgia	0.217	0.175
Kazakhstan	0.287	0.292
Kyrgyzstan	0.754	0.353
Moldova	0.648	0.564
Ukraine	0.763	0.229

Table 3: Loadings on the common CIS factor (γ_i)

Country	Estimate	Standard Error
Armenia	0.414	0.128
Azerbaijan	0.461	0.116
Belarus	0.422	0.128
Georgia	0.381	0.103
Kazakhstan	0.528	0.144
Kyrgyzstan	0.206	0.164
Moldova	0.223	0.093
Russia	0.761	0.114
Ukraine	0.590	0.124

Table 4: Loadings on the common global factor (δ_i)

The loadings on the common CIS component of all the countries in our sample are positive, conveying the congruent comovement of the business cycles within the region on average. Belarus has the highest CIS loading, followed by Armenia and Ukraine, and Georgia has the lowest. The loadings on the common global component of all the CIS countries in our sample are also positive, signifying positive comovement of the business cycles with the world on average for our sample period. Among the CIS countries, Russia has the highest loading on the global component, followed by Ukraine and Kazakhstan. Kyrgyzstan and Moldova have the lowest loadings, which highlights the discongruity of these countries' business cycles within the sample.

Variance Decomposition Results

Although the factor loadings inform us on the direction of comovement with the global and the CIS component, it does not provide us the relative importance of different factors in the variation of real GDP growth of each country in our analysis. For this purpose, we perform a variance decomposition analysis that decomposes the variations in GDP growth of each country into global, CIS and idiosyncratic components as outlined in equations (5) and (6). Table 5 reports the shares of different components in total variance of the countries' growth:

Country	CIS Component	Global Component	Idiosyncratic Component
Armenia	0.404	0.125	0.470
Azerbaijan	0.173	0.167	0.660
Belarus	0.471	0.124	0.405
Georgia	0.015	0.118	0.867
Kazakhstan	0.027	0.233	0.740
Kyrgyzstan	0.178	0.033	0.789
Moldova	0.183	0.054	0.762
Russia	0.294	0.424	0.282
Ukraine	0.181	0.269	0.550

Table 5: Shares of the Components in Total RGDP Growth Variation: higher values signify more importance of a component)

The variance decomposition results reported in Table 5 provide interesting insights into the business cycle synchronization of different CIS countries. Belarus has the highest share of common variation explained by the CIS component, followed by Armenia. Georgia has the smallest share of its total variation explained by the common CIS component, which accentuates its long-affirmed stance to distance away from Russia's sphere of influence. The importance of the CIS factor for Russia is not as high as one might have expected. The shares of the common CIS component in total variations of the CIS countries are quite small, pointing to the low level of business cycle synchronization within the region. The shares of total variation explained by the global component are also quite modest for these countries. Russia has the highest share of total variation explained by the global component among the CIS countries, followed by Kazakhstan and Ukraine.

Rolling Dynamic Factor Model

To examine the sensitivity of the relative importance of the common factors to regional and worldwide macroeconomic changes over time, we extend our dynamic factor model to a rolling dynamic factor model with a window size of 11 years. The window size is determined by the length of the data as well as the time period we want to focus our study on.

Below is the plot of the evolution of the CIS factor loadings, global factor loadings, and RGDP growth rates for our CIS countries in 2012-2016. In red color - CIS factor loading, in blue - global factor loading, in black - RGDP growth rate[11]:

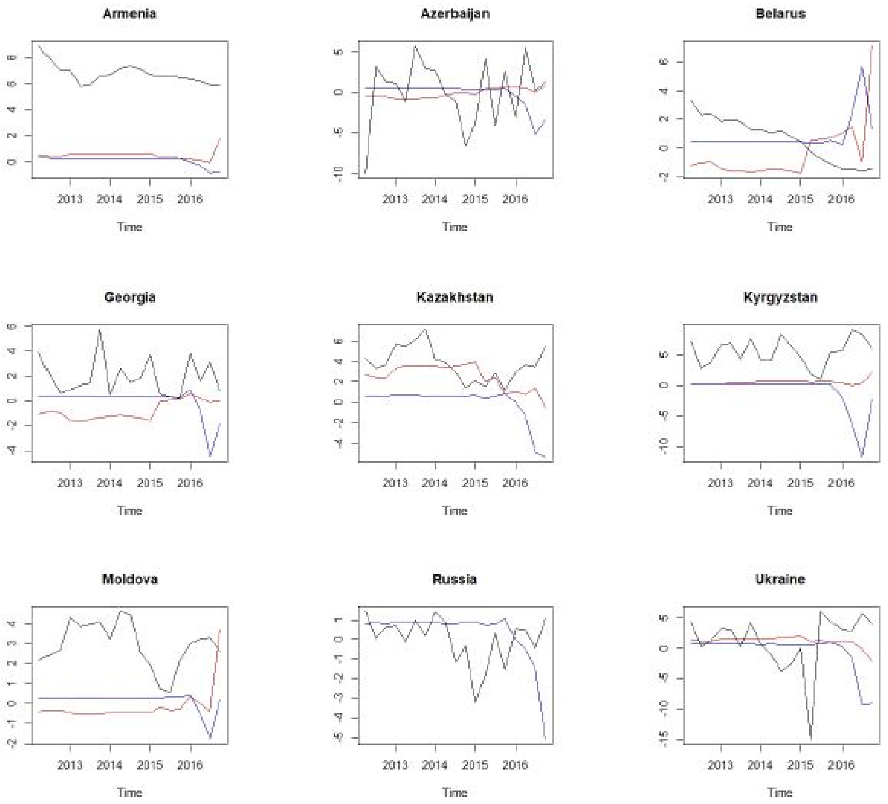


Figure 3: Evolution of CIS factor loadings (red), global factor loadings (blue), and RGDP growth rates (black).

Figures 4 and 5 depict how the shares of the common components in total variation of growth rates fluctuated in 2012-2016:

[11]Russia's CIS factor loading is assumed to be 1 for parameter estimation and thus does not fluctuate over time.

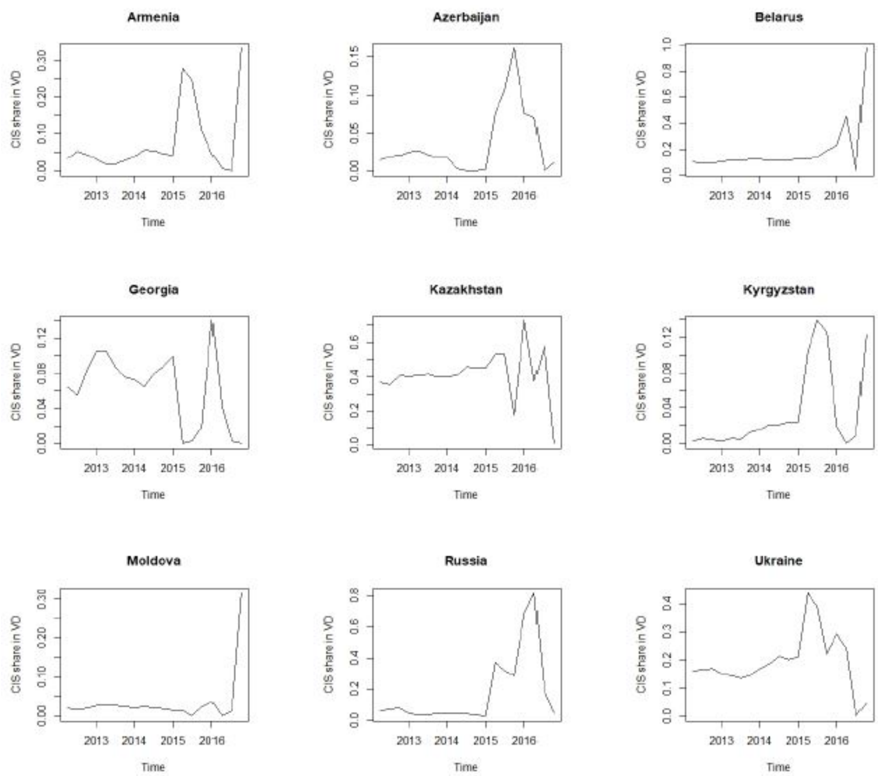


Figure 4: Increase in Business Cycle Synchronization within CIS in 2015-16 (depicts the importance of the CIS factor via variance decomposition)

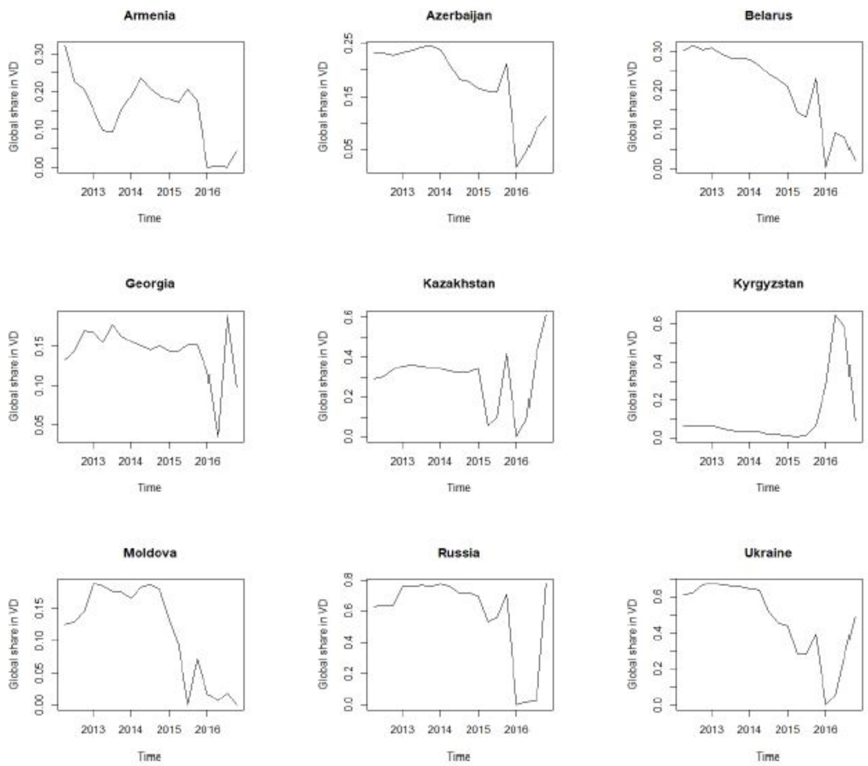


Figure 5: Decrease in Business Cycle Synchronization with the Rest of the World in 2015-16 (depicts the importance of the global factor via variance decomposition)

The results from the rolling DFM provide interesting insights into how the role of different components have evolved over time. The role of the CIS component increased in 2015, and was unstable following that. On the other hand, the influence of the global component dropped in 2015, but also showed some instability afterwards. We find that after 2014 the presence of the global factor in business cycle synchronization of the CIS countries fell and that the importance of the CIS factor increased and also became more volatile. The spike in the role of the CIS factor and the decline of the global factor in the variation of business cycles as measured by real GDP growth coincides with the Russian sanctions after the Russo-Ukrainiain conflict. The variance decomposition results suggest that sanctions on the dominant country within the region may have unintended consequences with the overall region switching off from the global economy. For some countries, this disconnect as measured by the share of the global component was short-lived, but it is interesting to observe the business cycle dynamics of these countries during this time period. We seek to assess this instability in the comovements through the trade angle. It is beyond the scope of this paper to present a causal study of possible trade diversion for Russia from the West to the CIS due to the sanctions. However, we would like to review some evidence that points to the sanctions bringing Russia and the CIS closer. Figures 6-8 present trade data from the IMF and the World Bank. (For detailed description of these figures, readers are referred to Appendix A.)

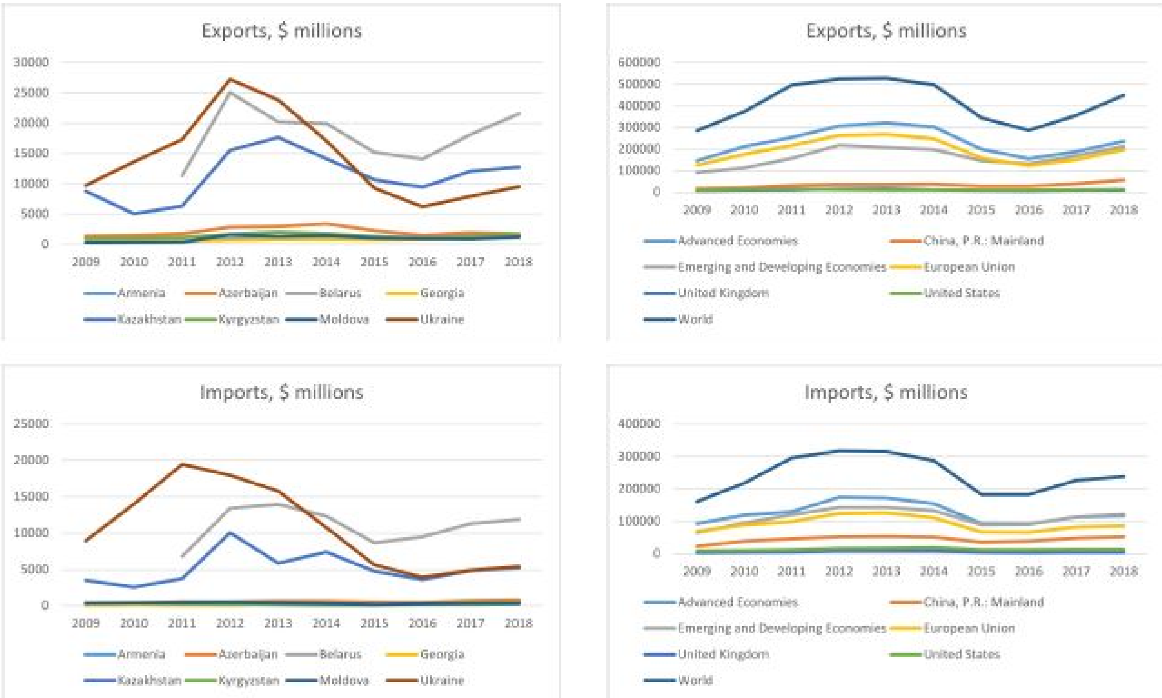


Figure 6: Russian Trade Volume with the CIS and Globally

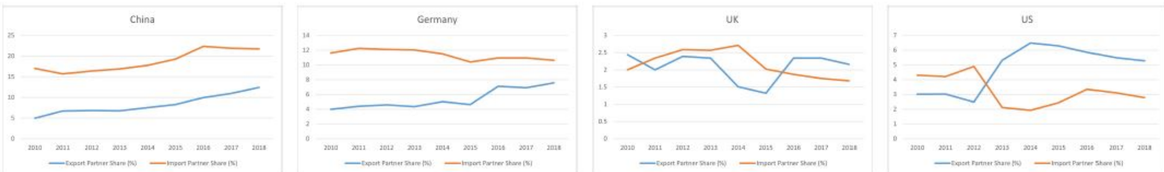


Figure 7: The share of total Russian merchandise trade (export and import) accounted for by a non-CIS partner country.

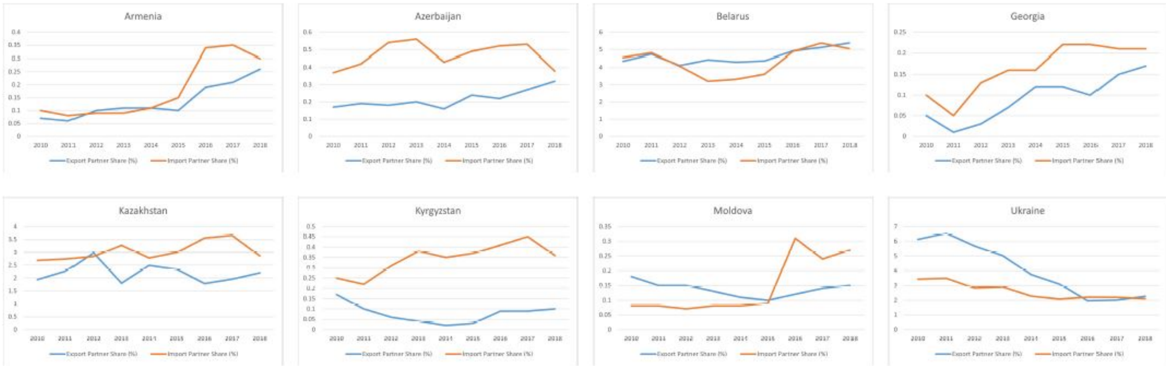


Figure 8: The share of total Russian merchandise trade (export and import) accounted for by a CIS partner country.

2014 marked the official start of the ongoing Russo-Ukrainian geopolitical and military conflict and subsequent sanctions imposed by the West on Russia. Information about the sanctions is taken from the Radio Free Europe/Radio Liberty organization's website.[12] February 2014 events - the revolution and new government in Ukraine and Russia's support of Crimean separatists - marked the monumental shift in Russo-Ukrainian relations. Following these events, the first wave of sanctions hit on March 3rd when the US suspended military cooperation, trade, and investment talks with Russia. On March 27th the US announced a ban on issuance of export licenses for defense products or services to Russia. April 7th became the effective start of the Ukrainian crisis as pro-Russian protesters attacked the Ukrainian security service office. The U.S. retaliated on April 28th by placing restrictions on Russian imports deemed conducive for its military capabilities. On July 16 the U.S. Treasury imposed sanctions on two major Russian banks and energy companies and on July 18th European Investment Bank adjourned funding for Russian projects. On July 29th the US placed sanctions aimed at sectors of Russian economy and the EU restricted access to capital access for Russian state-owned banks. Russia countered on August 6th by banning the import of most foodstuffs from the US, the EU, and other countries that sanctioned it.

On March 4, 2015 all U.S. sanctions imposed on Russia in 2014 were extended by one year. On June 22, 2015 the EU economic sanctions against Russia were extended till January 31, 2016. Russia answered by prolonging the food import ban till August

[12]https://www.rferl.org/a/russia-sanctions-timeline/29477179.html

6, 2016. On March 2, 2016 the US economic sanctions were renewed by one year, and the EU economic sanctions were restated till January 31, 2017. Russia again extended the food import ban till December 31, 2017. Throughout the following years, involved states have renewed functioning sanctions by half-a-year or a year. The EU and US have extended their sanctions against Russia in June 2020, according to the websites of the European Council and the U.S. Department of State.

Among the CIS countries Russia has the biggest trade volume and volatility with Belarus, Kazakhstan, and Ukraine. This is in line with our finding that Belarus and Ukraine are two of the countries with highest loadings on the CIS factor. For these countries both the export and import volumes were declining since 2012 till they hit the lowest points in 2016, and have been on an upward trend following that. With the remaining CIS countries trade volume profiles have been quite flat overall, with a brief increase in 2014 and a subsequent small decrease in 2015. Russia's trade with the non-CIS regions saw a moderate decrease in export and import volumes in 2014 followed by a bigger drop in 2015, with exports hitting the lowest point in 2016 and imports - in 2015.

It is difficult to attribute the 2014 changes in trade flows purely to the sanctions since Russia's economy had already been restrained since 2013 due to sluggish investment and moderate global recovery (October 2014 IMF WEO[13]). The global slowdown in 2015 and lower oil prices likely had immediate and lagged effects as well. Yet in 2015-17 the import shares of Russian merchandise trade accounted for by CIS countries was increasing for most CIS countries while it was decreasing for Germany, UK, and US. Although the import shares for some countries returned to the 2014-levels in 2018, they stayed on levels higher than the 2014 ones for Armenia, Belarus, Georgia, and Moldova. We also note that the export shares for most CIS countries has been on the rise since 2016 while it flattened or decreased for Ukraine, Germany, UK, and US. Thereupon, we surmise that there was at least a temporary trade redirection for Russian exports and possibly a more permanent one for the imports. This may help explain the decrease in synchronization

[13] International Monetary Fund. (2014). World Economic Outlook: Legacies, Clouds, Uncertainties. Washington, DC, October.

with the global component and the increase in synchronization with the CIS component: although there was a decrease in the volume of trade, trade flows between Russia and the CIS became more directed at one another. Our observations resound certain aspects of the work done by Belin and Hanousek (2020). Using difference-in-difference approach, Belin and Hanousek (2020) determine that Western sanctions on Russian exports (on extract equipment) had no statistically significant impact on Russian trade inflows while Russian retaliatory bans on foodstuff imports had statistically significant negative effect on the inflows. Western sanctions aimed at exports did not have the same ramifications as Russian sanctions targeted at imports.

Frankel and Rose (1998) established that trade and synchronization are integral. They found evidence supporting their hypothesis that more integration leads to more trade, which in turn leads to higher business cycle correlation. Hence, more integration among countries with correlated business cycles might amplify the underlying mechanisms of the international trade. This amplification then might generate more correlation of the business cycles through conversion of some of the idiosyncratic shocks into common shocks. This is consistent with our findings: we saw a boost in synchronization within CIS in 2015, which we can ascribe to the 2014 Russo-Ukranian conflict growing into a common shock for the CIS countries. Moreover, Russia bears a considerable impact on the regional economies as a channel for spillovers from Europe (IMF, 2012). As Russia's trade and other connections with the West suffered, it transmitted to the whole region. Thus, as Russia became more disconnected with the global cycle, the CIS countries had to follow suit. The overall instability in the synchronization in 2014-2016 could be rationalized by countries adapting and readjusting to the aftermaths of the sanctions and the global slowdown.

2.6 Conclusions

This paper studies business cycle synchronization in the CIS countries. We also examine if the role of different factors in the evolution of business cycles has changed over time. To do so, we adopt a dynamic factor model that decomposes the variations in RGDP growth into three components: global factor, CIS factor and idiosyncratic factors. The global factor allows us to separate Russian influence from the rest of the world's influence in business cycle synchronization. Our results show that business cycles as measured by growth rate of RGDP in the CIS countries are not very much synchronized with the global and the common CIS factor, though the relative share of different factors shows significant degree of heterogeneity across countries and over time.

One of our key findings is that in 2015 the shares of total variation explained by the CIS and the global factors moved in opposite directions. The 2014 Russian sanctions and the global slowdown in 2015 have turned the CIS countries closer to Russia, even if for a a short time. These macroeconomic events also caused volatility in the dynamics of the CIS economies' cycles with the Russian and global cycles. It would be illuminating to reexamine this once more data becomes available to track the full long-term impact of these events.

Besides a limited data span, another limitation of our study to consider is that RGDP growth rates are just one way to approximate business cycle changes. RGDP growth rates may not always precisely capture changes happening in real time given their low periodicity. Additionally, the synchronization analysis presented in this paper is based on a particular method (dynamic factor modeling) and its attributable assumptions. The existence of more sophisticated techniques capable of addressing the potential endogenous time variation is possible, which may serve as motivation for further studies.

The paper confirms that there is plenty of room for the CIS countries to strengthen their integration. A bigger portion of trade and investment happens not within the region but with Russia and with other major economies, which intimates that there is unexplored potential to boost regional commerce and connections. However, countries may want to focus on their domestic development first. Given the low levels of regional synchronization, pushing for more binding centralized partnership that may be beneficial primarily for the bigger economies could be premature for the rest of the region.

Chapter 3

Exchange Rate Spillovers in the CIS

3.1 Introduction

After the disintegration of USSR in 1991 the former member states, severely unprepared for such a drastic change, set out on mostly uncoordinated transition paths. Although the former USSR states formed a regional intergovernmental organization, the CIS, their business cycles have not been strongly synchronized on regional level (Blockmans et al. 2012, Vymyatnina and Antonova 2014). Synchronization on the financial side has been less identified. Regional banking systems are dominated by domestic ownership, and local financial asset markets are nascent (Barisitz 2009, 2014). Budding financial ties are relatively weak, characterized by distinct dissimilarity in the speed and scope of financial development in CIS (Cojocaru et al., 2016). Nevertheless, most of the countries across the region have tried to implement some forms of capital account liberalization schemes and thereupon have become more attached to the global and regional financial environments (Barisitz 2009, 2014). Moreover, as the CIS started to integrate into the global economic scene in early 2000s, the region became more interconnected (primarily indirectly) through trade and investment linkages to China and EU (IMF 2012, 2013). The waves of the global economic and financial troubles reached the CIS in 2007, and it did not leave the Great Recession unscathed. Regardless of its relative locational isolation and incipient real and financial networks, the CIS has been subject to more macroeconomic connectedness and consequently more exposure to systemic risk along its ongoing economic and financial development.

Given how uneven and mostly idiosyncratic economic and financial system developments have been in these countries, it is important for local policymakers to have an adequate understanding of how exposed they are to regional macroeconomic spillovers. In light of deepening and changing economic networks, understanding of the complex interconnectedness of institutions can help see some patterns in relationships or uncover potential sources of risk spillovers. Getting wind of the specifics of systematic risk in the region is greatly valuable to policymakers and financial market participants monitoring macro situation in the region. Brunnermeier et al. (2020) remind us that systemic risk surges anticipate future real activity weakening; hence, policymakers should pay attention to episodes of increased systemic risk due to them being harbingers of possible fast-approaching crisis and ensuing financial fragility. Meanwhile, financial market participants, especially those involved in forex market activities, can use this analysis to assess and adjust their portfolios. To the best of our knowledge, work on measuring regional macro systemic risk in the CIS region is yet absent, especially utilizing high-frequency data, which this paper intends to remedy. Furthermore, in Kishor and Giorgadze (2022) we find that business cycle connectedness of CIS economies regionally and globally has been relatively low but responsive to major regional changes. The analysis was performed using a dynamic factor model approach applied to quarterly real GDP data. However, RGDP growth rates may not always precisely capture changes happening in real time given their low periodicity, and the synchronization analysis in that work is contingent on the dynamic factor approach assumptions. Analyzing connectedness using higher frequency data can unearth more about the dynamics of the systemic risk allocation or build-up. In this paper we attend to both of these aspects by using daily data and a staple econometric technique developed specifically for the question of spillover analysis within a system/network.

While econometric and theoretic approaches to measuring systemic risk on micro level have been streamlined (i.e. CoVAR, MES, CES), systemic risk measurement on macro level has been unrefined due to its complexity. Smaga (2014) indicates the need for various approaches to measuring systemic risk due to its convoluted nature and absence of unanimity in related literature. For our purpose of analyzing regional CIS interconnectedness, we can think of the CIS as a common system and of the countries' macroeconomies as entities making up this system. These entities are interconnected and interact with each other within the system. Taking into account the multifaceted nature of systemic risk, its essential feature is the transmission of shocks between the linked components of the system, with this transmission having the ultimate potential to generate negative effects on the real economy (Smaga, 2014). Simply put, idiosynctratic risk may create contagion, which may aggrandize into systemic risk (Smaga, 2014). Likewise, Brunnermeier et al. (2020) explain that most systemic risk measures are non-causal, and deem that there are possibly two main sources of systemic risk: spillover risks and common exposure to shocks, both equally influential for financial stability.

Consistent with this thinking, we turn to the widely-used Diebold-Yilmaz (2012, 2014) methodology to evaluate the scope of systemic risk in our system of CIS countries. With the help of the Diebold-Yilmaz (hereafter: DY) approach, we evaluate CIS systemic risk through inspecting macroeconomic spillovers within the region proxied by exchange rates.[14] The DY approach suits our objectives since the biggest advantage of the model is its flexibility and circumvention of potentially erroneous or incomplete theoretical restrictions. The key idea in the DY methodology is to estimate shares of forecast error variation due to shocks coming from other variables (variance decomposition). These shares are the spillovers connecting our sample variables and determining the degree of connectedness, i.e. the scope of risk in the studied system. Our chosen variable of interest is the exchange rate, which offers unique advantages due to its high frequency availability and its critical importance to these developing countries.

In addition to knowing the scope of macro spillovers regionally, it is also meaningful to

[14]A notable example of application of this method is the April 2016 IMF Global Financial Stability Report, which uses it to apprehend financial spillovers across advanced and emerging market economies. A big advantage of this methodology is its ability to appraise directional specifics of the spillovers, a property explored by the April 2018 IMF Global Financial Stability Report in their evaluation of term premium spillovers among G4 countries. We turn to this advantage to perceive which countries on average drive the spillovers, or lead the contagion, in the region.

understand whether these risk spillovers have or long-lasting impacts: depending on the frequency behavior of macroeconomic risk, policy implications might differ. Shocks with disparate frequency responses bring about linkages with discrete degrees of persistence (Barunik and Krehlik 2017). This implies that regulators can adjust or improve policy prepations and responses depending on how persistent and penetrating a risk spillover is. We utilize the Barunik-Krehlik (2017, 2018) methodology (henceforth: BK) based on extending the DY framework to frequency domain decomposition to address this research goal of examining how spillovers behave on different time horizons.

We contribute to the literature on macroeconomic studies in the CIS by measuring and tracing their macroeconomic connectedness over time and establishing that it becomes more pronounced during not only consequential global events (i.e. 2007 subprime mortgage crisis) but also the regional ones, such as the 2014 Russo-Ukranian conflict. The time variation reveals that connectedness generally increased after the challenging period in 2015 marked by falling commodity prices, Russo-Ukranian conflict, and deceleration of demand from China. Our analysis exhibits that the network of these economies has become more vulnerable to systemic risk spillovers. Moreover, we find that bigger currencies in our sample, such as the euro and Russian ruble, and the ones following more flexible regimes (Armenia, Georgia, and Ukraine) on average are the transmitters of the shocks in our system, while the ones with less flexible regimes are more susceptible to spillover risks from other economies. This is a significant piece of information for policymakers in their exchange rate regime determination process. Furthermore, the Barunik-Krehlik frequency dynamics analysis shows that most of the connectedness occurs at the short-term horizon and that severe global shocks are most lasting and more influential for the risk of the system. Therefore, policymakers can develop policy responses and tools that would provide more resilient support at the onset of bigger-scale crises and that would make them better prepared for short-term bumps from regional spillovers.

The paper is organized in the following way: Section 2 provides a brief literature review, Section 3 describes the data, Section 4 explains the methodology, Section 5 presents the empirical results, Section 6 offers an additional specification, and Section 7 concludes.

3.2 Literature Review

A bigger part of literature on macroeconomic integration in the CIS region has focused on business cycles. Benzcur et al. (2007) discover that the business cycle fluctuations of CIS countries in their sample are more volatile and less persistent than elsewhere. They also establish that Russia, Belarus, Ukraine, and, to a lesser degree Kazakhstan and Moldova, exhibit similarities in GDP components (relative volatility, cyclicality, and persistence), in industrial production (relative volatility and persistence), and in the behavior of prices and interest rates. In a subsequent paper, Benczur and Ratfai (2014) find that the CIS countries have the highest output volatility in their sample mix of G7, EU, DE, CEE, CIS, LA, and OE countries. Kishor and Giorgadze (2022) find that the CIS business cycle synchronization is low on regional and global levels and that there is heterogeneity across countries and across time in this aspect. They also estimate that Russia and Ukraine are most globally-connected countries in the sample.

Caetano and Caleiro (2018) examine evolution of business cycle synchronization in the Eurasian region in 1990-2016. Their work maintains that belonging to an economic union enlarges business cycle synchronization within the union. Vymyatnina and Antonova (2014) comprehensively analyze the CIS regional union feasibility. The authors apply cointegration analysis, correlation and volatility measuring, and VAR modeling to measure the comovements of the business cycle synchronization within the Eurasian Customs Union (ECU) estbalished among Russia, Belarus, and Kazakhstan. Vymyatnina and Antonova conclude that the synchronization of business cycles of the three countries is more minor than desired, and the development of regional integration is a far-reaching concern. The authors believe that although the economic co-dependence and spillovers exist, expansion of integration is crucial for a successful economic union to emerge. Blockmans et al. (2012) voice similar concerns in their adaptation of Haas and Schmitter's (1964) conditions for successful implementation of economic unions to compare the Eurasian Economic Union's and the European Economic Community's relevant stances. The Eurasian Economic Union does not withstand the comparison favorably. Blockmans et al. identify that the relative sizes of the economies, distances between economic centers, unbalanced patterns of regional trade integration, and slow dynamics in capital and labor flows block the development of a well-functioning economic union in the region.

Another topic that has received some research attention is exchange rate pass-through in CIS: Korhonen and Wachtel (2006), Beckmann and Firdmuc (2013), Comunale and Simola (2018), to name a few. The overarching result from this area is that there is a relatively high degree of exchange rate pass-through in CIS. There is also some evidence for heterogeneity in short-run pass-through and for potentially higher long-run pass-through.

A pocket of literature has considered the usage of exchange rates in crisis research in CIS region. Fedorova and Lukasevich (2012) identify crisis episodes in CIS using the index of currency pressure developed by Eichengreen, Rose, and Wyplosz (1996). The authors find that inflation, M2, exports, and trade balance have statistically significant predictive roles in this model. An important remark about this methodology is that it produces some information about the trends in financial stability but does not explicitly indicate occurence of financial crisis. Among other helpful conclusions of this paper are that high inflation leads to real appreciation of the domestic currency; that financial crises often occur simultaneously with currency crises or after them; and that the spread of a crisis is more likely to occur among neighboring countries with close trade relations and small stocks of international reserves.

Furthermore, Kittelman et al. (2006) look at early currency crisis warnings based on Markov-switching and discover that Russia and Ukraine differ markedly from CEE countries in that indicators of financial vulnerability were more pertinent than fundamentals for these two CIS countries. This implies that the crises in Russia and Ukraine are less predictable suggesting that systemic risk monitoring is conspicuously needed. Finally, Korotin et al. (2019) suggest that using high-frequency Intrinsic Mode Functions, the Hilbert-Huang transformations of exchange rate data, could be used as early indicators of panic in the markets. Their analysis shows that the Russian rouble market does not follow the efficient market hypothesis and that it has a long memory. The authors conclude that the imposition of Russian sanctions was not the main cause of the currency crisis in 2014 and that the rouble exhibits strong correlation with the Brent oil price.

DY and BK metholodogies have been widely used among researchers measuring spillovers between various indicators, such as stock returns and oil prices, within the context of high-frequency data. For instance, Lovcha and Perez-Laborda (2020) investigate volatility connectdness between the U.S. natural gas and oil markets using these metholodogies. The authors find that most of their spillovers transpire at low frequencies, especially when volatilities are higher, implying that volatility shocks tend to have long-term effects. They also discover that during the 2000s North American natural gas crisis the relative importance of short-term (high-frequency) increased. For a large part of their sample the natural gas market was the net driver of volatility spillovers. Albulescu et al. (2019) apply the DY framework to six well-recognized commodity currencies and WTI to find that the oil price serves as a net transmitter of shocks to these currencies, especially towards AUD and NZD.

Kocenda and Moravcova (2019) implement the DY approach to study volatility spillovers between the new EU forex currencies - Czech, Hungarian, and Polish currencies - and the dollar/euro exchange rate as a proxy for the world forex market. The authors uncover that the highest level of volatility connectedness took place during the Great Recession and that Hungarian currency is dominant in volatility transmission mechanism in their sample. Kocenda and Moravcova mention that identifying and computing volatility spillovers can help central bank policymakers coordinate their activities when one of the currencies undergoes spikes in volatility. This thought is notably appropriate to CIS, which has long flirted with the idea of more cohesive regional integration but has not shown predisposed policy alignments for that.

3.3 Methodology

The steps we take for our analysis are the following: (1) run VAR(1)[15] model of the stationary exchange rate differences and get the variance-covariance matrix of the residuals/shocks; (2) perform 100-day ahead FEVD (forecast error variance decomposition) to obtain variance shares described in Section 3.2; (3) put together the population connectedness table consisting of spillovers explained in Section 3.3; (4) estimate the resonance of spillover shocks across time frequency horizons by using the BK frequency domain extension of the model described in Section 3.4.

3.3.1 Diebold-Yilmaz method of macroeconomic connectedness

The DY approach has become widely utilized in economic and financial studies due to its robust simplicity and intuitive appeal in measuring connectedness via spillovers (Lovcha and Perez-Laborda, 2020). Its central question - how much does a shock to one variable affect future uncertainty of another variable - is principally relevant to our goal of estimating individual country contributions to regional connectedness in addition to the overall index. The DY method is centered around measuring directional spillovers in a generalized VAR framework. The notation here follows Diebold and Yilmaz (2012). The model takes covariance-stationary N-variable VAR(p)[16] series: $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$, where ε is a vector of iid shocks and $\varepsilon \sim (0, \Sigma)$. The moving average representation of the series is $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, with the NxN coefficient matrices A_i following the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + ... + \Phi_p A_{i-p}$ and A_0 being a NxN identity matrix and $A_i = 0$ for i < 0. The core of the approach is to use the transformations of the moving average coefficients, that is the variance decomposition approach. Variance decomposition gives us the portion of the H-step ahead error variance in forecasting x_i caused by shocks to x_j, $\forall j \neq i$ for each i. Diebold and Yilmaz utilize the generalized VAR framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), hereafter KPPS, to obtain order-invariant variance decomposition to bypass the requirement for orthogonal shocks.

[15]The standard BIC criterion gave the 1 lag specification.
[16]We are employing VAR(1) specification in our analysis.

VAR innovations in this model can be contemporaneously correlated and the sum of the contributions to the forecast error variance may not be one.

3.3.2 Variance shares

The H-step ahead error variance in forecasting x_i is divided into *own variance shares*, the fractions of the variance created by idiosyncratic shocks to x_i, for i = 1,2,...,N, and into *cross variance shares*, or *spillovers*, the fractions attributed to shocks to x_j, $\forall j \neq i$. The KPSS H-step-ahead forecast error variance decomposition is denoted as

$$d_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)},$$

where σ_{jj} is the standard deviation of the error term for the jth equation or the jth diagonal element of Σ; e_i is the selection vector with one as the ith element and zeros otherwise; A_h is the coefficient matrix mutliplying the h-lagged shock vector in the infinite moving-average representation of the non-orthogonalized VAR; and Σ is the covariance matrix in the non-orthogonalized VAR. These entries make up the H-step generalized variance decomposition matrix $D^g = [d_{ij}^g]$.

As mentioned previously, the shocks in this GVD framework are not necessarily orthogonal, and thus the sum of forecast error variance shares may not be one (i.e. the row sums of D^g may not equal one, $\sum_{j=1}^{N} d_{ij}^{g}(H) \neq 1$). Therefore, we normalize each share (i.e. each row entry) by the row sum as:

$$\tilde{d_{ij}^{g}}(H)^{17} = \frac{d_{ij}^{g}(H)}{\sum_{j=1}^{N} d_{ij}^{g}(H)}$$

By construction, $\sum_{j=1}^{N} \tilde{d_{ij}^{g}}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{d_{ij}^{g}}(H) = N$. We use these normalized shares in calculating total directional connectedness and total connectedness as explained

[17] Note that we drop (H) going forward for convenience but it is always implied that measures are attributed to a given forecast horizon H.

further.

3.3.3 Spillovers/Connectedness

The population connectedness table The connectedness table consists of $D^g = [d^g_{ij}]$ described in 3.2 in the center with added rightmost column with row sums (From others), bottom row with column sums (To others), and the grand average at the bottom right:

	x_1	x_2	$\ldots$	x_N	From others
x_1	d^g_{11}	d^g_{12}	$\ldots$	d^g_{1N}	$\sum_{j=1}^{N} d^{\tilde{g}}_{1j}, j \neq 1$
x_2	d^g_{21}	d^g_{22}	$\ldots$	d^g_{2N}	$\sum_{j=1}^{N} d^{\tilde{g}}_{2j}, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	d^g_{N1}	d^g_{N2}	$\ldots$	d^g_{NN}	$\sum_{j=1}^{N} d^{\tilde{g}}_{Nj}, j \neq N$
To others	$\sum_{i=1}^{N} d^{\tilde{g}}_{i1}, i \neq 1$	$\sum_{i=1}^{N} d^{\tilde{g}}_{i2}, i \neq 2$	$\ldots$	$\sum_{i=1}^{N} d^{\tilde{g}}_{iN}, i \neq N$	$\frac{1}{N} \sum_{i,j=1}^{N} d^{\tilde{g}}_{ij}, i \neq j$

Pairwise directional connectedness Pairwise directional connectedness from j to i, the off-diagonal entries of $\tilde{D}^g$:

$$C^g_{i \leftarrow j} = d^g_{ij}$$

In general, $C^g_{i \leftarrow j} \neq C^g_{j \leftarrow i}$, and there are $N^2 - N$ individual pairwise directional connectedness measures. These measures are akin to bilateral exports and imports for each in a group of N countries. A natural extension would be to calculate net pairwise directional connectedness measures: $C^g_{ij} = C^g_{j \leftarrow i} - C^g_{i \leftarrow j}$. Net pairwise directional connectedness measures are comparable to bilateral trade balances and there are $\frac{N^2-N}{2}$ of them in total.

Total directional connectedness The off-diagonal row sums are the amounts of the H-step forecast error variance of a variable coming from shocks to all other variables. On the other hand, the off-diagonal column sums are the amounts of the H-step forecast error variance that a variable contributes to shocks to all other variables. Thus, the off-diagonal row and column sums are labeled "From others" and "To others" respectively in the connectedness table and represent the total directional connectedness of a variable[18].

Total directional connectedness from others to i is:

$$C^g_{i\leftarrow\bullet} = \sum_{j=1, j\neq i}^{N} \tilde{d}^g_{ij}$$

Total directional connectedness from i to others:

$$C^g_{\bullet\leftarrow j} = \sum_{i=1, i\neq j}^{N} \tilde{d}^g_{ij}$$

These measures resemble total exports and total imports for each in a group of N countries, and there are 2N total directional connectedness measures (one "to others"/"trasmitted" value and one "from others"/"received" value per each in N). Net total directional connectedness is $C^g_i = C^g_{\bullet\leftarrow i} - C^g_{i\leftarrow\bullet}$. Net total directional connectedness values are analogous to the total trade balances of each in a group of N countries and there are N of them in total.

Total connectedness Total volatility spillover index, the grand total of the off-diagonal entries in $\tilde{D}^g$:

$$C^g = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{d}^g_{ij}}{\sum_{i,j=1}^{N} \tilde{d}^g_{ij}} * 100 = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{d}^g_{ij}}{N} * 100$$

There is one single total connectedness measure, just as there is one single value of total world exports or imports - which are equal to each other.

[18]These values are normalized for easier interpretation as described in 3.2.

3.3.4 Barunik-Krehlik Frequency Domain Connectedness

BK (2017, 2018) supplemented the DY framework by incorporating basics of spectral analysis to the connectedness measures. The method makes use of the Fourier transforms of the impulse response functions (the frequency responses) to acquire spectral representation of GFEVD (generalized forecast error variance decomposition). To achieve that, we are obtaining the portion of forecast error variance in the frequency domain at a given frequency band that is ascribed to shocks in another variable (Barunik and Krehlik, 2018). The aggregate connectedness measure on a frequency band d is then defined as:

$$\tilde{C^d} = C^d * \Gamma(d),$$

where $\Gamma(d)$ is the spectral weight, or the contribution of frequency band d to the overall behavior of the system (i.e. how important a band is/how much variance of the system is created here), and C^d is the total connectedness measured in the connectedness table for the frequency band d[19]. Note that if we sum up the $\tilde{C^d}$'s over the range of frequency bands we decide to disintegrate the data into, we will end up with the DY total connectedness measure: $\sum_d \tilde{C^d} = C^g$. Please see BK 2017 and 2018 for details.

3.4 Data

Exchange rate as the variable of choice There are compelling reasons to use exchange rates for our research aim. First of all, Andries and Sprincean (2021) stress the importance of utilizing high-frequency data in systemic risk studies, and the availability of daily exchange rate data is particularly important in the absence of sufficient quality and high-frequency data on interest rates and other banking or financial health indicators for the CIS economies[20]. Furthermore, exchange rates are an important health-of-an-economy indicator as they contain an aggregate reflection of the state of real and financial aspects of an economy. Moreover, the changes in exchange

[19] BK call these measures *within* spectral band measures.

[20] Additionally, Kiani (2010) argues that given the SOE (small open economy) status of the CIS countries, interest rates may not be the most viable monetary policy tool available to them whilst exchange rates may be playing a more poignant role in their economies and policy toolkits.

rates hold valuable information indicative of shifts or adjustments not only in an economy's fundamentals but also in regional and international macroeconomic climates and, accodingly, in systemic risk withal. As Engel (2014) remarks, it is notoriously difficult to model movements in currency rates, and hence to forecast them. Park and An (2020) explain that the lack of an established theory on the underlying causes of currency comovement pertains to the dearth of research in this area. However, the lack of ascertained theoretical and empirical exchange rate determinants is beneficial for our purposes since the movements in exchange rates are picking up the large variety of observed and latent macroeconomic matters occuring simultaneously and interconnectedly, which is consistent with Brunnermeier at al.'s (2020) definition of systemic risk mentioned in the introduction. Finally, exchange rates are particularly relevant for the CIS due to their economies being dominated by commodities trade.[21] Oil and other commodity trade is usually priced in USD, making exchange rate movements imperative for these countries.

Data description Exchange rate data in terms of national currency per USD was taken from the Investing.com website which quotes daily market-based rates. Estimations done with daily data generally give sound approximations of volatility (Barunik et al., 2017) and we take advantage of the availability of market-based data to conduct our study. The sample (such that there is an observation for each country) runs from January 24, 2006 till July 1, 2020 for the total of 2,713 observations per currency. The graphs below illustrate the rates of euro and 9 CIS countries - Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Russia, and Ukraine - for the sample period. As is apparent from the graphs, exchange rates are non-stationary; thus, we use the stationary first-differences of the exchange rates for our analysis.

[21] Please see the table in the Appendix B for detailed information.

3.5 Empirical Results

3.5.1 Exchange Rate Spillovers among CIS countries

Table 6 below presents the population connectedness table from our empirical analysis in the format defined in Section 3.3.3.

Country	Armenia	Azerbaijan	Belarus	Euro	Georgia	Kazakhstan	Kyrgyzstan	Moldova	Russia	Ukraine	From others
Armenia	98.71	0.02	0.11	0.05	0.05	0.04	0.40	0.02	0.47	0.13	**0.13**
Azerbiajan	0.01	99.14	0.18	0.13	0.10	0.05	0.10	0.00	0.26	0.02	**0.09**
Belarus	0.43	0.01	77.71	0.10	0.80	2.45	0.08	0.03	18.25	0.13	**2.23**
Georgia	0.13	0.47	0.85	95.48	0.47	0.35	0.27	0.00	1.60	0.37	**0.45**
Euro	0.02	0.03	0.01	0.53	98.54	0.06	0.28	0.31	0.21	0.02	**0.15**
Kazakhstan	0.10	0.04	2.99	0.59	0.14	89.65	0.39	0.11	5.60	0.41	**1.04**
Kyrgyzstan	0.39	0.08	0.07	2.94	0.06	0.82	95.12	0.01	0.13	0.38	**0.49**
Moldova	0.04	0.01	0.12	0.18	0.13	0.24	0.04	97.65	0.61	0.97	**0.23**
Russia	0.58	0.06	17.53	0.16	1.11	4.44	0.04	0.08	75.64	0.38	**2.44**
Ukraine	0.06	0.05	0.14	0.10	0.06	0.08	0.47	0.91	0.15	97.99	**0.20**
To others	**0.18**	**0.08**	**2.20**	**0.48**	**0.29**	**0.85**	**0.21**	**0.15**	**2.73**	**0.28**	**7.44**

Table 6: The Spillovers/Connectedness Table
Note: a country's own variance portion is in red along the diagonal - the lower this value, the higher the country's connectedness; off the diagonal are the pairwise directional spillovers; in bold are the total directional spillovers to and from a country; underlined is the main spillover aggregate index

Table 6 gives the full-sample population connectedness table: total spillover index amounts to 7.44, meaning that 7.44% of total forecast error variation in the system is explained by spillovers between the countries. This is a rather sizeable result taking into account the idiosyncracies of regional economies as well as the difficulty in assessing the quantitatively important predictable component in exchange rates movement. When we look at the diagonal entries of the connectedness table representing the (unadjusted) proportion of variance explained by own shocks, we see that Russia, Belarus, and Kazakhstan have the lowest amounts, making them the most connected countries in our sample. Accordingly, these three countries have largest spillovers with each other. Notably, these three countries make up the Eurasian Customs Union established in 2010, suggesting that there might be a connection between engaging in tighter economic relations and thus having larger connecting risk spillover chanels.

Table 7 below displays the net total directional position of a country in our sample's system as explained in detail in Section 3.3.3. It holds the difference between how much a country contributed to all other country's error variance and how much all other countries contributed to its error variance, i.e. how much risk it transmitted to others minus how much risk spilled over from others. The net receivers of the shocks - the ones with a negative net total directional position - are inferred to be in a more vulnerable position than the net givers of the shocks, the ones with a positive net directional position.

Country	Net Spillover Position
Armenia	0.047
Azerbaijan	-0.009
Belarus	-0.028
Georgia	0.026
Euro	0.144
Kazakhstan	-0.184
Kyrgyzstan	-0.281
Moldova	-0.087
Russia	0.292
Ukraine	0.079

Table 7: Net Directional Spillover/Connectedness Position
Note: a negative value implies that a country on average is a net receiver of shocks in this system; a positive value - a transmitter of shocks

Table 7 indicates whether countries in our sample in general are transmitting or receiving shocks (the difference between total directional connectedness to others and total directional connectedness from others for each country). The countries who are net transmitters of shocks in our sample are Armenia, Georgia, Russia, and Ukraine. As expected, euro is also a net transmitter of shocks. The countries who are net receivers of shocks in our sample are Azerbaijan, Belarus, Kazakhstan, Kyrgyzstan, and Moldova. Interestingly, some of net shock receivers - Belarus, Kazakhstan, and Moldova - have low values of capital account openness. It is also noteworthy that net shock receivers Azerbaijan and Belarus have been most reluctant to completely abandon more managed exchange rate regimes while by 2015 other countries moved toward floating regimes[22]. Policymakers would want to take note of this geographical specifics of spillover transmission - being a net transmitter vs a net receiver of shocks would entail differing policy approaches. Forex investors could use this information in their currency portfolio rebalancing.

[22] Azerbaijan has mostly pegged against the USD, and Belarus - USD and euro. Other two countries who have leaned on pegging is Kazakhstan (peg to USD and the rouble) and Kyrgyzstan (mostly unofficial peg to USD).

3.5.2 Dynamic Connectedness and Spillovers

We found that on average the spillover index is 7.44% in our sample, which means that 7.44% of the total error variance is attributed to risk spillovers between the countries. Does it stay approximately the same over time or does it go up during turbulent times? To determine how systemic risk changes over time, we calculate the DY spillover indices in a rolling manner (window = 100 days) with the same forecast horizon of 100 days. Figure 1 exhibits the results. The increase in risk during macrocrises - 2007 subprime mortgage crisis, 2008-09 Great Recession, European debt crisis in 2011 and 2012, 2014 Russo-Ukranian war, 2014-15 commodity price plunge and Russian financial crisis, 2020 Great Lockdown - is striking.

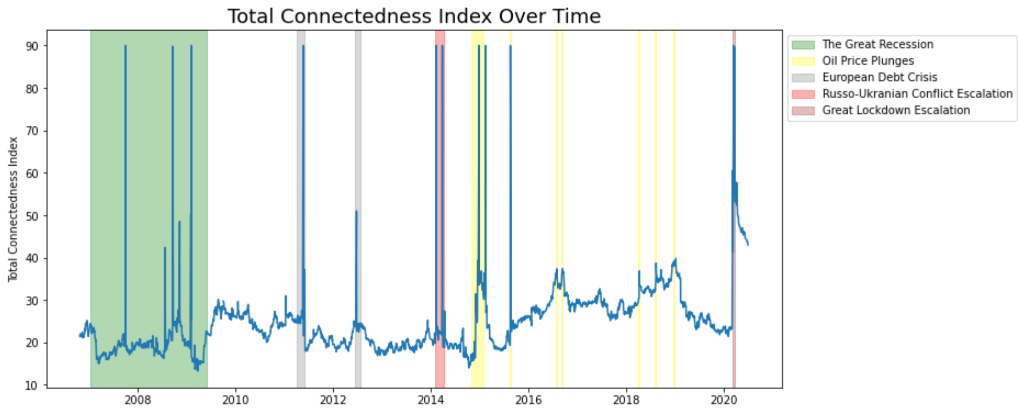


Figure 9: Total Dynamic Connectedness, Full Sample
Spikes during the Great Recession, the oil price plunges, the European debt crisis, the Russo-Ukranian conflict escalation, and the Great Lockdown escalation; the average increase in spillovers after 2015

As exhibited by the figure above, we observe a visible upward shift in average connectedness since 2015. To corroborate this visual observation, we separate the data into two subsamples - from 2006 till 2014 and from 2015 till 2020 and repeate the analysis separately for the two periods. As anticipated, total connectedness index value is 3.23 for the 2006-2014 period while it is 13.37 for 2015-2020. This detection corresponds to our previous work where we unearth that the dynamics of business cycle synchronization within the region changed in 2015. Using dynamic factor model analysis, we show that in 2015 synchronization with the regional CIS factor spiked while the comovement with the global factor dropped for all the countries in our sample during that period. Our current connectedness study is remarkably consistent with this result.

Our findings fit with the extensive literature documenting that connectedness within various markets (stocks, forex, debt, etc) increases during crisis times. For example, using cross-quantilogram network methodology for 205 European financial institutions, Deev and Lyocsa (2020) ascertain that interconnectedness during bad times exceeds interconnectedness during bullish times when stock prise spike. Another example is an inter-market spillover study between 4 major equity and forex markets using the DY methodology, Leung et al. (2017) discover a general intensification of spillovers during crisis times.

Additionally, our analysis parallels the work by Park and An (2020) on global comovement of different currencies with the Chinese RMB. Applying the linear regression framework developed by Frankel and Wei (1994) for 34 currencies and RMB, Park and An (2020) detect that the currencies displayed more comovement with RMB after the 2008 global financial crisis. They also determine that currencies presided by more flexible exchange rate regimes exhibit more comovement with the RMB. It is useful for the policymakers and forex investors to know that currencies following more flexible regimes on average transfer shocks in the system and the ones with more rigid regimes are more vulnerable to external disturbances.

3.5.3 Discussion of the Dynamic Results

Our estimations indicate that macroeconomic connectedness intensified after 2015. To deliberate this finding, we consider how the exchange rate regimes evolved in CIS. As appropriate for their transition status, CIS countries have heavily experimented with varied combinations of exchange rate and monetary policy schemes in search of stability and accommodation of policy goals. Figure 10 depicts the progression of exchange rate regimes for the CIS countries from 2006 to 2018 based on the corresponding IMF Annual Reports on Exchange Arrangements and Exchange Restrictions. It shows de facto exchange rate arrangements and monetary policy frameworks (in parenthesis) in a given year[23]. Colors are matched by the exchange rate arrangements. It is remarkable how most of the countries moved towards more relaxed exchange rate arrangements in 2015. 2015 was an especially hard year for the region: the 2014 Russo-Ukrainian conflict was in full bloom, affecting all of the region; oil prices were at their lowest; and the world economy was shaken up by the slowdown in Chinese economic activities. The authorities found it excessively burdensome to keep the stricter exchange rate regimes up and relaxed them to different degrees. Our model picks up this outstanding regional shift thoroughly well.

Figure 10: Exchange Rate Regimes: Shifts towards Flexible in 2015

There is some evidence that this shift towards more exchange rate flexibility might have been a prudent decision. Using PVAR (panel vector autoregression) impulse-response function analysis for 63 commodity-exporting countries over the period 1980-2017, Al-Sadiq et al. (2021) find that flexible regimes allow for a smoother commodity terms-of-trade shock adjustment. The authors gather that pegged and flexible regimes are associated with systematically different adjustment processes of real GDP per capita to a negative terms-of-trade shock.

[23]Countries often switch around the arrangements during a year, IMF captures the most accurate information to the date.

3.5.4 Directional Connectedness Over Time

Rolling DY decomposition also allows us to trace the behavior of shocks of each country individually. Figures 11-20 show the time-variation of directional connectedness (spillover indeces from 3.3.3) to and from each country in the sample. Directional connectedness from other countries (the graphs on the right) overall looks comparable for all countries in the sample, fluctuating within the same rather low range and spiking during major macroeconomic events. This implies that in the bad times all of the countries are susceptible to risk spillovers from other countries in a similar fashion. On the other hand, directional connectedness to other countries (the graphs on the left) shows more variety from country to country while manifesting during critical macroeconomic events as well.

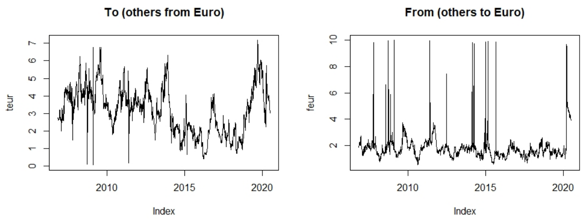


Figure 11: Euro (left: spillovers to other currencies; right: spillovers from other currencies)

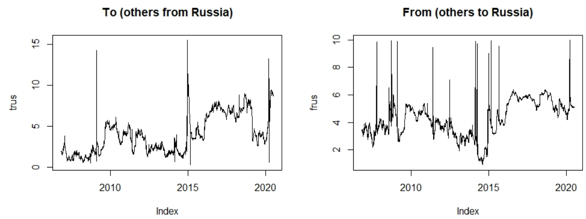


Figure 12: Russia (left: spillovers to other currencies; right: spillovers from other currencies)

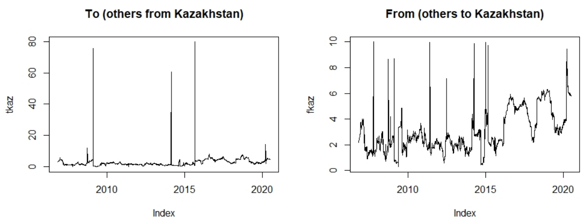


Figure 13: Kazakhstan (left: spillovers to other currencies; right: spillovers from other currencies)

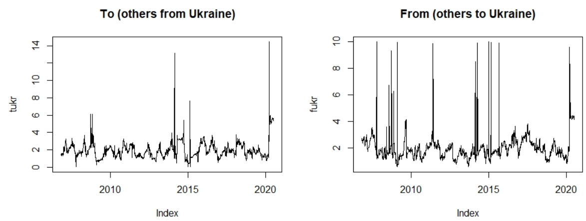


Figure 14: Ukraine (left: spillovers to other currencies; right: spillovers from other currencies)

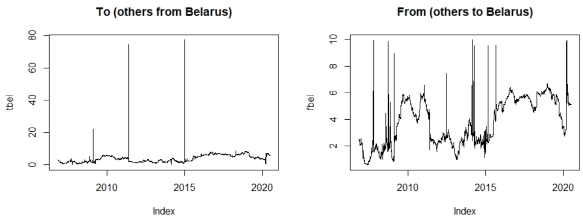


Figure 15: Belarus (left: spillovers to other currencies; right: spillovers from other currencies)

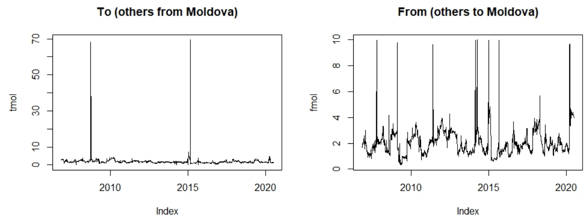


Figure 16: Moldova (left: spillovers to other currencies; right: spillovers from other currencies)

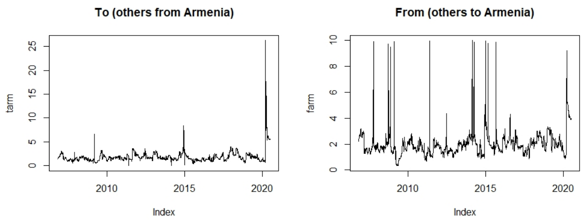


Figure 17: Armenia (left: spillovers to other currencies; right: spillovers from other currencies)

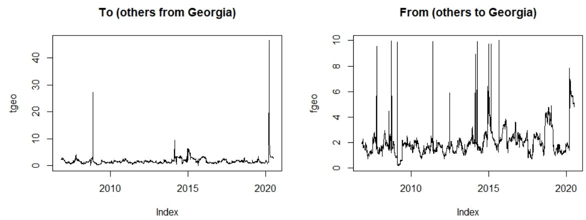


Figure 18: Georgia (left: spillovers to other currencies; right: spillovers from other currencies)

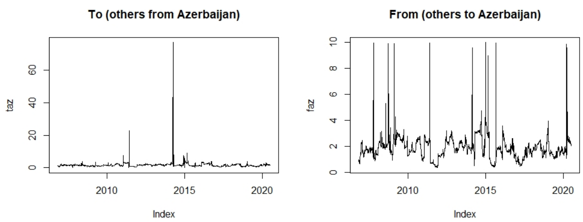


Figure 19: Azerbaijan (left: spillovers to other currencies; right: spillovers from other currencies)

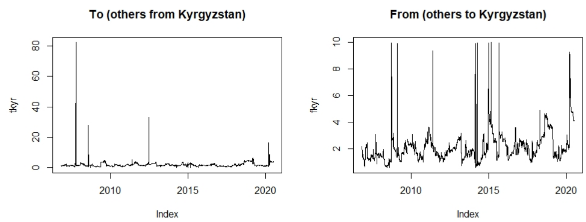


Figure 20: Kyrgyzstan (left: spillovers to other currencies; right: spillovers from other currencies)

The euro's spillovers to other currencies (depicted on the left) spiked during the Great Recession, during European debt crisis, and when the ECB cut the interest rates to negative in 2019. Russia's spillovers to other exchange rates peaked during the Great Recession, the ruble's devaluation in December 2014, and the pandemic escalation. Kazakhstan's spillovers to other countries increased during the Great Recession, the 2014 oil price plunge, and the tenge's devaluation in September 2015. Ukraine's spillovers to other currencies heightened during the 2014 Russo-Ukranian conflict and the pandemic escalation. Belarus' spillovers to other exchange rates rose during the currency's devaluations in October 2011 and in December 2014. Armenia and Georgia's spillovers to other economies spiked during the pandemic escalation. Azerbaijan's spillovers to others peaked during the 2014 oil price plunge. Kyrgyzstan's spillovers to others heightened during the Great Recession.

We also note that for majority of the currencies in the sample - Armenia, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Russia, and Ukraine - the risk spillovers from other countries (depicted on the right) increased from 2015. We notice this pattern especially with Belarus, Kazakhstan, and Russia, and we connect this with the Eurasian Economic Union coming into force on January 2015 and these three economies being the most involved in it. Moreover, although almost all of the former Soviet Union republics had to devalue their currencies as the result of the Russian ruble's shap devaluation that started in July 2014, Belarus and Kazakhstan's devaluations were the largest among the affected region.

3.5.5 Barunik-Krehlik Frequency Dynamics Results

One of the fundamental concerns about shocks is their perpetuation; the duration of macroeconomic stress from shocks construes policymaker responses. It is difficult for policymakers to identify the scope of macroeconomic risk with exact accuracy ex-ante. However, knowing how persistent various macroeconomic crisis have been historically can aid in the preparation and development of policy responses. An advantage of the high-frequency DY estimation is its organic extension to the examination of the periodic behavior of connectedness via frequency domain spectral analysis.

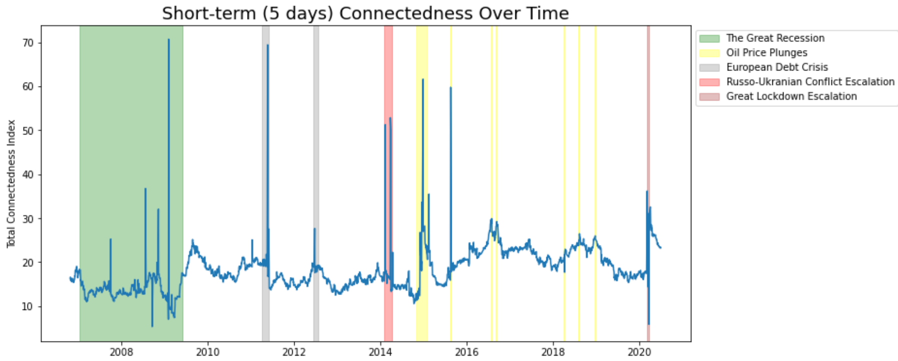


Figure 21: Connectedness at a high frequency - shocks here are least persistent and are being transmitted for up to 5 days

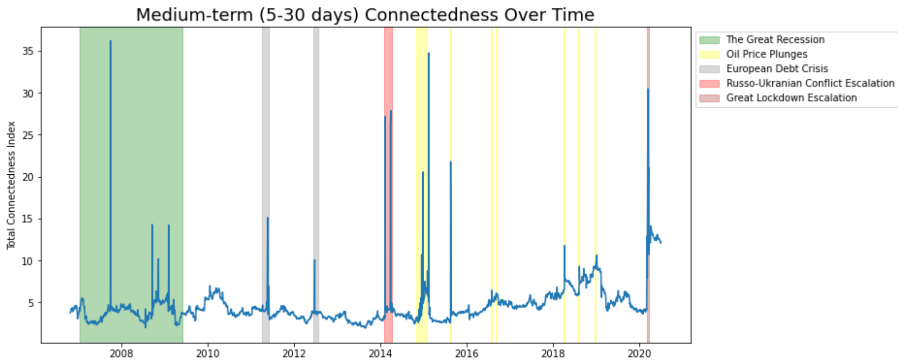


Figure 22: Connectedness at a medium frequency - shocks here are moderately persistent and are being transmitted for up to a month

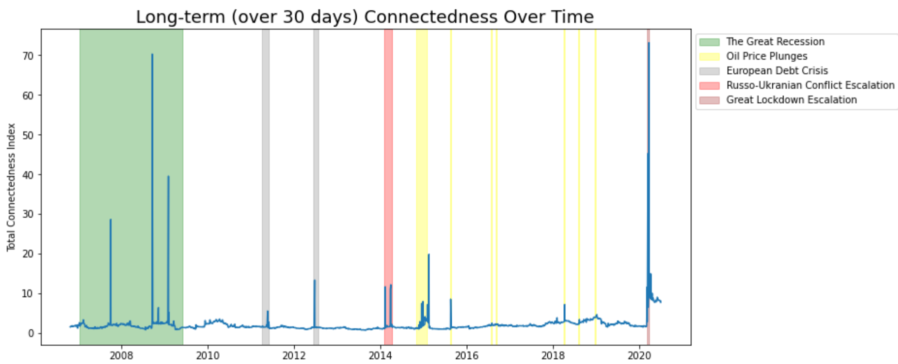


Figure 23: Connectedness at a medium frequency - shocks here are persistent and are being transmitted for longer than a month

Figures 21-23 present the results from the BK frequency decomposition model attained in the rolling manner (window = 100 days). The most long-lasting risk linkages are created during notable regional and global events: 2007 subprime mortgage crisis, 2008-09 Great Recession, 2014 Russo-Ukranian war, 2014-15 commodity price plunge and Russian financial crisis, and the 2020 Great Lockdown. These events corresponded with the highest risk of propagation. Among these events extensive global shocks, such as the Great Recession and the pandemic escalation, are most persistent: they have higher overall spillovers on all frequency bands, and more so in medium and long term.

In the short run, the Great Recession, the European Debt Crisis, the Russo-Ukrainian conflict, and the oil price plunges are the most impactful events in our system. In the medium run, the 2007 subprime mortgage crisis, the Russo-Ukrainian conflict, the oil price plunges, and the Great Lockdown are the most poignant. In the long run, the 2007 subprime mortgage crisis, the Great Recession, and the Great Lockdown resonate the most. These observations suggest that regional economic and political events, such as debt crisis and disputes, as well as the oil price changes drive the short- and medium-run system-wide risk. These regional events are also more transitory relative to the large-scale global shocks.

Frequency Horizon	Average	Standard Deviation	Maximum Value Date
Short-term	18.13	4.62	February 4, 2009
Medium-term	4.51	2.33	October 3, 2007
Long-term	2.01	2.7	March 25, 2020

Table 8: Summary of the Connectedness Values across Frequency Horizons

Overall, we see that most of the connectedness takes place at high frequencies/short-term, implying that shocks between the currencies overall have short-run impacts on regional connectedness. As compiled in Table 8, short-term band spillovers experience relatively higher overall values and range, with the average of 18.13 and the standard deviation of 4.62. The spillover indices also peak at different times for each frequency band: the short-term band reaches its maximum during the Great Recession; the medium-term band - during the 2007 subprime mortgage crisis; and the long-term band - during the pandemic escalation. We conclude that the type and scale of a macroeconomic event matters and that policymakers should be aware of the reverberations of global shocks with the respect to their vulnerability to risk spillovers and to adjust their policy toolkit to account for risk transmission from regional events as well.

3.6 Additional Specification

Seeing how influential commodity trade, specifically of the minerals such as oil, is to the CIS, it is worthy of attention to look at an association between macroeconomic connectedness and oil and gas markets. To estimate how the exchange rates interact with oil and gas prices in our spillovers setting, we make a supplementary specification adding WTI, Brent, and Henry Hub spot gas prices[24] to our 10 currencies. Tables 9 and 10 below give the results of this model.

Country	Net Spillover Position
Armenia	0.035
Azerbaijan	-0.001
Belarus	-0.074
Georgia	0.008
Euro	0.005
Kazakhstan	-0.156
Kyrgyzstan	-0.223
Moldova	-0.073
Russia	0.112
Ukraine	0.054
WTI	0.291
Brent	0.08
Gas	-0.063

Table 9: Net Directional Spillover/Connectedness Position
Note: a negative value implies that a country on average is a net receiver of shocks in this system; a positive value - a transmitter of shocks

Country	Armenia	Azerbaijan	Belarus	Euro	Georgia	Kazakhstan	Kyrgyzstan	Moldova	Russia	Ukraine	WTI	Brent	Gas	From others
Armenia	98.56	0.02	0.10	0.05	0.05	0.04	0.36	0.02	0.43	0.12	0.01	0.15	0.09	**0.11**
Azerbiajan	0.01	98.99	0.16	0.12	0.10	0.05	0.10	0.01	0.22	0.02	0.12	0.07	0.02	**0.08**
Belarus	0.43	0.01	77.17	0.12	0.76	2.42	0.10	0.03	17.90	0.14	0.14	0.75	0.03	**1.76**
Georgia	0.14	0.50	0.84	94.91	0.45	0.42	0.33	0.00	1.59	0.38	0.15	0.20	0.09	**0.39**
Euro	0.02	0.04	0.01	0.54	93.35	0.05	0.21	0.29	0.19	0.02	2.12	2.62	0.53	**0.51**
Kazakhstan	0.10	0.04	2.95	0.61	0.13	89.40	0.40	0.10	5.53	0.39	0.03	0.09	0.21	**0.82**
Kyrgyzstan	0.36	0.09	0.07	3.02	0.04	0.88	94.67	0.02	0.11	0.32	0.02	0.19	0.21	**0.41**
Moldova	0.04	0.01	0.11	0.15	0.16	0.23	0.05	97.54	0.62	0.98	0.07	0.04	0.00	**0.19**
Russia	0.56	0.06	17.06	0.14	1.03	4.35	0.03	0.07	74.50	0.39	0.33	1.32	0.17	**1.96**
Ukraine	0.05	0.05	0.16	0.10	0.05	0.06	0.42	0.92	0.17	97.79	0.09	0.13	0.00	**0.17**
WTI	0.00	0.09	0.09	0.19	1.32	0.00	0.00	0.02	0.01	0.07	78.64	19.19	0.38	**1.64**
Brent	0.07	0.05	0.28	0.10	2.06	0.03	0.18	0.03	0.01	0.02	21.12	75.05	1.01	**1.92**
Gas	0.12	0.03	0.04	0.06	0.56	0.04	0.24	0.00	0.17	0.06	0.94	1.30	96.44	**0.27**
To others	**0.15**	**0.08**	**1.68**	**0.40**	**0.52**	**0.66**	**0.19**	**0.12**	**2.07**	**0.22**	**1.93**	**2.00**	**0.21**	**10.23**

Table 10: The Spillovers/Connectedness Table
Note: a country's own variance portion is in red along the diagonal - the lower this value, the higher the country's connectedness; off the diagonal are the pairwise directional spillovers; in bold are the total directional spillovers to and from a country; underlined is the main spillover aggregate index

[24] Data on these three variables was taken from the Fred website.

Adding the three commodities does not substantially change total connectedness[25] but displays interesting relationships within the sample. The net directional positions of the countries remain, with Azerbaijan, Belarus, Kazakhstan, Kyrgyzstan, and Moldova being the net receivers of shocks, and Armenia, Georgia, Euro, Russia, and Ukraine being the net transmitters of the shocks. Importantly, WTI and Brent are net transmitters and gas is net receiver of shocks on average in our sample. A lot of the net valuation for WTI and Brent comes from their strong bilateral relationship: WTI is responsible for 21.12% of unadjusted shocks to Brent in GVD breakdown while Brent is responsible for 19.19% of unadjusted shocks to WTI. Second strongest bilateral relationship for WTI is with euro: WTI accounts for 2.12% of the unadjusted shocks to euro in our GVD scheme and in turn receives 1.32% of the unadjusted shocks from euro. We see a similar pattern for Brent but with slightly higher values: Brent accounts for 2.62% of the unadjusted shocks to euro and in turn receives 2.06% of the unadjusted shocks from euro.

Both WTI and Brent on average transmit shocks to gas in our sample. As for the oil and gas exporters in our sample - Azerbaijan, Kazakhstan, and Russia - all three currencies on average receive shocks from WTI and Brent. The situation with gas is different: only Kazakhstan on average is net receiver of shocks from gas while Russia is balanced and Azerbaijan is a net giver.

Relationship between Total Connectedness and Oil and Gas Prices

To further explore the relationship between macroeconomic comovement in CIS and oil and gas prices, we run standard OLS regresssions of total connectedness we got from the DY model on the oil and gas prices and on the volatility of prices.[26] We take WTI and Brent crude oil for oil prices and Henry Hub spot gas prices from the section above.

[25]It increases largerly by the virtue of having more variables and variance being non-negative.

[26]We measure volatility by 20-day rolling standard deviations.

	Dependent variable:		
	connectedness		
	(1)	(2)	(3)
wti	-0.143^{***}		
	(0.006)		
brent		-0.124^{***}	
		(0.005)	
gas			-1.240^{***}
			(0.072)
Constant	34.981^{***}	34.235^{***}	29.655^{***}
	(0.446)	(0.432)	(0.325)
Observations	2,546	2,546	2,546
R^2	0.190	0.177	0.104
Adjusted R^2	0.189	0.177	0.104
Residual Std. Error (df = 2544)	6.952	7.004	7.307
F Statistic (df = 1; 2544)	594.898^{***}	548.348^{***}	296.683^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 11: Regressions of the connectedness index on WTI oil price (1), on Brent oil price (2), and on Henry Hub gas price (3)
All coefficients are negative, signifying an inverse relationship for all three prices with the connectedness index

	Dependent variable:		
	connectedness		
	(1)	(2)	(3)
wti	0.761^{***}		
	(0.089)		
brent		0.802^{***}	
		(0.101)	
gas			-2.129^{***}
			(0.760)
Constant	22.650^{***}	22.539^{***}	25.127^{***}
	(0.277)	(0.304)	(0.230)
Observations	2,546	2,546	2,546
R^2	0.028	0.024	0.003
Adjusted R^2	0.028	0.024	0.003
Residual Std. Error (df = 2544)	7.612	7.627	7.710
F Statistic (df = 1; 2544)	73.762^{***}	63.563^{***}	7.848^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 12: Regressions of the connectedness index on the volatility of the WTI oil price (1), on the volatility of the Brent oil price (2), and on the volatility of theHenry Hub gas price (3)
The coefficients for the two oil price volatilities are negative, signifying an inverse relationship between oil price volatility and the connectedness index; the coefficient for the gas price volatility is positive, signifying a positive relationship between gas price volatility and the connectedness index

The results in Tables 11 and 12 paint a convincing picture: when oil and gas prices decrease, total connectedness increases; and when oil price volatility increases, total connectedness increases as well. The times when oil and gas price fall and oil price volatility rises usually happens during various macroeconomic troubles, and systemic risk increases during those troubles. Interestingly, gas price volatility is inversely related to total connectedness, implying that as gas price volatility increases, connectedness falls. We attribute this difference between oil and gas price volatility relationships with connectedness to oil and gas price having opposite roles in disturbance transmission in our sample (oil price - net giver of shocks, gas price - net acceptor).

3.7 Conclusions

In today's globally interconnected world macroeconomic risk a given country faces cannot be considered without the regional and global context. Regardless of how small or relatively closed an economy is, it is bound to receive or transmit macroeconomic spillovers to and from its neighbors; macroeconomic risk linkages are inevitable. The region of interest in this paper, the Commonwealth of Independent States, or the CIS, is no exception. By employing the prominent DY and BK metholodogies based on variance decomposition in a VAR model of 9 CIS currencies and the euro we study the progression of macroconomic connectedness in the region. This measure of systemic risk maintains that spillovers increase significantly during macroeconomic shocks, and that the vulnerability to spillover risks has increased regionally after 2015. The BK frequency dynamics extension of the analysis asserted that although short-term connectedness dominates the overall variance of the system, more severe macroeconomic shocks resonate greatly on all three horizons, i.e. they impact the system more deeply and for a longer time.

Although each country has had a mostly idiosyncratic combination of exchange rate and monetary policy arrangements, macroeconomic shocks concur with substantial comovement of changes in exchange rates across the region. It is hardly a coincidence that the average level of connectedness amplified after many countries in the region turned towards more flexible exchange rate arrangements in 2015, a particularly arduous period for the region. Euro and Russian ruble and currencies historically following more flexible exchange rate regimes (Armenia, Georgia, and Ukrania) on average transfer shocks in the system while the currencies that have been more inclined to peg (Azerbaijan, Belarus, Kazakhstan, Kyrgyzstan) on average find themselves at the receiving end of shocks. This finding provides an important point of consideration to central bankers arranging the exchange rate regimes.

Policymakers can take note of our findings which show that macroeconomic spillovers increase during difficult times and that widespread crises have larger propagation risk and persistence, while forex investors can incorporate our findings into their portfolio management strategies. First of all, central banks should keep carefully monitoring exchange rate movements of neighboring countries and globally-important currencies. The central banks practicing more rigid exchange rate regimes should understand the higher likelihood of exposure to spillover risks and be sufficiently prepared with regard to their foreign exchange reserves and related matters to weather the shocks with minimum repercussions. The results of our additional specification analysis suggest that policymakers should also watch the trends and forecasts of major commodities such as oil since the connectedness increases when these markets are turbulent. The WTI crude oil price in particular is a big transmitter of shocks for these developing countries. Finally, the countries in the region need to pay special attention to the euro and Russian ruble since these two currencies are major carriers of shocks in the sample's system.

Chapter 4

Commodity Prices and Exchange Rates: The Downside Risk Relationship

4.1 Introduction

Commodity export dependence has been an economic reality for many developing countries, and this phenomenon has increased worldwide from 2008-2009 to 2018-2019, a trend that is not looking to change soon (Commodities and Development Report by UNCTAD, 2021). Figure 24 demonstrates how important commodity trade is for selected commodity export dependent countries[27], expressed by the GDP percentage shares of commodity exports for these countries[28]. The pitfalls associated with commodity export dependence have been among the major concerns of recent macroeconomic developments. While the issues related to reliance on commodity export performance are extensive - macroeconomic instability caused by high trade and budget deficits, deteriorating terms of trade over the long-term, uncertain export revenues due to the high volatility of commodity prices - perhaps the most acute and far-reaching issue is the impact of commodity price changes on the stability of exchange rates. As we know, the central banks of emerging and developing countries care greatly about the exchange rate due to it being a central determinant of a nominal anchor in a small open economy. A vital component of the resiliency of economic activity is monetary stability,

[27] UNCTAD defines a country to be commodity export dependent if more than 60% of its total merchandise exports consist of commodities.

[28] It is instructive to compare the values in Figure 1 with that of some non-commodity dependent economies: for Albania this share of GDP attributed to commodity exports is 4.7%, for Turkey - 4.5%, for Germany - 4.4%, for Lebanon - 4%.

which is usually conjoined with at least moderate exchange rate stability in the medium term. Big swings in the exchange rate, big depreciations in particular, can thwart price stability - and can do that in non-linear and even intermittent ways (Carstens, 2019). Understanding the dynamics of the commodity price and exchange rate relationship is critical for commodity exporting emerging economies due to these economies largely being price takers in these markets and thus being directly exposed to that price volatility. To our knowledge we have yet to come across an analysis of downside (depreciation) risk to exchange rates coming from commodity prices, which may have notable policy-related relevance especially seeing that an increasing amount of countries are moving towards a flexible exchange rate. This paper addresses this literature gap.

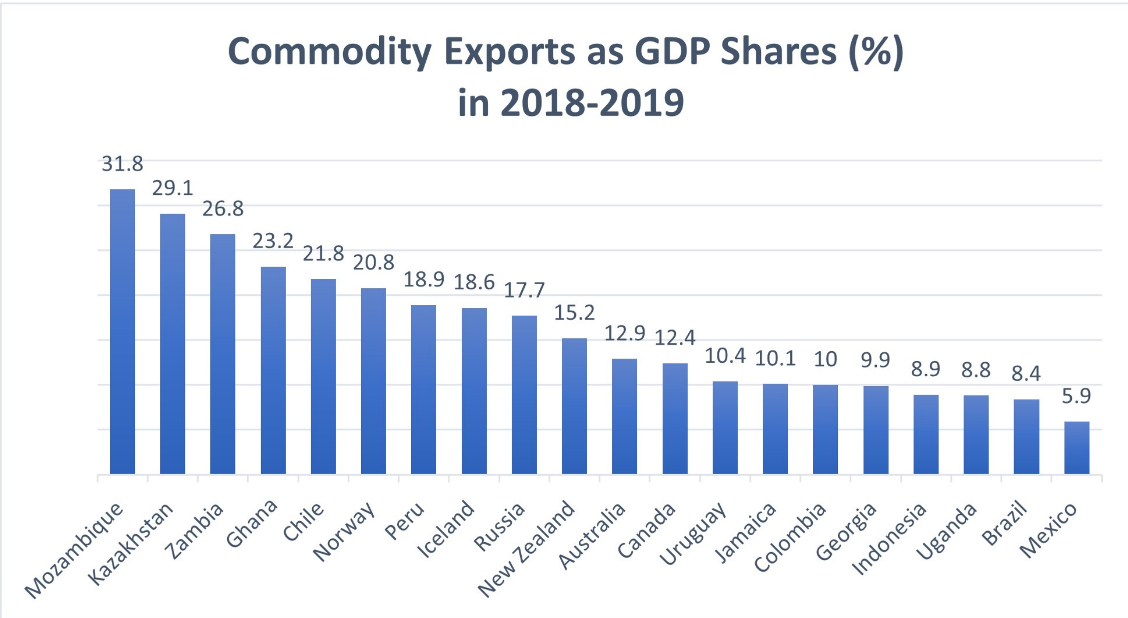


Figure 24: Commodity Dependence, Sample Countries

The central forecast of a macroeconomic variable may not be informative for policymakers as it often does not capture the full story and the nature of downside risk. The nonlinear and tail relationship between commodity prices and exchange rates has been garnering research attention, highlighting the actuality that much of the macroeconomic and financial strain happens during rare or extreme events. For example, Wang and Wu (2012) and Chen et al. (2016) present that oil and currency markets display tail dependence structure, and Reboredo (2012) detects weak association between oil price increases and the USD appreciation. Our research aim is to further examine the nonlinearity in the commodity price - exchange rate relationship and to estimate the tail risk of the impact of commodity price changes on the exchange rate changes. We apply Adrian et al.'s (2019) vulnerable growth approach to carry out our empirical goals. This growth-at-risk approach entails using the quantile regressions to estimate the full conditional distributional behavior and calculating tail risks, or conditional values-at-risk, the expected shortfall and longrise. We are considering commodities beyond oil in our analysis,[29] and our sample's higher-frequency monthly data comes from the World Bank. While oil has remained world's most traded commodity, given the changing environmental policies and the ongoing transition towards a low-carbon future globally, the importance of metals and minerals other than oil has been increasing and projected to grow more over time (World Bank, 2017). Non-oil commodity trade has been expanding[30], and many emerging and developing countries are leading exporters in these markets (see the data section for more information), which has a direct and multifaceted effect on their economies, including the important exchange rate channel.

The major contribution of our work is the evidence of an important connection between commodity prices and exchange rates at higher quantiles, or at the right tail[31]. While the coefficient of this relationship is close to zero around the mean, or in normal times, it becomes noticeably negative or more negative at the right tail[32]. The right tail

[29]We focus on those countries defined by UNCTAD as commodity-dependent in its 2021 State of Commodity Dependence Report and as having floating exchange rate regimes as per IMF's 2020 Annual Report on Exchange Rate Arrangements and Exchange Restrictions. This selection leaves Australia, Brazil, Chile, Colombia, Ghana, Iceland, Indonesia, Jamaica, Kazakhstan, Mozambique, New Zealand, Norway, Peru, Russia, Uganda, Uruguay, and Zambia. Canada and Mexico are not officially commodity-dependent economies as per the UNCTAD definition, but we are including them since they are important exporters of a number of commodities. We also add Georgia, a small transition economy with floating exchange rate regime active in copper trade.

[30]The exports of metals (as an HS Code 92 product group) grew by 41.6% from 2020 to 2021, according to The Observatory of Economic Complexity (OEC), an online data visualization and distribution platform reporting trade data from UNCTAD.

[31]The exchange rate is expressed in local currency per USD terms; hence, a positive change means depreciation, weakening against the USD, and a negative change means appreciation, strengthening against the USD.

[32]During large depreciation episodes which the right tail signifies, changes in commodity prices have a more negative relationship with exchange rates, meaning that a decrease in commodity price will put more pressure on the exchange rate.

implies tension in the currency market, an ongoing currency weakening. Thusly, commodity price changes become impactful when currency markets are under stress. This finding suggests that commodity price changes may be an affiliated indicator of downside risk to exchange rate changes. We also find that during depreciation the lag of the exchange rate coefficient is more positive. This means that depreciation episodes conditional on commodity prices tend to perpetuate more, adding to the downward pressure on the currency; i.e. large depreciation lasts longer feeding into itself. Moreover, we find that this increase in downside risk happens during appreciation episodes as well for some developing sample countries. Additionally, we see that this downside risk relationship does not hold for precious metals and developed countries with higher levels of export diversification. Our next prominent finding is that the tail risk measures show that depreciation episodes exhibit larger maximum values than appreciation episodes, and that during the Great Recession these values peaked for most countries. Importantly, overall the volatility of these risk values increased after the Great Recession, and the magnitude of the depreciation (downside) risk conditional on commodity price changes has broadened for most of the countries in our sample.

Our findings ratify the prominent observation that small open economies that rely on commodity export performance have been exposed to increasingly more risk related to the commodity price swings in the global markets. Currency depreciation, especially prolonged depreciation, is economically undesirable for many reasons, with the heftiest one being the inflationary consequences, and our findings show that commodity price changes may play a contributing role during bigger depreciations. Ensuing policy implications are that the central bankers of commodity-exporting countries should closely monitor the trends in commodity prices, and that they should anticipate larger pressure from commodity price changes during currency weakening episodes and consider revitalizing their policy toolset to better account for this exposure.

The paper is structured as follows: Section 2 gives the literature review, Section 3 talks about the methodology, Section 4 informs about the data, Section 5 cover the empirical results, and Section 6 concludes.

4.2 Literature Review

The long-debated relationship between the exchange rates and commodity prices has been widely researched. The very essential question in this area is the direction of this relationship: which variable influences which, and a bigger portion of existing research has looked at this relationship from the standpoint of exchange rates affecting the commodity prices. As Zhang et al. (2016) explain, ordinary observation and economic rationale based on demand for small open-economy currencies point to the causality going from commodity prices to exchange rates, while the present value model of forward-looking exchanges rates presupposes the opposite direction of causality, and the debate between these two views remains moot. From the policymaking viewpoint it is arguably more helpful to look at this relationship from the opposite direction, how commodity prices impact exchange rates, and recent research interest has been turning in this direction. The role of commodity prices in finessing exchange rate predictability has increased in the past decades (Rossi, 2013). One of the findings of our previous chapter indicates that oil prices are on average net transmitters of shocks to currencies in our sample of 9 developing countries and the Euro. In a similar vein, Albulescu et al. (2019)'s work shows that oil price is a net giver of shocks to 6 currencies of commodity exporters, with more impact happening short-term, or at higher time frequency. Kohlscheen et al. (2017) find that even at high frequency commodity prices predict exchange rate movements of commodity exporters up to two months ahead. The authors also show that simple linear predictive models with country-specific commodity export price indexes as predictors edge out random-walk benchmarks in out-of-sample estimations.

Chen and Rogoff's (2003) influential paper proposes commodity prices to be a possible new macroeconomic fundamental explaining exchange rates, especially the so-called commodity currencies. In their work, Zhang et al. (2016) examine the causal relationships of four emblematic commodity currencies - Australia, Canada, Chile, and Norway - and their dominating exporting commodities - gold, copper, and crude oil - using high-frequency data and multiple horizons. Their results indicate that unconditional and conditional (on equity prices) causality stemming from commodity prices to exchange rates is stronger than causality in the opposing direction for multiple horizons. Zhang et al. (2016) also find that causality is stronger at short horizons and weakens with the length of the horizons. Thus, they offer convincing evidence in support of the macroeconomic-based setup in the commodity price - exchange rate dynamics.

A recent work by Liu et al. (2020) provides more evidence in favor of the validity of the ability of commodity prices to predict exchange rates. The authors drew a factor from prices of 17 common commodities including crude oil and demonstrated that the average commodity returns can competently predict the level and excess returns to Australian, Canadian, New Zealand's, and South African currencies both in-sample and out-of-sample. Liu et al. (2020) determine that the predictability of excess currency returns is economically significant as well. They offer relevant policy implication for investors: agents with mean-variance preferences who make their wealth allocation decision between domestic and foreign bonds can enhance their portfolio performance by using commodity forecasts of currency returns rather than historical average forecasts. Liu et al. (2020) also mention that nonlinearity in the joint dynamics of commodity prices and exchange rates is worth closer consideration.

Ferraro et al. (2015) consider Canadian, Australian, Norwegian, South African, and Chilean currencies and crude oil, gold, and copper prices and estimate that commodity prices exhibit solid predictive ability for currencies at daily frequencies. They find that this predictive strength fades at lower frequencies. Ferraro et al. (2015) also discover that using contemporaneous rather than lagged commodity prices maintains the robustness of the predictive relationship. As authors expound, their work suggests that the exchange rates of small open commodity exporting economies echo movements in commodity prices, and that these movements are immediately reflected in exchange rates without necessarily foreboding future changes, bearing in mind that commodity prices have a significant unit root constituent. Thus, the predictive ability is transitory and the relationship is short-lived so that high-frequency data is imperative in capturing it. This paper provides a convincing corrective explanation to the well-known preceding work by Chen et al.

(2010), which uses low-frequency quarterly data and finds less robustness in the predictive relationship of commodity prices to exchange rates. It is worth noting that Chen et al. (2010) take up the forward-looking view of the exchange rates which makes them less likely to reflect commodity price fluctuations, which are generally more responsive to short-term demand gaps.

4.3 Methodology

Our empirical approach is based on Adrian et al. (2019). Adrian et al.'s (2019) work is a flagship of growth-at-risk, or vulnerable growth, literature. This literature was built around the Value-at-Risk concept that was developed by banks in the early 1990s after the stock market crash of 1987 to improve bank risk management. The gist of the vulnerable growth approach is the ability of financial conditions to predict the left (negative) tail of the GDP growth distribution, which represent the calamitous macroeconomic health scenarios (Chulia et al., 2021). In the post-Great Recession macroeconomic climate, the central bankers' notion as risk managers has resurged, and many of them have considered downside risk measures incorporating distribution of risk around modal (rather than median) forecasts (Delle Monache et al., 2021). International regulators have taken well to this approach, and assessing the lowest quantiles of GDP distribution predicted by financial conditions one or several quarters ahead has become a common practice. Adrian's et al. (2019) work is quentessential in this strand of the literature as it presents a viable methodology for assessing downside risk via predictions of lower quantiles of the conditional distribution of real output growth. Adrian et al.'s (2019) main finding - the negative correlation between financial conditions and lower quantiles of the distribution of future real economic growth - proposes that financial conditions could be a related signal of downside risk to real economy (Monache et al., 2021)[33].

[33] An example of an application of Adrian et al.'s (2019) approach is Lang and Forletta (2019)'s work that appraises future downside risks to return-on-assets distributions as represented by the estimated lower 5th quantiles of their model. This bank capital-at-risk tool offers macroprudential managers a way to appraise the additional amount of bank resilience called-for in case macrofinancial imbalances unravel and systemic risk realizes. Similarly, Elekdag et al. (2020) build on Adrian et al.'s (2019) growth-at-risk technique to analyze determinants of profitability of large euro area banks by focusing

Our goal is to examine the nonlinearity and tail behavior of the impact of commodity price changes on the exchange rates fluctuations. Adrian et al.'s (2019) widely cited methodology of applying quantile regressions to forecasting and subsequently extrapolating conditional distributions based on these regressions fits our agenda well.

Our empirical approach can be divided into three steps. First, we estimate the quantile regressions (the forecasting exercise). The coefficients that we get from these regressions constitute our main findings. Secondly, we use the estimated quantile regressions from the first step to estimate the full conditional distributions by using the skewed t-distributions. In particular, the quantile regressions produce approximations of empirical conditional quantile functions. We transform the empirical conditional quantile functions into a density function, an estimated conditional distribution, by fitting a parametric inverse CDF function with a known density function - the skewed t-distribution - to these quantile functions[34]. Thirdly, we measure the downside and upside risks, i.e. how vulnerable the predicted exchange rate changes' path is to unexpected (positive and negative) shocks conditional on commodity price changes. These risks are estimated as expected shortfall and longrise values, which are the total probability mass owing to the right and left tails of the conditional distribution attained in the second step.

The equations below are due to Adrian et al. (2019)[35].

First step - Quantile regressions:

Let y_{t+h} be the change in exchange rate from t to $t+h$, and x_t be the vector of conditioning variables (a constant, commodity price change, and lag of the exchange rate change). In a quantile regression of y_{t+1} on x_t the regression slope β_t is the one that

on bank profitability distributions. Another example of Adrian et al's (2019) approach is Figueres and Jarocinski (2020)'s paper, which evaluates how different measures of financial conditions in euro area forecast future output growth and downside risks.

[34] As Adrian et al. (2019) explain, mapping of the estimated quantile functions into a probability distribution function is complex due to the approximation error and estimation noise. The authors substantiate their straightforward method by virtue of it making fewer parametric assumptions and being computationally much less burdensome. The authors confirm the robustness of their methodology by evaluating two alternative econometric approaches to getting the estimated conditional distribution. See Section III in Adrian et al. (2019) for details.

[35] Our empirical approach implementation is based upon Len Kiefer's adaptation of the Adrian et al.'s (2019) work as described in his personal blogpost: http://lenkiefer.com/2018/12/12/vulnerable-housing/.

minimizes the quantile weighted absolute value of errors:

$$(1)\ \hat{\beta}_\tau \underset{\beta_\tau \in \mathbb{R}^k}{\operatorname{argmin}} \sum_{t=1}^{T-h} \left(\tau \cdot \mathbf{1}_{(y_{t+h} \geq x_t\beta)} |y_{t+h} - x_t\beta_\tau| + (1-\tau) \cdot \mathbf{1}_{(y_{t+h} < x_t\beta)} |y_{t+h} - x_t\beta_\tau|\right),$$

where $\mathbf{1}_{(\cdot)}$ is the indicator function. The predicted value from the regression is the quantile of y_{t+h} conditional on x_t,

$$(2)\ \hat{Q}_{y_{t+h}|x_t}(\tau|x_t) = x_t\hat{\beta}_\tau.$$

<u>Second step - Conditional distributions:</u>

Upon estimating the quantile regressions, we use the resulting coefficients to fit conditional distributions, the skewed t-distributions. The skewed t-distribution, a part of a general class of mixed distributions, was established by Azzalini and Capitanio (2003) to smooth the quantile function and to retrieve a probability density function:

$$(3)\ f(y;\mu,\sigma,\alpha,\nu) = \frac{2}{\sigma} t(\frac{y-\mu}{\sigma};\nu)\, T\left(\alpha\, \frac{y-\mu}{\sigma} \sqrt{\frac{\nu+1}{\nu + (\frac{y-\mu}{\sigma})^2}};\ \nu+1\right),$$

where $t(\cdot)$ and $T(\cdot)$ respectively stand for the PDF and the CDF of the student t-distribution; μ is is the location, σ is the scale, α is the shape, and ν is the fatness of the distribution.

Subsequently, we choose the four parameters of the skewed t-distribution f, $\{\mu_t, \sigma_t, \alpha_t, \nu_t\}$, to minimize the distance between our estimated quantile function $Q_{y_{t+h}|x_t}(\tau)$ from (2) and the quantile function of the skewed t-distribution $F^{-1}(\tau;\mu,\sigma,\alpha,\nu)$ from (3) to match the 5, 25, 75, and 95 percent quantiles:

$$(4)\ \{\hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\nu}_{t+h}\} = \underset{\mu,\sigma,\alpha,\nu}{\operatorname{argmin}} \sum_{\tau} \left(\hat{Q}_{y_{t+h}|x_t}(\tau|x_t) - F^{-1}(\tau;\mu,\sigma,\alpha,\nu)\right)^2,$$

where $\hat{\mu}_{t+h} \in \mathbb{R}$, $\hat{\sigma}_{t+h} \in \mathbb{R}^+$, $\hat{\alpha}_{t+h} \in \mathbb{R}$, and $\hat{\nu}_{t+h} \in \mathbb{Z}^+$.

<u>Third step - Tail risk calculations:</u>

To describe downside and upside risks to exchange rate changes, we calculate the expected shortfall and expected longrise using the fitted skewed t-distributions from the previous step. Note that in our case depreciations/devaluations happen at the upper tail of the exchange rate changes distribution (a positive change in the exchange rate, an increase, means that the currency is weakening against the USD). Thus, the expected longrise is the measure of the downside risk in our case. These calculations summarize the tail behavior of the conditional distribution in absolute terms:

For a chosen target probability π:

$$(5)\ SF_{t+h} = \frac{1}{\pi}\int_{0}^{\pi} \hat{F}^{-1}_{y_{t+h}|x_t}(\tau|x_t)\,d\tau; \qquad LR_{t+h} = \frac{1}{\pi}\int_{1-\pi}^{1} \hat{F}^{-1}_{y_{t+h}|x_t}(\tau|x_t)\,d\tau$$

4.4 Data

The considered commodities in our sample include aluminum, coffee (arabica), copper, crude oil, gold, iron ore, lead, palm oil, platinum, sheep meat, tin, and zinc. We chose the commodities based on data availability and their relevance for the sample countries' economies.

The monthly commodity price and (nominal) exchange rate data comes from the World Bank[36]. All variables are first-differenced to make the data stationary and suitable for our forecasting exercises. The following table gives us the relevant information about the sample data.

[36]The sample periods are different for each country, depending on the timing of the implementation of a (consistent) flexible exchange rate regime. We aimed to have at least ten years worth of data for each country.

Country	Currency	Commodity	Sample Period	Observations (per variable)
Australia	Australian dollar	gold and iron	January 1974 - March 2022	579
Brazil	Brazilian real	iron and soybeans	January 1994 - March 2022	339
Canada	Canadian dollar	oil	January 1979 - March 2022	519
Chile	Chilean peso	copper	January 1988 - March 2022	411
Georgia	lari	copper	December 1995 - December 2021	313
Colombia	Colombian peso	coffee (arabica) and oil	January 1988 - March 2022	411
Ghana	cedi	gold and oil	January 1999 - October 2021	274
Iceland	Icelandic krona	aluminum	January 1981 - March 2022	495
Indonesia	Indonesian rupiah	palm oil and tin	January 1994 - March 2022	339
Jamaica	Jamaican dollar	aluminum	January 1987 - August 2021	416
Kazakhstan	tenge	oil	January 1997 - December 2021	300
Mozambique	metical	aluminum	January 1991 - October 2021	370
New Zealand	New Zealand dollar	sheep meat	January 1974 - March 2018	531
Norway	Norwegian krone	oil	January 1977 - March 2022	543
Russia	ruble	gold and oil	August 1992 - March 2022	356
Mexico	Mexican peso	lead	January 1989 - March 2022	399
Peru	sol	zinc	January 1990 - March 2022	387
South Africa	rand	gold and platinum	January 1982 - March 2022	483
Uganda	Ugandan shilling	gold	December 1992 - December 2021	388
Uruguay	Uruguayan peso	soybeans	January 1990 - March 2022	387
Zambia	kwacha	copper	January 1992 - October 2021	358

Table 13: Sample Data

Selected Commodities and Major Exporters

This section gives us brief information about the considered countries and commodity markets. The countries in our sample are either principle worldwide exporters of a given commodity, or a given commodity is important for the countries' export baskets, or both. As we see, commodities apart from oil have considerable global economic importance, and the countries considered in our sample are active or prominent global exporters of these commodities[37]. Information below is from The Observatory of Economic Complexity (OEC), an online data visualization and distribution platform reporting trade data from UNCTAD. Values are as of 2020.

- Aluminum (Iceland, Jamaica)

  Raw aluminium was 67th most traded product in the world, while aluminium oxide was 249th and aluminium ore was 453rd. Raw aluminium was Iceland's most important export item (33.5% of the total exports). Iceland belongs to the top-10 exporters of raw aluminium. This market is more evenly distributed among exporting countries.

  Jamaica is in the top-10 biggest exporters list for aluminium ore, and aluminium ore was Jamaica's 3rd-largest export item in its basket (6.7%). Jamaica is in the top-10 biggest exporters list for aluminium oxide, and aluminium oxide was Jamaica's largest export item in its basket (37.8%).

- Coffee (Brazil, Colombia)

  Coffee was the world's 112th most traded product. Brazil was its top world exporter (16.5% of total exports), and Colombia - 4th (8.25%). For Brazil, coffee was its 6th most important export product, and for Colombia - 3rd.

- Copper (Chile, Zambia, Georgia)

  Copper ore was in the 44th place of the world's most traded products, while raw copper was in the 232nd place. Chile (34.6%) and Peru (14.9%) prevailed as world's

[37]As mentioned previously, aside from the economic importance for the country's economy, another factor in our sample selection was data availability.

top exporters of copper ore, while Zambia (40.1%) and Chile (13.1%) were top-2 raw copper exporters in the world.

Raw copper was the largest item in Zambia's export basket (52.6%). Copper ore was also Georgia's largest export taking up 21.1% of its export basket.

- Crude oil (Russia, Kazakhstan, Ghana)

  Crude oil/petroleum was the world's 3rd most traded product. Russia was the world's second-biggest exporter having exported 11.6% world exports after Saudia Arabia who was first with 15%. Crude oil was Russia's largest export taking up 22.5% of its export basket.

  Kazakhstan belongs to the world's top-10 crude oil exporters. Crude oil was Kazakhstan's largest export accounting for 49.6% of its export basket.

  Ghana is not a relatively significant oil exporter on the world arena; however, crude petroleum was Ghana's second-largest export product with 20.6% of its export basket after gold.

- Gold (Australia, Ghana, Russia, Uganda)

  Gold was the world's 6th most traded product. This market is spread among many exporters from each major region. Switzerland was the largest exporter with 16.2% of the market, followed by Hong Kong with 7.8%, UAE with 6.8%, Russia with 4.4%, and Australia with 4.2%. For Australia and Russia, gold was the 4th most important export product in their export baskets.

  South Africa provided 3.1% of world's gold exports (largest African exporter of gold), and gold was its biggest export (12.8% of its basket). Ghana accounted for 1.4% of world's exports, and gold dominated its export basket (45.1%). Uganda is not amongst the world's largest gold exporters, but gold exports took up 55.9% of its total export basket.

- Iron ore (Australia, Brazil)

Iron ore was in the 13th spot of the world's most traded products. This market is heavily dominated by Australia, who supplied 56% of world exports. Iron ore was the biggest export in Australia's export basket (31.8%).

- Lead (Mexico)

  Lead (ore) was 419th most traded product worldwide. This market is led by Mexico who was responsible for 27.4% of world exports. In Mexico's export basket lead was not in its top-5 but it was its 3rd most-exported mineral commodity product behind crude oil and copper ore.

- Palm oil (Indonesia)

  Palm oil placed 104th on the list of the world's most traded products. Indonesia and Malaysia prevailed as this product's lead exporters with 52.4% and 31.1% of the world exports. It was the biggest product in its domestic export basket.

- Platinum (Russia, South Africa)

  Platinum ranked as 43rd most traded product in the world. South Africa (18.8%) and Russia (16.6%) lead global platinum export market. Platinum was South Africa's 2nd biggest export and Russia's 6th largest export.

- Sheep meat (New Zealand)

  Sheep (and goat) meat were listed as 381st most traded product worldwide. Australia (36.4%) and New Zealand (34.6%) dominate this export market. Sheep (and goat) meat was 2nd most exported product in New Zealand's export basket.

- Soybeans (Brazil, Uruguay)

  Soybeans held the 42nd spot of the world's most traded products. This market is largerly led by Brazil, who accounted for 44.7% of world exports. Soybeans topped Brazil's export basket list (13.4%).

  Uruguay was in top-10 global soybeans exporters, and in domestic export basket soybeans were in 5th spot with 4.8% of total exports.

- Tin (Indonesia)

  (Raw) tin positioned as the world's 557th most traded product. Indonesia was by far the world's largest exporter of this product (34.1%), succeeded by Malaysia (10.1%) and Peru (10%). Tin wasn't among Indonesia's biggest exports within its relatively well-diversified basket but was its 4th largest export product from the metals category.

- Zinc (Peru)

  Zinc (ore) was 369th most traded product worldwide. Peru was the world's second-biggest exporter responsible for 12.8% of world exports behind Australia who was first with 17.4%. In Peru's export basket zinc ore was not in top-5 but it was its 4th most-exported mineral commodity product after copper ore, petroleum gas, and iron ore.

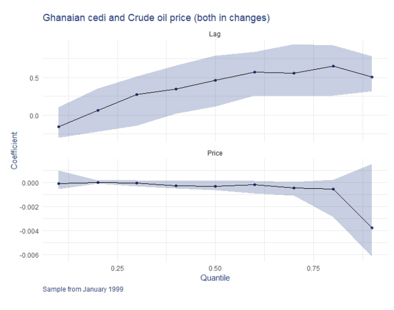
4.5 Empirical Results

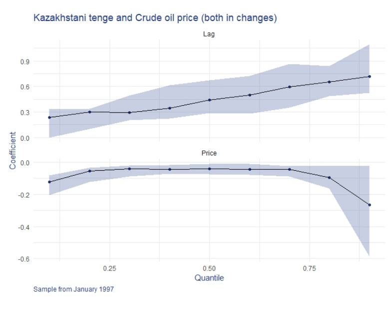
As mentioned in the methodology section, the coefficients associated with the quantile regressions from the first empirical estimation step offer the main finding of our work. The first (autoregression) coefficient represents the impact of the lag of exchange rate changes on the (current) exchange rate changes. The second coefficient represents the effect of the commodity price changes on the exchange rate changes, the key relationship of interest. Section 5.1 presents the plots of these coefficients (by deciles), with the lag coefficient on the top row and the commodity price change coefficient on the bottom row. Section 5.2 displays the results from the third estimation step, the downside and upside risk calculations. These calculations are done by estimating expected shortfall and longrise and are highly informative. The results from the second step are offered in the Appendix C.

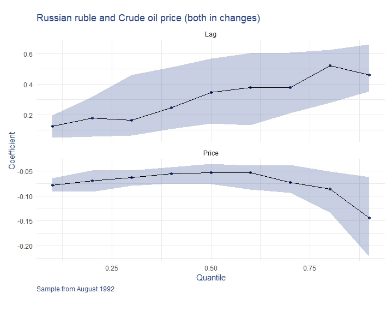
4.5.1 Main Finding: Increase of the Downside Risk during Depreciation Episodes

Our main finding - the existence of asymmetry in the impact of commodity prices on exchange rates at higher quantiles - is illustrated in the graphs below. The relationship exhibits two features, which pertain to the abovementioned two coefficients from the quantile regressions. Firstly, at higher quantiles of changes in exchange rates (or at the right tail) - meaning during large depreciations - the lag (AR) coefficient is more positive, implying more persistence of the lag. This means that larger depreciations last longer. Then, the second coefficient representing the effect of commodity price changes on exchange rate changes is more negative at the right tail. This implies that during large depreciations a decrease in commodity prices is associated with more depreciation.

The examined economies are tightly bound with the movements in the considered commodity markets either through being important global exporters of the commodity or through this commodity taking up a big share of their exports baskets, or both, as is the case with Australia and Brazil. The currencies of these countries are more responsive to the price movements of the considered commodities at the higher quantiles, signifying that this exposure is stronger when these currencies are already depreciating, reinforcing the currency weakening dynamics.

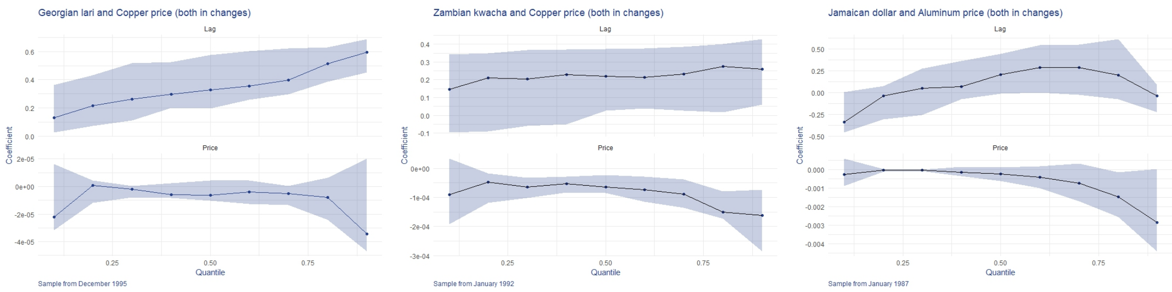






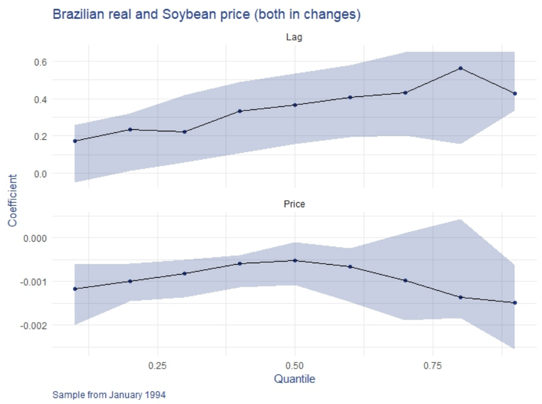
We see from the graphs above that crude oil examplifies the clearest and most distinct case of this remarkable pattern for its emerging economy exporters. For all three exporting countries - Ghana, Kazakhstan, and Russia - crude oil is either the largest or second largest product in their export baskets. These countries have relatively low levels of export diversification, so their dependence on their crude oil exports cannot be understated[38].

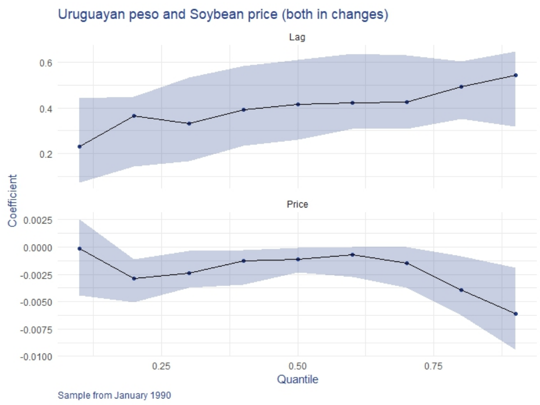
This relationship is quite strong for the group of countries above as well, which are all major players in the respective commodity markets. Australia is actively involved in a variety of commodity trade with iron ore being its largest export product overall. Australia also is the largest exporter of iron ore worldwide. For a developed economy, Australia has a remarkably low economic complexity ranking, underlining its reliance on commodity trade. Although lead is not Mexico's top export, Mexico is the largest lead exporter on the global arena. Similarly, zinc is not Peru's main export product but Peru is the second-largest zinc exporter internationally.



The feature is quite apparent for Zambia and Georgia and copper prices, too. While these two countries are relatively modest exporters on the global scale, copper-related commodities dominate the export baskets for these two small economies. The evidence for Jamaica is alike: Jamaica is a rather small exporter of aluminum-related commodities on the global scale, yet these commodities take up a bigger portion of its export basket.

[38] As mentioned before, in our sample we have the economies that follow floating exchange rate regimes so that there is enough variation in the exchange rate to perform the analysis. Thus, countries such as Saudi Arabia that have a fixed exchange rate regime are not included in this work.

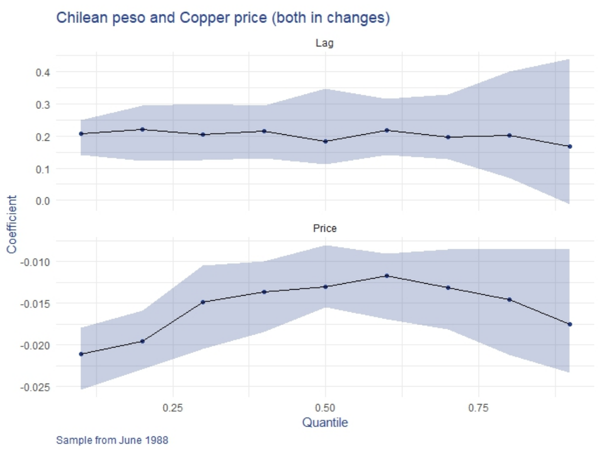


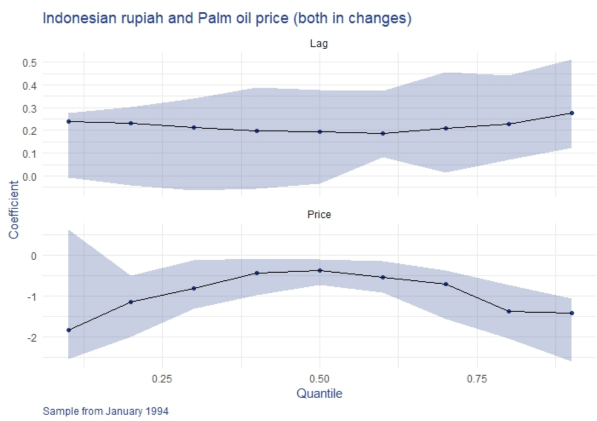


The relationship holds for Brazil and Uruguay with regard to soybean prices. Brazil is a juggernaut in the soybean market, accounting for almost half of world's exports in 2020. While soybeans' rank in Uruguay export basket is relatively lower and the country is not a major global exporter in this market, given how large the global soybean trade volume is, being one of the prominent international players in this market is economically influential for the country and is worth considering in our context.

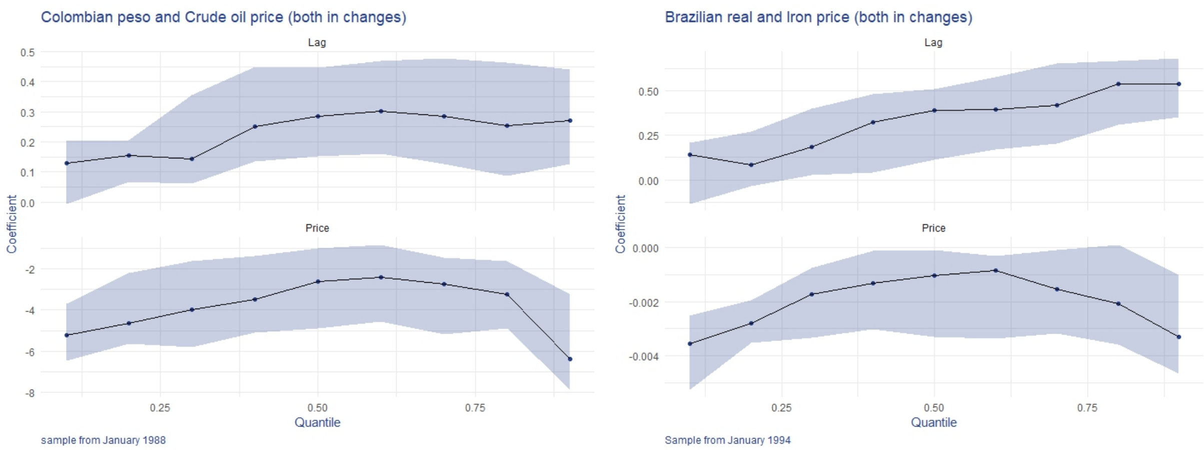
Increase of the Downside Risk during both Depreciation and Appreciation Episodes

Here we see that for a number of countries and commodities the relationship between commodity price changes and exchange rate changes is symmetric - the coefficient becomes negative (or more negative) at both lower and higher quantiles, i.e. during both appreciation and depreciation episodes. This conveys that these economies are more sensitive to commodity price movements at both tails, when there is already either a positive and negative pressure on the currency taking place.

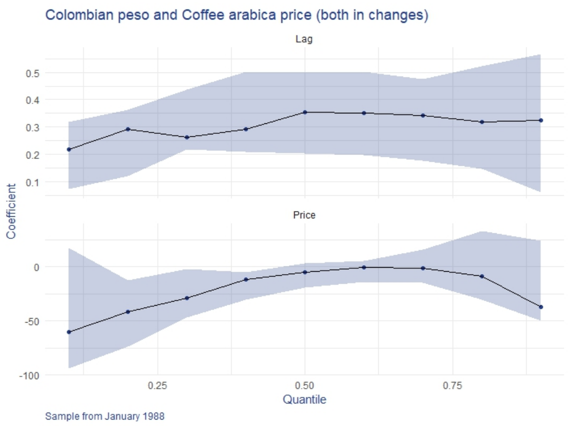


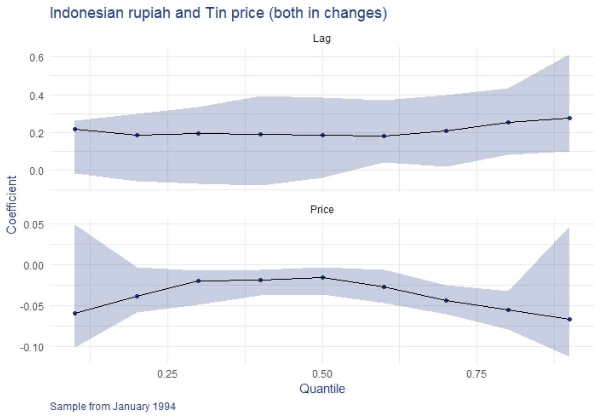


Chile is the largest player in the copper-related commodity market, heading the global top exporter list for copper ore and refined copper markets. Copper-related commodities trade is vital for Chile's economy, accounting for about a half of its export basket. Copper-related commodities global trade volume is immense, so being a leading exporter on this market can be directly connected to the exchange rate being more sensitive to the price changes at both appreciation and depreciation quantiles. Palm oil trade is valuable for Indonesian economy: it dominated the corresponding global market accounting for 52.4% of the world exports, and palm oil held the first place in Indonesia's export basket. Palm oil global trade volume is quite sizable, and heavily dominating this market can help understand the mechanism of this relationship.



For Colombia crude oil is its biggest export item (23.2% of the total basket). Colombia has a relatively small exporter presence in global crude oil market but it is the second-largest Latin American exporter of this commodity. Crude oil global trade volume is one of the largest among all products, and being involved in this trade - even if not being a major player - can expose economy to a lot of related macroeconomic movement and thus can induce this relationship. Iron ore trade is important for Brazil's economy: iron ore was the second-largest product in Brazil's export basket. Brazil is also the second-largest world exporter of this commodity. Like copper-related commodity trade, iron ore's global trade scale is colossal, and being one of the largest exporters in such a market may be driving this relationship.

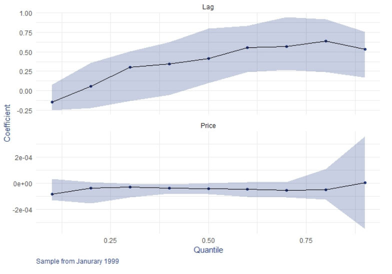


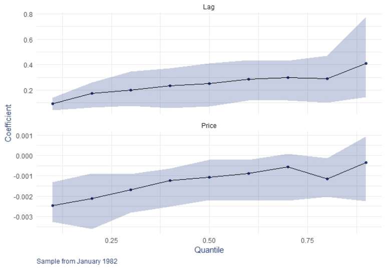


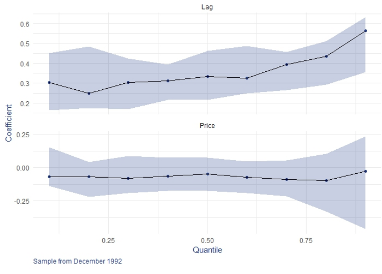
Colombia is a prominent world exporter of coffee, belonging to the top-5 exporter list. Coffee trade has a notable fourth place in its export basket. Although Colombia is not a main exporter of this commodity, global coffee trade scale is substantial, so fluctuations in this market can have a macroeconomic impact that we see here. Given Indonesia's relatively decent economic complexity standing, (raw) tin had a relatively moderate place in its export basket. Yet, Indonesia led the global top tin exporter list, providing 34.1% of the world's exports in this market. Although tin global trade volume is relatively humble, towering above other exporters in this convincing manner can help explain this feature.

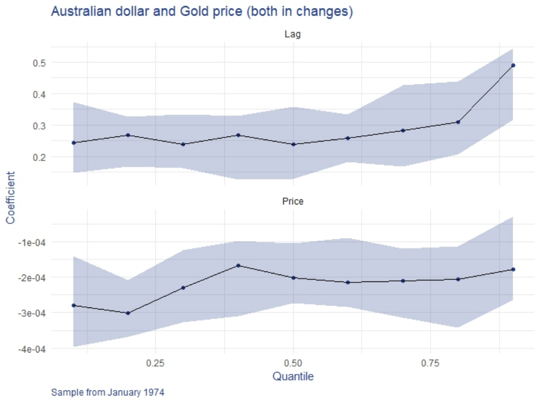
Mostly Flat Relationship for Precious Metals

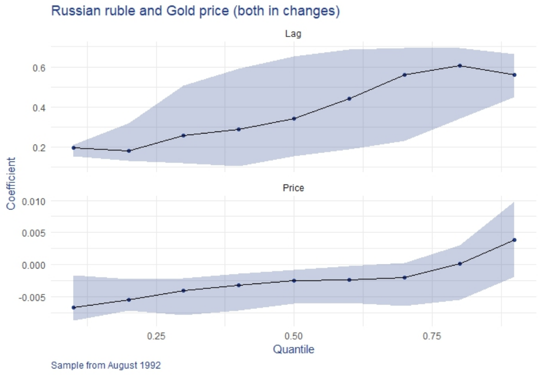
It is quite unlikely to be a coincidence that gold and platinum, the precious metals, do not exhibit the relationship we observe for other commodities for the major gold and platinum exporters. Precious metals are considered to be largely discongruent with the prevailing cycles of other commodities.

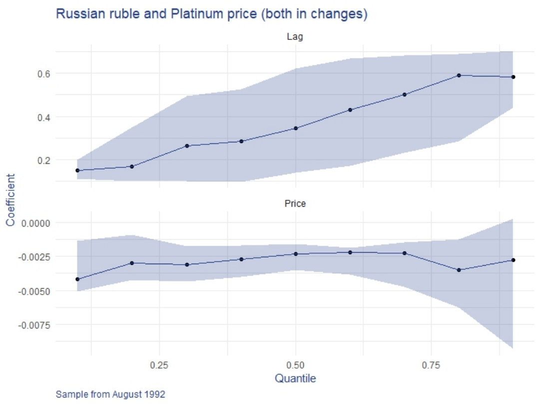


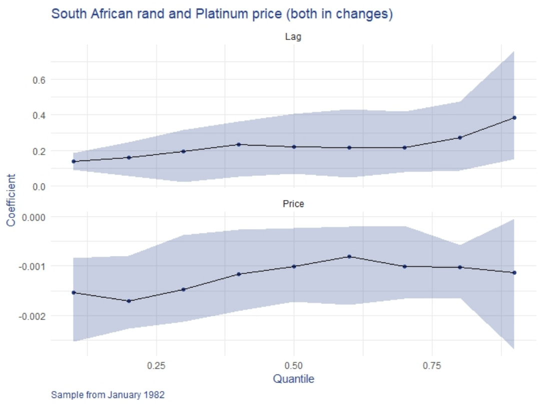




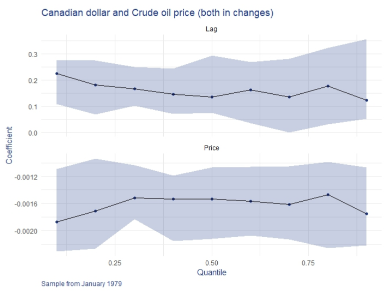


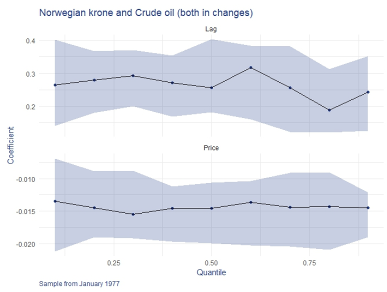


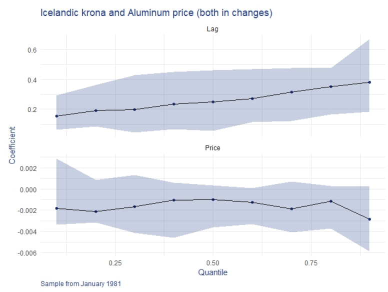




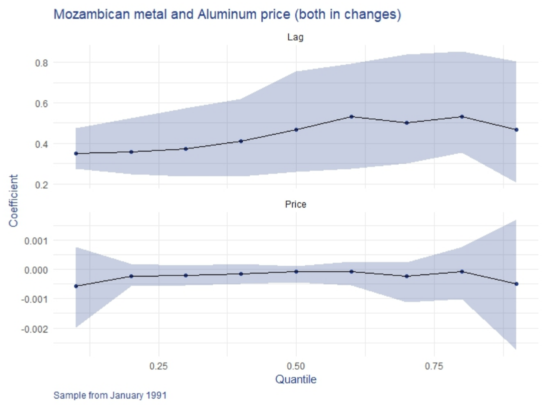
No asymmetry

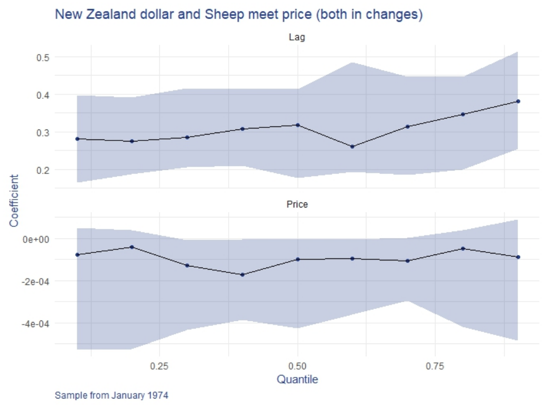






Canada and Norway are both quite prominent exporters on the global crude oil market. Although crude oil tops the export basket list for both of these economies, their export baskets are relatively well-diversified as compared to developing economies. Moreover, their overall macroeconomic positioning has been more stable, with more apt macroeconomic policy tools at work. Iceland is a relatively minor exporter of aluminum-related commodities on the global scale, but this commodity reigns its export basket. Similar to Canada and Norway, Iceland has decent export diversification and an overall sound macroeconomic credibility.





While aluminium-related commodity exports are central to Mozambique's export basket, this country is a negligible player on the global arena in this market. Conversely, although New Zealand is second-largest sheep (and goat) meat exporter worldwide, due to New Zealand's well-diversified export basket, this commodity trade is not consequential for its economy. Also, global sheep meet trade scale is relatively small.

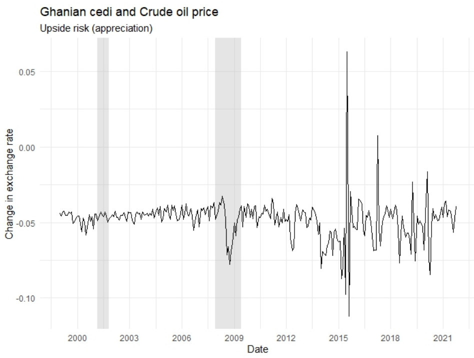
4.5.2 Tail Risk Calculations

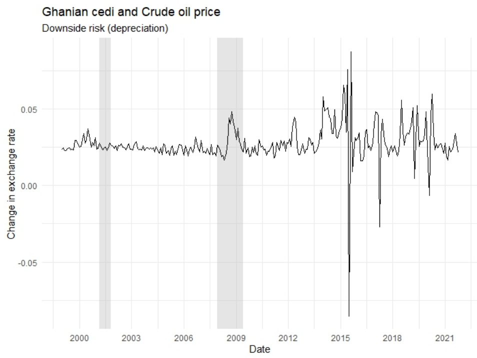
The graphs below display the time evolution of the calculated tail risk measures of expected shortfall and longrise. Once we get the coefficients from the quantile regressions and use them to fit the skewed t-distributions, we then utilize these estimated conditional distributions to calculate the size of the exchange rate change at risk[39]. Here depreciations/devaluations happen at the upper (right) tail of the exchange rate changes distributions since a positive change in the exchange rate indicates that the currency is weakening against the USD. Thusly, the expected longrise is the measure of the downside risk in our case. On the other hand, the upside risk involves a big appreciation, which happens at the left tail of the conditional distribution in our exercise. The expected shortfall is the gauge of the upside risk here. In the graphs

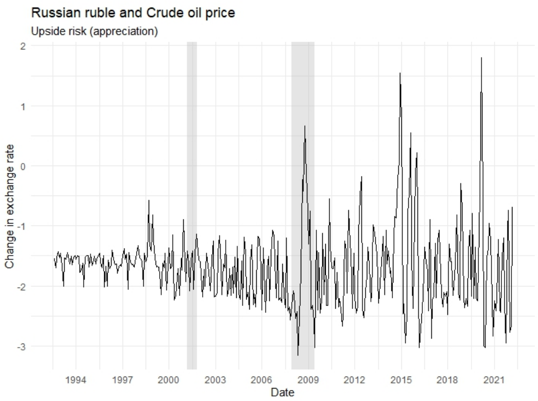
[39] Note that these calculations were performed for the combinations of countries and commodities whose relationship exhibited the main finding feature from 5.1, except for Kazakhstan, which does not have enough variation in the appreciating direction for the upside risk calculation.

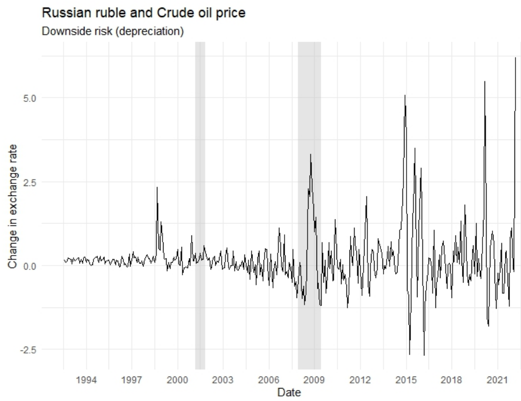
below we have the upside risk on the left and the downside risk on the right for a given country.

Ghana and Russia (crude oil)









We see from the graphs above that for both oil-exporting countries, Ghana and Russia, the tail risk measures were impacted by the Great Recession, the collapse of commodity boom cycle in mid-2014, and the pandemic. For both countries the volatility and the range of these risk measures increased post-Great Recession. There is a small difference between the two countries, however. As we see from Table 14, the importance of oil exports for Ghana increased over time, in particular there has been a big jump from 2015 to 2020. Meanwhile, the relative size of oil exports in Russia's economy has been roughly the same and even lessened over the past decade. We can see this reflected in Russia's downside risk being relatively less effected after mid-2014 as compared to Ghana. On the other hand, Ghana's upside risk looks to have improved more than Russia's. As a globally larger oil exporter, Russia's risk measures were more troubled by the pandemic than Ghana's.

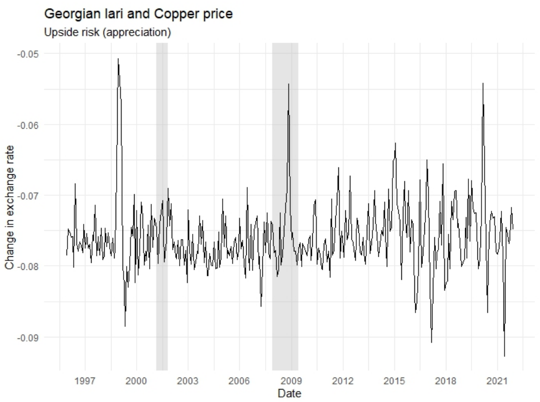
Year	%-age of Country Export Basket	%-age of World Exports
2000	< 0.1	< 0.1
2005	0.64	< 0.1
2010	< 0.1	< 0.1
2015	12.6	0.24
2020	20.5	0.42

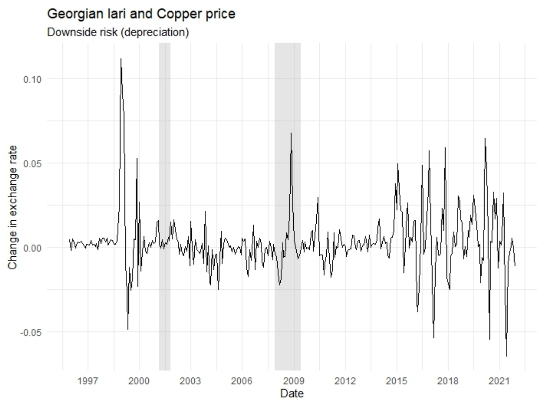
Table 14: Ghana and crude oil exports

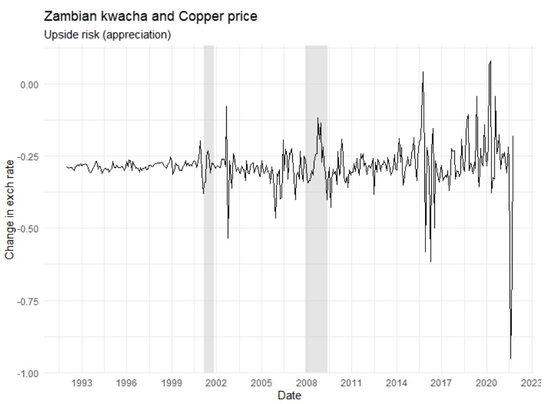
Year	%-age of Country Export Basket	%-age of World Exports
2000	23.2	7.19
2005	36.8	11.6
2010	35.7	11.7
2015	27.2	11.9
2020	22.5	11.5

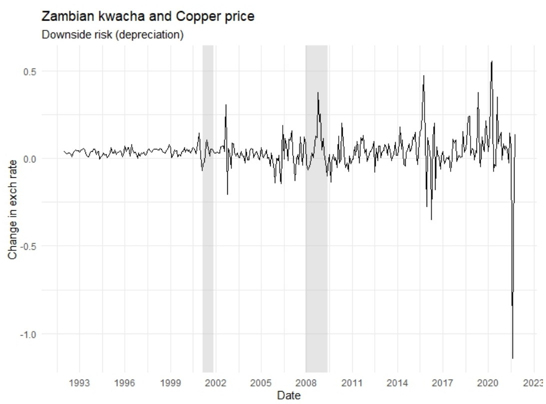
Table 15: Russia and crude oil exports

Georgia and Zambia (copper)









The graphs above demonstrate that the tail risk measures peaked for both copper-exporting economies, Georgia and Zambia, during the Great Recession, the crash of this commodity's boom cycle in late 2015, and the pandemic. We note that the volatility of the tail risk measures increased after 2015. The importance of copper-related exports has grown for both countries, as evidenced in Tables 16 and 17. Yet we do not see any noticeable improvement in the upside risk for either of these countries.

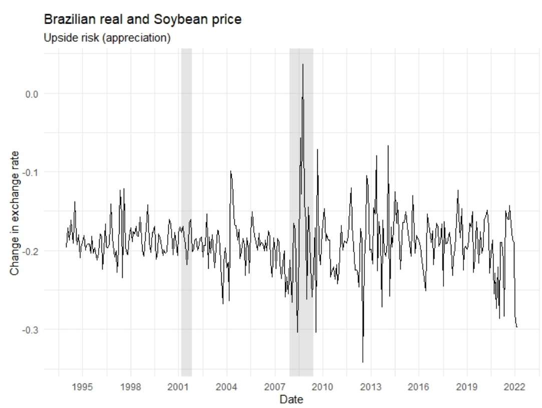
Year	%-age of Country Export Basket	%-age of World Exports
2000	2.67	0.25
2005	2.85	0.22
2010	3	0.16
2015	9.81	0.59
2020	21.2	1.35

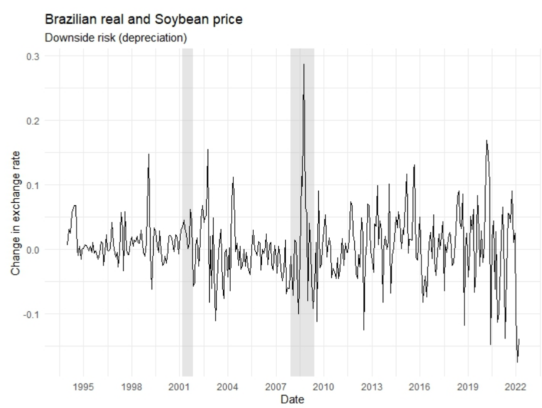
Table 16: Georgia and copper ore exports

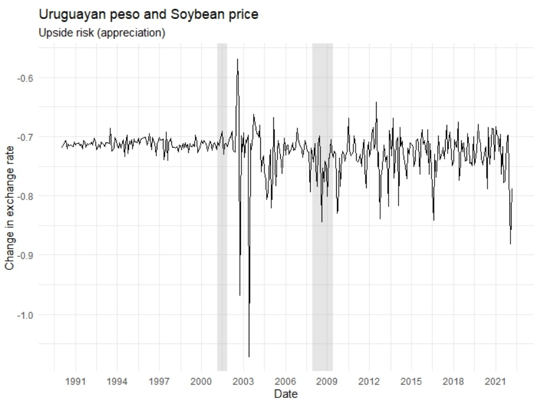
Year	%-age of Country Export Basket	%-age of World Exports
2000	1.33	0.92
2005	0.48	0.35
2010	14.6	17.3
2015	18.3	27.1
2020	52.3	39.7

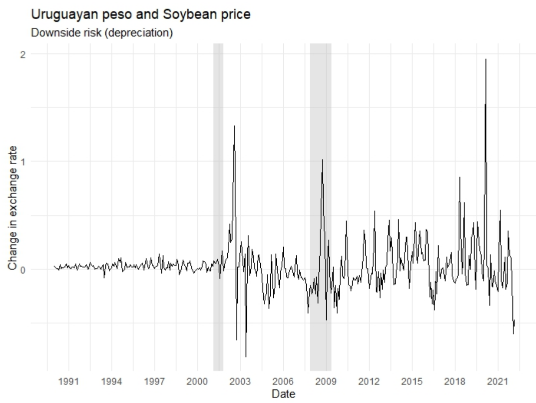
Table 17: Zambia and raw copper exports

Brazil and Uruguay (soybeans)









Upon looking at the above graphs, we notice that for the soybeans-exporting Brazil and Uruguay the Great Recessions and - to a lesser degree - the soybeans price drop in late-2014 and the pandemic disturbed the tail risk values. The volatility of these values increased after the Great Recession. Interestingly, the price boom cycle bust in 2014-2015 did not affect these values as much as we witnessed with the previous two commodities. As Tables 18 and 19 point out, Brazil's presence in the soybean market has significantly increased over time, while Uruguay's presence was expanding till 2015 and slowed down afterwards. We can see this reflected in Brazil's downside risk worsening after 2015 more than Uruguay's.

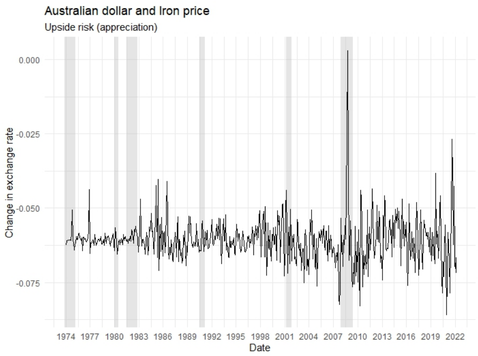
Year	%-age of Country Export Basket	%-age of World Exports
2000	3.75	33
2005	4.56	34.3
2010	5.36	27.8
2015	10.8	40.8
2020	13.3	44.8

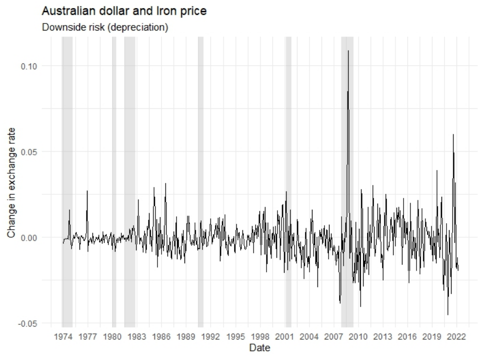
Table 18: Brazil and soybeans exports

Year	%-age of Country Export Basket	%-age of World Exports
2000	0.19	0.054
2005	2.03	0.51
2010	3.5	0.63
2015	5.42	0.86
2020	4.73	0.57

Table 19: Uruguay and soybeans exports

Australia (iron ore)



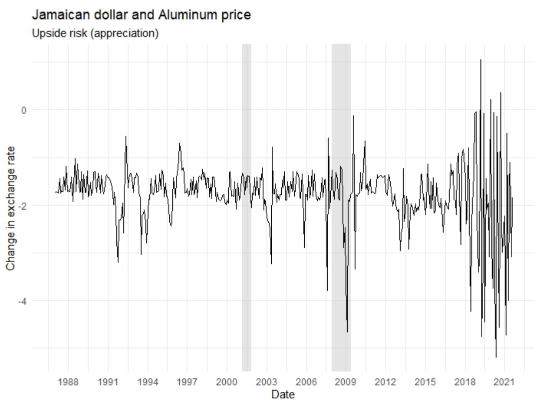


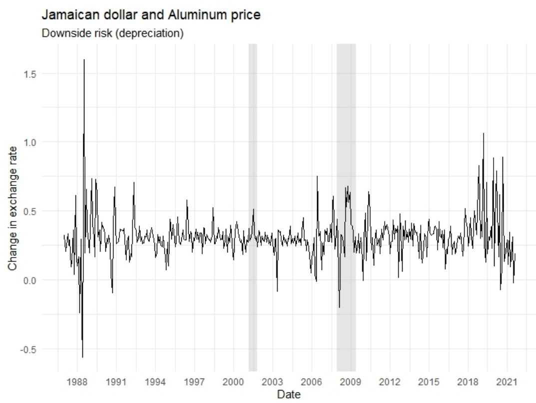
Australia's tail risks (conditional on iron ore prices) have been effected mostly by the Great Recession and the pandemic. The magnitude of the volatility of these risk measures increased after the Great Recession. It is noteworthy that the iron price drop in late-2015 did not seem to have a substantial impact, besides perhaps a marginal worsening of the upside risk. A possible explanation is that albeit iron ore's relative size among Australian domestic export products have been varying over time, its global presence in the market has been colossal and increasing over time (see Table 20 below).

Year	%-age of Country Export Basket	%-age of World Exports
2000	4.33	28.8
2005	8.04	28.1
2010	20.5	41.6
2015	18.5	53.1
2020	31.9	56.2

Table 20: Australia and iron ore exports

Jamaica (aluminum)



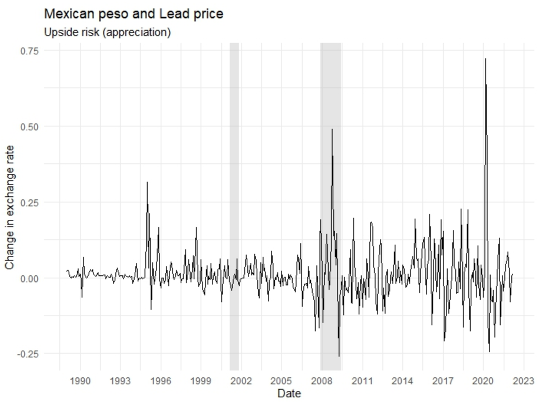


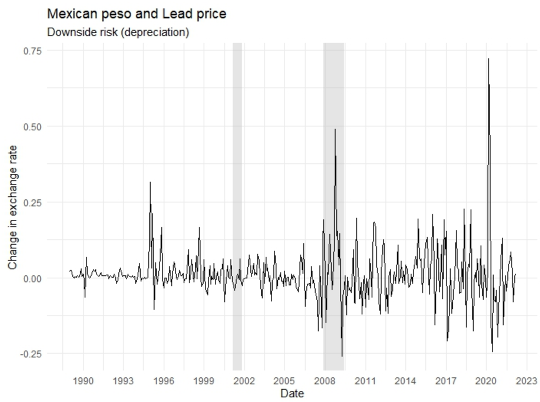
Jamaica's tail risk values (conditional on aluminum prices) have been perturbed mostly by the Great Recession and the softening of this commodity's price in 2018. Both risk measures have been more volatile since mid-2018.

Year	%-age of Country Export Basket	%-age of World Exports
2000	3.3	4.58
2005	5.48	5
2010	8.26	4.91
2015	9.37	3.56
2020	6.43	1.61

Table 21: Jamaica and aluminum ore exports

Mexico (lead)



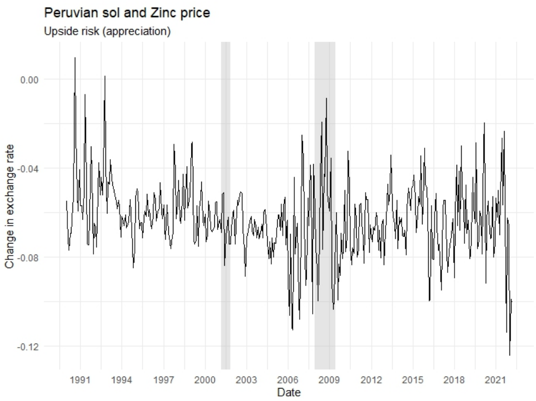


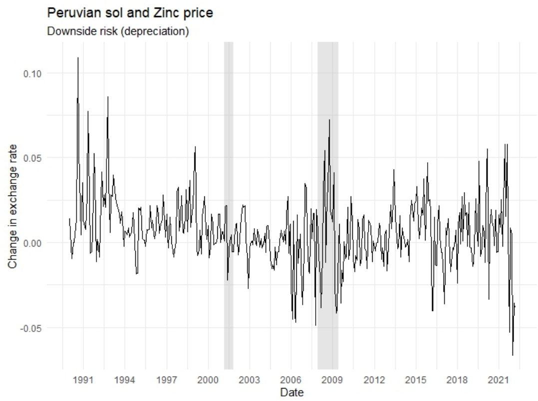
Mexico's tail risk values (conditional on lead prices) spiked during the Great Recession and especially the pandemic. These values did not rise as sharply during the 2015 price drop as we saw with the other commodities, but the volatility of the values did increase after 2015. This can be explained by Mexico's global portion in this market increasing from 2010 to 2020.

Year	%-age of Country Export Basket	%-age of World Exports
2000	< 0.05	3.24
2005	< 0.05	0.49
2010	0.083	4.92
2015	0.33	22.8
2020	0.4	27.4

Table 22: Mexico and lead ore exports

Peru (zinc)





Peru's tail risk values (conditional on zinc prices) shot up following the early 1990s recession, during the Great Recession, and to a lesser degree during the pandemic. The amplitude of these risk values increased post-Great Recession, but the upside risk has somewhat improved. Peru's global place in this market contracted slightly from 2010 to 2020, with Australia overtaking its lead.

Year	%-age of Country Export Basket	%-age of World Exports
2000	1.63	13
2005	1.87	17.4
2010	4.09	19.3
2015	3.53	16.3
2020	2.5	12.3

Table 23: Peru and zinc ore exports

All-in-all, there are two important observations from this exercise of calculating expected shortfall and longrise, the conditional value-at-risk measures quantifying extreme (or tail) events. Firstly, the risk of depreciation (graphs on the right) generally have larger magnitudes than the values of appreciation (graphs on the left), i.e. they are larger in scope. Secondly, the swings of appreciation and depreciation risk increase during major crises; we can see it especially with the Great Recession which affected all of the considered cases.

4.6 Conclusions

Inflationary consequences of currency depreciations has challenged policymakers of many emerging economies, especially since their participation in global financial integration increased in the late 90's (Souza and Carvalho, 2011). We find that commodity price changes have a larger negative impact on currency changes during periods of more persistent depreciation. That means that commodity price drops perpetuate ongoing currency depreciation episodes, potentially stalling the process of exchange rate rebound and adding to the existing inflationary strains. Thus, the relevant policy implication for improving macroeconomic stability for commodity trade-dependent economies lies in building more resilience towards this dependence, i.e. giving more attention and effort to export diversification.

Our findings also suggest that commodity price changes may be an associated signal of downside risk to exchange rate changes. Moreover, we find that since the Great Recession, and after the commodity price cycle bust in 2015 in particular, the tail risk measures of the exchange rates conditional on commodity prices have increased. This provides evidence that in the recent years commodity-exporting countries have become more vulnerable to macroeconomic risk via the exchange rate channel. As more commodity-exporting developing countries are moving towards flexible exchange rate regimes, they need to be aware of this risk channel and take appropriate precautions and monetary policy arrangements.

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Appendix

Appendix A

The State-Space Representation of the Dynamic Factor Model

<u>Measurement Equation:</u>

$$
\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \\ y_{4t} \\ y_{5t} \\ y_{6t} \\ y_{7t} \\ y_{8t} \\ y_{9t} \\ y_{10t} \\ y_{11t} \\ y_{12t} \\ y_{13t} \\ y_{14t} \end{bmatrix}
=
\begin{bmatrix}
1&0&0&0&0&0&0&0&0&0&0&0&0&0&\eta_1&\delta_1 \\
0&1&0&0&0&0&0&0&0&0&0&0&0&0&\eta_2&\delta_2 \\
0&0&1&0&0&0&0&0&0&0&0&0&0&0&\eta_3&\delta_3 \\
0&0&0&1&0&0&0&0&0&0&0&0&0&0&\eta_4&\delta_4 \\
0&0&0&0&1&0&0&0&0&0&0&0&0&0&\eta_5&\delta_5 \\
0&0&0&0&0&1&0&0&0&0&0&0&0&0&\eta_6&\delta_6 \\
0&0&0&0&0&0&1&0&0&0&0&0&0&0&\eta_7&\delta_7 \\
0&0&0&0&0&0&0&1&0&0&0&0&0&0&1&\delta_8 \\
0&0&0&0&0&0&0&0&1&0&0&0&0&0&\eta_9&\delta_9 \\
0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&\delta_{10} \\
0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&\delta_{11} \\
0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&\delta_{12} \\
0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&\delta_{13} \\
0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&1
\end{bmatrix}
\begin{bmatrix} \eta_{1t} \\ \eta_{2t} \\ \eta_{3t} \\ \eta_{4t} \\ \eta_{5t} \\ \eta_{6t} \\ \eta_{7t} \\ \eta_{8t} \\ \eta_{9t} \\ \eta_{10t} \\ \eta_{11t} \\ \eta_{12t} \\ \eta_{13t} \\ \eta_{14t} \\ c_{1t} \\ c_{2t} \end{bmatrix}
$$

<u>Transition Equation:</u>

$$
\begin{bmatrix} \eta_{1t} \\ \eta_{2t} \\ \eta_{3t} \\ \eta_{4t} \\ \eta_{5t} \\ \eta_{6t} \\ \eta_{7t} \\ \eta_{8t} \\ \eta_{9t} \\ \eta_{10t} \\ \eta_{11t} \\ \eta_{12t} \\ \eta_{13t} \\ \eta_{14t} \\ c_{1t} \\ c_{2t} \end{bmatrix}
=
\begin{bmatrix}
\phi_1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\
0&\phi_2&0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\
0&0&\phi_3&0&0&0&0&0&0&0&0&0&0&0&0&0 \\
0&0&0&\phi_4&0&0&0&0&0&0&0&0&0&0&0&0 \\
0&0&0&0&\phi_5&0&0&0&0&0&0&0&0&0&0&0 \\
0&0&0&0&0&\phi_6&0&0&0&0&0&0&0&0&0&0 \\
0&0&0&0&0&0&\phi_7&0&0&0&0&0&0&0&0&0 \\
0&0&0&0&0&0&0&\phi_8&0&0&0&0&0&0&0&0 \\
0&0&0&0&0&0&0&0&\phi_9&0&0&0&0&0&0&0 \\
0&0&0&0&0&0&0&0&0&\phi_{10}&0&0&0&0&0&0 \\
0&0&0&0&0&0&0&0&0&0&\phi_{11}&0&0&0&0&0 \\
0&0&0&0&0&0&0&0&0&0&0&\phi_{12}&0&0&0&0 \\
0&0&0&0&0&0&0&0&0&0&0&0&\phi_{13}&0&0&0 \\
0&0&0&0&0&0&0&0&0&0&0&0&0&\phi_{14}&0&0 \\
0&0&0&0&0&0&0&0&0&0&0&0&o&0&\phi_{15}&0 \\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&\phi_{16}
\end{bmatrix}
\begin{bmatrix} \eta_{1t-1} \\ \eta_{2t-1} \\ \eta_{3t-1} \\ \eta_{4t-1} \\ \eta_{5t-1} \\ \eta_{6t-1} \\ \eta_{7t-1} \\ \eta_{8t-1} \\ \eta_{9t-1} \\ \eta_{10t-1} \\ \eta_{11t-1} \\ \eta_{12t-1} \\ \eta_{13t-1} \\ \eta_{14t-1} \\ c_{1t-1} \\ c_{2t-1} \end{bmatrix}
+
\begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \\ e_{5t} \\ e_{6t} \\ e_{7t} \\ e_{8t} \\ e_{9t} \\ e_{10t} \\ e_{11t} \\ e_{12t} \\ e_{13t} \\ e_{14t} \\ v_{1t} \\ v_{2t} \end{bmatrix}
$$

Remaining Dynamic Factor Model Parameter Estimates

Parameter	Estimate	Standard Error
AR(1) coefficient, CIS component (β_1)	0.966	0.051
S.E., CIS component (σ_{v_1})	0.150	0.061
AR(1) coefficient, global component (β_2)	0.753	0.088
S.E., global component (σ_{v_2})	0.605	0.074

Table 24: Parameters of the Common Components (all are statistically significant)

Country	Estimate	Standard Error
Armenia	0.033	0.167
Azerbaijan	-0.184	0.128
Belarus	0.067	0.169
Georgia	-0.389	0.119
Kazakhstan	0.086	0.131
Kyrgyzstan	0.200	0.133
Moldova	0.870	0.058
Russia	-0.062	0.147
Ukraine	-0.075	0.139
Switzerland	0.284	0.144
UK	0.296	0.163
US	-0.073	0.153
China	0.921	0.052
EU	0.146	0.341

Table 25: AR(1) Coefficients of the Idiosyncratic Components (ϕ_i) (some noisiness in the estimates)

Country	Estimate	Standard Error
Armenia	0.736	0.077
Azerbaijan	0.828	0.077
Belarus	0.699	0.075
Georgia	0.876	0.080
Kazakhstan	0.863	0.080
Kyrgyzstan	0.906	0.084
Moldova	0.379	0.039
Russia	0.569	0.062
Ukraine	0.773	0.074
Switzerland	0.630	0.065
UK	0.510	0.057
US	0.710	0.073
China	0.381	0.039
EU	0.389	0.071

Table 26: Standard Errors of the Idiosyncratic Components (σ_{e_i}) (all are statistically significant)

Discussion of the Russian trade flow evidence Figures 6-8

The export and import shares of total Russian merchandise trade accounted for by China have been on an upward trend since 2011. Although the import share flattened in 2016, it looks like trade with China was mostly unaffected by the 2014-15 events. On the other hand, the export and import shares accounted for by Germany fell in 2015, and while the export share recovered in 2016, the import share remained on the downward trend. We see a similar situation with UK. The situation with US is different: the export share did not recover after its 2016 decrease, and the import share followed a positive trend from 2014 till 2016 but also went on a downward trajectory since 2016. The 2014-15 events seem to have affected import shares more permanently than export shares.[40]

In 2015-2017 the import shares of total Russian merchandise trade accounted for by CIS countries were increasing for most CIS countries. In 2018 the import shares for Kazakhstan and Kyrgyzstan dropped to their 2014 levels, and for Azerbaijan - to a level slightly below the 2014 level. However, while the import shares for Armenia, Belarus, Georgia, and Moldova decreased in 2018 as well, they remaine above their 2014 levels. The changes in export shares of total Russian merchandise trade accounted for by CIS countries were not as pronounced but still noteworthy. The export shares levels for all countries except Kazakhstan and Ukraine were slightly higher than their respective 2014 levels in 2018, but not as much as their import share counterparts.

The export and import shares of total Russian merchandise trade accounted for by Ukraine have been on a decline since 2011. The export share flattened in 2015 and the import share - in 2016, and thus the prior Russian trade deficit with Ukraine faded in 2016. Russian trade with Belarus went to balanced from a slight surplus in 2016 as well. Yet the past Russian trade deficit with Armenia changed to surplus in 2014, and similarly with Moldova - in 2015. This leads to us to a conclusion that the 2014-15 events led to a reshuffling of Russia's patterns of trade, with CIS countries increasing and Germany, UK, and US decreasing their presence in Russian imports.

[40] We should keep in mind that the preceding struggles of Russian economy may be entagled in these trade developments.

Appendix B

Country	KAOPEN	Income Group	Top Exports
Armenia	1.63	Lower middle	Copper Ore, Gold, Rolled Tobacco, Hard Liquor, Ferroalloys
Azerbaijan	0.06	Upper middle	Crude Petroleum, Petroleum Gas, Refined Petroleum, Tomatoes, Gold
Belarus	-1.22	Upper middle	Refined Petroleum, Potassic Fertilizers, Cheese, Delivery Trucks, Crude Petroleum
Georgia	2.33	Lower middle	Copper Ore, Cars, Ferroalloys, Wine, Packaged Medicaments
Kazakhstan	-1.22	Upper middle	Crude Petroleum, Petroleum Gas, Refined Copper, Ferroalloys, Radioactive Chemicals
Kyrgyzstan	0.35	Lower middle	Gold, Precious Metal Ore, Dried Legumes, Refined Petroleum, Scrap Copper
Moldova	-1.22	Lower middle	Insulated Wire, Sunflower Seeds, Wine, Corn, Seats
Russia	0.87	Upper middle	Crude Petroleum, Refined Petroleum, Petroleum Gas, Coal Briquettes, Wheat
Ukraine	-1.92	Lower middle	Corn, Seed Oils, Iron Ore, Wheat, Semi-finished Ore

Table 27: Country Info

KAOPEN is a popular index invented by Chinn and Ito (2006) used to quantify a country's capital account openness; the larger the value, the more financially open a country is.[41] As a reference point, the US has a KAOPEN value of 2.33. Income group indicates which of the four income group classifications (low, lower middle, upper middle, high) as per the World Bank Atlast method the countries belonged to in 2016. Top Exports column designates the products our countries exported the most in 2019[42].

[41]Values are as of 2016.

[42]Data is taken from the oec.world website.

Appendix C

Density

Here we present the plots of the conditional probability distributions we recover when estimating the skewed t-distributions described in the Methodology section (the second step). This exercise was done for the combinations of countries and commodities whose relationship exhibited the main finding feature from 5.1 and was the preliminary step before calculating the tail risk measures of expected shortfall and longrise. The graphs are grouped by predicted appreciation (leftward shift of the density) or depreciation (rightward shift of the density) of the exchange rate in March 2022 (as compared to 2021)[43].

<u>Predicted Appreciation</u>

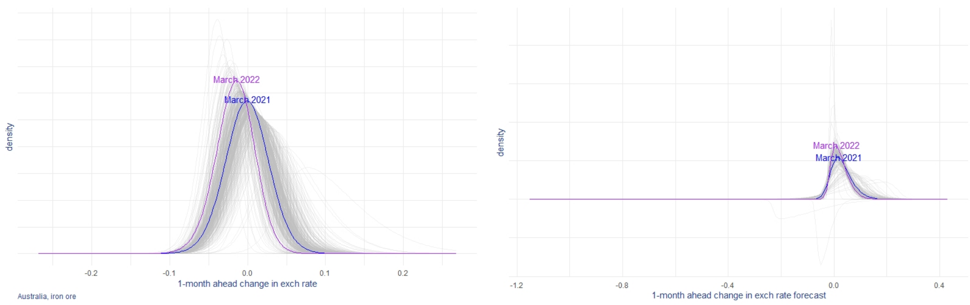


Figure 25: Australia on the left, Ghana on the right

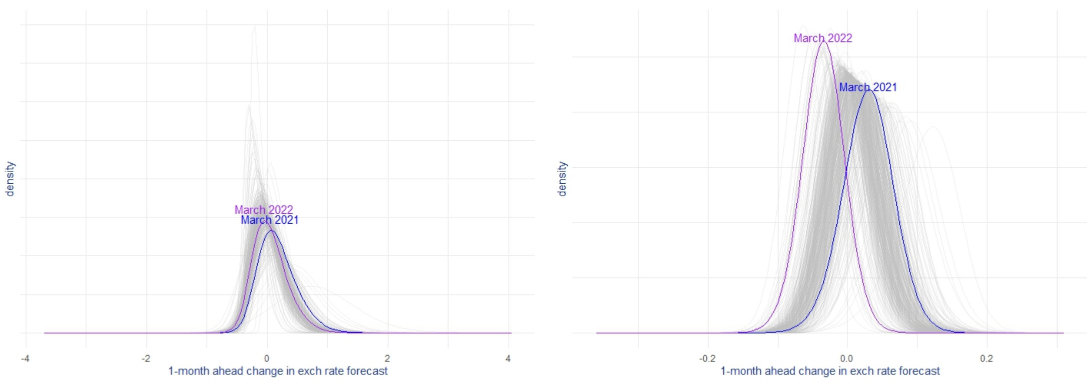
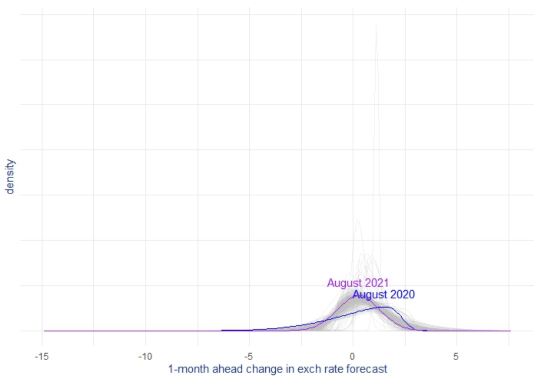


Figure 26: Mexico on the left, Peru on the right

[43]For several countries we have different months depending on data availability.



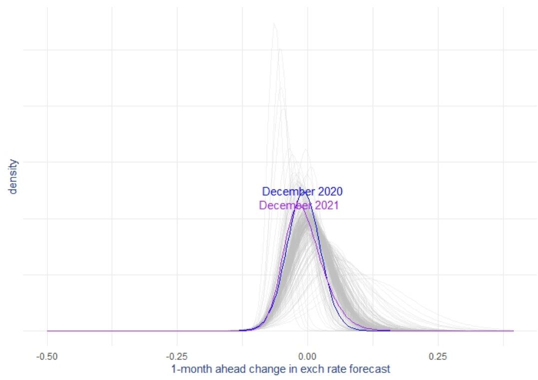
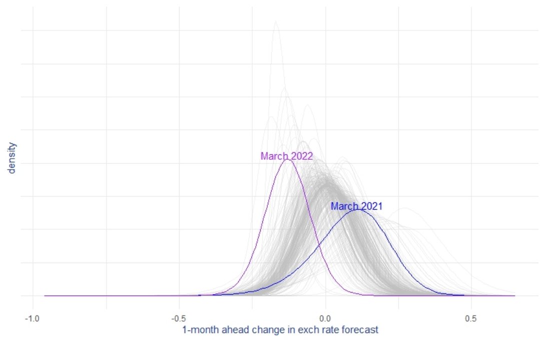


Figure 27: Jamaica on the left, Georgia on the right



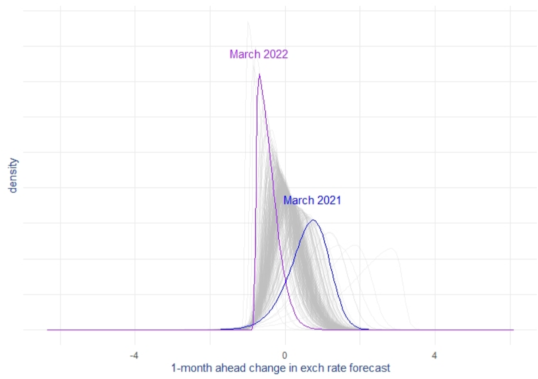
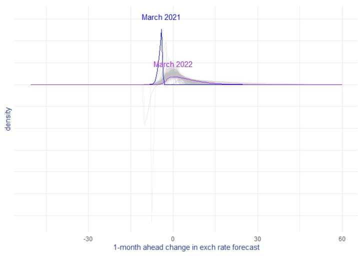
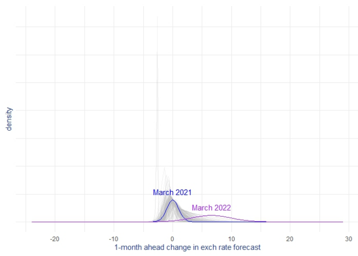


Figure 28: Brazil on the left, Uruguay on the right

Predicted Depreciation





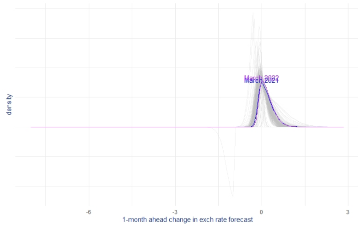


Figure 29: Kazakhstan on the left, Russia in the center, Zambia on the right