The Output Effects of Commodity Price Volatility: Evidence from Exporting Countries*

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Abstract

This paper analyses the impact of commodity price volatility on real economic activity in commodity exporting countries using Structural Vector Autoregressions with Multivariate GARCH-in-Mean errors. To capture the distinct export structures of the different countries we build country specific commodity export price indices. We find a significant negative impact of commodity price volatility on real output for the oil exporters in our sample. Impulse response analysis shows that the increase in volatility that accompanies a commodity price shock negatively affects the response of real output. For countries relying on mineral and food exports, point estimates are predominantly statistically insignificant. Our findings are robust to several variations in lag length, sample and data.

JEL-Classification: C32, E32, F43, O13, Q43

Keywords: Commodity Price Uncertainty, Commodity Exporters, VAR-MGARCH-in-mean

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1 Introduction

The first decade of the new century witnessed a steep increase in commodity prices, followed by an even steeper decline during the financial crisis of 2008 before prices started to surge to unprecedented heights again since 2009. As a consequence of these large fluctuations, commodity price volatility reached historically high levels. This development gained attention by both policymakers and policy advisors worldwide. The G20 summit in 2011, for instance, identified commodity price volatility as one of the concerning issues for future economic development. It is feared that increased volatility creates uncertainty over future price levels which complicates investment and hampers economic growth. This concern is supported by a seminal theoretical literature analyzing investment under uncertainty (Bernanke 1983, Pindyck 1991, Dixit and Pindyck 1994). Moreover, there is a prominent empirical literature on the negative impact of general economic uncertainty, quantified by measures of volatility, on economic aggregates (Ramey and Ramey 1995, Bloom 2009).

With respect to commodity price volatility, recent research has established a negative effect of uncertainty in oil prices on output in the United States. Notable contributions by Elder and Serletis (2010, 2011) show that oil price volatility dampens real output at the business cycle frequency. In the same vain, Bredin et al. (2011) detect a negative oil price volatility effect for four other G7 countries. However, oil is not the only commodity of interest. Many countries rely on revenues from non-oil primary commodity exports as a significant source of income. Empirical results on output effects of commodity price volatility concerning a broader basket of commodities are mixed. While Blattman et al. (2007) and Cavalcanti et al. (2012) find negative effects of volatility on economic growth for primary exporters, results from Arezki and Gylfason (2011) indicate that volatility is even beneficial for growth in democratic countries. In addition, these studies differ in an important aspect from the studies on oil price volatility as they analyze the relationship between commodity price volatility and output over long time periods with homogeneous panel techniques. This raises concerns that econometric results might particularly be driven by non-controllable institutional changes over time or questionable homogeneity assumptions across countries.

In this paper we contribute to the literature by extending the existing research on oil price uncertainty and real output to a broad basket of commodities. At the same time, we fill a gap in the literature on commodity price volatility as we consider individual countries at the business cycle frequency to avoid shortcomings of existing studies. As they are most heavily affected by price swings, we focus on a set of countries where commodities account for a large share of exports. We consider a basket of 48 different commodities ranging from energy inputs, metals, and agricultural raw materials to food and use international trade data to construct country specific commodity export price indices based on the 48 items to capture the particular effect of volatility on output. Methodically, we follow Elder and Serletis (2010, 2011) and employ a vector autoregression (VAR) which is augmented by multivariate GARCH (MGARCH) errors. To capture the impact of volatility on output, the GARCH errors are linked to the mean equation (GARCH-in-mean).

Our main results can be summarized as follows: we find that commodity export price volatility has a negative effect on real output for the oil exporting countries in our sample. Impulse Response Analysis shows that the production enhancing effect of a positive export price shock on the real economy is dampened by the associated increase in volatility. For the other countries in our sample that mainly rely on non-energy commodity exports like minerals, metals, and food, commodity price volatility is estimated to have no significant effect on real output.

The remainder of this work begins with a brief overview of the related literature on the economic impacts of commodity price volatility and uncertainty (section two). Section three presents our approach regarding the country selection and the commodity price indices while section four describes the econometric setting. Empirical results, impulse response analysis, and policy implications are given in section five with concluding remarks following in the last sections.

2 Commodity Price Volatility and Economic Activity

The concerns of policy makers link commodity price volatility to economic uncertainty which impedes investment decisions and, thus, negatively affects output. Such a negative effect of general uncertainty on output is both theoretically and empirically well established.

Bernanke (1983), Pindyck (1991) and Dixit and Pindyck (1994) show that higher uncertainty about expected future cash-flows can lead companies to defer investment as the value of waiting for new information increases. As a result, uncertainty about future conditions causes fluctuations in aggregated output, a reasoning also known as the ‘real options’ channel. Edelstein and Kilian (2009) stress the fact that price volatility can also have demand side effects: uncertainty about future prices, especially of energy prices, might hamper real activity through a diametrical effect on consumer spending.

Bloom (2009) provides empirical evidence for the ‘real options’ theory on the firm level. In periods of increased uncertainty firms choose to “wait-and-see” rather than to pursue decisions which would have taken place under normal circumstances. From a macroeconomic perspective, a seminal empirical study by Ramey and Ramey (1995) finds a negative link between output and output variability. Bloom (2009) uses multiple measures of stock market volatility to capture uncertainty and finds that industrial production in the US drops in response to an uncertainty shock. Gourio et al. (2013) use simulations in an open economy Real-Business-Cycle model and VAR estimations to analyze the impact of increased uncertainty in several other developed countries. They find that increased uncertainty, as measured by volatility, lowers output and also has a significant impact on other variables. Carrière-Swallow and Céspedes (2013) extend this analysis to a set of developing countries and find that increased global uncertainty leads to a sharper fall in investment and consumption in economies with less developed financial markets.

Altogether, there is substantial theoretical and empirical evidence that uncertainty, measured by volatility, can have adverse effects on output. Commodities are necessary imports in industrial countries and an important source of income for others that rely on primary commodity exports. Therefore, the development of commodity price volatility has triggered attention by both policy makers and the scientific community. A lot of research has focused on identifying the drivers of the recent price surge and the causes for the increased volatility but there is also a considerable literature discussing the macroeconomic effects of commodity price volatility.

A recent contribution by Elder and Serletis (2010) uses a structural VAR accomodated by GARCH-in-mean errors to analyze the impact of oil price uncertainty on real economic activity in the US.[1] In a bivariate system containing real GDP growth and the real price of oil they find that uncertainty about the oil price has a significant negative effect on real economic activity over the post OPEC (post 1974) period. Uncertainty about future oil prices is thereby measured as the conditional standard deviation of the forecast error of the oil price change. In a follow-up paper, Elder and Serletis (2011) detect the negative effect also for monthly data on industrial production and manufacturing. Similar work by Elder and Serletis (2009), Bredin et al. (2011) and Rahman and Serletis (2012) shows that the volatility effect is not limited to US data but also appears in four of the G7 countries (UK, US, France, and Canada).

[1] The impact of commodity price shocks at the business cycle frequency has been studied by numerous researchers. This has been done both in theoretical frameworks as well as with empirical methods (for instance, Hamilton 2003 or Kilian 2009). The impact of commodity price uncertainty, however, is a far less researched field with the strand following Elder and Serletis (2010) being the notable exception.

The effect of uncertainty regarding a broader basket of commodities has only been studied in panel frameworks covering long time periods. Blattman et al. (2007) use a unique dataset to investigate the impact of commodity price and terms of trade developments on growth between 1870 and 1939. For the then less industrialized, commodity export dependent nations, the terms of trade volatility was mainly driven by the volatility of their primary export commodities. The authors show that differences in volatility between primary commodity prices account for a meaningful share of growth differences within this group of countries. For the already highly industrialized countries in Western Europe and the US, meanwhile, volatility changes did not play a significant role. This is explained by their more diversified export structure and better insurance mechanisms which were already in place. Cavalcanti et al. (2012) use a more recent panel dataset of 118 countries for the period 1970-2007. They build country-specific terms-of-trade indices based on commodities only. Using both dynamic panel techniques with multi-year averages and a pooled mean group estimator with yearly data, they find that commodity terms-of-trade volatility is not related to output growth for countries with a diverse export basket. However, it negatively affects growth for a subset of primary commodity exporters.[2]

Arezki and Gylfason (2011), on the other hand, take a similar approach, a panel with up to 158 countries from 1970 to 2007, but investigate the relationship between commodity price volatility and non-resource GDP, total GDP subtracted by the real value of natural resource rents. In contrast to the other research, they find a positive effect of commodity price volatility on growth, albeit only in democracies. The effect in autocracies is not significant. They explain their finding with an increase in national savings taking place in democracies while savings do not increase in autocracies.[3]

Altogether, the existing evidence points rather towards a negative effect of commodity price volatility on output for exporting countries. However, the work by Arezki and Gylfason (2011) shows that this result relies on the measurement of both output and volatility. Moreover, several caveats about these studies remain. The existing literature treats groups of countries

[2]The negative impact of volatility is connected to a slower accumulation of human and especially physical capital and not with a slower growth of total factor productivity. This underlines the possibility of a negative investment effect due to increased volatility, as outlined in the theoretical literature. In a similar vein, van der Ploeg and Poelhekke (2009) show in a dynamic panel setting that commodity price volatility can help explaining the "natural resource curse", i.e. lower growth rates in countries abundant with primary commodities. They find that countries which heavily rely on a small number of commodities tend to grow slower than countries with a more diverse export basket and link this finding to the higher exposure to price volatility.

[3]Several explanations are conceivable for the differing results of Arezki and Gylfason (2011). On the one hand, they compute volatility at an intra-annual frequency which might deviate from the yearly measures applied by the other authors. On the other hand, their estimation of non-resource GDP might strongly differ from other GDP measures triggering the different results.

as homogeneous regarding the effect of volatility. This assumption appears unwarranted given that trade structures between countries often differ heavily even if both can be classified as commodity exporters. Furthermore, the results strongly depend on how countries are grouped, for example exporters vs. non-exporters or democracies vs. autocracies. Lastly, given the rather long sample periods induced by yearly observations and multi-year averages, it is also possible that changes regarding the institutional structure of countries influence the results.

Our analysis contributes to the commodity volatility literature by avoiding shortcomings of existing studies as we focus on individual countries, shorter time spans and the business cycle frequency. We restrict our sample to countries where commodity exports are an important source of income. A negative volatility effect should be most pronounced in these countries, as they are heavily affected by price swings. To investigate the impact of commodity price volatility on output at the business cycle frequency, we apply a structural VAR-GARCH-in-mean approach similar to Elder and Serletis (2010). Our study is therefore also a complement to the Elder and Serletis strand of the oil price uncertainty literature. We extend the existing research, which has mainly analyzed commodity importing countries, to commodity exporters. Moreover, we include a broad basket of possible export commodities in our analysis. While many countries earn significant revenues from commodity exports, only some of them rely mainly on oil. This analysis yields first evidence whether the uncertainty effect is limited to oil and oil importers or also appears for commodity exporting countries and their broad set of different commodities.[4]

3 Country Selection and Commodity Price Indices

3.1 Country Selection

Our analysis focuses on countries whose exports consist to a large extent of primary commodities. The group of possible candidates mainly encompasses developing countries in Africa, Central Asia, and Middle and South America. Unfortunately, output data on a business cycle frequency are not available for most of these countries. For this reason, we restrict our analysis to the

[4]Our work is related to a similar study by Choi and Kim (2012), however, there are several important differences to their approach. Firstly, we consider a different set of countries as our focus is on commodity exporters. More importantly, our country specific price indices differ substantially from the general IMF commodity price index employed by Choi and Kim (2012). Building country specific indices yields valuable information and is in accordance with the commodity literature. It also allows for larger estimation samples as our indices cover a longer time period than the IMF index. Moreover, we control for volatility induced by changes in exchange rates and the general price level by converting the indices to real terms. Lastly, our analysis takes the possibility of a spurious relation in the data caused by the major recession in 2008 into account.

following countries: Australia, Brazil, Canada, Chile, Indonesia, Mexico, New Zealand, Norway, and South Africa.[5]

This choice is based on a threshold which requires commodities to account for at least 30 % of total exports in 2008. Using the threshold ensures that the countries in our sample are highly exposed to swings in commodity prices. More importantly, their export share is considerably higher than in industrial countries considered to be major commodity importers.

Table 1: Share of Commodities in Exports

	share of comm. in total exp.	share of petrol. in comm. exp.		share of comm. in total exp.	share of petrol. in comm. exp.
Australia	0.67	0.16	Mexico	0.21	0.82
Brazil	0.44	0.21	New Zealand	0.34	0.20
Canada	0.39	0.65	Norway	0.77	0.88
Chile	0.71	0.03	South Africa	0.39	0.06
Indonesia	0.56	0.38			

Table shows the value share of the 48 commodities included in the commodity price indices in total exports and the value share of petroleum products in the 48 used commodities. Numbers are author's own calculations based on UNCTAD trade data from 2008.

Table 1 shows the value share of commodities in total exports for our sample countries calculated with UNCTAD trade data. The only country for which exports lie below the threshold is Mexico, however, the share of commodity exports in official trade data for Mexico is known to be downward biased due to the extended workbench function of the so called 'Maquilla Sector' (Jiménez and Tromben 2006). This means that the share of commodities in exports is larger than the official UNCTAD data suggest. A noteworthy fact is that the commodity value shares for some countries in our sample are mainly driven by petroleum products (Canada, Norway, Mexico, and, to a lesser extent, Indonesia). For other countries petroleum plays only a minor role as minerals, metals, and food constitute the major share of commodity exports (Australia, Brazil, Chile, New Zealand, and South Africa). Furthermore, the importance of commodities can also be deduced from the share of commodity exports in GDP (Table 4 / Appendix). This share exceeds 10 % for almost all our sample countries which further underlines the role of commodities in these economies.

[5]Notable omissions from the sample include countries in South America like Argentina, Colombia, Peru or Paraguay, where monthly data on industrial production are to some extent available going back to the 1980s. However, both the noisy and crisis driven industrial production series as well as the recurring currency crisis prevent us from obtaining trustworthy results for these countries.

3.2 Commodity Export Price Indices

For our empirical analysis, we construct country specific commodity price indices. This has the advantage that we do not have to rely on general commodity price measures like the index published by the IMF. Instead, country specific commodity export structures, which differ substantially between our sample countries, are taken into account.

Using country-specific indices is not a uniform approach in the literature. Dehn (2000) argues that the concept of 'excessive co-movement' of commodity prices led many researches to use general measures. However, Cashin et al. (1999) show that this co-movement is mainly driven by outliers in the data. Therefore, we follow contributions like Dehn (2000) and construct country specific commodity price indices. In particular, we apply the approach of UNCTAD (2012) which allows for the inclusion of a broad range of commodities and relies on the UNCTAD trade database to ensure data consistency.

Price indices are computed as geometric Laspeyres indices with a fixed base period as introduced by Deaton and Miller (1995):

$$I_{i,t}^{b} = \prod_{j} P_{j,t}^{W_{j,i}}. \tag{1}$$

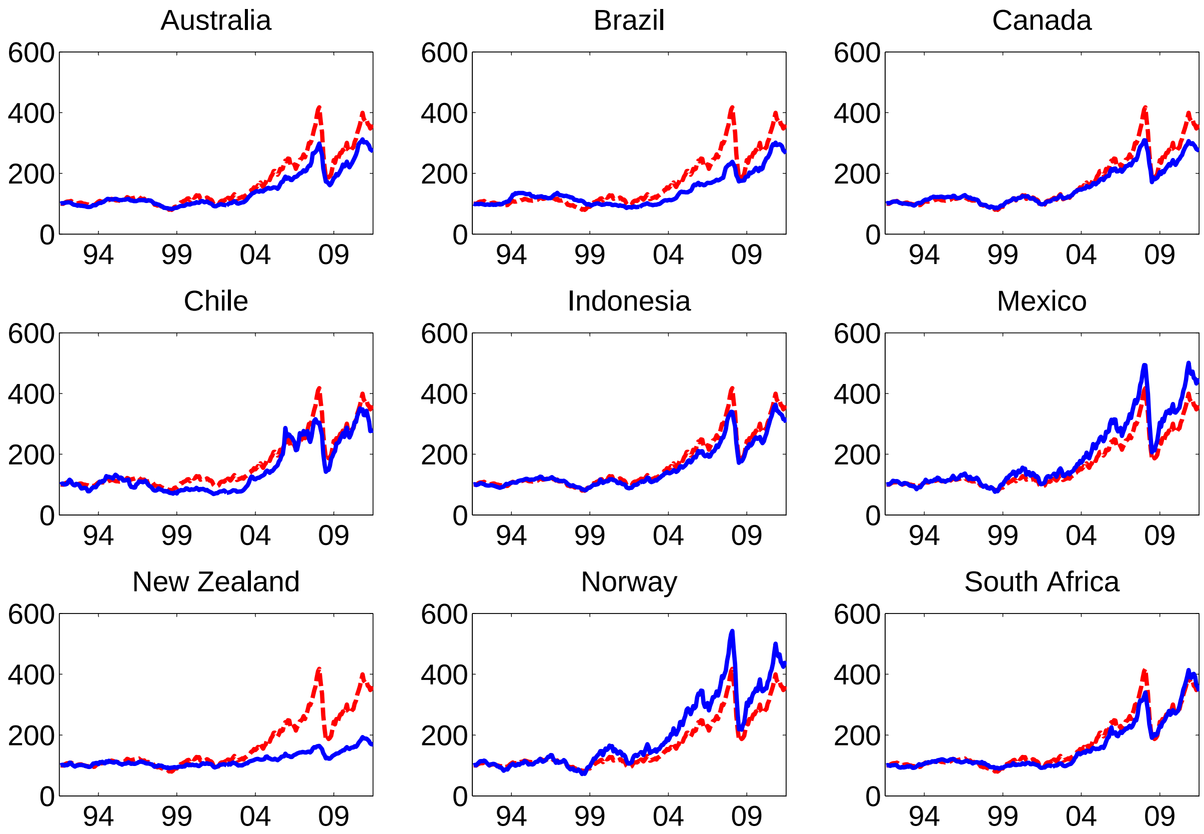
$I_{i,t}$ is the value of the commodity index in country i at time t, $P_{j,t}$ is the international dollar price of commodity j at time t and the weight W_j is the value share of this commodity j in country i's commodity export basket in a base period b. The baskets are based on monthly prices of 48 commodities which cover minerals and metals, agricultural raw materials, and both food and energy commodities. Together, these commodities account for the major share of the commodities traded worldwide over the past decades. Trade data is taken from the UNCTAD database while price data are based on the IMF database and UNCTAD computations.[6]

We follow UNCTAD (2012) and take 1995, which is in the midst of our sample, as the base year for the export weights. Not surprisingly, however, the indices are robust to changing the base period to 2000 or 2008.[7]

[6] We computed the country specific commodity weights based on trade volume matrices for imports and exports publicly available at the UNCTAD database. A detailed description of the included commodities can be found in the data appendix. We are grateful that Jörg Meyer at UNCTAD provided us with the commodity price series of UNCTAD (2012). Unfortunately, some of the prices for the included commodities rely on UNCTAD calculations and are not available at public databases so that our sample ends in 2011.

[7] In fact, the correlation analysis displayed in Table 2 (Appendix) reveals that changes in indices with different base years are almost perfectly correlated. This implies that commodity export structures for different countries stay quite constant over time. We attribute this fact to the long-run nature of investment in extraction facilities, the existence of certain commodities in specific places such as copper in Chile, and rather constant natural and climatic

Figure 1: Nominal Commodity Export Price Indices (with IMF index as benchmark)



Figures show the nominal commodity export prices indices for the individual countries (blue lines). As a benchmark and for comparison, they are plotted along the general IMF commodity index (red dashed lines). Base year for the indices is 1995.

The constructed nominal indices are displayed in Figure 1 and reveal two interesting facts. Firstly, there are pronounced differences between countries despite a general co-movement. Secondly, the co-movement consists of rather stable prices until the onset of the commodity boom in the last decade.

3.3 Other Data

As a proxy for real output we use seasonally adjusted real indices of industrial production. This has the advantage that data is available on a monthly frequency which ensures a sufficient number of observations for a consistent estimation. More importantly, the commodity price indices are also available on a monthly frequency. Using industrial production allows us to

conditions. The exception in our sample is Brazil where the structure of commodity exports seems to have slightly changed over the past decades, presumably due to the rising importance of iron ore and soy beans. Even in this case, however, there is still a strong correlation between changes in indices with base year '95 and '08. Given these results, we do not consider using time-varying weights in our analysis.

make use of their full information content. For Australia and New Zealand, no monthly index of industrial production is available. In this case, we use quarterly data on real GDP (Australia) and manufacturing production (New Zealand) as a measure of real output and take quarterly averages of the commodity price index.[8] Further data include foreign exchange rates, both spot market and PPP adjusted, and consumer prices to convert the indices to real terms. Data on industrial production and the other variables are taken from the OECD database and the IFS statistics of the IMF.

Our earliest starting date with monthly data is January 1980. Prior to 1980, commodities exhibited long periods of rather constant prices with rare but rapid adjustments. By choosing this starting date we avoid modeling a possible break in commodity markets after which prices were more flexible. For Australia and New Zealand less data are available due to the quarterly frequency. Here, we report results starting in 1974 (Australia) and 1977 (New Zealand), however, results prove to be robust to letting the estimations start later.

Our sample ends in December 2011. As a robustness check, we also run several estimations with a shortened sample up to December 2007. In doing so we intend to ensure that our results are not solely driven by the 2008 economic crisis. This is because we fear that the simultaneous increase in volatility and decline in industrial production, caused by the global turmoil on financial markets, might spuriously induce a correlation that is not present in tranquil times.

3.4 Converting Commodity Export Price Indices to Real Terms

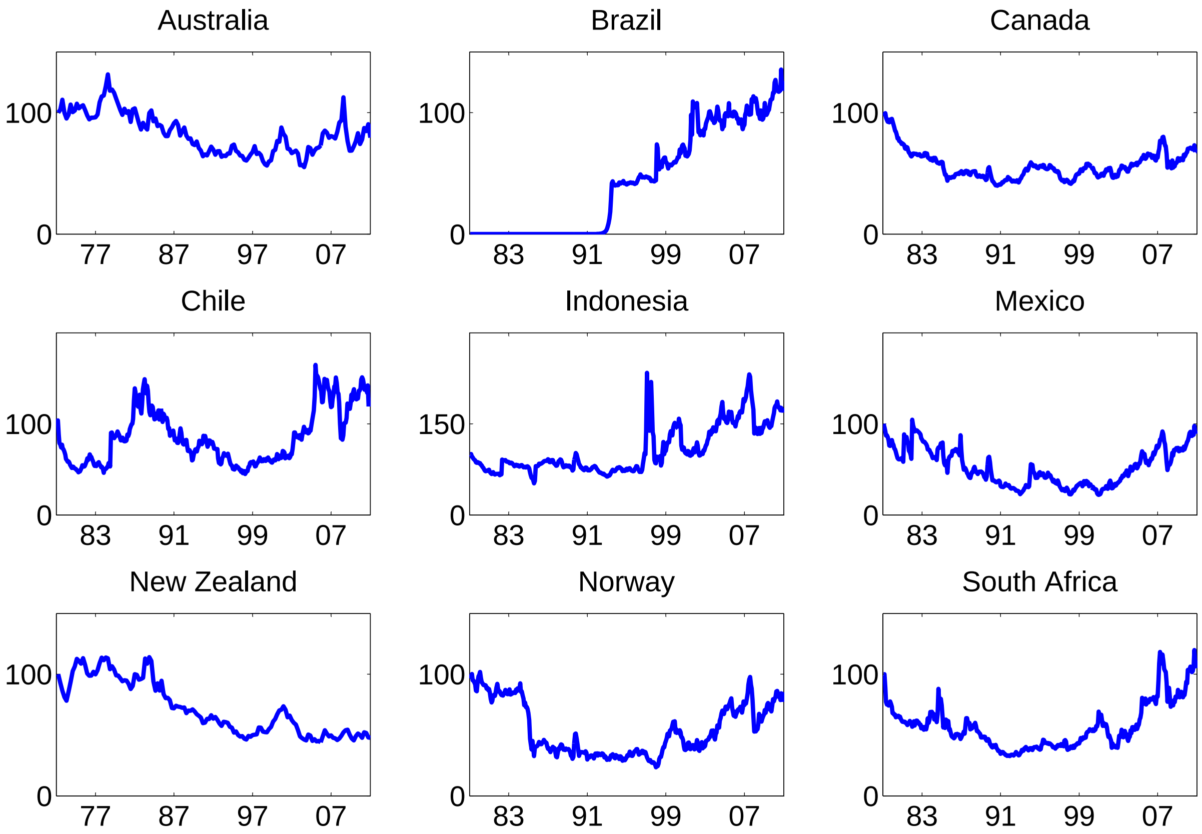
For investment decisions and real output, real and not nominal prices are crucial. Therefore, we convert the nominal indices to real terms for the VAR-GARCH-in-mean estimations. Doing this also takes the volatility in the foreign exchange rate and in consumer prices into account.[9] To convert the nominal US dollar indices to real terms, they are in a first step multiplied with the respective foreign exchange rate. The resulting nominal local currency indices are then deflated by the country specific consumer price index (CPI) to have a real measure of commodity price developments.

The real commodity export indices are shown in Figure 2. In general, they display the same

[8]Quarterly GDP for New Zealand is available only since 1987. Therefore, we use the manufacturing series and not real GDP as otherwise the sample would consist of far less than 100 observations.

[9]Another possibility to control for foreign exchange rates and local consumer prices would be to include them as endogenous variables in the estimation. However, including additional variables in the VAR-GARCH-in-mean estimation considerably enlarges the parameter space. For this highly nonlinear models, the maximum likelihood estimation procedure faces difficulties optimizing over an extensive parameter space. We hence stick to a parsimonious bivariate model in real terms.

Figure 2: Real Commodity Export Price Indices



Figures show the real commodity export prices indices with 1995 as base year for the commodity weights.

patterns as their nominal counterparts. The period of stagnating commodity prices is hereby associated with a deterioration in real terms while the recent surge is also visible in real prices. Also, some of the real indices display more volatility than the nominal ones which is mainly induced by foreign exchange rate movements. This feature is most pronounced for the emerging economies in the sample: Brazil, Mexico and Indonesia. Therefore, we treat the results for these countries with caution. In particular, we estimate the model over different restricted samples to take several crisis periods into account.

Our econometric approach strongly relies on stationarity of the data for a consistent estimation. Therefore, we take logarithmic differences of both the real export commodity price indices and industrial production to ensure stationarity, i.e. we analyze the underlying relationship in growth rates.[10] This is in accordance with the literature on oil price uncertainty (Elder and Serletis 2010, 2011, Rahman and Serletis 2011, Bredin et al. 2011) and consistent with the business cycle perspective of this work.

[10]Results of unit root tests can be found in Table 6 in the appendix. They predominantly point towards series being non-stationary both for industrial production and real commodity price indices.

4 The VAR-MGARCH-in-mean model

The empirical model for our main analysis is a (bivariate) vector autoregression (VAR) which is augmented by GARCH-in-mean errors, as developed in Engle and Kroner (1995) and Elder (2003). In its structural form, the model for the conditional mean can be written as follows:

$$By_t = C + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + \Lambda(L) H_t{}^{1/2} + \varepsilon_t, \tag{2}$$

where y_t is a n-dimensional vector containing the realization of the endogenous variables in period t. Conditional on the information set at period t, F_{t-1}, the structural innovations are assumed to be independently normally distributed: $\varepsilon_t | F_{t-1} \sim N(0, H_t)$. Moreover, we assume that the structural disturbances, ε_t, are uncorrelated, as common in the literature on structural VARs. To identify the structural system a sufficient number of identification restrictions has to be imposed on matrix B. One way of doing this are zero restrictions of the Cholesky form as in a homoskedastic VAR.

Volatility of commodity prices is measured by the conditional standard deviation of the structural innovations, $H_t{}^{1/2}$. This can also be interpreted as the standard deviation of the one-step-ahead (structural) forecast error. As such, $H_t{}^{1/2}$ is a measure of dispersion in the forecast and, therefore, proxies uncertainty about future commodity price developments.

In the VAR-GARCH-in-mean specification, the variables contained in y_t are affected by conditional volatilities if the elements in $\Lambda(L)$ significantly differ from zero. Several lags of H_t could be included in the mean equation. It has to be kept in mind, however, that H_t itself is already correlated with its past realizations. Therefore, we decide to follow Elder and Serletis (2010, 2011) and include only the contemporaneous conditional standard deviation. This has two main advantages. Firstly, testing the effect of commodity price volatility on real output comes down to the statistical significance of a single element. Moreover, the already large parameter space is not further extended.

For the specification of the conditional variance in H_t, several multivariate GARCH models have been proposed in the literature. We use the VEC model (Bollerslev et al. 1988) which can be written as follows:

$$h_t = k + \sum_{i=1}^{q} F_i \eta_{t-i} + \sum_{j=1}^{r} G_j h_{t-j}, \tag{3}$$

with $\eta_{t-i} = vech(\varepsilon_{t-i}\varepsilon'_{t-i})$, $h_t = vech(H_t)$, $\varepsilon_t = H_t{}^{1/2} z_t$ and $z_t \sim N(0, I)$. In this model, the conditonal variance H_t is affected by its own past realizations as well as the lagged innovations contained in $\varepsilon\varepsilon'$. As the ε's are uncorrelated innovations from the structural form, the matrices F_i and G_j are diagonal. Given the empirical evidence supporting the superiority of the parsimonious GARCH(1,1) specification (for instance, Hansen and Lunde 2005), we choose a lag length of $q = r = 1$.

The system of equations is estimated consistently in one step by applying a full information maximum likelihood (FIML) approach. In contrast to homoskedastic VARs, this includes the matrix of structural parameters B which cannot be recovered in a second step by a Cholesky decomposition or maximum likelihood.[11] Under standard regularity conditions these estimates are asymptotically normal and efficient. For statistical inference we employ the inverse of the Fisher information matrix which equals the asymptotic covariance matrix.

To identify the model, we restrict the B matrix so that industrial production reacts instantaneously to innovations in real commodity prices but not vice versa. The economic reasoning is that the commodity exporting countries in our dataset are too small to affect world market prices of commodities right away. This identification strategy is broadly in line with work on oil prices in industrial countries by Elder and Serletis (2010) or Bredin et al. (2011).[12] To further analyze the dynamic properties of our estimated models we use Impulse Response Functions (IRFs) for the SVAR-GARCH-in-mean as derived by Elder (2003). This is necessary since standard IRFs do not apply to this nonlinear model. A detailed description of this approach can be found in the appendix.

[11]B cannot be retrieved separately since the information matrix is no longer diagonal as in the homoskedastic VAR (Elder 2003). A more intuitive explanation is that a reduced form estimation of the model would include fully equipped matrices in the variance equation. Retrieving B from the long-run variance does then not result in the diagonal covariance structure of F and G the structural model implies. Therefore, this diagonal structure is imposed in the estimation and simultaneously estimated with Cholesky type shocks.

[12]Bredin et al. (2011) suggest that a shock to industrial production affects inflation in a country only with a lag. Translating this assumption to our work implies that shocks to industrial production affect real commodity prices only with a lag. Other researchers dealing with US data, like Elder and Serletis (2011), assume that oil reacts instantaneously to output shocks as oil prices can adjust rapidly to new information. This, however, is not necessarily plausible for our work as countries are too small to have an immediate effect on international prices and not all commodities in our indices are traded on highly liquid markets.

5 Is Commodity Export Price Volatility Harmful?

5.1 Estimation Results

Estimation results from our analysis with the VAR-GARCH-in-mean-model can be found in Tables 2 and 3. The first table reports the estimated MGARCH equations. We find significant GARCH effects in the commodity export price series for all sample countries and, with the exception of Chile, also in the series on industrial production. The degree of persistence in conditional volatility differs between countries, for instance, price volatility is very persistent for Canada while less so for Chile. The significance of the GARCH effects supports the VAR-MGARCH specification. Further evidence in favor of the VAR-MGARCH is given by the Schwartz information criterion. For all sample countries except New Zealand, the Schwartz criterion points towards a better fit of the model compared to a conventional homoskedastic VAR.

Table 3 reports the point estimates of the coefficient measuring the effect of commodity price volatility on real output. The parameter capturing this is $\Lambda_{(1,2)}$, the upper off-diagonal element of the volatility spillover matrix Λ. In the reported estimations, we restricted the elements of Λ measuring spillovers from industrial production volatility to zero. This is empirically supported by the Schwartz information criterion and individual significance tests, and in line with economic reasoning as volatility in the industrial production series should not affect world market commodity prices. The parameter capturing the spillover of export price volatility on the commodity price itself is not reported as it is of lesser interest and predominantly found to be insignificant. Lag lengths for our baseline estimations are selected by the Schwartz information criterion (SIC) which yields parsimonious models and residuals free from autocorrelation. As alternative specifications, estimations based on the Akaike (AIC) criterion are also reported.

Our results show that commodity price volatility is indeed estimated to have an adverse effect on real output. This finding, however, is not robust for all countries. We find a statistically significant negative effect in almost all specifications for the oil exporting countries in our sample: Canada, Indonesia, Mexico, and Norway. For the other countries which export mainly mineral and food commodities, the volatility spillover coefficient is predominantly found to be statistically not significant, even though it mostly has the negative sign implied by theory. In the remainder of this section, we present the result in detail and show that they are robust to several different specifications. In the next sections, we investigate the dynamic response of real output to a commodity price shock for Canada and Norway using impulse response functions and look

Table 2: Estimates of Variance Equations for Baseline Models

First Equation: $h(com)_t = k_1 + F_1 \varepsilon\varepsilon'(com)_{t-1} + G_1 h(com)_{t-1}$

Second Equation: $h(ip)_t = k_2 + F_2 \varepsilon\varepsilon'(ip)_{t-1} + G_2 h(ip)_{t-1}$

Sample	Lags	F	G	Sample	Lags	F	G	Sample	Lags	F	G
Australia				**Brazil**				**Canada**			
74-11	1	0.08	0.86**	95-11	1	0.25**	0.14	80-11	3	0.20**	0.60**
		(0.08)	(0.22)			(0.10)	(0.12)			(0.05)	(0.11)
		0.36**	0.41*			0.55**	0.00			0.05*	0.92**
		(0.15)	(0.24)			(0.18)	(-)			(0.02)	(0.04)
SIC (VAR):			923.97	SIC (VAR):			2250.73	SIC (VAR):			3083.38
SIC(VAR-MGARCH):			907.10	SIC(VAR-MGARCH):			2198.24	SIC(VAR-MGARCH):			3028.19
Chile				**Indonesia**				**Mexico**			
91-11	2	0.24**	0.00	86-11	2	0.36**	0.63**	80-11	1	0.57**	0.00
		(0.09)	(-)			(0.04)	(0.05)			(0.14)	(-)
		0.07	0.29			0.76**	0.00			0.22**	0.75**
		(0.05)	(0.28)			(0.18)	(-)			(0.04)	(0.05)
SIC (VAR):			2794.09	SIC (VAR):			4056.98	SIC (VAR):			3929.14
SIC(VAR-MGARCH):			2785.49	SIC(VAR-MGARCH):			3798.99	SIC(VAR-MGARCH):			3848.79
New Zealand				**Norway**				**South Africa**			
77-11	1	0.06	0.73**	80-11	3	0.35**	0.36**	90-11	2	0.35**	0.41*
		(0.04)	(0.20)			(0.10)	(0.14)			(0.10)	(0.19)
		0.65**	0.24			0.78**	0.00			0.14*	0.06
		(0.25)	(0.21)			(0.14)	(-)			(0.07)	(0.37)
SIC (VAR):			-1390.93	SIC (VAR):			4595.16	SIC (VAR):			2769.94
SIC(VAR-MGARCH):			-1389.43	SIC(VAR-MGARCH):			4482.89	SIC(VAR-MGARCH):			2752.21

Table shows the estimated autoregressive MGARCH parameters for our baseline models with the lag length based on the Schwartz information criterion (constant terms are not reported). Parameters violating the non-negativity constraint necessary in the VECH are restricted to zero. In addition the Schwartz criterion for the VAR-MGARCH-in-mean and a homoscedastic VAR with the same lag length are given.
* - significance on 10% level, ** - significance on 5% level.

at possible policy conclusions emerging from the results.

Point estimates for Canada and Norway, two developed countries whose commodity exports consists to a large part of petroleum (Table 1), clearly indicate a negative impact of commodity export price volatility on real output. This holds for the complete sample and for a sample excluding the crisis period since 2008. Results for Indonesia display a similar negative impact in estimations starting with the earliest available data in 1986. Albeit it terminated its OPEC membership in 2008 and became a net crude oil importer, the country has been a net petroleum exporter for most of the sample period. Further estimations for Indonesia control for a possible bias due to the Asian crisis, which heavily affected the country, by letting the sample start in

Table 3: Estimates of Commodity Price Volatility Coefficient

VAR-Equation: $ip_t = c + \sum_{i=1}^{p} a_{1,t-i} ip_{t-i} + \sum_{i=1}^{p} a_{2,t-i} com_{t-i} + \Lambda_{(1,2)} h(com)_t + \varepsilon_t$											
Sample	Lags	Obs	$\Lambda_{(1,2)}$	Sample	Lags	Obs	$\Lambda_{(1,2)}$	Sample	Lags	Obs	$\Lambda_{(1,2)}$
Australia				**Brazil**				**Canada**			
74-11	1	150	**-0.11***	95-11	1	203	0.07	80-11	3	380	**-0.18****
			(0.07)				(0.06)				(0.07)
	4	147	**-0.18****		5	199	-0.01		6	377	**-0.17****
			(0.08)				(0.06)				(0.08)
74-07	1	134	-0.19	03-11	1	107	-0.07	80-07	3	332	**-0.40****
			(0.35)				(0.18)				(0.19)
	4	131	-0.24		4	104	0.24		6	329	**-0.35****
			(0.31)				(0.66)				(0.19)
Chile				**Indonesia**				**Mexico**			
91-11	1	250	**-0.34***	86-11	2	309	**-0.10****	80-11	1	382	-0.04
			(0.19)				(0.05)				(0.02)
	3	248	-0.30		3	308	**-0.08****		2	381	-0.05
			(0.19)				(0.03)				(0.03)
91-07	1	202	-0.24	99-11	1	155	**-0.25****	96-11	1	191	-0.07
			(0.29)				(0.11)				(0.07)
	3	200	-0.11		4	152	-0.08		2	190	-0.10
			(0.29)				(0.14)				(0.08)
New Zealand				**Norway**				**South Africa**			
77-11	1	137	0.24	80-11	3	380	**-0.29****	90-11	2	261	-0.02
			(0.19)				(0.09)				(0.10)
	2	136	-0.10		6	377	**-0.37****		3	260	-0.04
			(1.14)				(0.10)				(0.10)
77-07	1	121	0.15	80-07	3	332	**-0.39****	90-07	2	213	0.13
			(0.60)				(0.14)				(0.12)
	2	120	-0.01		6	329	**-0.42****		3	212	0.11
			(0.04)				(0.10)				(0.13)

Table shows the estimated parameter measuring the direct impact of conditional commodity price volatility on output. We report results from both our baseline specification with the lag length based on the Schwartz information criterion and, as a measure of robustness, from a specification including more lags based on the Akaike criterion. Values in parentheses are asymptotic standard errors based on inverse of the Hessian.
* - significance on 10% level, ** - significance on 5% level.

1999. The point estimates confirm the negative volatility impact found over the whole sample range even though significance is partly affected by the smaller sample period. For Mexico, results from the main specification show a negative effect with significance given at the 15% level. The robustness analysis, moreover, yields strong evidence in favor of a significant negative volatility impact. UNCTAD trade data indicates that Mexico's commodity exports mainly consist of petroleum (Table 1). Crude oil is Mexico's single biggest export item and very important for the Mexican government budget (Banco Central de Mexico 2013). The baseline estimations for Mexico, nevertheless, have the shortcoming that the sample includes various crisis episodes. Additional estimations which exclude the "Tequila-Crisis" 1995 yield negative but insignificant estimates. However, they rely on far less observations than the baseline and could still be affected by later crisis episodes.

For the other countries that export mainly minerals and food, coefficients are predominantly found to be insignificant, albeit by and large they have the expected negative sign. Significance in the estimations for Australia and Chile seems to be driven by the 2008 economic crisis as it vanishes in the sample which excludes this episode. The other countries do not display any significant point estimates at all even if we take possible break points into account. For instance, we start baseline estimations for Brazil in 1995 due to the visible break point in the real price index in 1994, connected to foreign exchange and inflation turmoil as well as monetary alignment. A different sample beginning in 2003 tries to account for the Brazilian currency crisis 98/99 and the Argentinian crisis 2001 but does not yield significant results neither. The same holds true for New Zealand and South Africa where the samples start with the earliest available output data and shorter ones exclude the 2008 crisis.

To ensure the robustness of the results, we use different measures. Firstly, we apply an alternative approach to construct real commodity price indices. Instead of the nominal exchanges rates, we use PPP-adjusted ones to address possible excess volatility issues in spot exchange rates. As a further robustness check, we analyze the relationship between commodity price volatility and real output in a single equation autoregressive distributed lag (ADL) framework with different volatility measures that were computed beforehand (univariate GARCH, rolling 3-month and 12-month standard deviations). This ensures that general findings are not solely driven by the model or the volatility measure. Results from both robustness exercises strongly support our main findings. A detailed description of the robustness analysis can be found in appendix B.

Lastly, given the point estimates of $\Lambda_{(1,2)}$ some initial conclusions regarding the economic significance of the volatility effect can be drawn. As an example, we do 'back-of-the-envelope' calculation for the two countries where the effect was found to be significant in all specifications: Canada and Norway. An average change in commodity price uncertainty is associated with a drop in the monthly growth rate of industrial production by about 15 basis points in Canada and by about 34 basis points in Norway.[13] These calculations underline the impression that commodity price volatility matters for real economic activity in these countries. It is necessary, however, to treat these 'back-of-the-envelope' calculation with caution. Firstly, they ignore dynamic interactions between the variables. Secondly, they might ignore possible relevant

[13] We take the standard deviation of the GARCH series to be an average shock to real commodity price uncertainty.

reactions in other variables as they are based on a bivariate system.

5.2 Impulse Response Analysis

So far, we have considered the statistical significance of the parameter capturing the impact of commodity price volatility on real output. To get a comprehensive picture, we are also interested in looking at how the spillover parameter $\Lambda_{(1,2)}$ affects the dynamic response to a commodity price shock. A standard approach to analyze the dynamics following a shock in VAR analysis is the use of Impulse-Response-Functions (IRF). However, a standard IRF analysis would not take the effect of volatility on the mean into account. Therefore, we use the IRFs by Elder (2003) specifically developed for the SVAR-GARCH-in-mean model. To illustrate the dynamic effects of commodity price shocks and uncertainty, IRFs for Canada and Norway are reported as the spillover coefficient is found to be significant for these countries in all specifications. In Figures 3 and 4, we show the response of real output to a real commodity price shock taking the volatility effect into account (blue solid line) and the response with the in-mean parameter $\Lambda_{(1,2)}$ restricted to zero (red dashed line). This can be understood as a counterfactual analysis of how responses would differ if the volatility effect was not present.[14]

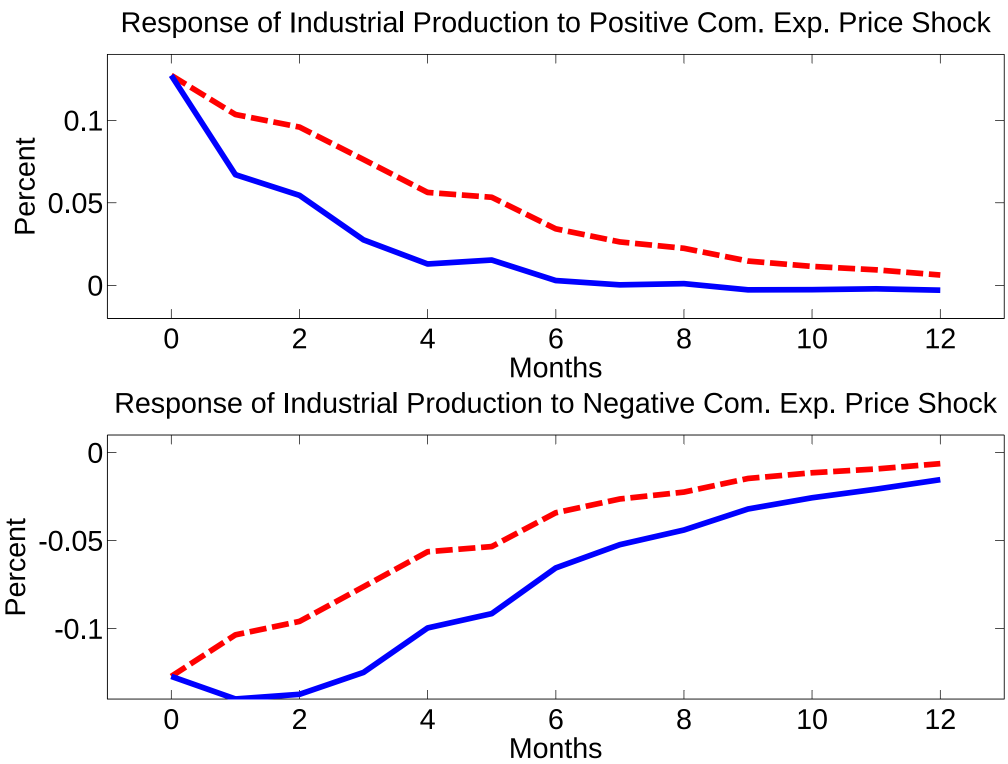
The IRFs for Canada and Norway show that the initial response of industrial production to a shock which increases commodity export prices is estimated to be positive. After the initial impulse industrial production remains above its equilibrium value for several periods before the shock fades out, both in the IRFs with and without the volatility augmentation.[15] Different economic mechanisms can help to explain this pattern (Solheim 2008). Export revenues and, therewith, domestic activity initially increase with the price shock if the demand for commodities is rather inelastic. Furthermore, expenditures and investment in mining and commodity extraction rise leading to an increase in the supply of goods and services to these industries. Lastly, domestic commodity extracting companies gain value with rising prices resulting in a positive wealth effect.[16]

[14]The IRFs show responses where $\Lambda_{(1,2)}$ has been restricted to zero after the estimation, i.e. using the same values for all the other parameters. This reflects the counterfactual nature of this exercise building on the IRFs by Elder (2003). Another approach is to reestimate the model with $\Lambda_{(1,2)}$ restricted to zero. Doing this yields qualitatively similar results regarding the effect of uncertainty.

[15]The pattern is less pronounced for Norway where responses alternate around the mean after the initial positive periods. This feature can be explained by the less persistent, but negatively autocorrelated production series.

[16]Two things have to be noted. Firstly, this pattern appears to be in contrast to findings for Canada by Elder and Serletis (2009) whose results indicate that industrial production does not react to a positive oil price shock in a similar setting. Different to us, they do not consider commodity export prices and do not adjust their oil price series for changes in the Canadian price level. The confidence bands in Figure 6, moreover, show that the positive

Figure 3: Response Functions with and without (dashed line) volatility influence - Canada



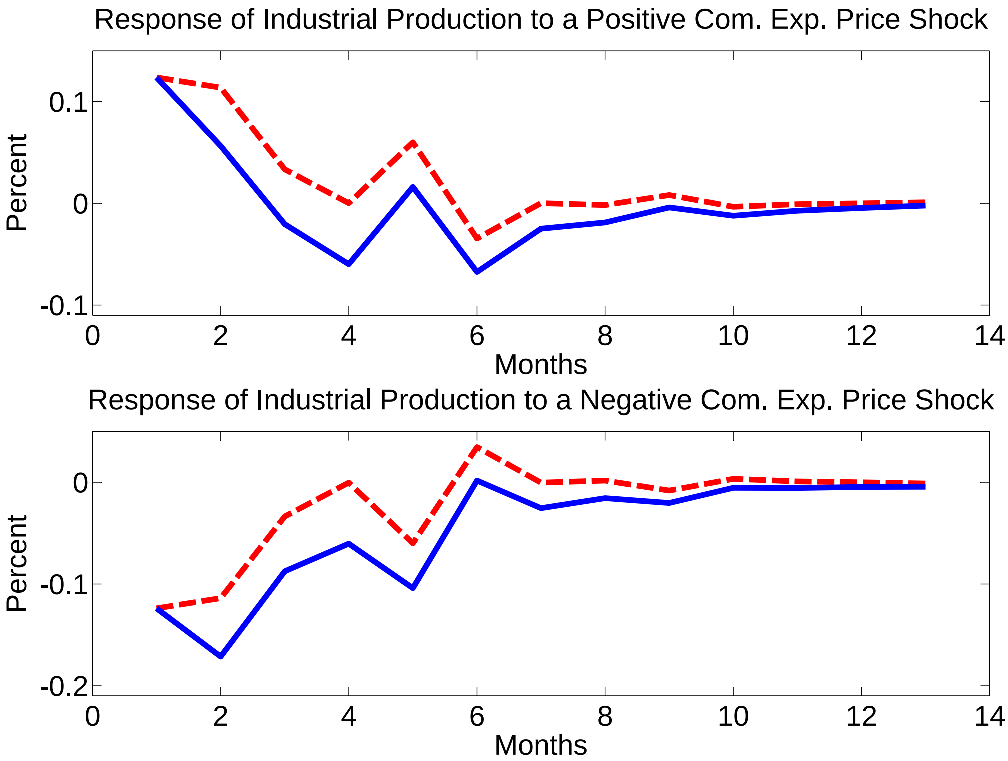
Note: The blue (solid) line displays the response of real output to a one standard deviation real commodity price impulse. It is calculated using the estimated coefficients from the SVAR-MGARCH-in-mean model based on the method developed by Elder (2003) that takes the dynamic impact of volatility on the mean (Λ) into account. The red (dashed) line shows the same dynamic response with the spill-over Matrix Λ restricted to zero. It can understood as a counterfactual analysis to illustrate the impact of volatility.

While displaying the same general pattern, the responses with and without the volatility effect deviate substantially. The positive reaction to the commodity price change is far less pronounced if the increase in uncertainty is taken into account. In fact, the response for Norway shows that industrial production growth even falls slightly below its mean between a quarter and half a year after a commodity shock. Responses stay below their homoscedastic counterparts for a prolonged period while both revert back to the equilibrium. In general, the differences in dynamics are determined not only by the estimated VAR parameters, but crucially depend on the MGARCH. The more persistent the GARCH process, the longer it takes for the uncertainty effect to fade out.

Two distinct channels can explain why the increase in uncertainty hampers the positive effect

effect significantly prevails only for the initial periods. Secondly, there are also theoretical arguments why rising commodity prices can have a diametral impact on output not only in importing, but also in exporting countries: real exchange rate appreciations, lower economic activity among trading partners, less disposable household income. For Norway, nevertheless, Solheim (2008) shows that the response of output to an oil price shock is positive.

Figure 4: Response Functions with and without (dashed line) volatility influence - Norway

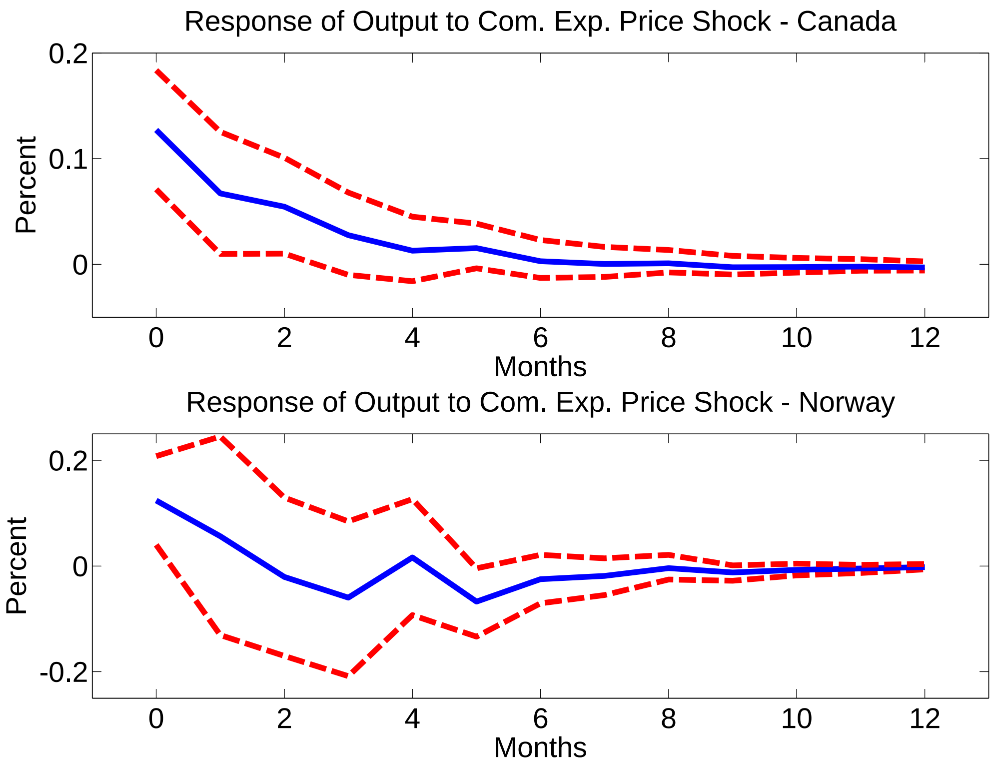


Note: The blue (solid) line displays the response of real output to a one standard deviation real commodity price impulse. It is calculated using the estimated coefficients from the SVAR-MGARCH-in-mean model based on the method developed by Elder (2003) that takes the dynamic impact of volatility on the mean (Λ) into account. The red (dashed) line shows the same dynamic response with the spill-over Matrix Λ restricted to zero. It can understood as a counterfactual analysis to illustrate the impact of volatility.

of a commodity export price shock. Firstly, volatility dampens the expansion in investment of commodity related businesses. This is in line with the discussed real option theory on investment under uncertainty (Bernanke 1983, Pindyck 1991, Dixit and Pindyck 1994). Secondly, exports are negatively affected through the external demand channel. For oil, it is well established in the literature that an increase in oil price uncertainty is associated with a fall in output in industrial countries (Bredin et al. 2011). This can explain why an increase in commodity price uncertainty has adverse effects for oil exporting countries: it lessens export revenues and, thereby, industrial production due to an uncertainty induced fall in worldwide output and oil demand. For Canada, this effect might even be exacerbated by its close trade links to the US whose economy is strongly affected by oil price uncertainty (Elder and Serletis 2010, 2011). Norway, meanwhile, also exports other energy commodities like natural gas. Baffes (2007) shows that there is a strong link between the price developments of oil and natural gas which makes it unlikely that losses due to oil price uncertainty can be compensated by other energy commodities.

Unlike in a linear homoskedastic VAR model, the IRFs for the nonlinear VAR-MGARCH-in-mean model are not symmetric for positive and negative shocks (Elder 2003). Beginning with Mork (1989), several authors find that responses to positive and negative oil price shocks differ. For these reasons, we also report IRFs for negative commodity price shocks. Compared to their positive counterparts they display an inverted pattern where real output is lowered for several months. As before, the dampening effect of uncertainty leads to the volatility accounting IRFs being below the restricted ones.

Figure 5: Response Functions with volatility influence - Confidence bands



Note: The blue line displays the response of real output to a one standard deviation real commodity price impulse. It is calculated using the estimated coefficients from the SVAR-MGARCH-in-mean model based on the method developed by Elder (2003) that takes the dynamic impact of volatility on the mean (Λ) into account. Red dashed lines are 68% confidence intervals calculated by parametric bootstraps of the parameter values (5.000 draws from the underlying Gaussian distributions).

Lastly, in Figure 5 we display the volatility including responses to positive commodity price shocks with 68 % confidence bands constructed as proposed by Elder and Serletis (2010).[17] The

[17] As standard bootstrapping procedures commonly used for IRFs cannot be applied in this context, Elder and Serletis (2010) propose to use a parametric bootstrap where parameters are drawn from normal distributions with their respective estimated mean and standard deviation. We follow this suggestion, however, we keep the MGARCH parameters constant to ensure a stationary variance process which guarantees mean reversion.

confidence bands show that the response to a commodity shock turns positive with statistical certainty only for the first few months (Canada) or the initial period (Norway) if the uncertainty effect is taken into account. Furthermore, the intervals indicate that the counterfactual analysis has to be treated with a bit of caution: the restricted IRFs fall into the confidence bands of the volatility accounting ones. Therefore, we are reluctant to draw conclusions regarding the magnitude of the volatility effect from the counterfactual analysis by, for instance, measuring the gap between the two responses.

5.3 Policy Implications

We find a significant negative impact of commodity price volatility on output for the oil exporting countries in our sample. The results imply that the effect prevails not only for oil, but for a basket of exported commodities in these countries which mainly adds other energy commodities. From a policy perspective, it supports the view that decision makers should take commodity price uncertainty into account. In particular, our results constitute an additional argument for approaches aimed at reducing the volatility in international commodity markets. One strategy to achieve this is to improve market transparency and data availability on derviate markets where pricing is often difficult because there is a lack of timely data about stocks. The over- or underestimation of stocks by market participants can lead to sudden price adjustments. This problem has also been recognized by policy makers. One example for a policy measure to increase data availability is the establishment of the Joint Organisations Data Initiative (JODI). Several agencies and over 90 nations participate in JODI and promote data on petroleum production, consumption and stocks. A complementary suggestion to reduce volatility is the limitation of positions that financial investors can take in futures contracts. This approach is favored by economists and policy makers who regard the financialization of commodity markets as the reason for the increased fluctuations over the last years (Mayer 2012). In this spirit, limiting the activities of non-traditional market participants could shape markets towards risk sharing and hedging activities by suppliers and producers who use commodities as inputs in their production activities.

6 Conclusion

Commodity price volatility has been an issue on the policy agenda since the beginning of the new century. Policy makers fear a dampening effect of increased commodity price uncertainty on output. Such a negative effect has been found in empirical studies with long run panel data, however, this finding is not undisputed. At the same time, a growing literature finds a negative effect of oil price uncertainty on output in the US and other oil importing industrial countries.

In this study, we contribute to the literature by analyzing the effect of country specific commodity price volatility on real output at the business cycle frequency for a group of commodity exporting countries. We find a negative impact of price volatility on real output for the oil exporting countries in out sample. For the non-oil exporters, meanwhile, we do not find a significant negative effect. Our results add to the existing literature on oil price uncertainty (Elder and Serletis 2010, 2011, Bredin et al. 2011). At the same time, they are a useful supplement but not in contradiction to the literature that finds negative long-run effects of commodity price volatility (Blattman et al. 2007, Cavalcanti et al. 2012).

To explain the dissimilarities between oil exporters and mineral and food exporters at the business cycle frequency, future research is necessary. Ensuing projects could analyze how differences between commodities regarding the maturity of delivery contracts, market structures, or storage capacities affect the possibilities to hedge against price uncertainty.

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A Included Commodities

The 48 included commodities cover about 75 percent of world commodity exports and imports over the past decades (UNCTAD 2012). Included in the selection are 16 food commodities (beef, other meat, fish, fishmeal, crustaceans, wheat, rice, barley, maize, meal, fruits and nuts, sugar, coffee, cocoa, tea, and spices), 13 agricultural raw materials (tobacco, hides and skins, oil seeds for soft oils, oil seeds for fixed oils, rubber, rough wood, sawn wood, cotton, jute, vegetable textile fibres, wool, fixed vegetable fats and oils, and other vegetable fats and oils), 13 minerals and metals (crude fertilizer, iron ore, copper ores, nickel ores, aluminium ores, ores of other base metals, silver, copper, nickel, aluminium, lead, zinc, and tin) as well as 6 energy commodities (coal, crude petroleum, refined petroleum, residual petroleum products, liquefied propane and butane, and natural gas). Not included are both diamonds and gold, albeit they are often categorized as commodities. On the one hand, there is no world price for diamonds, on the other hand, gold prices are strongly influenced by its role as a store of value.

B Robustness

First indication of robustness is already given by variations in the lag length (SIC, AIC) which did not qualitatively alter the results. Another robustness check relates to the use of foreign exchange rates to convert the commodity export price indices. Cashin and McDermott (2002) find that commodity price volatility increased after the break-up of the Bretton-Woods system of fixed exchanged rates. The authors argue that instead of measuring volatility in the commodity price series one might actually measure exchange rate volatility. This concern could, in theory, also apply to our work. We address this issue by using OECD and IMF data on Purchasing Power Parity (PPP) adjusted exchange rates to build the real indices. PPP exchange rates display far less variability than nominal spot exchange rates but are only available on a much lower frequency.[18]

Results for the estimations with PPP adjusted real commodity price indices can be found in Table 7 (Appendix D). They remain qualitatively the same as with the nominal exchange rates. Coefficients are still estimated to be negative and significant for Canada, Norway, and Indonesia. For Mexico, the evidence for a negative effect is even stronger than in our baseline estimations. Meanwhile, significance is predominantly not found for the other countries.

[18] Purchasing power adjusted exchange rates are available for most OECD countries on a quarterly basis while the IMF only provides PPP adjusted exchange rates on a yearly basis. We use the quarterly series and apply exponential interpolation to convert them to the monthly frequency.

To further evaluate the robustness of our results, we apply a different approach to investigate the commodity price uncertainty effect by using measures of volatility that are computed beforehand. These measures are then included as exogenous variables in models explaining industrial production. Such an approach has the caveat that it suffers from the generated regressor problem (Pagan 1984). It is, nevertheless, a useful tool to check the robustness of our results from the consistent one step VAR approach.

We apply the following volatility measures: univariate GARCH volatility[19] and historical volatility given by rolling 3-month and 12-month standard deviations of the real commodity price indices.[20] Despite its widely use, it is not undisputed to approximate uncertainty by GARCH volatility. Applying different measures based on historical volatility is a good comparison for the GARCH results.

These measures are included in an autoregressive distributed lag (ADL) model along with log differences of the real commodity export index and of industrial production. The ADL Model takes the form:

$$y_t = \beta_0 + \sum_{i=1}^{p} \beta_{t-i} y_{t-i} + \sum_{i=1}^{q} \alpha_i x_{t-i} + \gamma z_t + \varepsilon_t, \tag{4}$$

with y_t the log growth rate of industrial production, x_t the log growth rate of the country specific commodity price index, and z_t the alternative volatility measure.

The estimated coefficients for the volatility spill-over parameter γ can be found in Table 8 (Appendix D). The results largely confirm the results of the VAR-MGARCH-in-mean analysis. For Canada, Mexico, and Indonesia (longer sample) all types of volatility have a significant negative effect on output while no significant effects can be detected for Australia, South Africa, New Zealand, Chile, and Brazil. Only for Norway, there is a deviation from the VAR-MGARCH-in-mean results in certain aspects. In estimations for Norway, only the GARCH volatility is significant and negative. This can be explained by the fact that one-time oil price shocks are highly reflected in the GARCH volatility while the historical volatility series are more smooth. These smoother long term fluctuations do not capture the production dampening uncertainty caused by the large oil price shocks as the GARCH process does.

[19] Univariate GARCH volatility, hereby, refers to the GARCH standard deviation inferred from an autoregression of the real commodity price growth rates.

[20] Several candidates for volatility measures emerge from the literature: historical volatility, realized volatility, implied volatility, and univariate GARCH volatility. Both realized and implied volatility, however, are not applicable to our study as they would require all individual commodities to have price series on a daily basis or daily option markets. Certain commodities, like iron ore for instance, are not traded on commodity exchanges what makes compiling data impossible.

C Impulse Response Functions by Elder (2003)

Dynamic properties of VAR models are usually displayed using Impulse-Response-Functions (IRFs). Standard IRF analysis, however, cannot be conducted as the VAR-MGARCH-in-mean is a highly nonlinear model where the dynamic response to a shock might depend on the size and the sign of the shock, on the initial conditions, and on future shocks. Elder (2003), nevertheless, derives a closed-form solution for structural VAR models with multivariate GARCH-in-mean errors based on the interpretation that IRFs can be understood as the revision in the conditional forecast of the element of variable y_i in period $t+k$ given an impulse $\varepsilon_{i,t}$ and the information set ψ_{t-1}:

$$\frac{\partial E\left(y_{t+k} \mid \varepsilon_{i,t}, \psi_{t-1}\right)}{\partial \varepsilon_{i,t}}. \tag{5}$$

Given this definition, Elder (2003) is able to construct the following IRF for structural VAR-MGARCH-in-mean models:

$$\frac{\partial E\left(y_{t+k} \mid \varepsilon_{i,t}, \psi_{t-1}\right)}{\partial \varepsilon_{i,t}} = \sum_{\tau}^{k-1} \left[\Theta_\tau \Pi_0 (F+G)^{k-\tau-1} F\right] \iota_1 + \left(\Theta_k B^{-1}\right) \iota_0. \tag{6}$$

Thereby, Θ is the moving average representation of the VAR process while $\Pi_0 = B^{-1}\Lambda$ and F, G are the parameter matrices from the multivariate GARCH. $\iota_0 = \frac{\partial \varepsilon_t}{\partial \varepsilon_{i,t}}$ is a $Nx1$ vector of initial shocks with an impulse $\varepsilon_{i,t}$ in the i^{th} spot and zeros elsewhere. The second term on the RHS, $\left(\Theta_k B^{-1}\right)\iota_0$, can thus be interpreted as the conventional IRF without any feedback from the GARCH process. $\iota_1 = \frac{\partial E\left(vec(\varepsilon_t' \varepsilon_t) \mid \varepsilon_{i,t}, \psi_{t-1}\right)}{\partial \varepsilon_{i,t}}$ is a N^2x1 vector of initial shock derivatives with $2\varepsilon_{i,t}$ in the $N(i-1)+i$ spot and zeros elsewhere. The first RHS term, $\left[\Theta_\tau \Pi_0 (F+G)^{k-\tau-1} F\right]\iota_1$, can be seen as an correction term to the conventional IRF because it takes both the GARCH-in-Mean term Π_0 and the underlying dynamics in the second moments (through F and G) into account.

D Additional Tables

Table 4: Share of Commodities in Exports and GDP

	share of comm. in total exp.	share of comm. exp. in GDP		share of comm. in total exp.	share of comm. exp. in GDP
Australia	0,74	0,13	Mexico	0,26	0,07
Brazil	0,53	0,06	New Zealand	0,26	0,07
Canada	0,47	0,14	Norway	0,79	0,30
Chile	0,84	0,30	South Africa	0,46	0,13
Indonesia	0,61	0,16			

Table shows the value share of total commodity exports in total exports and in total GDP. Numbers are author's own calculations based on UNCTAD trade data and Worldbank data from 2008.

Table 5: Correlations of Export Indices with Different Base Years

I^{95}/I^{00}	I^{00}/I^{08}	I^{00}/I^{08}	I^{95}/I^{00}	$\triangle I^{00}/I^{08}$	I^{00}/I^{08}	I^{95}/I^{00}	I^{00}/I^{08}	I^{00}/I^{08}
Australia			**Brazil**			**Canada**		
0.94	0.89	0.90	0.96	0.84	0.76	0.94	0.96	0.91
Chile			**Indonesia**			**Mexico**		
0.99	0.99	0.99	0.99	0.93	0.92	0.99	0.99	0.99
New Zealand			**Norway**			**South Africa**		
0.97	0.94	0.95	0.99	0.98	0.97	0.98	0.97	0.96

Table shows correlations between growth rates of real commodity price indices with different base years (95,00,08).

Table 6: Unit Root Test Results

DF	DF (tr.)	KPSS	KPSS (tr.)	DF	DF (tr.)	KPSS	KPSS (tr.)	DF	DF (tr.)	KPSS	KPSS (tr.)
Real Commodity Indices											
Australia				**Brazil**				**Canada**			
74-11				**95-11**				**80-11**			
-2.14	-2.80	0.92**	0.30**	-3.46	-4.23**	1.69**	0.19**	-3.13**	-3.23**	0.48**	0.46**
74-07				**03-11**				**80-07**			
-1.70	-2.53	1.11**	0.22**	-1.78	-3.61**	0.87**	0.15**	-3.90**	-3.08	0.68**	0.40**
Chile				**Indonesia**				**Mexico**			
91-11				**86-11**				**80-11**			
-1.74	-1.94	0.59**	0.29**	-2.20	-4.70	1.73**	0.15**	-2.30	-2.02	0.63**	0.55**
91-07				**99-11**				**96-11**			
-1.61	-1.68	0.30*	0.24**	-2.13	-2.30	0.92**	0.10	0.17	-2.33	1.38**	0.31**
New Zealand				**Norway**				**South Africa**			
77-11				**80-11**				**91-11**			
-1.57	-2.15	1.26**	0.25**	-2.14	-1.45	0.53**	0.52**	-1.11	-1.77	0.77**	0.54**
77-07				**80-07**				**91-07**			
-1.37	-2.17	1.11**	0.19**	-2.01	-1.32	0.75**	0.48**	-1.41	-1.21	0.51**	0.43**
Real Commodity Indices (PPP Exchange Rates)											
Australia				**Brazil**				**Canada**			
74-11				**95-11**				**80-11**			
-1.68	-1.15	0.55**	0.31**	0.09	-2.67	1.47**	0.36**	-2.54	-2.57	0.55**	0.24**
74-07				**03-11**				**80-07**			
-1.64	-1.13	1.00**	0.21**	-1.78	-3.61**	0.87**	0.15**	-3.09**	-1.27	0.77**	0.56**
Chile				**Indonesia**				**Mexico**			
91-11				**86-11**				**80-11**			
-1.19	-2.27	1.14**	0.41**	-1.04	-3.02	1.50**	0.11	-2.63*	-2.36	0.63**	0.56**
91-07				**99-11**				**96-11**			
-0.60	-1.20	0.49**	0.36**	-1.34	-3.02	1.50**	0.11	-1.46	-3.88**	1.38**	0.19**
New Zealand				**Norway**				**South Africa**			
77-11				**80-11**				**91-11**			
-1.36	-1.42	0.83**	0.26**	-2.60*	-2.57	0.56**	0.55**	0.68	-1.98	1.43**	0.46**
-1.76	-2.42	0.95**	0.17**	-2.48	-1.27	0.77**	0.47**	2.80	0.91	0.80**	0.36**
Industrial Production											
Australia				**Brazil**				**Canada**			
74-11				**95-11**				**80-11**			
4.78	-0.54	1.42**	0.36**	-0.69	-3.99**	1.70**	0.17**	-1.23	-1.90	2.12**	0.24**
74-07				**03-11**				**80-07**			
4.27	-1.42	1.45**	0.37**	-1.59	-2.97**	1.05**	0.11	-0.93	-2.06	2.08**	0.16**
Chile				**Indonesia**				**Mexico**			
91-11				**86-11**				**80-11**			
-1.03	-2.69	1.65**	0.17**	-1.90	-1.76	1.78**	0.39**	0.34	-2.21	2.12**	0.27**
91-07				**99-11**				**96-11**			
0.03	-1.66	1.33**	0.34**	-0.89	-4.72**	1.45**	0.11	-1.72	-2.66	1.28**	0.17**
New Zealand				**Norway**				**South Africa**			
77-11				**80-11**				**91-11**			
-1.57	-2.15	1.26**	0.25**	1.02	-1.76	2.27**	0.54**	-1.16	-2.45	1.78**	0.13*
-1.34	-2.23	1.15	0.20**	0.97	-2.16	2.14**	0.44**	0.75	-2.14	1.70**	0.12*

Table shows results of unit root tests on the real commodity price indices, the real commodity price indices with PPP exchange rates, and the industrial production series. DF refers to the augmented Dickey-Fuller Test while KPSS is the Kwiatkowski-Phillips-Schmidt-Shin test. Both tests are carried out in specifications with and without a linear trend (tr.).

* - significance on 10% level, ** - significance on 5% level.

Table 7: Estimates of Commodity Price Volatility Coefficient (PPP Exchange Rates)

VAR-Equation: $ip_t = c + \sum_{i=1}^{p} a_{1,t-i} ip_{t-i} + \sum_{i=1}^{p} a_{2,t-i} com_{t-i} + \Lambda_{(1,2)} h(com)_t + \varepsilon_t$

Sample	Lags	Obs	$\Lambda_{(1,2)}$	Sample	Lags	Obs	$\Lambda_{(1,2)}$	Sample	Lags	Obs	$\Lambda_{(1,2)}$
Australia				**Brazil**				**Canada**			
74-11	2	150	**-0.08****	95-11	1	203	0.05	80-11	3	380	**-0.20****
			(0.03)				(0.28)				(0.06)
	4	147	**-0.10****		5	199	0.06		6	377	**-0.20****
			(0.03)				(0.18)				(0.07)
74-07	1	134	0.01	03-11	1	107	-0.09	80-07	3	332	**-0.34****
			(0.02)				(0.30)				(0.13)
	4	131	0.01		4	104	-0.13		6	329	**-0.33****
			(0.02)				(0.27)			(0.05)	(0.13)
Chile				**Indonesia**				**Mexico**			
91-11	1	250	-0.29	86-11	2	309	**-0.10****	80-11	1	382	**-0.14****
			(0.21)				(0.05)				(0.04)
	3	248	-0.29		3	308	**-0.08****		2	381	**-0.11****
			(0.22)				(0.03)				(0.04)
91-07	1	202	-0.25	99-11	1	155	**-0.25****	96-11	1	191	-0.06
			(0.30)				(0.11)				(0.04)
	3	200	-0.24		4	152	-0.08		2	190	-0.04
			(0.32)				(0.14)				(0.04)
New Zealand				**Norway**				**South Africa**			
77-11	1	137	0.30	80-11	3	380	**-0.37****	91-11	2	249	-0.01
			(0.24)				(0.07)				(0.13)
	2	136	-0.03		6	377	**-0.44****		3	248	-0.03
			(0.04)				(0.08)				(0.13)
77-07	1	121	-0.01	80-07	3	332	**-0.40****	91-07	2	201	-0.20
			(0.03)				(0.08)				(0.27)
	2	120	-0.02		6	329	**-0.43****		3	200	-0.19
			(0.04)				(0.07)				(0.28)

Table shows the estimated parameter measuring the direct impact of conditional commodity price volatility on output. Different to our baseline specifications, real commodity price indices are constructed using PPP adjusted real exchange rates. We report estimations with lag length based on the Schwartz information criterion and on the Akaike criterion. Values in parentheses are asymptotic standard errors based on inverse of the Hessian.
* - significance on 10% level, ** - significance on 5% level.

Table 8: Results from ADL models with alternative volatility measures

Estimated Equation: $y_t = \beta_0 + \sum_{i=1}^{p} \beta_{t-i} y_{t-i} + \sum_{i=1}^{q} \alpha_i x_{t-i} + \sum_{i=1}^{r} \gamma_i z_{t-i} + \varepsilon_t$

y_t: Δ industrial production, x_t: Δ country specific commodity price index, z_t: alternative volatility measure

Sample	GARCH	SD 3	SD 12	Sample	GARCH	SD 3	SD 12	Sample	GARCH	SD 3	SD 12
Australia				**Brazil**				**Canada**			
74-11	-0.13	-0.01	-0.03	95-11	-0.01	0.01	-0.07	80-11	-1.87**	-0.11**	-0.09**
	(-0.79)	(-0.45)	(-1.11)		(-0.03)	(0.25)	(-0.79)		(-2.55)	(-3.54)	(-2.28)
74-07	0.28	-0.01	-0.21**	03-11	-0.23	-0.01	0.00	80-07	-10.67**	-0.16**	-0.12
	(0.36)	(-0.12)	(-2.40)		(-0.47)	(-0.29)	(0.07)		(-2.02)	(-3.06)	(-1.63)
Chile				**Indonesia**				**Mexico**			
91-11	-0.06	-0.04	-0.01	86-11	-0.32**	-0.06*	-0.07*	80-11	-0.21**	-0.07**	-0.05**
	(-0.03)	(-0.60)	(-0.10)		(-2.56)	(-1.87)	(-1.80)		(-3.68)	(-5.22)	(-2.99)
91-07	-0.33	-0.06	-0.09	99-11	0.27	0.07	-0.01	96-11	-0.39*	-0.05**	-0.07*
	(-0.11)	(-0.85)	(-0.73)		(0.40)	(1.19)	(-0.04)		(-1.80)	(-2.31)	(-1.74)
New Zealand				**Norway**				**South Africa**			
77-11	-0.05	0.07	-0.05	80-11	-1.36**	0.04	-0.03	90-11	-0.44	-0.06	-0.06
	(-0.22)	(1.61)	(-0.73)		(-2.40)	(0.69)	(-0.38)		(-0.65)	(-1.00)	(-0.78)
77-07	-0.03	0.06	-0.02	80-07	-1.27**	0.03	-0.01	90-07	0.01	0.00	0.05
	(-0.12)	(1.43)	(-0.34)		(-1.97)	(-0.48)	(-0.15)		(0.01)	(-0.06)	(0.01)

Table displays results from estimations of ADL models with alternative volatility measures. Univariate GARCH volatility refers to the GARCH standard deviation inferred from an autoregression of the real commodity price growth rates. The other measures are rolling 3-month and 12-month standard deviations of the real commodity price indices. T-values are reported in parentheses. * - significance on 10% level, ** - significance on 5% level.

E Additional Figures

Figure 6: Estimated commodity price GARCH series for baseline models

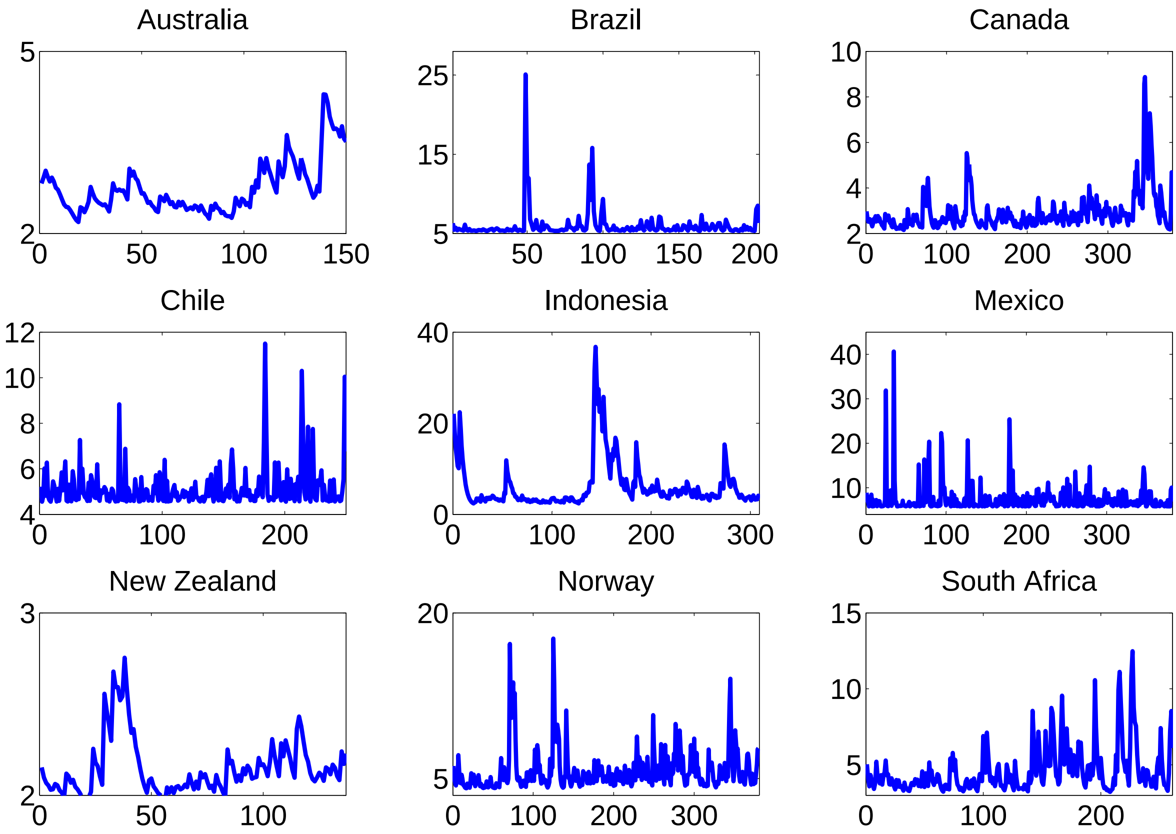

Figure shows the GARCH series of the real commodity price growth rates inferred from the estimated baseline MGARCH-VAR-in-mean models.