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

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Abstract

The last decade witnessed historically high levels of commodity price volatility. Policy makers fear that the induced increase in uncertainty about future prices dampens economic activity. Recent contributions by Elder and Serletis (2010) and Bredin et al. (2011) use Structural Vector Autoregressions with Multivariate GARCH-in-Mean errors and show that uncertainty about future oil prices decreases output in four G7 countries. This paper builds on these contributions and analyzes whether the uncertainty effect also affects commodity exporting countries, and, more importantly, whether it appears only for oil or also for a broader basket of commodities. 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.

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

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

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1 Introduction

In the first decade of the new century commodity price volatility reached historically high levels. Commodity prices began to increase steeply after 2000 before an even steeper decline followed during the financial crisis of 2008. Since 2009 prices started to surge to unprecedented heights again. These large fluctuations 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.[1]

In line with the theoretical literature on investment under uncertainty (Bernanke 1983, Pindyck 1991, Dixit and Pindyck 1994) it is feared that increased volatility creates uncertainty over future price levels which complicates investment and hampers economic growth. The fear is supported by recent contributions which find a negative effect of uncertainty about future oil prices on real output in four G7 countries. This paper sheds new light on the policy concerns as it empirically analyzes whether the uncertainty effect also impacts commodity exporters, and, more importantly whether it is limited to oil or also appears for a broad basket of different commodities.

A considerable number of studies has empirically analyzed the impact of general economic uncertainty, quantified by measures of volatility, on economic aggregates (Ramey and Ramey 1995, Bloom 2009, Gourio et al. 2013, Carrière-Swallow and Céspedes 2013). The impact of commodity price uncertainty, however, is a far less researched field. A notable exception is a recent contribution by Elder and Serletis (2010) who use a structural VAR accomodated by GARCH-in-mean errors to analyze the impact of oil price uncertainty on real economic activity in the US.[2] In a bivariate system containing real GDP growth and the real price of

[1] For example, Nicolas Sarkozy, then President of the French Republic and representing the French G20 presidency, addressed the G20 agriculture ministers' meeting during his opening speech: "Volatility, let us be absolutely clear about this, is a scourge. Volatility is a scourge for small farmers and for consumers, as well as for the stability of States; volatility is a threat because it endangers agricultural productivity for years to come: what farmer can commit himself to major investment when he is at risk of losing a third of his income the following year? What businessman would risk investing in such an unstable market?"

[2] The only other strand of the literature analyzing commodity price volatility and output uses homogeneous panel techniques over long time periods and reaches mixed results (Cavalcanti et al. 2012, Arezki and Gylfason 2011). While Cavalcanti et al. (2012) find negative effects of volatility on economic growth for primary commodity 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. Our study can also be understood as filling a gap in this literature by considering individual countries at the business cycle frequency to avoid the shortcomings of these existing studies.

oil they find that uncertainty about the future oil price has a significant negative effect on real economic activity over the post OPEC (post 1974) period. Uncertainty 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 same negative effect also with 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 this volatility effect is not limited to US data but also appears in four of the G7 countries (UK, US, France, and Canada).

Oil, however, is not the only commodity of interest. Commodities are necessary imports in industrial countries and an important source of income for others that rely on primary commodity exports. Many countries generate revenues from non-oil primary commodity exports like minerals, metals, and agricultural products, as a significant source of income. In this paper we therefore extend the existing research on oil price uncertainty and real output to a broad basket of commodities.

We restrict our analysis 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. Our sample, moreover, includes both countries where petroleum products constitute an important share of commodity exports and countries that mainly export other commodities. This approach allows us to draw first conclusions about two related questions: Firstly, our analysis investigates whether the results of Elder and Serletis (2010, 2011) are limited to oil importers or if they also apply for commodity exporting countries. More importantly, our results yield first evidence whether the uncertainty effect is a peculiar feature of oil or if it is comparable for a broad set of different commodities.

Methodically, the paper builds on Elder and Serletis (2010, 2011) and employs 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). Furthermore, we use international trade data to construct country specific commodity export price indices based on a basket of 48 different commodities ranging from petroleum products, metals, and agricultural raw materials to food. In doing so we assure that the distinct commodity export structures of the sample countries are taken into account.[3]

[3] As we use the VAR-GARCH-in-mean model to analyze the output effects of commodity price uncertainty, our work is also 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 commodity export price indices differ substantially from the general IMF price index employed by Choi and Kim (2012). Building country specific indices yields valuable information and allows

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 increase in volatility accompanying a commodity export price shocks has dampening effects on the real economy. These findings support recent results by Elder and Serletis (2010, 2011) and Bredin et al. (2011) and show that they can be extended to oil exporting countries. For the other countries in our sample that mainly rely on non-energy commodity exports like minerals, metals, and agricultural products, commodity price volatility has no significant effect on real output. This result indicates that oil and uncertainty about its future price have a special position within the group of commodities.

The paper is structured as follows: Section 2 describes the included countries and the constructed commodity price indices while Section 3 briefly describes the VAR-GARCH-in-mean model. Empirical results and impulse response analysis are given in Sections 4 and 5 with concluding remarks following in Section 6.

2 Included Countries and Specific Commodity Price Indices

2.1 Included Countries

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 following countries: Australia, Brazil, Canada, Chile, Indonesia, Mexico, New Zealand, Norway, and South Africa.[4]

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

for a distinction both between countries and between different commodities (e.g. oil vs. non-oil). 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.

[4]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.

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. The importance of commodities can also be inferred from the share of commodity exports in GDP (Table 4 in the appendix). This share exceeds 10 % for almost all our sample countries which further underlines the relevance of commodity exports for these economies.

Our sample of countries not only allows us to investigate whether the results for uncertainty about future prices can be generalized to commodity exporters. It also allows us to test whether the results of the literature are a peculiar property of uncertainty about oil prices or if they translate to a broad basket of commodities. For this purpose, our sample of countries can be split into two groups: oil exporters and non-oil exporters.

For some countries in our sample commodity exports are mainly driven by petroleum products. The UNCTAD trade data in Table 1 show that this applies to Canada, Norway, and Mexico whose commodity exports consists to more than two thirds of oil (petroleum products).[5] The only other country with a share of more than one-fifth of oil in commodity exports is Indonesia. 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. Therefore, we consider it, along with Canada, Norway, and Mexico, as an oil exporter in our analysis.

[5]For instance, crude oil is Mexico's single biggest export item and very important for the Mexican government budget (Banco Central de Mexico 2013).

For the other countries in our sample, petroleum products play only a minor role. Their major share of commodity exports consists of minerals, metals, and agricultural products. Hence we will consider this group of countries, Australia, Brazil, Chile, New Zealand, and South Africa, as non-oil (commodity) exporters.

2.2 Commodity Export Price Indices

For our empirical analysis, we construct country specific commodity price indices. This takes the country specific commodity export structures, which differ substantially between our sample countries, are taken into account. We apply on the approach of UNCTAD (2012) which includes 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):

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

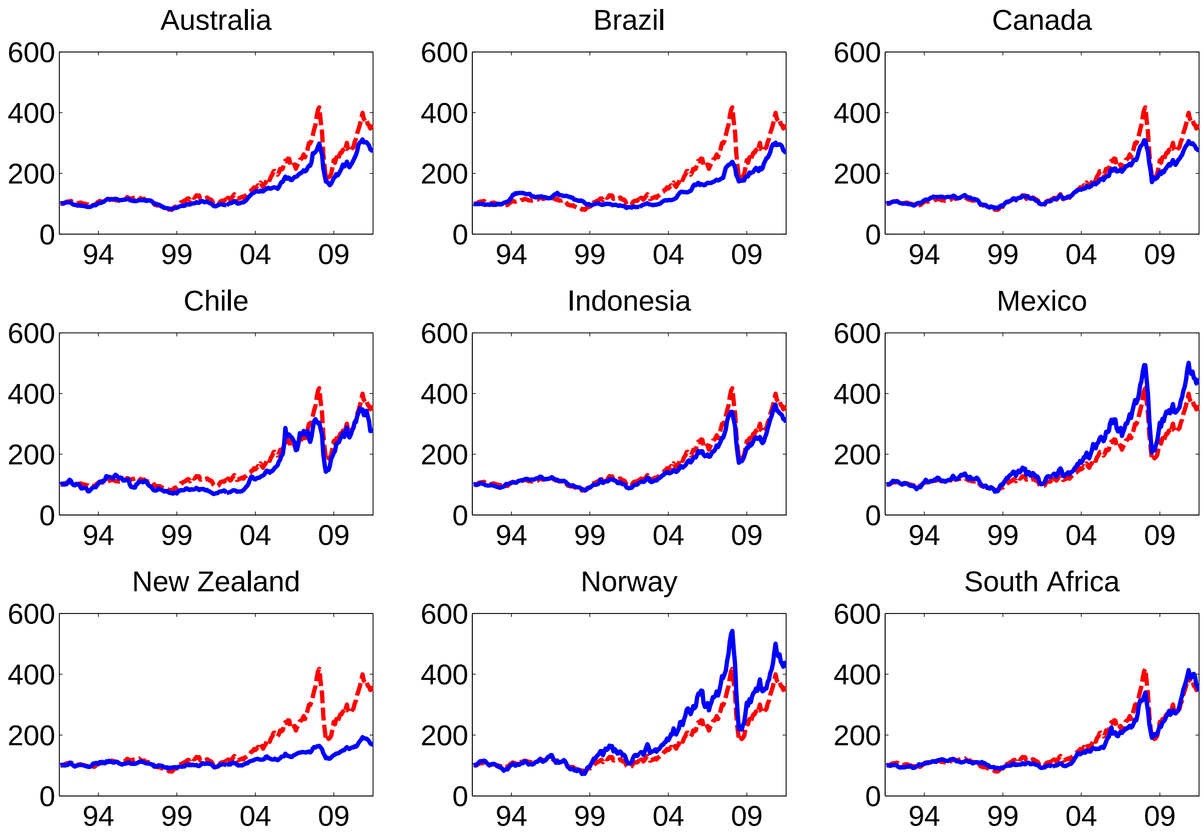
$I_{i,t}$ is the value of the commodity index in country i at time t, $P_{j,t}$ is the international dollar price of commodity j at time t and the weight W_j is the value share of this commodity j in country i's commodity export basket in a base period b. The baskets are based on monthly prices of 48 commodities which cover minerals, metals, agricultural raw materials, food, petroleum products, and other 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]

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.

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

[6]We computed the country specific commodity weights based on trade volume matrices for imports and exports publicly available at the UNCTAD database. We follow UNCTAD (2012) and take 1995, which is in the midst of our sample, as the base year for the export weights. The indices, however, are robust to changing the base period to 2000 or 2008. 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.

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.

this also takes the volatility in the foreign exchange rate and in consumer prices into account.[7]

2.3 Real Output Measure

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 make use of their full information content. For Australia and New Zealand, no monthly index of

[7]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. 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.

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] Data on industrial production, foreign exchange rates (both spot market and PPP adjusted), and consumer prices are taken from the OECD database and the IFS statistics of the IMF.

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.[9] 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.

2.4 Sample Period

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 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

[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]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.

(2003). In its structural form, the model can be written as follows:

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

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

with y_t being an n-dimensional vector which contains the realization of the endogenous variables in period t. Equation (2) specifies the mean of y_t, whereby, conditional on the information set at period t, Ω_{t-1}, the structural innovations are assumed to be independently normally distributed, $\varepsilon_t|\Omega_{t-1} \sim N(0, H_t)$, and uncorrelated. For the specification of the conditional variance H_t in equation (3) the VEC model (Bollerslev et al. 1988) is used 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. Following Elder and Serletis (2010, 2011), we choose a parsimonious lag length of $q = r = 1$.

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 making ${H_t}^{1/2}$ a measure of dispersion in the forecast and, therefore, a proxy of 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 the advantage that testing the effect of commodity price volatility on real output comes down to the statistical significance of a single element.

To identify the structural system a sufficient number of identification restrictions has to be imposed on matrix B. We use zero restrictions as in a homoskedastic VAR and allow industrial production to react instantaneously to innovations in real commodity prices but not vice versa.[10] 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 in line with

[10]Different to a homoskedatic VAR, B cannot be recovered in a second step by a Cholesky decomposition or maximum likelihood since the information matrix is no longer diagonal (Elder 2003). The system of equations is, therefore, estimated consistently in one step by applying a full information maximum likelihood (FIML) approach.

work on oil prices in industrial countries by Elder and Serletis (2010) or Bredin et al. (2011).[11] 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 description of these IRFs can be found in the appendix.

4 Is Commodity Export Price Volatility Harmful?

4.1 Empirical Results

We find significant GARCH effects in the commodity export price series for all sample countries and predominantly also in the series on industrial production. These significant GARCH effects support the VAR-MGARCH specification. Further evidence in favor of the VAR-MGARCH-in-mean is given by the Schwartz information criterion. For almost all the criterion points towards a better fit of the model compared to a corresponding homoskedastic VAR.[12]

Table 2 and 3 report the point estimates for the oil and non-oil exporting countries. The parameter capturing the effect of commodity price volatility on real output is $\Lambda_{(1,2)}$, the upper off-diagonal element of the volatility spillover matrix Λ.[13] Lag lengths for our baseline estimations are selected by the Akaike information criterion (AIC) which yields residuals free from autocorrelation. As a robustness specification, estimations based on the Schwartz criterion (SIC) confirming our main results can be found in Table 6 in the appendix.

[11]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 prices react instantaneously to output shocks as they can adjust rapidly to new information. This, however, is not necessarily the case in 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.

[12]The estimated MGARCH equations can be found in Table 4 in the appendix. The table also contains the Schwartz information criterion for our baseline VAR-MGARCH-in-mean and for the corresponding homoskedastic VAR model.

[13]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 predominantly found to be insignificant and not reported.

4.2 Oil Exporting Countries

Our results show that commodity price volatility is indeed estimated to have an adverse effect on real output for oil exporting countries. The point estimates for Canada and Norway 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. Hereby, the baseline estimation starts with the earliest available data in 1986. A further estimation controls for a possible bias due to the Asian crisis, which heavily affected the country, by letting the sample start in 1999. 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. 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.

Table 2: Estimates of Commodity Price Volatility Coefficient: Oil Exporters

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	$\Lambda_{(1,2)}$
Canada					**Indonesia**				
Baseline	80-11	3	377	**-0.17****	*Baseline*	86-11	2	308	**-0.08****
				(0.08)					(0.03)
Fin. Crisis excluded	80-07	3	329	**-0.35****	*Asian Crisis excluded*	99-11	1	155	**-0.25****
				(0.19)					(0.11)
Mexico					**Norway**				
Baseline	80-11	2	381	-0.05	*Baseline*	80-11	6	377	**-0.37****
				(0.03)					(0.10)
Tequila Crisis excluded	96-11	2	190	-0.10	*Fin. Crisis excluded*	80-07	6	329	**-0.42****
				(0.08)					(0.10)

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.

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 two of the oil exporting countries: 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.[14] 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 reactions in other variables as they are based on a bivariate system.

4.3 Non-Oil Exporting Countries

For the other countries that export mainly minerals, metals, and agricultural commodities, coefficients are predominantly found to be insignificant, albeit by and large they have the expected negative sign. Significance in the estimations for Australia is driven by the 2008 economic crisis as it vanishes in the sample which excludes this episode. The other countries, Chile, New Zealand, and South Africa, do not display any significant point estimates at all.[15] The same holds true for Brazil where we take possible break points into account. 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.

4.4 Robustness

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 estimations strongly support our main findings. A detailed description of the robustness analysis can be found in appendix B.

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

[15] Estimations for Chile and South Africa start with the earliest available output data.

Table 3: Estimates of Commodity Price Volatility Coefficient: Non-Oil Exporters

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	$\Lambda_{(1,2)}$
Australia					**Brazil**				
Baseline	74-11	4	147	**-0.18****	*Baseline*	95-11	5	199	-0.01
				(0.08)					(0.06)
Fin. Crisis excluded	74-07	4	131	-0.24	*Argent. Crisis excluded*	03-11	4	104	0.24
				(0.31)					(0.11)
Chile					**New Zealand**				
Baseline	91-11	3	248	-0.30	*Baseline*	77-11	2	136	-0.10
				(0.19)					(1.14)
Fin. Crisis excluded	91-07	3	200	-0.11	*Fin. Crisis excluded*	77-07	2	120	-0.01
				(0.29)					(0.04)
South Africa									
Baseline	90-11	3	260	-0.04					
				(0.10)					
Fin. Crisis excluded	90-07	3	212	0.11					
				(0.13)					

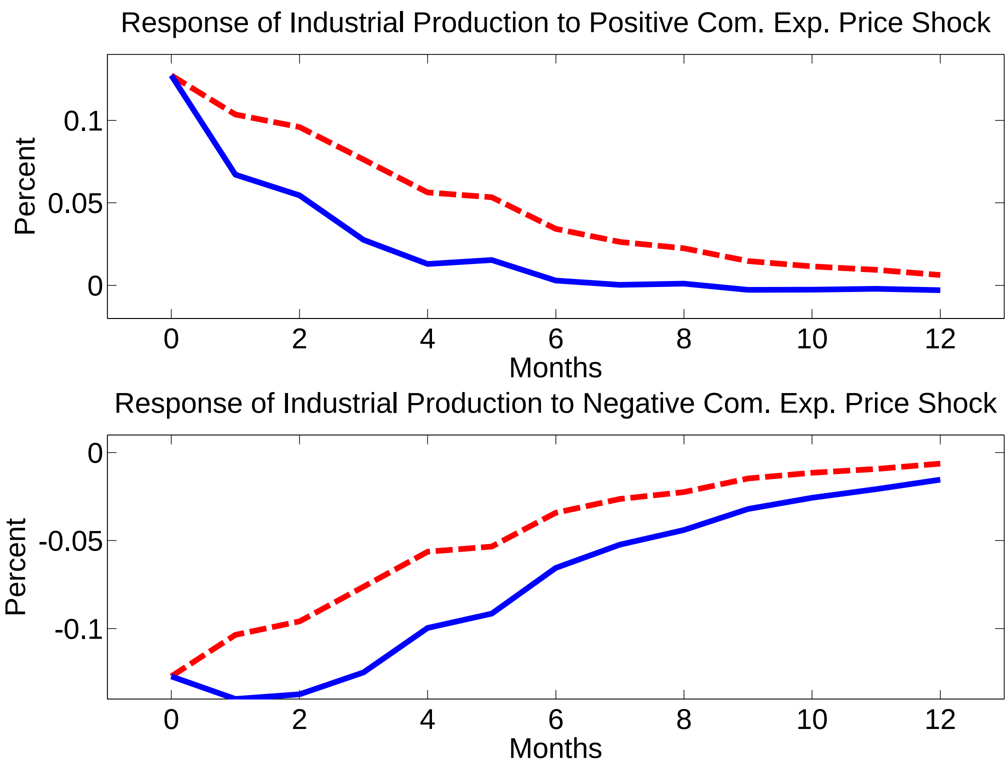
Table shows the estimated parameter measuring the direct impact of conditional commodity price volatility on output. We report results from both our baseline specification with the lag length based on the Schwartz information criterion and, as a measure of robustness, from a specification including more 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.

5 Dynamic Impact of Commodity Export Price Shocks

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 volatility affects the dynamic response to a commodity price shock. For this purpose, we use the Impulse-Response-Functions (IRF) by Elder (2003) specifically developed for the SVAR-GARCH-in-mean model. To illustrate the dynamic long run effects, we display IRFs for Canada and Norway, two of the oil exporting countries, for which the spillover coefficient is found to be significant. In Figures 2 and 3, 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.[16]

[16]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

Figure 2: 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.

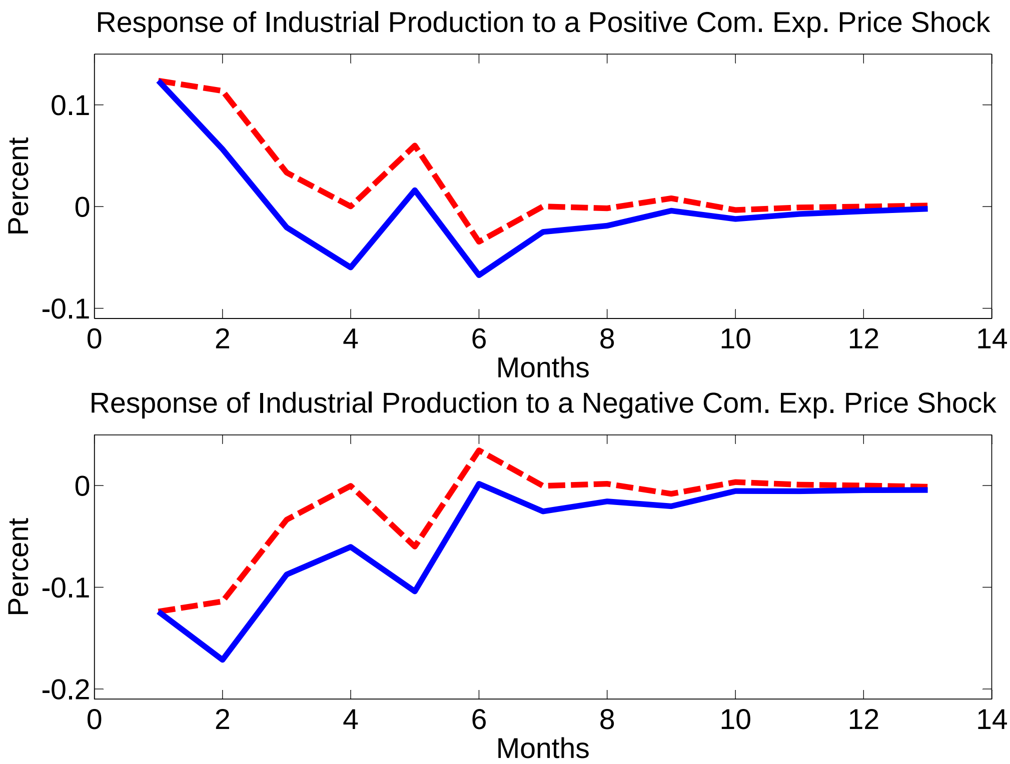
The IRFs for Canada and Norway show that the initial response of industrial production to a shock which increases commodity export prices is estimated to be positive. After the initial impulse industrial production remains above its equilibrium value for several periods before the shock fades out, both in the IRFs with and without the volatility augmentation.[17]

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

similar results regarding the effect of uncertainty.

[17]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 (oil) is rather inelastic. Furthermore, expenditures and investment in 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. 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. Furthermore, it has to be noted 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 3: 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.

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 of a commodity export price shock. Firstly, volatility dampens the expansion in investment of commodity related businesses in line with the 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.

Lastly, it has to be noted that we treat the counterfactual analysis with a bit of caution. 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.[18] Furthermore, the restricted IRFs fall into the confidence bands of the volatility accounting ones. We are hence 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.

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. Using VAR-MGARCH-in-mean models, such a negative effect of uncertainty about future oil prices has been found for the US and other oil importing industrial countries (Elder and Serletis 2010, 2011, Bredin et al. 2011).

[18]Responses to positive commodity price shocks with 68 % confidence bands are given in Figure 5 in the appendix.

In this study, we extend this line of research and analyze whether uncertainty also has negative effects for commodity exporting countries. In particular, we build country specific commodity price indices and investigate whether the uncertainty effect is limited to oil or also appears for a broad basket of commodities.

We find a negative impact of price volatility on real output for the oil exporting countries in out sample. Impulse response analysis shows that the increase in volatility that accompanies a commodity price shock negatively affects the response of real output for a prolonged period. For the non-oil exporters, meanwhile, we do not find a significant negative effect. Our results indicate that oil and uncertainty about its future price play a distinct role within the group of commodities.

To explain the dissimilarities between oil exporters and exporters of minerals, metals, and agricultural products, more research is necessary. Future projects could analyze how differences between the commodities regarding the maturity of delivery contracts, market structures, or storage capacities affect the possibilities to hedge against price uncertainty.

From a policy perspective, our results constitute an additional argument for approaches aimed at reducing the volatility in international oil 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 oil as an input in their production activities.

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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.[19]

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.

[19]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[20] and historical volatility given by rolling 3-month and 12-month standard deviations of the real commodity price indices.[21] 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.

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

[21] 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: 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.

Table 6: 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)
74-07	1	134	-0.19	03-11	1	107	-0.07	80-07	3	332	**-0.40****
			(0.35)				(0.18)				(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)
91-07	1	202	-0.24	99-11	1	155	**-0.25****	96-11	1	191	-0.07
			(0.29)				(0.11)				(0.07)
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)
77-07	1	121	0.15	80-07	3	332	**-0.39****	90-07	2	213	0.13
			(0.60)				(0.14)				(0.12)

Table shows the estimated parameter measuring the direct impact of conditional commodity price volatility on output. This table results from both our baseline specification with the lag length based on the Schwartz information criterion as a measure of robustness. Values in parentheses are asymptotic standard errors based on inverse of the Hessian.
* - 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

GARCH	SD 3	SD 12	GARCH	SD 3	SD 12	GARCH	SD 3	SD 12
Australia			**Brazil**			**Canada**		
74-11			95-11			80-11		
-0.13	-0.01	-0.03	-0.01	0.01	-0.07	-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			03-11			80-07		
0.28	-0.01	-0.21**	-0.23	-0.01	0.00	-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			86-11			80-11		
-0.06	-0.04	-0.01	-0.32**	-0.06*	-0.07*	-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			99-11			96-11		
-0.33	-0.06	-0.09	0.27	0.07	-0.01	-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			80-11			90-11		
-0.05	0.07	-0.05	-1.36**	0.04	-0.03	-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			80-07			90-07		
-0.03	0.06	-0.02	-1.27**	0.03	-0.01	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 4: Estimated commodity price GARCH series for baseline models

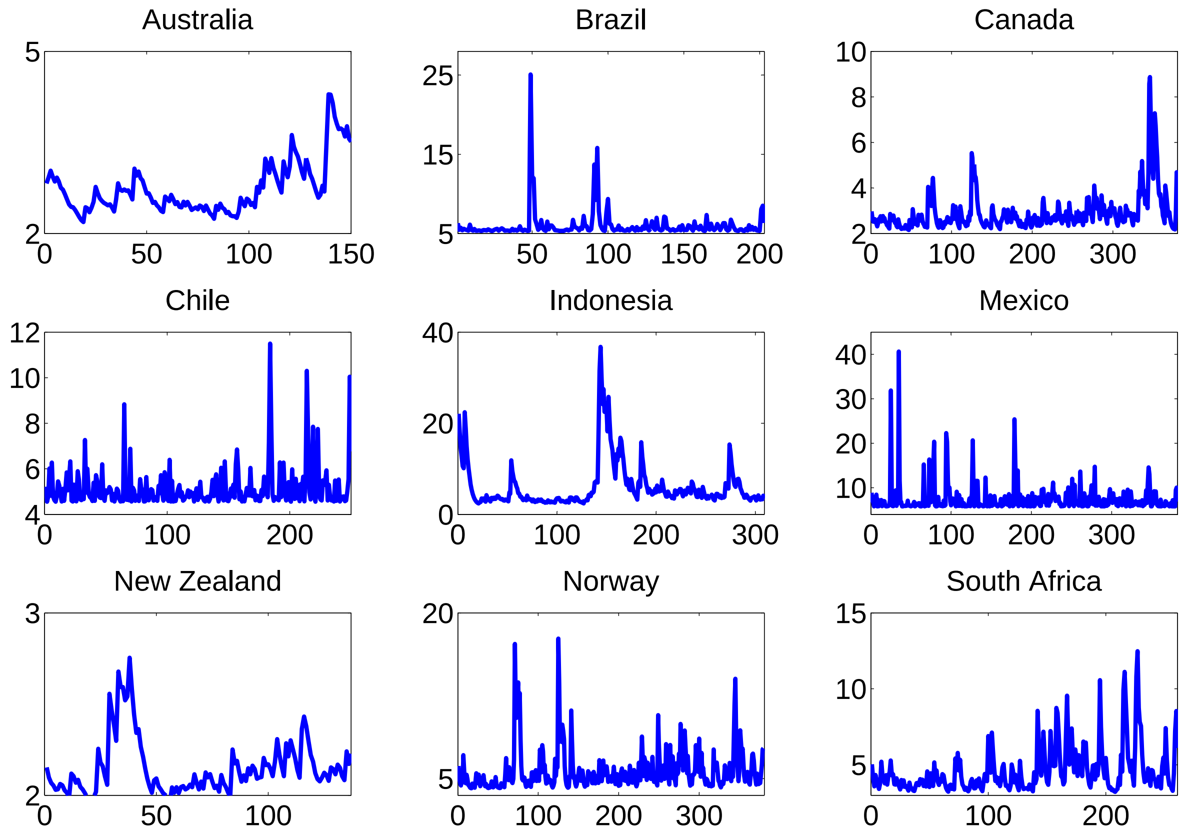
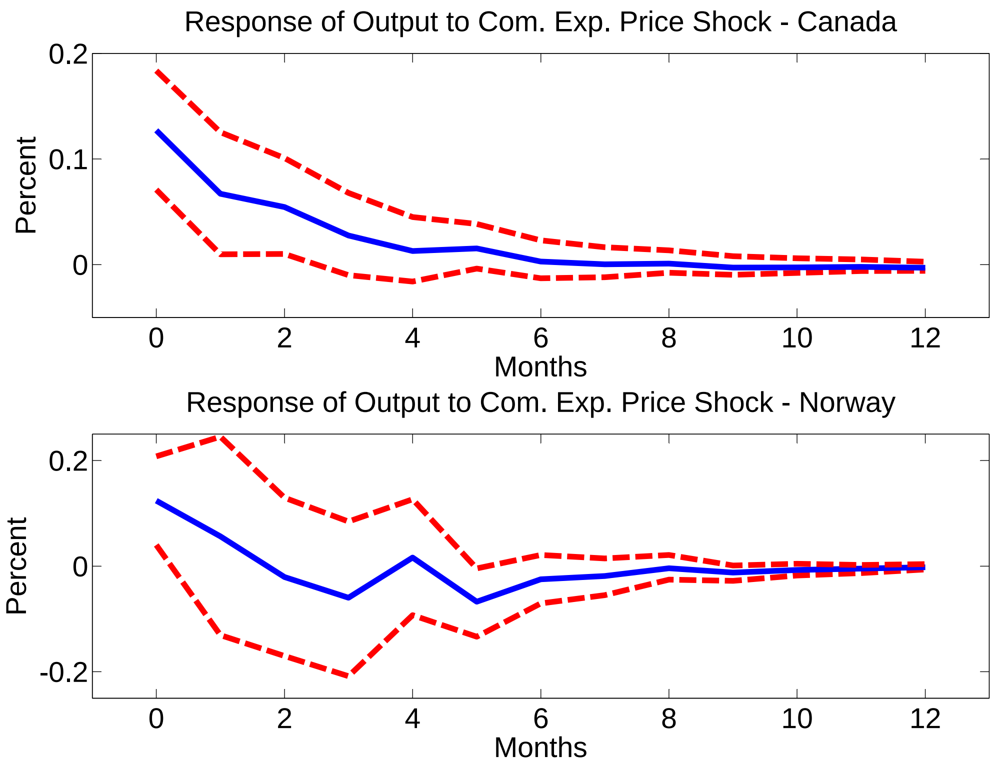


Figure shows the GARCH series of the real commodity price growth rates inferred from the estimated baseline MGARCH-VAR-in-mean models.

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). 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.