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Testing Shock Transmission Channels to Low-Income Developing Countries

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Testing Shock Transmission Channels to Low-Income Developing Countries

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Abstract

The paper examines the transmission of business cycle fluctuations and credit conditions from advanced and emerging market economies to Low-Income Developing Countries (LIDCs), using a global vector autoregressive (GVAR) framework and related country-specific error correction models. We compile a dataset on bank credit, exports, output, and real effective exchange rate for 24 LIDCs and 16 Advanced and Emerging Markets, accounting for 74 percent of World GDP, from 1990Q1 to 2013Q4. Impulse response analyses show that business cycles in oil- and commodity-exporting, as well as frontier LIDCs are more synchronized with those in emerging market economies. Furthermore, credit conditions in the US seem to have a significant impact on exports and real economic activity in LIDCs, while these variables are basically unresponsive to credit availability in emerging markets or economies in other parts of the world.

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ACRONYMS AND ABBREVIATIONS

AIC	Akaike Information Criterion
AE	Advanced Economies
ADF	Augmented Dickey Fuller
BIS	Bank of International Settlement
BRICS	Brazil, Russia, India, China, and South Africa
CPI	Consumer Price Index
EM	Emerging Market
FDI	Foreign Direct Investment
FM	Frontier Markets
GIRF	Generalized Impulse Response Functions
GVAR	Global Vector Autoregressive
IED	Income Elasticity Demand
IFS	International Financial Statistics
LICs	Low-Income Countries
LIDCs	Low-Income Developing Countries
OECD	Organization for Economic Corporation and Development
OIR	Orthogonalized Impulse Responses
OLS	Ordinary Least Squares
VARX	Vector Auto Regression
VECMX	Vector Error Correction
VIX	CBOE Volatility Index
WEO	World Economic Outlook

I. INTRODUCTION

International business cycles and financial conditions are transmitted to Low-Income and Developing Countries (LIDCs)[1] through various channels. The existing literature has examined spillovers from systematically important countries, including the United States, Euro Area, UK, Japan and Canada to emerging markets (e.g., China, India, and Brazil) and vice versa. Despite LIDC's trade and financial ties to both advanced and emerging market economies, little empirical work has been produced to assess the implications of global macroeconomic and financial fluctuations for various subgroups of low-income countries (LICs).

The purpose of this paper is to assess the transmission of business cycles and financial conditions from advanced and emerging market economies to LIDCs. Are LIDCs more or less exposed to the international business cycle than emerging markets? Which are the strong drivers of LIDCs business cycles, advanced, or emerging markets? The answer to this question provides insight into regional dependencies and the potential need to diversify trade partner structures.

How about LIDCs exposure to the international financial cycle? What are the implications of contractions in the financial sector and stricter credit conditions in various parts of the world for LIDCs and its different country subgroups? That is a key question for policymakers. Despite the often presented argument of financial isolation during the recent financial turmoil (originating in 2007) being a "blessing in disguise" (Berman and Martin, 2010) for many of the LIDCs, those countries more inserted into global value chains actually felt the direct lending channel impacting availability of capital and the wider economic activity.

Hence, regardless of the degree of integration into global financial markets, LIDCs were exposed through alternative transmission channels—foremost the trade channel. Indeed, these countries rely largely on foreign demand, with exports comprising between 30–40 percent of their GDP. Thus the lack of demand, which characterized the global financial crisis, had measurable adverse effects for LIDCs.

In this paper we estimate a Global Vector Autoregression model (GVAR) to explore business cycles and financial conditions spillovers to LIDCs. The GVAR methodology has become the workhorse model for empirical research on spillovers (e.g., Dees and others, 2007a) as it

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[1] The LIDC group includes all countries that a) fall below a modest per capita income threshold (US$2,500 in 2011, based on Gross National Income); and b) are not conventionally viewed as emerging market economies (EMs). There are 60 countries in this group, accounting for about one-fifth of the world's population; sub-Saharan Africa (SSA) accounts for some 57 percent of the LIDC population, with a further 28 percent living in Asia. While sharing characteristics common to all countries at low levels of economic development, the LIDC group is strikingly diverse, with countries ranging in size from oil-rich Nigeria (174 million) to fisheries dependent Kiribati (0.1 million), and in 2013 per capita GDP terms from Mongolia (US$3,770) to Malawi (US$270). The 10 largest economies in the group account for two-thirds of total group output (as measured in PPP terms). For details see policy paper Macroeconomic Developments in Low-Income Developing Countries (IMF, 2014).

allows the combination of country-specific models into a global model, by relating domestic variables to country specific foreign variables in a consistent manner.

We build upon the work by Canales-Kriljenko, Hosseinkouchack, and Meyer-Cirkel (2014) and expand the sample coverage to 24 LIDC countries. The main obstacle in including lower income countries in empirical exercises is the lack of sufficiently long time series in a quarterly frequency. For many of the countries, official data compilation exercises only start in the 1990s. To expand the data, we rely on a non-linear interpolation methodology to obtain quarterly time series out of annual data and available related higher frequency data, following work by Fernandes (1981).

Our main results are:

- Oil exporting countries have rather more attuned business cycles to advanced economies or emerging markets, compared to oil importers.

- Frontier LIDCs, despite presenting lower trade integration, are also exposed to international business cycles.

- Credit contractions in the US have significant impacts on exports and output of frontier LIDCs, but no such effect is found for credit conditions in the other regions of the world.

The rest of the paper is organized as follows: Section II summarizes the related literature; Section III describes the dataset compiled; Section IV discusses the methodology employed; Section V outlines and discusses the estimation results; and Section VI concludes.

II. WHERE DO WE COMPLEMENT THE LITERATURE

This paper complements work done by Canales-Kriljenko, Hosseinkouchack, and Meyer-Cirkel (2014), which explores the effect of global financial shocks to sub-Saharan African countries. The expanded scope of this paper looks at export demand elasticities in more detail, particularly incorporating the impact of the real effective exchange rate into the system of equations. Furthermore, we improve the quality of the underlying data by interpolating GDP using available higher-frequency indicators; while we also expand and segment the panel of countries so as to identify impacts by economic-typology. We find that business cycle uncertainty and fluctuations in advanced markets have a measurable impact on the economic activity of LIDCs. Furthermore, our estimations indicate that credit contractions in the US have a considerable impact on exports and output of subgroups of LIDC, a relationship that could not be verified for the different subgroups of sub-Saharan African countries.

Samake and Yang (2014) also estimate a GVAR model, using annual data, to investigate the business cycle transmission from BRICS (Brazil, Russia, India, China, and South Africa) to LICs (Low Income Countries) through trade, FDI, output, and exchange rate channels. They find that there is a significant direct spillover from BRICS to LICs, with trade being the most important channel. Our paper differs from theirs in several respects, besides the different

GVAR model specification. First, we entertain a broader focus in terms of examining the spillovers not only from BRICS to LIDCs, but also from advanced economies, emerging markets, and other countries in the world. In addition, we consider the credit channel as another potential shock transmission conduit. Finally, we estimate the model using quarterly data.

Several other papers in the literature, adopting different methodology, have examined the transmission of shocks into LIDCs. Berg and others (2011), using cross country OLS regression analysis, study the effects of the global financial crisis (2007–09) on growth in (mainly non-fuel exporting) LICs. Similar to us, they find that the growth declines, can on average, be well explained by the decline of export demand. Espinoza, Jahan, and Dabla-Norris (2012), employing VAR methodology and dynamic panel models, estimate the spillovers from a subset of Emerging Market leader countries to LICs and show that economic activity in LICs is significantly affected by foreign shocks. Further, they perform regional stratification of the LICs to document the linkages between Emerging Market leaders and specific LICs regions.

Raddatz (2007), using a panel vector autoregression approach, quantifies the impact of external shocks (commodity price fluctuations, natural disasters, and the role of the international economy) on the poor economic performance of LICs. The main finding suggests that only a small fraction of output volatility in a typical LIC can be explained by external factors; instead, internal factors are the main sources of fluctuations.

Mishra, Montiel, and Spilimbergo (2010) focus on the monetary transmission mechanisms in LICs to understand if transmission channels operate differently in LICs compared to advanced and emerging market economies. They find that, due to the LICs' weak institutional framework, reduced role of securities markets, imperfect competition in the banking sector and the high cost of bank lending to the private sector, the traditional monetary transmission channels (interest rate, bank lending, and asset prices) are impaired; additionally, the exchange rate channel is undermined due to central banks' supporting the currency.

III. DATASET

The dataset in this paper covers 40 countries, of which 24 are LIDCs and 16 are G20 countries. Those countries account for 74 percent of world GDP and the LIDCs in our sample account for 62 percent of LIDCs GDP. Only those LICs have been excluded, for which no sufficient data coverage existed. From the G20 countries that we consider, three that originally joined the Euro Area on January 1st, 1999 (France, Germany, and Italy) are grouped together using the average 2006–2008 US real GDP. Therefore, the final number of countries considered in the analysis is 38 (see Table 1).

Table 1. Countries and Regions

Advanced and Emerging Market Economies		Low-Income Country Economies	
United States	Argentina	Bangladesh	Honduras
United Kingdom	Brazil	Bolivia	Kenya
Japan	Mexico	Burundi	Maldives
Korea	China	Cameroon	Myanmar
Canada	Turkey	Cape Verde	Nepal
Australia	India	Comoros	Nigeria
Euro Area	Indonesia	Congo	Papua New Guinea
France		Dominica	Samoa
Germany		Gambia	Sudan
Italy		Ghana	Uganda
		Grenada	Vanuatu
		Guyana	Zambia

The variables included in the analysis are real output (y_{it}), real exports (ex_{it}), real effective exchange rate ($reer_{it}$), domestic private credit (crd_{it}), oil price (oil_t), global credit ($loan_t$), and the VIX index (vix_t). More specifically:

$$oil_t = \log(OIL_t)$$

$$loans_t = \log\left(\frac{LOANS_t}{CPI_t}\right)$$

$$vix_t = \log(VIX_t)$$

$$y_{it} = \log\left(\frac{GDP_{it}}{CPI_t}\right)$$

$$ex_{it} = \log\left(\frac{EXP_{it}}{CPI_t}\right)$$

$$reer_{it} = \log(REER_{it})$$

$$crd_{it} = \log\left(\frac{CREDIT_{it}}{CPI_t}\right)$$

where GDP_{it} is the nominal gross domestic product of country i at time t in national currency, CPI_{it} is the consumer price index,[2] EXP_{it} is nominal exports to the world in terms of US dollars, $REER_{it}$ is the real effective exchange rate, $CREDIT_{it}$ is nominal domestic private credit in national currency, OIL_t is the oil price index, VIX_t is a measure of U.S.

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[2] The CPI_t stands for the US CPI.

equity market volatility that is widely-used as a proxy for global risk,[3] and $LOANS_t$ is the nominal global credit available to the world for all sectors.

The data series for all 40 advanced, emerging, and LIDCs are available in quarterly frequencies, for the period 1990Q1–2013Q4, with the exception of the GDP series for the LIDCs, available only annually. To overcome the problem with quarterly frequency data availability for the GDP series, we adopt an interpolation technique proposed by Fernandez (1981), which we discuss in further detail later.

The choice of data series that serves as a proxy for domestic private credit is guided by the existing literature as well as by the availability of data (see for e.g., Xu, 2012). In our analysis, the private credit series correspond to "Claims on private sector from deposit money banks," extracted from the IMF International Financial Statistics (IFS), series 22d. The deposit money banks refer to commercial banks and other financial sector institutions that accept deposits and extend credit to nonfinancial corporations. We focus particularly on credit extended to nonfinancial corporations for its central role as a banking development indicator in the empirical finance literature.

In addition to domestic private credit, we also account for global credit conditions. To this end, the variable that we use as a proxy corresponds to "External positions of banks: Claims on all sectors," Table 6a from the BIS locational banking statistics. The locational banking statistics of the BIS provides quarterly data on international financial claims and liabilities of the BIS reporting banks. To construct the global credit variable, we consider the asset side of the reporting banks and we sum up the claims on all sectors in the counterparty locations of all BIS reporting banks. In this way, we are able to measure the total credit availability (all sectors in the economy) for all the countries in the world.

For the remaining variables considered in our analysis, including output, exports, and real effective exchange rates, the data was drawn from various IMF data sources including the DTTS, WEO and IFTS. The data on oil prices and the VIX index was extracted from Bloomberg. The first section in the appendix contains a more detailed description of the data sources and the transformations applied in constructing the time series used in the analysis.

A. Overcoming Challenges with Data Availability

The data availability for LIDCs often represents a challenge. In particular, GDP series for LIDCs are often available only in annual frequency. Therefore, we rely on the Fernandes (1981) method for temporal disaggregation method. That method, which is regression based, consists in interpolating the low frequency series (annual) to higher frequency (quarterly) using the information from associated "indicator series." The advantage of this method,

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[3] The VIX is derived from options prices on the S&P 500 index, and informs us about volatility and risk pricing in the US equity market. The VIX is often given a broader interpretation, as it is highly correlated with broader measures of financial stress (such as the Financial Stress Index developed by the Federal Reserve Bank of St. Louis) and with bond market indicators, including spreads on sovereign bonds of emerging market countries (De Bock and de Carvalho Filho, 2015).

compared to the agnostic linear interpolation, is that it allows preserving as far as possible the short-term movements of the indicator series under the restriction provided by the annual data. In this way, the temporal disaggregation combines the relative strength of the less frequent annual data with the information provided by the more frequent (quarterly) data.

The high frequency (quarterly) series that we use as a benchmark in our exercise is "imports to the world," extracted from the IMF DTTS database. There are two reasons for this choice. First, even though a more natural benchmark would be an indicator of real activity such as industrial production, that is not available for the majority of the LIDCs for the entire sample period, whereas the imports series are available in quarterly frequencies for all the LICs. Second, imports represent an important component of aggregate demand and given their high correlation with GDP (for e.g., the correlation between US GDP and imports for the period 1990Q1–2013Q3 is 0.984), they can serve as an appropriate benchmark of economic activity.

Before interpolating the annual GDP series to quarterly using the Fernandez (1981) method, we examine its performance in comparison to the linear interpolation method, as well as, to adopting an alternative high frequency benchmark series—industrial production. To this end, we collected data on quarterly GDP for a subset of countries for which data were available (see Table 2 for the list of countries considered in this exercise) and calculated the correlation between the quarterly GDP and the interpolated GDP series obtained using the different interpolation methods. To account for the trend in the data, the correlations were calculated on the Hodrick-Prescott filtered GDP series with a smoothness parameter of 1600.

Table 2 provides the results of this exercise. The correlation between the GDP quarterly series and the GDP series interpolated using the Fernandez (1981) method (both when imports and industrial production were used as benchmarks) is higher than the correlation between the quarterly GDP series and the linearly interpolated series. This result holds true for all countries that were considered in this exercise. In addition, the industrial production series, when used as a benchmark, marginally outperform the imports series. However, guided by data availability for the LIDCs, for the interpolation of the GDP for the LIDCs, we used the imports series as a high frequency benchmark.

Table 2. Correlations of GDP and GDP Interpolated Series

	Imports (benchmark)	Ind.Prd. (benchmark)	Linear interp.
USA	0.938	0.940	0.864
Germany	0.927	0.951	0.587
Japan	0.914	0.929	0.654
Mexico	0.850	0.461	0.834
UK	0.817	0.915	0.750
Canada	0.934	0.903	0.694

Note: The table presents the correlations between the quarterly GDP series that are available for a subset of advanced and emerging economies and the quarterly GDP series interpolated using the different methods, i.e., the Fernandez (1981) method with imports and industrial production serving as benchmark high frequency series, respectively, and the linear interpolation method.

IV. METHODOLOGY

To examine the impact of external economic activity and credit conditions on LIDCs, we use the GVAR (Global Vector AutoRegressive) model, originally proposed in Peseran, Schuermann, and Weiner (2004) and further developed in Pesaran and Smith (2006) and Dees and others (2007a and 2007b). The GVAR model is a compact multi-country model, combining individual country specific models with both domestic and weighted average of foreign variables (based on the relative importance of the rest of the world for the country into consideration).

Suppose that the GVAR model covers $i = 0, 1, 2, ..., N$ countries. For each country i, there are individual VARX(p_i, q_i) models, which are vector autoregression models comprising of domestic, country-specific foreign, and global variables, of which the last ones denote observed global factors. The model for the i-th economy takes the form of:

$$\Psi_i(L, p_i)x_{it} = a_{i0} + a_{i1}t + \Phi_i(L, q_i)d_t + \Gamma_i(L, q_i)x_{it}^* + \varepsilon_{it}$$

$$\Psi_i(L, p_i)x_{it} = a_{i0} + a_{i1}t + \Phi_i(L, q_i)d_t + \Gamma_i(L, q_i)x_{it}^* + \varepsilon_{it}$$

where x_{it} is a $k \times 1$ vector of domestic variables (for instance, such as real GDP, real exports, real effective exchange rate, and real credit), x_{it}^* is a $k_{it}^* \times 1$ vector of country specific foreign variables, d_t denotes the $m_d \times 1$ matrix of global variables (for instance, such as oil price, the VIX index, and global credit conditions), a_{i0} and a_{i1} are the deterministic terms, denoting the intercept and the linear trend, respectively, ε_{it} and is the idiosyncratic country-specific shock. Finally, $\Psi_i(L, p_i) = \sum_{l=0}^{p_i} \Psi_{it}L^l$, $\Phi_i(L, q_i) = \sum_{m=0}^{q_i} \Phi_{im}L^m$, and $\Gamma_i(L, q_i) = \sum_{n=0}^{q_i} \Gamma_{in}L^n$, where L denotes the lag operator and p_i and q_i are the lag orders of the domestic and the foreign variables, respectively. The country-specific foreign variables in the vector x_{it}^* represent weighted averages, constructed using the trade weights, ω_{ij}, $j=0,1,2,...,N$. In this way, the trade weights capture the relative importance of country j for country i's economy and they are calculated as the ratio of the sum of exports and imports of country i with country j to the total trade of country i. Thus, the vector x_{it}^*, in the equation above, is given by:

$$x_{it}^* = \sum_{j=0}^{N} \omega_{ij}x_{jt}$$

where $\omega_{ij} = 0$ and $\sum_{j=0}^{N} \omega_{ij} = 1$, $\forall i,j=0,1,2,...,N$. The data on bilateral trade was obtained from the IMF Direction of Trade Statistics. In the analysis, we use trade weights that are calculated as averages during the period 2008–2013.

The reason for using the trade instead of financial integration weights to aggregate foreign variables for country i is twofold. First, given the weak integration of the LIDCs in the world financial markets, trade is their major linkage to the rest of the world. Second, the bilateral trade data are readily available for LIDCs from the DTTS database, opposite to the data on bilateral Foreign Direct Investment (FDI) (published by the OECD) or International Banking Statistics (published by the BIS).[4] Moreover, the asymptotic results corroborate the premise that the choice of weights used in the measurement of the foreign variables is not crucial, as long as, the so-called small open economy or "granularity" condition applies (see Chudik and Pesaran, 2009).

The estimation of the GVAR model involves the following steps. First, after determining its lag order using the Akaike Information Criterion, each individual country specific VARX model is written in a vector error correction form (VECMX) and estimated. After estimating the VECMX models and recovering the parameters of the VARX models for each country, the VARX models can be stacked together and solved as one system by taking into account the matrix of weights. In the interest of space, we abstract from detailed description of the model derivations and estimations, which can be found in Dees and others (2007a), among others.

A. Model Specification

Our GVAR model includes four country-specific variables (real output (y_{it}), real exports (ex_{it}), real effective exchange rate ($reer_{it}$), and domestic private credit (crd_{it})) and three common global variables (oil price (oil_t), global credit ($loan_t$), and the VIX index (vix_t)) for 40 countries. The original variables were transformed. First, the variables were seasonally adjusted, where necessary, using the TRAMO/SEATS method. Second, since the output and the domestic private credit series were in nominal national currencies, they were deflated by their respective CPIs. The export series, denominated in US dollars, were deflated by the US CPI for all countries. Finally, all series were transformed into logarithms, as presented in the description of the dataset in the previous section.

The choice of the variables in the GVAR model was guided by the consideration of an export demand equation, relating real exports to the real exchange rate and economic activity in trading partners (see for example, Senhadji and Montenegro, 1999). Further, we augment the export demand equation along two dimensions. First, we introduce private domestic credit into the model in an attempt to examine the effect of tighter domestic credit conditions in trading partners.[5] Second, we augment the model by including common global factors that may influence international trade, i.e., the three global variables: oil prices, a proxy for global credit conditions, and the VIX index. Oil prices have been shown to be an important

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[4] Interestingly, the asymptotic results corroborate the premise that the choice of weights used in the measurement of the foreign variables is not crucial, as long as, the so-called small open economy or "granularity" condition applies (see Chudik and Pesaran, 2009).

[5] Manova (2013) finds a significant impact of credit constraints on trade.

determinant of trade. The global credit variable serves as a proxy for global credit conditions. Finally, we also include the VIX index to account for markets' expectations of stock market volatility and to capture any noise that may arise due to market fear or potential "irrational exuberance."

The GVAR model depends on a key assumption that countries in the model behave as small open economies. That is, there cannot be long run feedback from the domestic to the foreign country specific variables, but short run feedback between the two types of variables is allowed. The test for weak exogeneity suggests that this requirement is in general satisfied, however not in the case of output in the model for the US economy. The implications of this result and how we deal with it is considered in the subsection below.

All countries in the model are treated as small open economies, except the US. To capture the dominance of the US economy, we follow Pesaran and Smith (2006) and adopt a different specification for the US VARX model, as outlined in Table 3 below. More specifically, the US VARX model allows for feedback from US macro variables to the global variables (oil price, global credit, and vix index).

Table 3. Model Specification

Country	Domestic Variables	Foreign Variables	Global Variables
US, $\forall i = 0$	$crd_{it} \quad y_{it} \quad ex_{it} \quad reer_{it}$ $vix_t \quad oil_t \quad loans_t$	$crd_{it}^* \quad y_{it}^* \, ex_{it}^* \quad reer_{it}^*$	
Rest of the World $\forall i = 1,2,..., N$	$crd_{it} \quad y_{it} \quad ex_{it} \quad reer_{it}$	$crd_{it}^* \quad y_{it}^* \, ex_{it}^* \quad reer_{it}^*$	$vix_t \, oil_t \quad loans_t$

Unlike previous contributions such as Dees and others (2007a and 2007b), our model does not construct the real exchange rate as a closed system. Instead, the real exchange rate is obtained from the IMF IFS database and therefore, it can be included as a foreign variable in the US model.

Unit root test

Following Pesaran, Schuermann, and Weiner (2004) and Dees and others (2007a and 2007b), we assume that the variables included in the model specification are integrated of degree one. To examine the validity of this assumption, we rely on the statistics on the ADF tests and the weighted symmetric estimation of ADF type regression (henceforth WS), suggested by Park and Fuller (1995). In selecting the lag length for the ADF and the WS unit root tests, we use the Akaike Information Criterion (AIC). The results from the two tests support the presumption that the variables of the model are, in general, integrated of degree one. Test results can be found for all countries and variables (domestic, foreign, and global) in the Supplement of the paper, available upon request.

Weak exogeneity test

As pointed out earlier, one of the main assumptions of the GVAR model is weak exogeneity, i.e., that there is no long run forcing effect from the country specific domestic to the foreign variables. To confirm the assumption, we perform a formal test for all country specific foreign variables, as well as for the global variables. Following Dees and others (2007a and 2007b), the test of weak exogeneity is performed as described in Johansen (1992) and Harbo and others (1998) and the results from the test for some of the major economies are summarized in Table 4.

Table 4. Weak Exogeneity Test

	F test	y_{it}^*	ex_{it}^*	$reer_{it}^*$	crd_{it}^*	oil_t	$loans_t$	vix_t
US	F(4, 70)	2.80**	1.45	0.42	0.08	-	-	-
EA	F(3, 74)	0.39	1.44	0.74	0.49	0.85	2.18	1.07
UK	F(3, 74)	2.26	1.17	0.30	0.79	1.07	1.07	1.31
China	F(1, 76)	0.19	0.57	0.53	0.02	0.36	0.12	0.25

Note: The table provides the F statistics for the Weak Exogeneity Test of the country specific foreign variables and the global variables in the model. "**" denotes significance at 5 percent.

Table 4 shows that the test fails to reject the weak exogeneity assumption only in the case of output in the US model. That is, there is evidence of a long run feedback from the US domestic to foreign output. We thus proceed by excluding the foreign output variable from the model for the US economy (as done in Pesaran, Schuermann, and Weiner, 2004).

Estimation of the country specific models

For each country in the sample, the lag order of the country specific VARX(p_i,q_i) model is computed using the AIC. Here, p_i denotes the lag order of the domestic variables and q_i denotes the lag order of the foreign country specific variables. Due to data limitations, the maximum lag order allowed for the GVAR model is two. The cointegration rank of each individual vector error correction model is computed using the Johansen's trace and maximal eigenvalue statistics. The lag order for the domestic and foreign variables as well as the number of the cointegrating relationships of the country models based on the trace statistics (at 95 percent critical value level) are presented in the second section of the Appendix.

V. RESULTS

To measure the effect of shocks, we estimate Generalized Impulse Response Functions (GIRF).[6] GIRFs estimate the effect on the response variable given a shock on the impulse

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[6] See Koop, Pesaran and Potter (1996) and Pessaran and Shin (1996).

variable, while also considering the expected shock on all other variables in the system. The advantage of the GIRF to the Orthogonalized Impulse Responses (OIR), proposed by Sims (1980), lies in the GIRF being unaffected by the ordering of the variables in the GVAR model.

Although the estimated GVAR allows inference on a rich array of shocks, for the sake of brevity, we will focus on the transmission of shocks arising in the US, advanced economies excluding US (AE), and emerging market economies (EM) to LIDCs. We look at the US economy individually because of its world economic dominance and its trade ties to the entire subset of LIDCs comprising our sample. Canada, the Euro Area (France, Germany, and Italy), Japan and the UK make up the AE group; Brazil, China, and India make up the EM group. All remaining countries, including (South) Korea, Australia, Argentina, Mexico, Turkey, and Indonesia, constitute the "other countries" in our groupings.

We report impulse response functions for LIDC country subgroups based on important common country characteristics. That is, we compare impulse responses for oil-exporting vs. importing countries, commodity-exporting vs. importing countries, and frontier economies vs. remaining LID countries (see Table 5).[7] The model also allows for estimation of country specific impulse responses, which are available upon request.

Table 5. LIDCs' Country Groupings

Comm. Exp.	Oil Exp.	Comm. Imp.	Oil imp.	Frontier
Bolivia	Cameroon	Bangladesh	Bangladesh	Bangladesh
Burundi	Congo	Cameroon	Bolivia	Bolivia
Congo	Ghana	Cape Verde	Burundi	Ghana
Guyana	Nigeria	Comoros	Cape Verde	Kenya
Nigeria	Papua N. G.	Dominica	Comoros	Nigeria
Papua N. G.	Sudan	Gambia	Dominica	Papua N. G.
Sudan		Ghana	Gambia	Uganda
Zambia		Grenada	Grenada	Zambia
		Honduras	Guyana	
		Kenya	Honduras	
		Maldives	Kenya	
		Myanmar	Maldives	
		Nepal	Myanmar	
		Samoa	Nepal	
		Uganda	Samoa	
		Vanuatu	Uganda	
			Vanuatu	
			Zambia	

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[7] Common dimensions used in identifying frontier markets (FMs) have included (i) a financial sector that is starting to share some similar characteristics of emerging market economies in terms of financial market depth; (ii) access to international capital markets; (iii) fast sustained growth; and (iv) sound institutions. (See Macroeconomic Developments in LIDCs: 2014 Report)

The impulse response functions we present below show the response to a one standard deviation negative shock to output and private credit.

Figure 1. Response of GDP to Negative Shock to EM's Output

LIDC Oil Exporters   **LIDC Oil Importers**
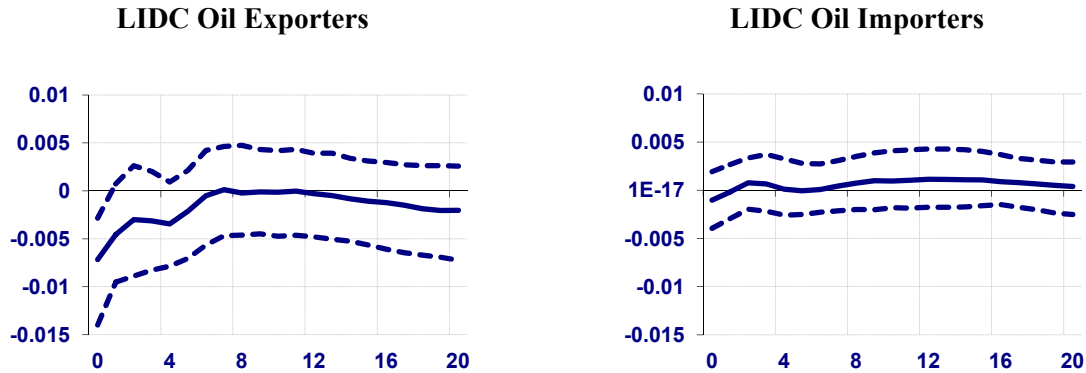
Note: The figure represents the bootstrap mean estimates with 90 percent error bands.

Figure 2. Response of GDP to Negative Shock to AE's Output

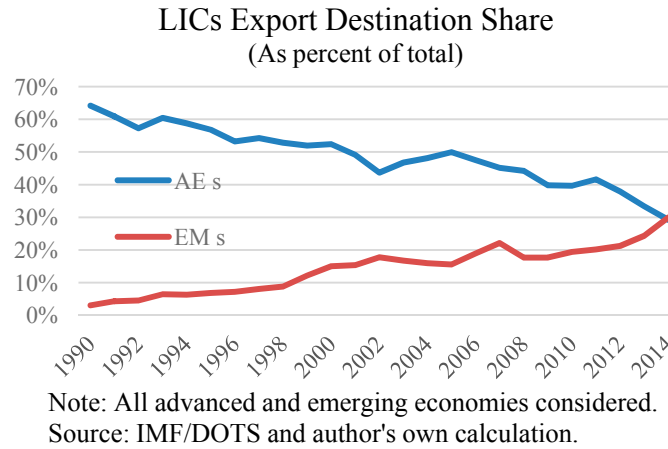**LIDC Oil Exporters**   **LIDC Oil Importers**
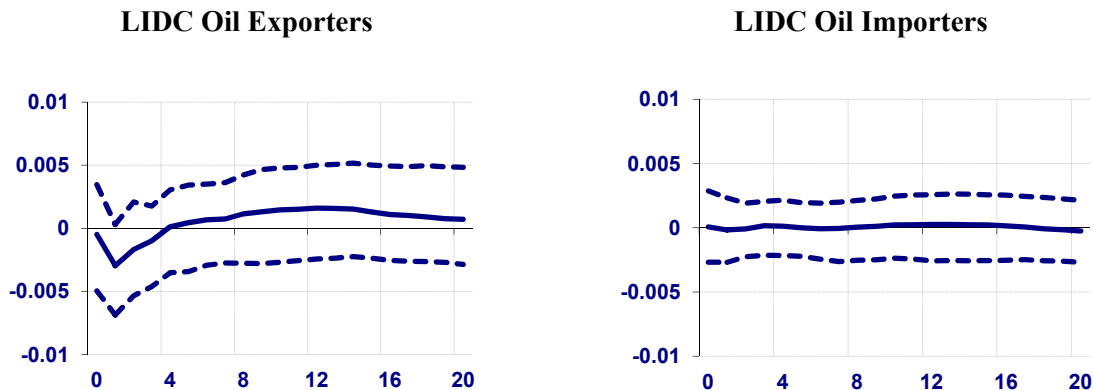
Note: The figure represents the bootstrap mean estimates with 90 percent error bands.

We start by examining the impact of shocks to output in AE, EM, and the US on real activity and exports in LIDCs. Subsequently, we perform the same analysis and assess the impact of credit shocks in AE, EM, and the US on output and exports in LIDCs.

Figures 1 and 2 above display the GIRFs of output in oil-exporting and oil-importing LIDCs to a one standard error negative shock to output in EM and AE, respectively. They show a significant negative response of output in oil-exporting countries to a negative shock in EM output compared to an insignificant response of oil importers. On the other hand, shocks to AE output (Figure 2) only have a brief and smaller negative impact on the output performance of oil exporters. Finally, output in both oil-exporting and oil-importing LIDCs fails to respond significantly to shocks to US output; the graphs have been omitted from the text and are available upon request. Overall, these results suggest that LIDCs exhibit more

synchronized business cycles with EMs rather than with other countries in the world, of which the results are strong and significant for oil-exporting countries in particular.

LICs Export Destination Share
(As percent of total)

Note: All advanced and emerging economies considered.
Source: IMF/DOTS and author's own calculation.

The importance of emerging markets as trade partners for LICs has continuously increased over time. As the above figure shows, EMs have, as of late, overtaken traditional partners as importers of LIDCs' exports. Together with the fact that EMs show higher income elasticity of demand to oil, as will be discussed below, a more robust synchronicity of business cycle between oil exporting LICs and EMs seems intuitive. Having that as a backdrop, the results above, indicating a more robust relationship between output fluctuations of EMs and LICs compared to AEs, are less surprising.

Figure 3 presents the impact on exports of LIDCs oil-exporters vs. importers to a one standard error negative shock to US output. The GIRFs demonstrate a significant response of oil-exporting countries (after three quarters), in contrast to the insignificant response of oil importers. The significant impact of output volatility on exports seems to reflect three main issues, the larger integration of oil-exporting LIDCs into the global economy via trade and financial links, wealth effects and a presumably higher income elasticity of the demand for oil than other LIDC exports (e.g., agricultural products). In precise terms, their exports to GDP ratio stands at about 38 percent, compared to the lower 33 percent average of oil-importing countries. Furthermore, it is well documented that commodity based LIDCs' exhibit lack of diversity in exports,[8] leaving them substantially exposed to international oil price shocks and demand for oil. Turning now to the comparison group, the oil-importing LIDCs tend to be exporters of primary and mostly agriculture products. Because of Engel curve arguments, it is plausible to assume that the demand for primary and agriculture

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[8] Commodity exporting countries often encounter Dutch disease type of pressures on currency valuation, thereby reducing the competitiveness of other sectors vis-à-vis foreign markets.

products to have small income elasticity,[9] and would thereby be more insulated from demand shocks from the output fluctuations of importing countries.

It is interesting to note that shocks to output in AE and EM do not seem to have a significant impact on exports of either oil-exporting or importing countries (the figures have been omitted for conciseness). If exports are not the channel of transmission, other mechanisms need to be at play. Potential culprits could be wealth effects (as slowdowns in EM growth presage lower permanent income for LIDC oil exporters) and slowdowns in cross-border lending or FDI flows, both of which would have an impact on local demand and capital investment.

Figure 3. Response of Exports to Negative Shock to US Output

LIDC Oil Exporters   **LIDC Oil Importers**
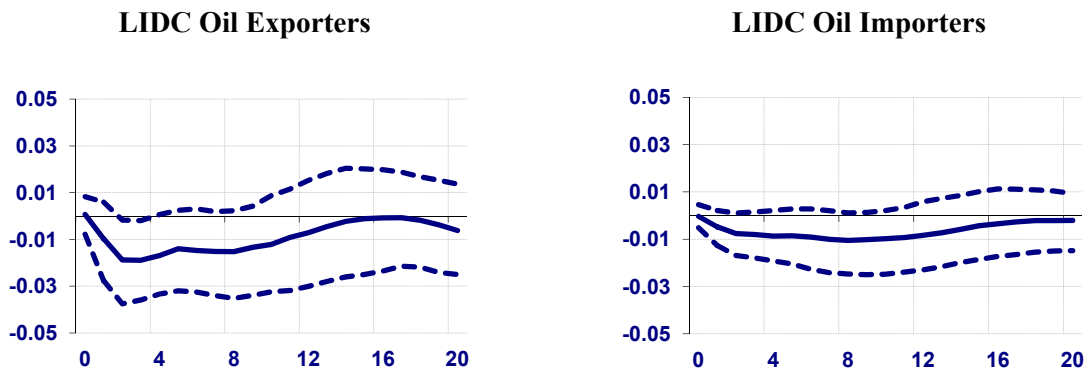
Note: The figure represents the bootstrap mean estimates with 90 percent error bands.

The stronger reaction functions of oil exporters can further be explained by considering the income elasticity demand (IED) for oil. For the US, the IED for oil has historically been around one, implying that for a 1 percent drop in output, the economy would reduce oil consumption by 1 percent (Hamilton, 2009). Despite the fact that this ratio has been declining for the US in the past decade, it is still significant. Hence, the participation of the US in the trade export share of LIDCs is, at least in the short term, most likely to leave oil-exporting countries vulnerable to US business cycles through exports.

Subsequently, to test for the possibility that financial spillovers can also be at play, we consider the transmission of a one standard error negative shock to private credit in (i) EM, (ii) AE, and (iii) US to output and exports in oil-exporting and importing countries. It turns out that credit conditions in EM and AE do not seem to have a significant effect on LIDCs' output and exports (the charts with these results are available upon request); whereas credit conditions in the US affect significantly the output in LIDCs oil exporters, as shown in Figure 4. In addition, exports in both LIDCs oil exporters and importers react significantly to

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[9] There is no extensive empirical literature trying to estimate precise income demand elasticities by product categories, some informative results can be found from the University of Nebraska, http://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=1102&context=agecon_cornhusker

credit condition in the US, but the responses of exports in oil-exporting LIDCs are more pronounced, as shown in Figure 5. These results document the importance and influence of the US economy as a dominant "banker."

The stronger influence of the US compared to Europe is a conundrum. Statistically, shocks to US lending activity have a stronger significant influence onto economic/output conditions in oil-exporting LIDCs, compared to similar shocks in the EU. This is particularly surprising, since for a considerable cross-section of the LIDCs, particularly those in sub-Saharan Africa, the cross-border lending exposure of European banks is much larger.[10] One would therefore expect a credit contraction originating in Europe to spillover to local credit markets and real economic activity in a similar strength as one originating in the US. A potential explanation could be that many of the strong cross border credit linkages reflect special colonial ties, which might be inclined to be longer term engagement and less focused on shorter-sighted financial lending objectives. Hence, while a shock to credit in the US will immediately spillover to LIDCs, the possible longer-term European engagement would dampen the transmission. Another possibility is that credit shocks in the US are amplified by the response of other AEs while credit shocks to AEs are offset by US monetary policy.

Figure 4. Response of GDP to Negative Shock to US's Credit

LIDC Oil Exporters   LIDC Oil Importers
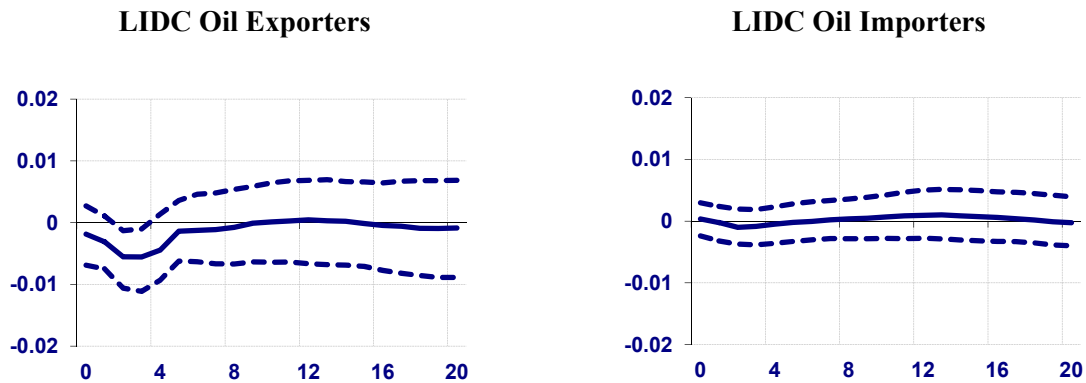
Note: The figure represents the bootstrap mean estimates with 90 percents error bands.

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[10] For further details, compare BIS Quarterly Review, September 2013 (page 20) or IMF's Regional Economic Outlook (Apr. 2012), Chapter 2

**Figure 5. Response of Exports to Negative Shock to US's Credit**

LIDC Oil Exporters   LIDC Oil Importers
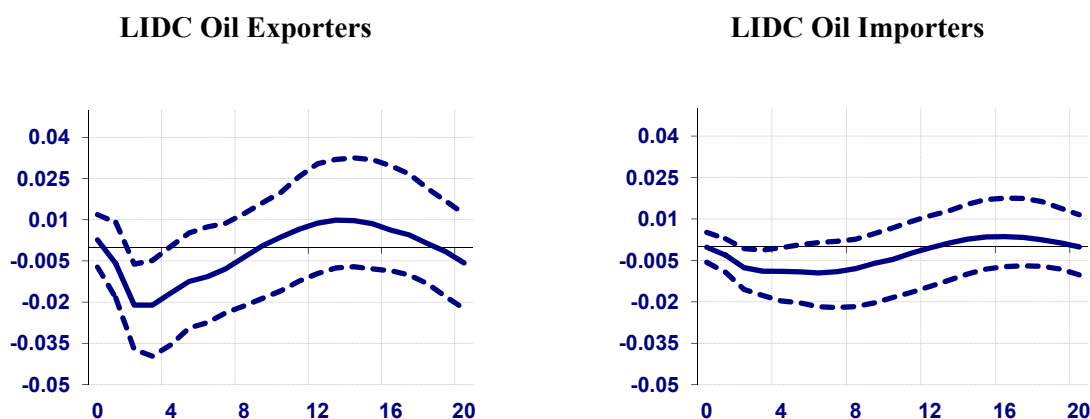
Note: The figure represents the bootstrap mean estimates with 90 percent error bands.

Finally, the figures displaying the transmission of output shocks from AE, EM, and US to output and exports to other LIDC subgroups, i.e., frontier markets (vs. other LIDCs) and commodity exporters (vs. importers), due to space considerations is omitted and is available upon request. The results from those analyses indicate that output and exports in commodity-exporting LIDCs is vulnerable to output shocks arising in AE, EM, and US, implying that commodity-exporting LIDCs are also exposed to global movements as oil exporters.[11] On the other hand, frontier LIDCs, despite their lowest exports to GDP ratio of 31 percent (compared to the ratio of oil and commodity exporters), are still similarly exposed to global business dynamics. Both output and exports in frontier LIDCs respond significantly to global output shocks. This result suggests that frontier markets, unlike other LIDCs, even though they fall behind oil and commodity exporters in terms of export-to-GDP ratio, they are more integrated into global financial markets and therefore also exposed to other shock transmission channels other than the trade channel alone.

Indeed, credit conditions in the US seem to have the strongest impact on frontier LIDCs markets. Figure 6 below presents the consolidated effect of a US credit contraction on the GDP of different regions. As argued before, the LIDCs frontier markets seem to be particularly hard hit. Therefore, despite their lower trade integration, they still do exhibit significant responses to global movements.

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[11] Indeed, exports to GDP ratio for LIDC commodity exporters is about 38 percent (compared to the 33 percent of commodity importers), which is exactly in par with the one of the oil-exporting countries.

Figure 6. IRFs to Negative Shock to US Private Credit in Different Regions

Response of GDP After Three Quarters

Response of Exports After Three Quarters
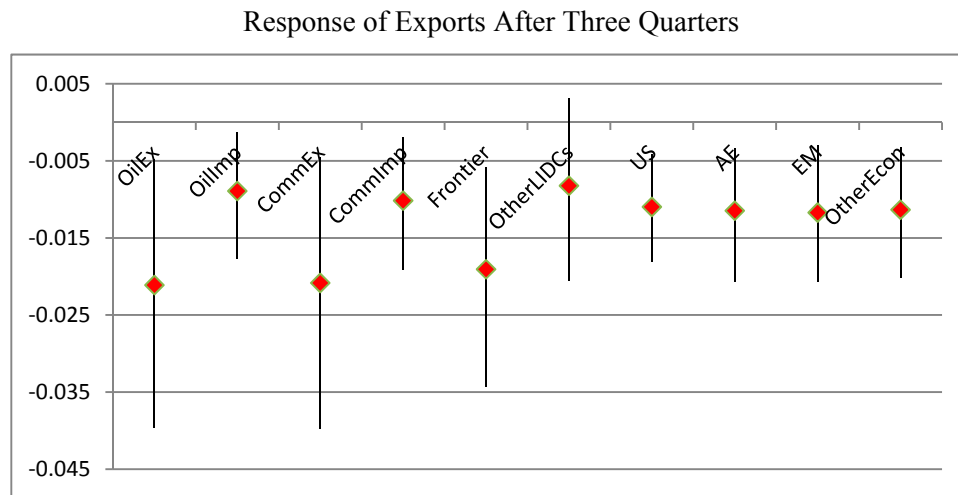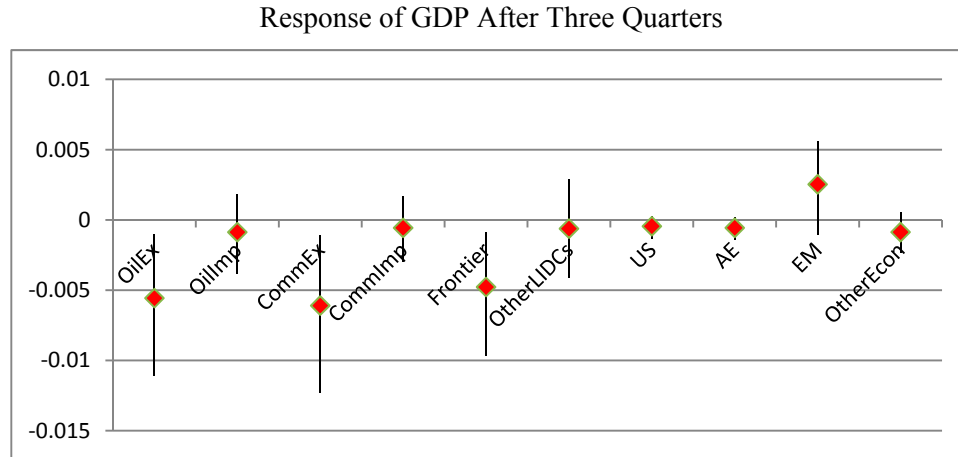
Note: The candlestick charts depict the mean estimates with 90 percent error bands.

VI. CONCLUSION

This paper estimates a GVAR model to study the transmission of business cycles and credit conditions from advanced and emerging market economies to LIDCs. For that purpose, we build a panel with quarterly data covering the period 1990Q1–2013Q4, comprising of 40 countries, of which 9 advanced, 7 emerging, and 24 LICs. The GVAR model specification is capable to capture some of the key characteristics of LIDCs, for e.g., their reliance on trade and foreign demand, while also being flexible enough to study the effects of global financial conditions on LICs in a systematic way.

The major findings of this paper suggest that different LIDCs subgroup of countries are exposed to shock transmission from the US, other advanced and emerging market economies along various dimensions. Particularly oil- and commodity-exporting countries, as well as frontier markets exhibit greater synchronicity of business cycles with emerging market economies. Furthermore, credit conditions in the US appear to matter for LIDCs oil and

commodity exporters and frontier market economies, whereas financial conditions in other parts of the world seem to be insignificant for LIDCs. Among many, two policy implications could be singled out from these results. For one, the diversification of both export components as well as export partners could help stabilize output fluctuations induced by business cycles in selected, fast growing emerging market economies. Secondly, searching for a broader spectrum of external financing channels could diminish the exposure to US credit supply.

Appendix

A. Data

This section describes the data and the methods used to create the dataset used in the estimation of the GVAR model. This dataset covers a wide range of macroeconomic time series for 24 LIDCs and a subset of 16 G20 countries for the period 1990Q1–2013Q4. All data are real (deflated with the CPI's of the corresponding currency) quarterly sequences and seasonally adjusted (using the multiplicative seasonal adjustment method), where necessary. The time-series were collected from various sources including IMF's WEO, IFS, IFTSTSUB, DTTS, and MBRF. All time series were converted to logs. Complete data series were available for the exports and the real effective exchange rate for both the G20 and the LICDs, as well as for all global variables (oil prices, the VIX index, and the variable denoting global credit availability). However, for some of the data series, including GDP, CPI and Claims to Private Sector, there were some gaps in the series (e.g., few quarters or years of data entries were missing). These gaps were filled in as follows: (i) if data points were missing for less than one year, the missing observations were obtained by linear interpolation; (ii) if data points were missing for over a year and the yearly series of the same variable were available, then the annual series were interpolated to obtain the quarterly missing series; (iii) if data points were missing for only a few (1–4) quarterly observations and no annual data were available, then only if the series featured a growth trend, the missing data points were obtained by using the average growth rate over the entire sample period to obtain the quarterly observations. In more detail:

- **GDP.** The GDP quarterly data were extracted from the quarterly WEO database and the missing observations were complemented by the annual WEO database following the method outlined above. The annual data for the LIDCs' GDP was extracted from the WEO database. The data was interpolated using the Fernandez (1981) approach to obtain quarterly data using imports as a high frequency benchmark series.

- **CPI.** The CPI quarterly data were extracted from the IFS database and the missing observations were complemented by the annual WEO database. Also the combined databases were adjusted to reflect the same base year for the CPI.

- **Private Claims.** The quarterly data for both LICs and G20 countries was obtained from the IFTSTSUB dataset (series 22d). The data for the period 1990Q1–2006Q4 was downloaded with the code "___22D..ZF…" and the data for the period thereafter was downloaded with the code "___22D..ZK…" Since the data is in national currency, in the case of France, Germany, and Italy, the series were converted from the national currency to EUR using the exchange rate at the introduction of the EUR. Note that the data for the Euro Area countries was downloaded directly from the IMF website.

B. Estimation Results

The table below presents the lag order for the domestic and the foreign variables as well as the number of the cointegrating relationships of the country models, based on the trace statistics (at 95 percent critical value level).

VARX(p_i, q_i) Order and Cointegration Relationships in the Country Models

	p_i	q_i	#Coint. Relationships
Argentina	2	1	2
Australia	2	1	2
Bangladesh	2	1	1
Bolivia	1	1	3
Brazil	2	1	2
Burundi	2	1	0
Cameroon	1	1	3
Canada	2	1	2
Cape Verde	2	1	1
China	2	1	1
Comoros	2	1	1
Congo	2	1	1
Dominica	2	1	1
Euro Area	2	1	3
Gambia	2	1	0
Ghana	2	1	2
Grenada	2	1	1
Guyana	2	1	1
Honduras	2	1	2
India	2	1	2
Indonesia	2	1	1
Japan	1	1	1
Kenya	1	1	3
Korea	1	1	2
Maldives	1	1	2
Mexico	1	1	2
Myanmar	2	1	2
Nepal	2	1	1
Nigeria	2	1	2
Papua New Guinea	2	1	2
Samoa	2	1	1
Sudan	2	1	2
Turkey	2	1	2
Uganda	2	1	2
UK	2	1	3
USA	2	1	4
Vanuatu	2	1	1
Zambia	2	1	2

Note: The table presents the lag order for the domestic and foreign country specific variables in the country VARX models based on AIC. The last column presents the number of cointegrating relationships in the country models based on the Johansen's trace and maximum eigenvalue statistics.

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