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School of Economics and Business

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Working Papers No. 9/ 2018

ISSN: 2464-1561

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September 11, 2018

Abstract

This paper identifies the effect of income shocks on the real price of oil. We find that for the period 1973-2016 shocks to world GDP created a response of a permanent rise in the oil price. In contrast, oil production does not correct the disequilibrium from a stable long-run equilibrium. Whereas shocks to GDP are persistent, shocks to the oil price are mostly transitory once we control for changes in world GDP and oil production. We find evidence of a structural change in the response of the oil price after 1973. We conjecture that the response of oil production is key to the differences.

JEL Classification: *C13, C22, Q02, Q43*

Keywords: *Oil Market, Real Oil Price, Commodity Markets, Cointegration*

*Acknowledgments: We appreciate the comments and suggestions from Rodrigo Caputo and Knut Einar Rosendahl. We also thank participants at the BI Norwegian Business School and Norwegian University of Life Sciences—School of Economics and Business. We thank Samantha Copeland for proofreading the draft of the paper.

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1 Introduction

Since 1973 the oil price has shown high levels of volatility. Alternative explanations have resorted to supply and demand factors and the role of speculation as possible causes explaining the variation in prices. Empirical models have used mainly a stationary framework where shocks are deemed to be mean reverting. However, there is evidence that the oil price can be described by a random walk without drift (Hamilton, 2009). More generally, Dvir and Rogoff (2014) have found cointegrating relationships between the oil price, production and inventory levels using annual data from 1900.

There are good reasons to believe that commodity markets have been influenced by permanent demand shocks. For example, Aguiar and Gopinath (2007) have documented that shocks to the growth rate of technology contribute more to the variability of output in emerging economies than in developed economies. It then seems feasible that the strong patterns of growth in emerging economies have contributed significantly to the demand in the commodity market, especially during the recent boom. If shocks are permanent, it raises the question of whether there is a permanent long-run relationship among the price of crude oil, income and oil production. We provide evidence that this is indeed the case for these three variables using quarterly data from the beginning of the 1970s.

We also find evidence that a long-run relationship in the oil market helps to predict oil prices. Indeed, this result is based on our multivariate error correction framework, and highlights the importance of accounting for long-run trends in the oil markets. In contrast, Hamilton (2009) using a simple univariate autoregression finds that common macroeconomic variables lack predictive power, and that the oil price can be approximated by a random walk. We also find that a permanent shock to world GDP leads to a significant hump-shaped response in oil prices. In contrast, price-demand specific shocks are entirely transitory. In fact, and in line with previous studies, we find that most of the variation in oil prices are derived from transitory shocks. We also provide evidence that the long run relationship does not forecast oil production. We conjecture that oil production has become more inelastic from 1973 onward.

We have extended the analysis to study the oil market using annual data from 1900 to 2016. We found that the long run relationship predicts the change in oil prices. Interestingly, in the early period, we find evidence of predictability for oil production. We conjecture that the differential response of production explains why shocks to income are mostly transitory in the early period.

Finally, we have explored whether world GDP also has an impact on another commodity, namely copper prices, on the period 1900-2016. We find indeed that the long run relationship predicts the copper prices and quantity. As a result, the response of the copper price to a shock to income is mostly transitory.

Our article contributes to three branches of the literature on commodity markets. First, our paper is relevant to the research on time series analysis of the oil price. Most papers have used a stationary framework. Kilian (2009) identifies supply, aggregate demand and specific oil demand shocks using data on world oil production growth, the index of real economic activity based on dry cargo bulk freight rate and real price of oil. He finds that aggregate demand shock generates long-term variation in the real price of oil, and the oil-market specific demand shock creates the sharp rise and drop in the oil price. Later Kilian and Murphy (2014) and Knittel and Pindyck (2016) use similar frameworks to study the role of speculation. In contrast, we have studied the oil price using a non-stationary framework. We are also able to link world GDP to commodity prices using annual data from the last century.

Second, our paper is related to a paper in international macroeconomics. Our paper builds on Aguiar and Gopinath (2007), and they find that shocks to growth in the emerging economy tend to be important for understanding consumption patterns. Our contribution is to assess the effect of income shock on the oil market through impulse responses and variance decomposition analysis. We find that income shock has a permanent effect on oil price.

Similarly, our paper is related to the recent theoretical contributions of Dvir and Rogoff(2009; 2014). They employ an extended commodity storage model explaining the persistence and volatility in the oil price. When aggregate demand has a persistent growth component (emerging economies), storage amplifies the shock's effect on the price. However, the magnifying effect of inventory is diminished when supply becomes flexible. Dvir and Rogoff (2014) find that cointegration among oil production, inventories, income and crude oil price can be explained using the storage model with stochastic income growth and different production scenarios. Our paper also uses a cointegration framework. We also show that the impact of income shocks depends on the relative supply elasticity.

Finally, our model is related to the small but growing body of literature on the comovement in commodity markets. Many papers have warned us about possible cointegration in the crude oil market. Kaufmann et al. (2004) and Dées et al. (2007) detect cointegration among crude oil price, days of forward consumption of oil stocks, OPEC production quota and capacity utilization. They employ an error correction model for the world oil market. The model includes three single equations, oil demand, oil supply and the function of price. Lakuma (2013) studies the extent of market power in the American crude oil industry through a vector error correction model for the demand and supply of oil for the period 2000–2012. He also estimates the model using a single-equation method. Our paper differs in that we have used data from more than 100 years. In our model, we estimate the long-run elasticities at equilibriums. We also show that the price is predictable using the long-run equilibrium among oil price, oil production and world GDP.

The remainder of the paper proceeds as follows. In section 2 we provide evidence for stochastic trends in the oil market. We show there is evidence for cointegration among world GDP, oil production and the oil price. We also estimate a stable long-run relationship. In section 3 we quantify the impact of shocks to world GDP on the price of oil. We show that income shocks generate a permanent effect on the oil price.

2 Stochastic trends in the oil market

In this section, we present evidence of cointegration in the oil market. We show that the latest period 1974:Q1–2016:Q4 is critical to the test for stochastic trends in our data. We start by explaining that world GDP, oil production and oil prices are non-stationary time series. We then establish that there is evidence for at least one cointegrating relationship among the series. Finally, we estimate a long-run relationship for the oil market.

Data. We use quarterly data for the period 1974:Q1–2016:Q4. We use West Texas Intermediate (WTI) price as the measure of crude oil price collected from FRED (2018). The crude oil production is collected from EIA (2018). We employ world GDP as the measure of global income. The world GDP series combines quarterly GDP index from Fagan et al. (2001) for the period 1974:Q1–2010:Q4 and Global Financial Data for the period 2011:Q1–2016:Q4. Nominal crude oil price and world GDP are deflated using the U.S. CPI obtained from the U.S. Bureau of Labor Statistics (2018).

Unit root test. We start by performing a standard unit root test for the oil price, oil production and world GDP. Using the augmented Dickey-Fuller (ADF) test (with a constant in the regression) we cannot reject the null hypothesis of a unit root.[1] Hence, no evidence suggests that these variables are stationary. This result is robust to other unit root tests.[2] We also find that this result is robust to different subsample periods: 1974:Q1–1994:Q4 and 1995:Q1–2016:Q4. Again, we cannot reject the null hypothesis of unit roots for all variables

[1] We use Bayesian information criteria to select the number of lags. We find four lags for the logarithm value of world GDP, 12 lags for the logarithm value of world oil quantity and two lags for the logarithm value of oil price. Similar results are obtained when using the Akaike information criterion. The p-value of the ADF test statistic of unit-root $\log(Y_t)$ is 41.5 percent, 93.5 percent for $\log(Q_t)$, and 30.3 percent for $\log(P_t)$.

[2] In particular, we used the Phillips and Perron test (with intercept). Indeed, we find no evidence to reject the null hypothesis that global GDP, world oil quantity and oil price are unit roots. The p-value of the test statistic for the logarithm value of world GDP is 88.0 percent for nonstationary, 25.3 percent for the logarithm value of world oil quantity, and 59.5 percent for the logarithm value of oil price.

in different subsample periods.[3]

Cointegration test. Since variables are nonstationary, we can test for an equilibrium relationship among the crude oil price, oil production and world GDP. To this end, we implement a Johansen's unrestricted cointegration rank test (trace test), which is based on the estimates derived from an error correction model. In panel (a) Table 1 we show the results of our cointegration test. In particular, we report the trace statistics for $r = 0, 1, 2$ where r is the number of cointegrating relationships. We find that for the period 1974:Q1–2016:Q4 we reject the null hypothesis for $r = 0$ at both 1 percent and 5 percent significant level, with the trace statistics of 59.5, and critical value of 26.8 at 1 percent significance level and 34.91 at 5 percent significance level. But we cannot reject the null hypothesis of $r \leq 1$ at any significance level, with test statistics of 19.3, critical value of 20.2 at 1 percent significance level and 20.0 at 5 percent level. Thus, we conclude that there is at most one cointegrating relationship among the series. We also implement the trace test for the sub-periods of the sample: 1974:Q1–1994:Q4 and 1995:Q1–2016:Q4. As shown in Table 1, the cointegrating relationship is very robust to the sub-sample period, such that we reject the null hypothesis of $r = 0$, but we can not reject the null hypothesis of $r \leq 1$ at both 1 percent and 5 percent significance level. Hence, we confirm that there is at most one cointegrating relationship in the sub-sample period 1974:Q1–1994:Q4 and 1995:Q1–2016:Q4.

The Long-run relationship in the oil market. Having determined the existence of one cointegrating vector, we can estimate a long-run relationship among the crude oil price, world oil production and global GDP. We estimate this relationship using a standard dynamic OLS regression as in Stock and Watson (1993).[4]

In panel (b) we show the results of the dynamic OLS estimation. We see that the estimates for world GDP and oil production are both significant. It is important to stress that the estimates represent the long-run relationship among the variables. In this sense, there is no claim about causality from any one variable to the other. The long-run relationship cannot be interpreted as a "demand" or "supply" equation, rather it reflects different equilibrium sequences over time, representing the "average" correlation between prices, global GDP and global oil production. In any case, the structure of the oil market can eventually affect the signs of parameters we find.

Having in mind that the long-run relationship is neither a "demand" nor "supply" equation, there is a positive relationship between global production and oil prices. In particular, the

[3]We use BIC index to select the number of lags using in the test. For the period 1974Q1–1994Q4, we use four lags for the logarithm value of world GDP, one lag for the world oil quantity and oil price. For the period 1995Q1–2016Q4, we use two lags for the world GDP, seven lags for the world oil quantity and three lags for oil price. See Appendix for details about the unit root test.

[4]This method generates asymptotically efficient estimators for cointegrating vectors. To estimate the long run relationship we start by determining the number of lags and leads using AIC and BIC tests. The tests suggest using one lagged and one lead variable.

Table 1: Johansen's Cointegration Test for Different Periods

(a) Johansen's test of cointegration

		Cointegrating rank H0: $rank(\Pi)=r$		
		$r = 0$	$r \leq 1$	$r \leq 2$
Trace statistics:	1974Q1–2016Q4	59.52	19.31	6.89
Trace statistics:	1974Q1–1994Q4	49.66	19.88	9.23
Trace statistics:	1995Q1–2016Q4	36.50	12.72	3.90
Critical value 5%		34.91	19.96	9.24
Critical value 1%		26.81	20.20	12.97

(b) Long run relationship:

$$\log P_t = \alpha_0 + \alpha_y \log Y_t + \alpha_q \log Q_t + controls_t + \epsilon_t$$

	coeff.	se.
α_y	-1.434	(0.292)
α_q	3.914	(0.692)
α_0	-7.505	(3.033)

Note: Table (a) shows the Johansen test of vector cointegration for different cointegration ranks. This vector includes the logarithm value of world GDP, $\log Y_t$, world oil production, $\log Q_t$, and crude oil price, $\log P_t$, for the period 1974:Q1–2016:Q4. Π is the coefficient for the lagged vector in the VEC model. Table (b) shows the dynamic OLS estimates for the long-run relationship among variables for the period 1974:Q1–2016:Q4. The $controls_t$ variable contains one lag and one lead of the differences of the right-hand side variables.

elasticity of oil price with respect to oil production is 3.9, whereas the elasticity of oil price with respect to global activity is -1.4.

3 Quantifying the Impact of Income Shocks on the Oil Price.

In this section, we use a simple three equation autoregression framework to quantify the effect of income shocks on the oil price. We borrow the identification scheme from Cochrane (1994) and estimate a model with world GDP as an exogenous variable. Consistent with the work of Aguiar and Gopinath (2007), we find that shocks to world GDP are permanent. We find significant predictability of the long-run relationship in the oil price. However, we do not find predictability in quantity production. We show that income shocks generate a persistent response in the oil price. Moreover, shocks to oil prices are mostly transitory in line with many papers in the literature (Hamilton, 2009 and Kilian, 2009). We conjecture that the response of oil production is critical to understand this result. As production becomes more inelastic, the persistent GDP shock creates the high volatility and persistent impact on the oil price.

3.1 Vector error correction model (VECM)

Let $\mathbf{Y}_t = [y_t, q_t, p_t]$ be a vector containing the logarithm values of our three variables world GDP, oil production and oil prices. $\triangle\mathbf{Y}_t$ denotes the vector of differences $[\triangle y_t, \triangle q_t, \triangle p_t]$. Let $\hat{\alpha}$ be the estimated long-run parameters we obtain in the previous section. Then we use this vector of parameters to estimate the following VECM:

$$\triangle\mathbf{Y}_t = c + \gamma\hat{\alpha}\mathbf{Y}_{t-1} + \sum_{j=1}^{J} A_j \triangle\mathbf{Y}_{t-j} + u_t \tag{1}$$

where c is the vector of constant estimates and γ is the vector of speed of adjustment coefficients $[\gamma^y, \gamma^q, \gamma^p]'$.

In Table 2 panel (a), we show the estimates of our VECM. In the case of the equation for prices, we obtain a significant coefficient of -0.073 for the speed of adjustment (related to the lagged error term). The value of this coefficient implies that each quarter oil prices change in order to correct 7 percent of long-run price misalignments. This value implies that the half-life [5] of past misalignments is 9.4 quarters, for example after 9.4 quarters movements in

[5] The half-life is equal to $\ln(2)/\gamma$.

Table 2: The Estimates of VEC Model and Variance Decomposition

(a) Vector autoregression

LHS		const.	LR term	$\triangle y_{t-1}$	$\triangle q_{t-1}$	$\triangle p_{t-1}$	R^2
				RHS variable			
$\triangle y_t$	coeff	0.003	-	0.436	-	-	19%
	s.e.	(0.001)		(0.069)			
$\triangle q_t$	coeff	0.003	0.001	0.743	-0.164	0.015	7.2%
	s.e.	(0.028)	(0.004)	(0.273)	(0.077)	(0.011)	
$\triangle p_t$	coeff	-0.570	-0.073	3.158	-1.266	0.182	11.8%
	s.e.	(0.183)	(0.024)	(1.792)	(0.501)	(0.074)	

(b) Variance decomposition

Due to	$\triangle Y_t$	$\triangle Q_t$	$\triangle P_t$	$\triangle Y_t - E_{t-1}\triangle Y_t$	$\triangle Q_t - E_{t-1}\triangle Q_t$	$\triangle P_t - E_{t-1}\triangle P_t$
				Variance of		
y shock	100	6.37	1.85	100	3.14	0.76
q shock	0	92.71	4.71	0	96.86	0.49
p shock	0	0.92	93.45	0	0	98.76

Note: Table (a) shows the estimates of the VEC model as in equation (1). Table (b) shows the variances of global GDP, world oil production and oil price growth.

prices reduce half of the long-term disequilibrium. The significance of γ^p also shows that oil price growth is predictable using the long-run relationship in the oil market. Interestingly, the R^2 is around 12 percent, which is larger than a simple univariate autoregression with four lags (AIC selected) with a R^2 of 5.6 percent. This comparison highlights the predictive effect of the long-run relationship.

Now, in the case of the short-run equation for quantities, we obtain a speed of adjustment coefficient of 0.001. This coefficient is not statistically different from zero. Hence, quantities do not adjust in order to correct past misalignments. Even in the case where we disregard the significance level, the speed of adjustment in oil quantities is only 0.1 percent, which implies a half-life of 300 quarters. Overall, we conclude that prices respond to past long-run misalignments, but quantities do not react or react extremely slow.

Impulse Responses. We now show impulse response functions to a one standard deviation shock of world GDP. We use a Cholesky decomposition scheme with the following ordering $\{y, q, p\}$. Hence, we assume that world GDP does not respond contemporaneously to shocks to neither world production nor oil prices. In Figure (1) we plot the response of the level of the variables to shocks to world GDP. In panel (a) we plot the response of world GDP and the oil price. We observe that the response of world GDP is almost flat, suggesting that the shock has a permanent effect on world GDP. In contrast, the response of oil prices is hump-shaped and significative. One could interpret a shock to GDP as shocks to global demand, and the delay response of the oil price suggests lagged supply adjustment induced by capacity investment and relatively inelastic oil supply. Overall, a one percent shock to world GDP generates a permanent increase in oil prices of 2.4 percent. In panel (b) we see that the impact of world GDP on oil quantities is permanent. In this case a one percent increase in world GDP leads to a permanent increase in oil quantities of 0.9 percent. All in all, we find evidence that shocks to world GDP are permanent and have a permanent impact on both oil prices and quantities, although the impact on oil prices is twice as large as the impact on quantities.

Oil price shock. In Table 2, we found that the speed of adjustment coefficient of oil quantities is small and not statistically different from zero. Thus, quantity is not predictable using the long-run relationship of world GDP, price of oil and world oil quantity in the error correction model, which is consistent with the view that in the long run oil production is relatively inelastic. As a result, most of the predictability comes from the auto-regressive term and lagged differences of GDP growth. In Figure 1 panel (c) we show that an oil price shock of one percent has a small impact on quantities, which is both small (0.2 percent) and not statistically different from zero after four quarters. The response of oil prices to this shock, as seen in Figure 1 panel (d), is statistically different from zero, relatively large (14.6 percent) and transitory. After 30 quarters the effect is no longer statistically different from zero.

Beveridge and Nelson decomposition. We now compare our long-run relationship with a trend component derived using a Beveridge and Nelson decomposition following Beveridge and Nelson (1981). The trend is computed after all transitory shocks have eventually disappeared. Figure 2 shows that the Beveridge and Nelson trend component is very similar to the long-run relationship used in our vector autoregression specification.[6] The decomposition shows a steady increase in the permanent component after 1985. We also can see that most of the run-up in the price starting in 2000 is due to transitory shocks.

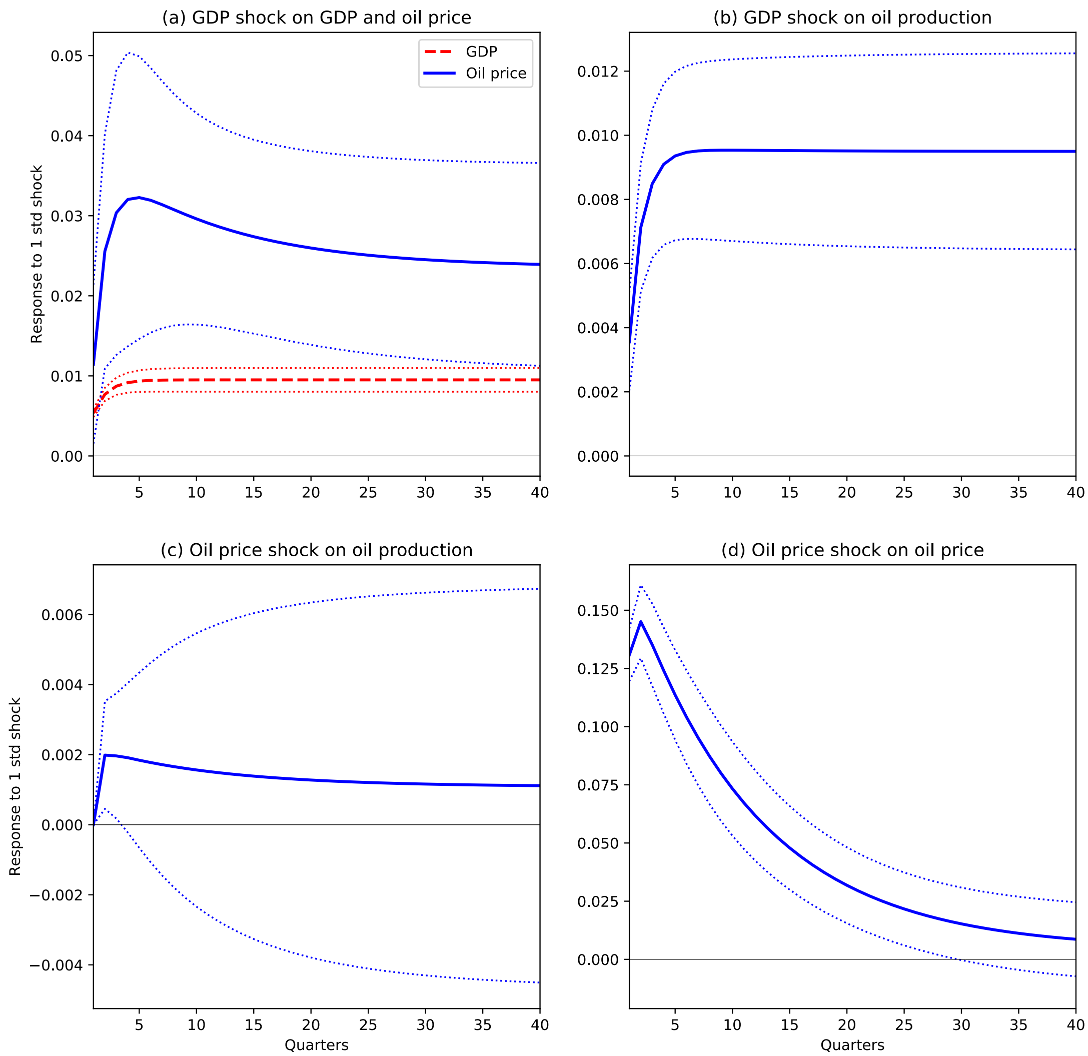
3.2 The importance of accounting for the long run behavior

To analyze the importance of accounting for the cointegrating vector we compare our benchmark model with a simple vector autoregression model. In particular, we re-estimate the model using a vector autoregression with the same three variables but this time without the error correction term.

In Figure 3 we plot impulse response functions to an oil price shock. The solid line

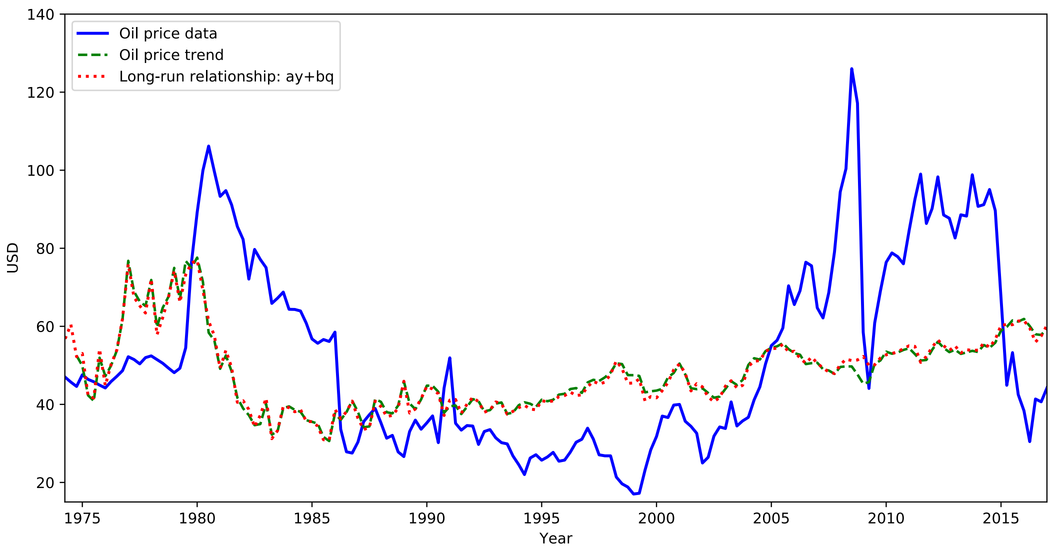
[6] The long-run relationship is computed as the predicted oil price in long run. That is $\hat{\alpha}_y \log Y_t + \hat{\alpha}_q \log Q_t$, where $\hat{\alpha}_y$ and $\hat{\alpha}_q$ are the dynamic OLS estimates from Table 1.

Figure 1: Responses of GDP and Oil Price to Structural Shocks



Note: Panel (a)–(d) show the cumulated responses using estimated parameters in equation (1). Panel (a) shows the response of oil price to one-standard-deviation oil price shock (the solid line) and GDP shock (the dashed line) respectively. Panel (b) shows the response of oil production to one-standard-deviation GDP shock. Panel (c) shows the response of oil production to one-standard-deviation oil price shock. Panel (d) shows the response of oil price to one-standard-deviation oil price shock. The dot lines denote the bootstrap one-standard-error bands.

Figure 2: Beveridge-Nelson Oil Price Trend and Long-Run Relationship of Oil



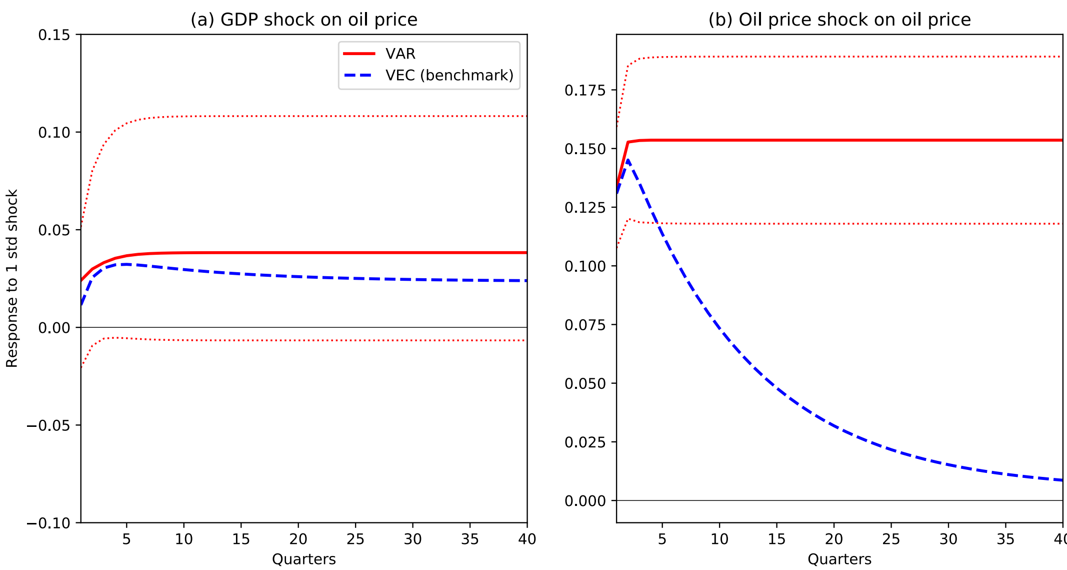
Note: The figure plots the Beveridge-Nelson components of the oil price. The solid line denotes the oil price data. The dashed line represents Beveridge-Nelson trend of oil price, computed using estimates from the VECM in equation (1). The dot line denotes the long-run relationship of $\hat{\alpha}_y \log Y_t + \hat{\alpha}_q \log Q_t$ where $\hat{\alpha}_y$ and $\hat{\alpha}_q$ are the DOLS estimates from panel (b) Table 1, Y_t and Q_t denotes the data on world GDP and global oil production.

represents the impulse response of our benchmark estimation, whereas the dotted line plots the impulse response in the estimation without the error correction term. We see that the response is almost permanent. Essentially, the model is similar to the behavior of an autoregressive model of the change in the oil price. In contrast, when the error correction mechanism is present, an oil price shock has no permanent effect. In this case, the reduction of the price to the pre-shock level is induced by the long-run relationship among the variables. Basically, comparing these two responses highlights the importance of the adjustment factor in term of the propagation of the price shock.

4 Further Analysis

In this section, we perform three additional analyses that complement our benchmark estimation. First, we compare our estimation with a stationary estimation framework. In particular, we compare with the standard VAR specification as in Kilian (2009). Interestingly, we show that both models capture similar short-run responses of oil prices to oil-specific demand shocks. The main differences are the response of prices to oil supply shocks. Second, we test the robustness of our estimates to a different sample period. Since there is

Figure 3: Responses of Oil Price to GDP and Oil Price Shocks: VEC Model and VAR



Note: Panel (a) and (b) show the impulse responses of oil price to one-standard-deviation of GDP and oil price shocks in VEC model and VAR model. The dashed line denotes the impulse responses in the VEC model, the benchmark case, in equation (1). The solid line denotes impulse responses in the VAR model of the vector $[\triangle logY_t, \triangle logQ_t, \triangle logP_t]$. In the VAR model we assume $\triangle Y_t$ is exogenous and exclusive, such that $\triangle logY_t = \sum_{i=1}^{N} a_i \triangle logY_{t-i} + a_0$ where a_i, $i = 0, 1, 2, ...$ are the coefficients. We employ $N = 1$ in the VAR model selected using AIC index. The dot lines denote the bootstrap one-standard-error bands for the impulse responses in the VAR model.

a structural break in the time series in 1973, we re-estimate our model using annual data from 1900 to 1973. We find production responses are key to the response of the model to exogenous income shocks. Finally, we also employ our empirical model to study the effect of income shocks on the copper market. We find similar effects in terms of predictability and the importance of transitory shocks.

4.1 Stationary vector autoregression

Now we compare our estimation from our error correction specification to a three-variable VAR specification similar to Kilian (2009), but on a quarterly frequency.[7] Our version of his estimation includes the change in oil production, an index of real economic activity constructed in Kilian (2009) and the level of the real price of oil. We include only one lag in the estimation which is different from the 24 lags specification in Kilian (2009).[8]

Since both models are non-nested, we compare the effect of oil demand and oil production shocks on oil prices. Figure 4 panel (a) compares the response of oil prices to a one standard deviation oil-demand or price shock. Notice that both impulse responses are strikingly similar. Recall that in our estimation the oil-demand shocks are mostly transitory which is consistent with the VAR framework. In panel (b) we show the response of oil price to an oil production shock. In the Kilian (2009) model, we see there is no significant impact of the production shock on the oil price.

4.2 Yearly Regressions

Our benchmark scenario uses quarterly data from 1973 to 2016, which is a period of high oil price volatility. In Figure 5 we plot world production of crude oil and the real oil price for the period 1900–2016. We observe that production grows consistently through most of the century to abruptly change its trend in 1973. As a result, the price changes follow a regime of high levels and volatility.[9]

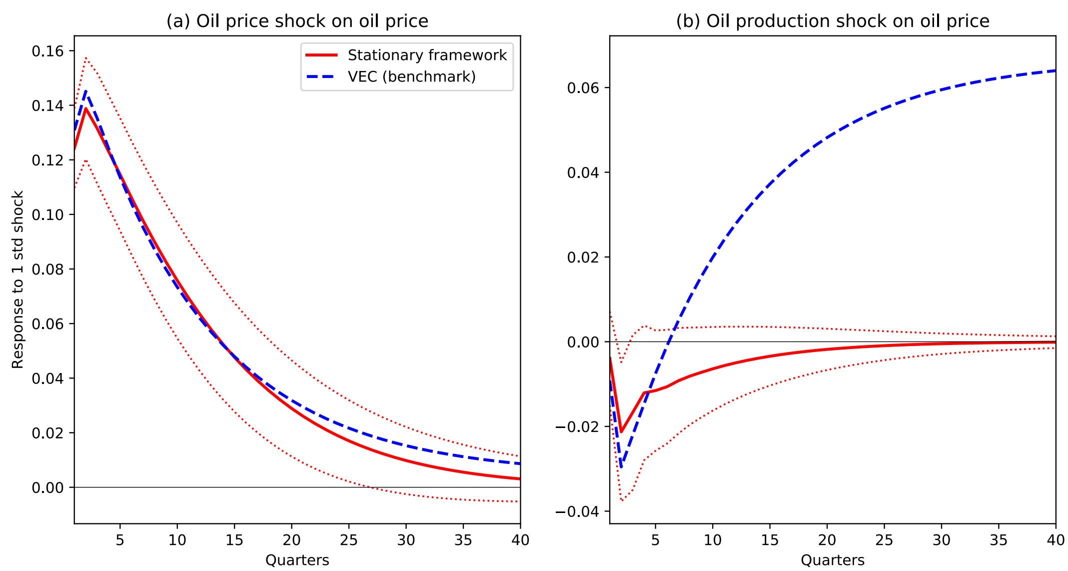
We estimate our vector autoregression to check the relative importance of permanent versus transitory shocks in the first period of relative price stability. In particular, we include the annual observations for the period 1900–1973. The test for non-stationarity shows that global GDP and world oil production are both unit roots. Interestingly, the null hypothesis

[7] The model in Kilian (2009) is estimated using monthly observations from 1973.1 to 2007.2

[8] We also check that the estimates are robust for a number of lags.

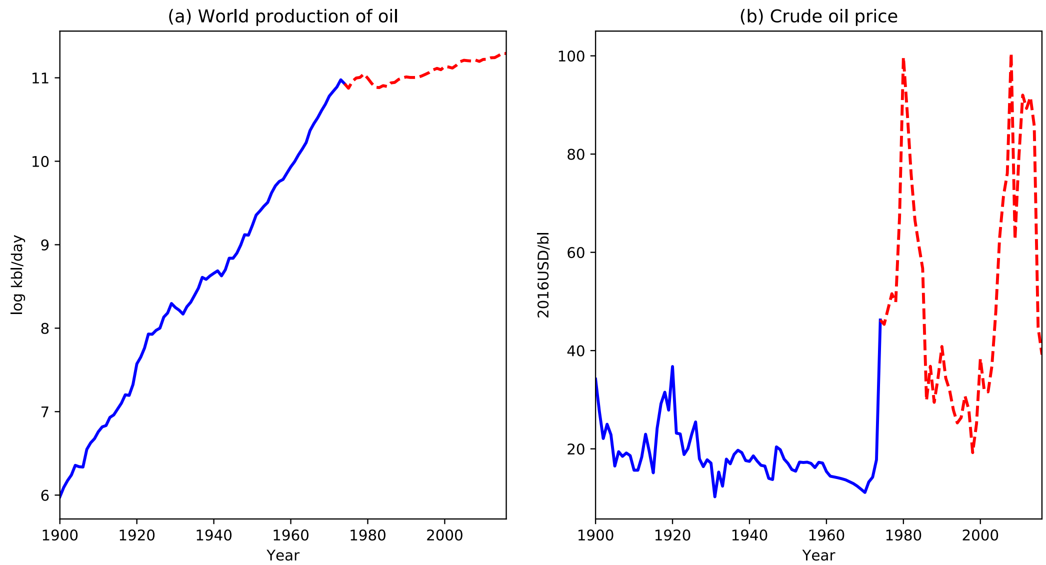
[9] The annual observations for the oil price are collected from BP (2018). We use the US CPI to deflate the oil price. World oil production is from Bouda Etemad and Toutain (1998) for the period 1900–1964, and BP (2018) for the period 1965–1973. World GDP is computed using global GDP per capita and world population from Database (2018). There are discontinuous data in 1900–1949. We interpolate the series assuming constant annual growth rate.

Figure 4: Responses of Oil Price to Oil Price Shock and Oil Production Shock: VEC Model and Stationary Framework



Note: Panel (a) and (b) show the impulse responses of oil price to the one-standard-deviation oil price shock and oil production shock in the VEC model and the stationary framework. The dashed line denotes the impulse responses in the VEC model, the benchmark case, in equation (1). The solid line denotes impulse responses in a stationary framework, the VAR model similar to Kilian (2009), on a quarterly frequency. One lag is employed the VAR model. The dot lines denote the bootstrap one-standard-error bands for the impulse responses in the VAR model.

Figure 5: World Production of Oil and Crude Oil Price 1900–2016



Note: Panel (a) and (b) show the annual observation of world oil production and crude oil price for the period 1900–2016. Panel (a) plots the world production of oil. The solid line is the annual series collected from Bouda Etemad and Toutain (1998) for the period 1900–1964 and BP (2018) for the period 1965–1973. The dashed line is annual average computed using quarterly observation of world oil production collected from *EIA (2018)*. Panel (b) plots the crude oil price. The solid line plots the annual series for the period 1900–1973 collected from BP (2018). The dashed line is annual average computed using quarterly observation of world oil production collected from *FRED (2018)* for the period 1974–2016.

of a unit root for real oil price at 5 percent significance level is rejected. We also find at least one cointegration relationship among the series for the period 1900–1973.

We then estimate equation (1) as in our benchmark estimation. Table 3 shows that as in the benchmark case the long-run relationship forecasts the change in the oil price. The adjustment parameter in the short-run price equation is 0.422. This means that every year 40 percent of the misalignment is corrected, and that the half-life of the error term in the short-run price equation is 1.6 years (six quarters). It is faster than the half-life of ten quarters in the estimation that goes from 1973 to 2016.

Now, in the case of the short-run equation for oil quantity, we see that the speed of adjustment is positive and statistically different from zero. The value is 0.08, which implies that the half-life of the error term in this equation is 8.7 years (35 quarters). This speed of adjustment is smaller than the one found in the price equation. Despite this fact, the speed of adjustment in oil quantities is much faster than the one found in the model estimated for the period 1973-2016. In particular, in the period 1900-1973 the half-life of 35 quarters is almost one-tenth of the 300 quarters half-life found in the period 1973 to 2016.

In order to compare the way in which global GDP shocks are transmitted to oil prices

Table 3: Estimates of VEC Model and DOLS for Period 1900–1973

(a) Vector autoregression1900–1973 annual data

LHS		RHS variable: const.	LR term	$\triangle y_{t-1}$	$\triangle q_{t-1}$	$\triangle p_{t-1}$
$\triangle y_t$	coeff	0.016	-	0.463	-	-
	s.e.	(0.004)		(0.106)		
$\triangle q_t$	coeff	-0.799	0.080	0.201	-0.090	0.013
	s.e.	(0.422)	(0.039)	(0.239)	(0.124)	(0.040)
$\triangle p_t$	coeff	4.557	-0.422	0.357	0.129	-0.052
	s.e.	(1.233)	(0.114)	(0.699)	(0.361)	(0.118)

(b) DOLS estimates for long-run relationship

	coeff.	se.
α_y	-0.419	(0.136)
α_q	0.066	(0.058)
α_0	10.640	(2.287)

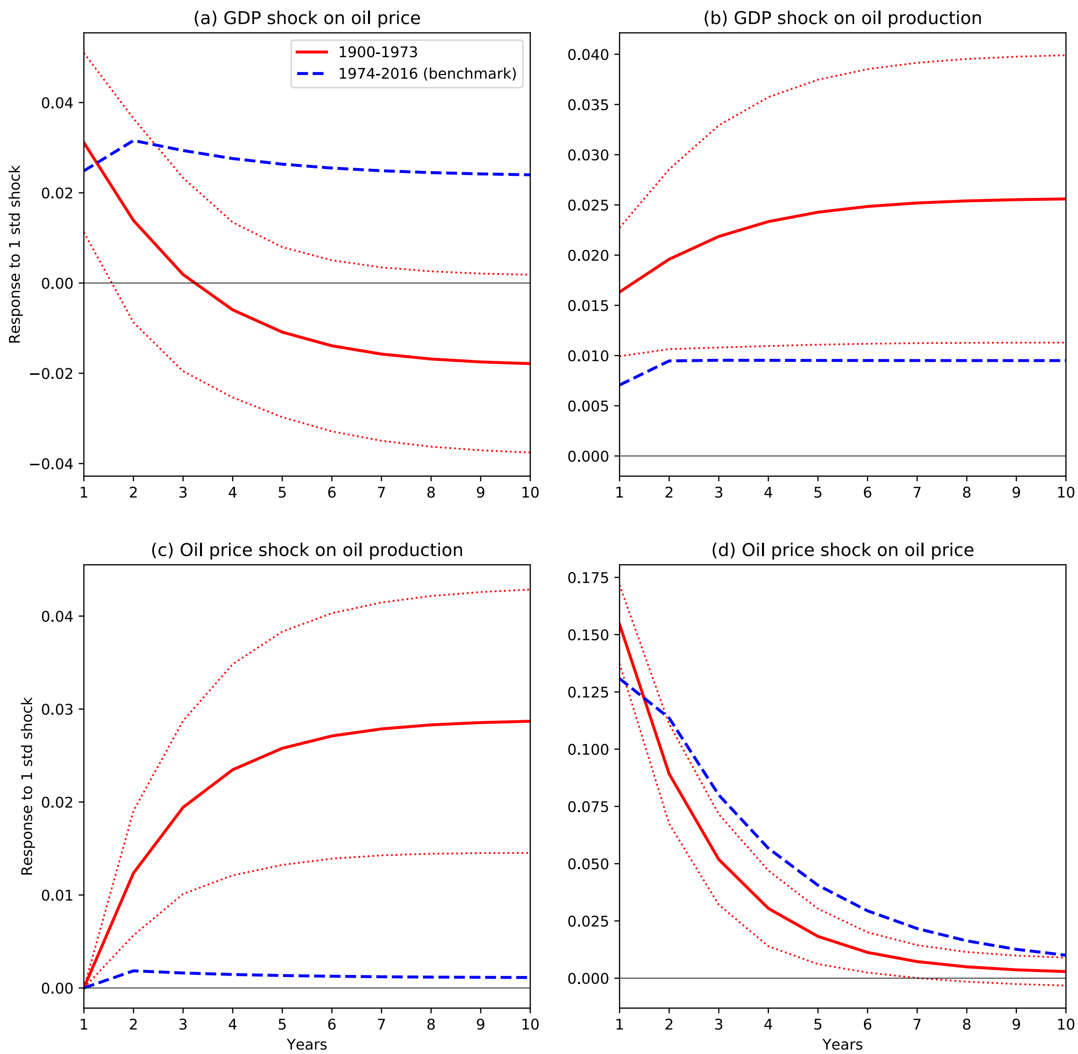
Notes: Table (a) shows the estimates of the VEC model using annual data for the period 1900–1973. Table (b) shows the DOLS estimations for the long-run relationship for the same period.

and quantities, we compare the responses of oil price and world oil quantity in two different subsamples. As shown in Figure 6 panel (a), in the 1900-1973 period a 1 percent shock to GDP generates an increase in prices of 3 percent. After two years the impact on prices is zero, hence this shock has a transitory effect on oil prices. In the second sample, from 1973 to 2016, this shock has a positive impact on prices, but its effect is permanent. In particular, the price of oil increases permanently by 3 percent. Now, in Figure 6 panel (b), we see that the impact on quantities is, in both samples, permanent. In this case, however, the responses are entirely different: in the 1973-2016 period quantities increase permanently by 0.8 percent. By contrast, in the period 1900-1973 quantities react much more in the face of the same shock. In this case, the quantities increase permanently by 2.5 percent. The collective behavior of prices and quantities in the face of a world GDP shock are coherent with a different market structure in each period. In particular, we conjecture that, in the first period, oil supply was much more elastic than in the second sample.

4.3 Copper

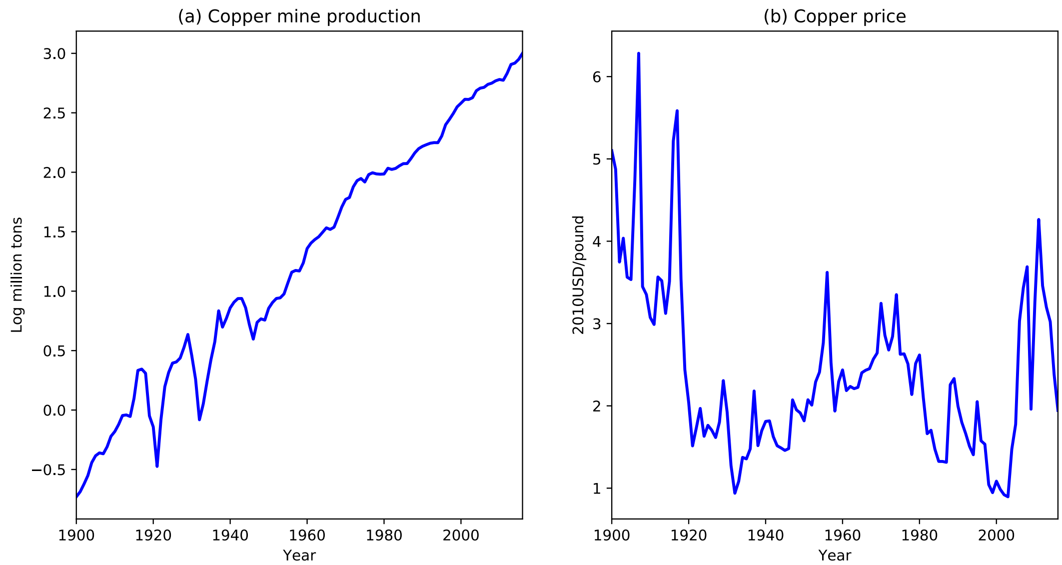
We found that we can identify the effect of world GDP on the price of oil once we account for the long run relationship in the market. In this section, we check whether we can identify a similar effect in the copper market. We use a three variable autoregression estimation

Figure 6: Response of Oil Price and Production to Structural Shocks for Different Periods



Note: Panel (a)–(d) show the impulse response of oil price and oil production to one-standard-deviation of GDP shock and oil price shock. The dashed lines denote the annual average of impulse responses in the benchmark case for the period 1974–2016. The solid lines denote the impulse responses in the model using annual data for the period 1900–2016. The estimates are shown in Table 3. When computing the impulse responses, the estimates of autoregressive terms $\triangle y_{t-i}$, $\triangle q_{t-i}$ and $\triangle p_{t-i}$ are fixed to zero if they are not estimated significantly. The dot lines denote the bootstrap one-standard-error bands for the impulse responses in the case using data for the period 1900–1973.

Figure 7: Copper Price and Mine Production



Note: Panel (a) and (b) show the annual data on world copper mine production and copper price for the period 1900–2016. The world copper mine production is collected from USGS (2018). The copper price is from Global Financial Data (2018), deflated using U.S. CPI obtained from the U.S. Bureau of Labor Statistics (2018).

again for world GDP, copper production and the real price of copper from 1900 to 2016. We use world copper production from USGS (2018).[10] The copper price is collected from Global Financial Data (2018)[11], and it is deflated using U.S. CPI from the U.S. Bureau of Labor Statistics (2018).

Our unit root test indicates that world copper production is non-stationary, but we do not find evidence to reject the null hypothesis that the real price of copper has a unit root. The Johansen's cointegration test indicates that the time series of world GDP, copper production and the price of copper are cointegrated. We can reject the null hypothesis of at least two cointegrating relationships ($r = 2$) at 1 percent significance level.

In Table 4 we compare the estimation for copper and oil in different periods. In panel (a) we compare the estimations for the period 1900-1973. We observe that for both copper and oil quantities and prices are predicted by the long run relationship. In particular, the estimates of the speed of adjustment rates for quantities for both oil and copper are statistically different from zero. For oil, it is estimated at 0.08 with a standard error of 0.04, and -0.137 with a standard error of 0.035 for copper. These estimates imply a half-life of 8.66 years for oil production and 5.06 years for copper production. Similarly, we find significant speed of

[10] We employ world mine production.

[11] We employ high-grade copper price.

Table 4: Estimates in the VEC Model for Oil and Copper for Different Periods

	(a) 1900–1973		(b) 1900–2016	
	Oil	Copper	Oil	Copper
Speed adj. γ_q	0.080	-0.137	-0.021	-0.058
	(0.039)	(0.035)	(0.013)	(0.023)
$t_{1/2}$ in production (years)	8.66	5.06	33.01	11.95
Speed adj. γ_p	-0.422	-0.223	-0.155	-0.190
	(0.114)	(0.056)	(0.053)	(0.049)
$t_{1/2}$ in price (years)	1.64	3.11	4.47	3.65

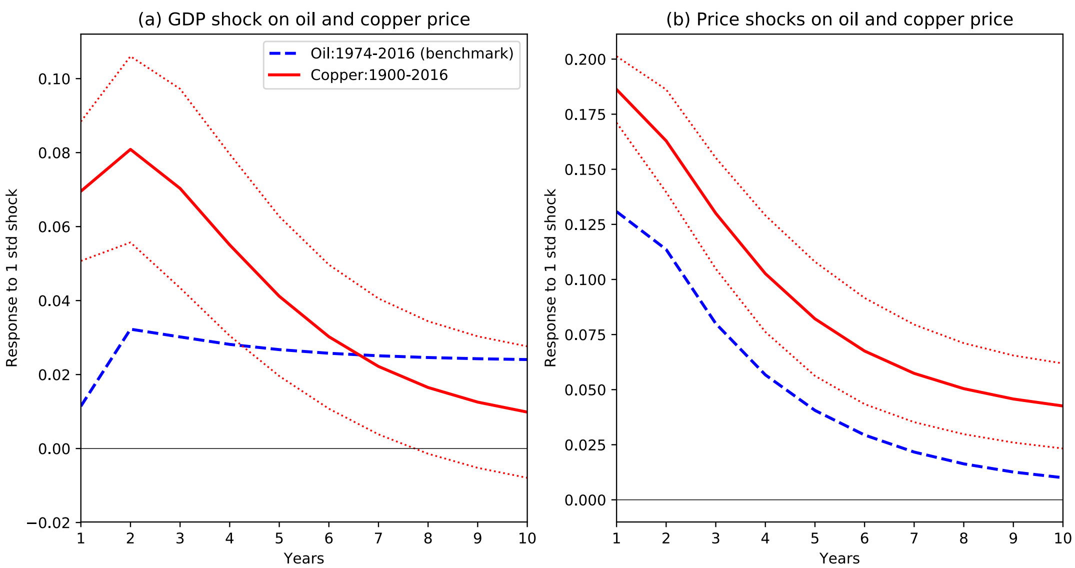
Note: Table shows the estimates of the adjustment rates in the VEC model for oil and copper in different time: 1900-1973 and 1900–2016. The half-life values are computed as $ln(2)/\gamma$.

adjustment parameters for oil prices. We find a stronger adjustment for oil with an estimate of -0.42 and -0.22 for copper. The half-life for the copper price is 3.11 years, and for oil price it is 1.64 years. In other words, the copper price takes twice as much time as the oil price to reduce half of the long-term disequilibrium.

In panel (b) we compare our estimation using the data for the period 1900–2016. Extending our estimation to include the latest period should shed light on the effect of the period 1974–2016. We observe that the estimate for adjustment parameter for oil price is small at -0.02 and insignificant. For the copper price, the adjustment parameter is estimated at -0.058 (which implies a half-life of about 12 years) which is smaller than for the whole period. In the case of oil, the fact that the speed adjustment parameters turn out to be insignificant is consistent with the previous analyses that it suggests a structural break in the year 1973 and the conjecture of an inelastic oil supply for the period 1974–2016. To the oil market, we do not find a dramatic break in the model for copper in the year 1973, although there is some evidence that the copper supply has adjusted quantities less strongly.

In Figure 8, we compare the impulse response functions for the copper price in the period 1900-2016 with our benchmark estimation for oil price in the period 1974-2016. In panel (a) we observe that the response of copper price to a GDP shock is mostly transitory, mainly explained by the significant response of quantity to the shock. In contrast, the response of oil price is permanent due to a relative inelastic response of supply. In panel (b) we plot the transitory component of the prices to a price shock. Interestingly, both copper and oil prices show a significant transitory component with similar persistence. The response for copper price shows a higher level of the impact over time than for the oil price.

Figure 8: Responses of oil and copper price to GDP and price shock



Note: Panel (a) and (b) plot the impulse responses of oil and copper price to one-standard-deviation GDP and price shock. The dashed lines denote the annual average of impulse responses of oil in the benchmark case for the period 1973–2016. The solid line denotes the impulse responses of copper in the model using annual data for the period 1900–2016. The estimates are shown in Table 4. When computing the impulse responses, the estimates of autoregressive terms $\triangle y_{t-i}$, $\triangle q_{t-i}$ and $\triangle p_{t-i}$ are fixed to zero if they are not estimated significantly. The dot lines denote the bootstrap one-standard-error bands for the impulse responses in the case for copper.

5 Conclusions

In this paper, we have shown how world GDP affects commodity prices. We have focused on explaining the effect on the oil price. We have identified the effect of income shocks on the oil price. We use a simple error correction model and found that for the period of 1973–2016, world GDP has had a permanent effect on the oil price. We also find that the long run relationship predicts the oil price. In contrast, the long run relationship cannot predict quantity production. Consistent with previous studies, most of the variation in oil price is due to transitory shocks. Our conjecture is that since production is relatively inelastic, the permanent shocks to income are transmitted to prices.

We have also extended the analysis to study the oil market using annual data from 1990 to 2016. We found that, still, the long run relationship predicts the change in oil prices. Interestingly, in the early period, we find evidence of predictability for oil production. We conjecture that the differential response of production explains that shocks to income are mostly transitory in the early period.

After that, we explored whether world GDP also has an impact on another commodity, namely copper prices, on the period of 1900–2016. We find indeed that the long run relationship predicts the copper prices and quantity. As a result, the response of the copper price to a shock to income is mostly transitory.

From the discussion in section 4, we find that a permanent shock to global activity is transmitted differently to both oil prices and quantities in different samples, and it depends on the way in which the oil market is structured. Developing a model which can account for this differentiated response goes beyond the scope of this paper, but is a natural extension of the research agenda.

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Appendix

A Unit root tests

This section shows different tests of unit roots for global GDP, world crude oil production and price of oil.

We perform augmented Dicky-Fuller (ADF) test and Phillip & Perron (PP) test for the logarithm values of world GDP, global oil production and crude oil price. The tests are performed for different periods, 1974Q1–2016Q4, 1974Q1–1994Q4 and 1995Q4–2016Q4. The test results are shown in the Table 5. We find that from both tests we can not reject the null hypothesis of the unit root for each series in different test periods.

Table 5: Unit root tests

(a) Augmented Dicky-Fuller test

	1974Q1–2016Q4			1974Q1–1994Q4			1995Q1–2016Q4		
	No.lags	DF stat.	p-value	No.lags	DF stat.	p-value	No.lags	DF stat.	p-value
$\log(Y)$	4	-1.725	0.415	4	-1.070	0.658	2	-1.432	0.525
$\log(Q)$	12	-0.164	0.935	1	-1.787	0.395	1	-1.176	0.620
$\log(P)$	2	-2.028	0.303	1	-1.249	0.593	1	-1.710	0.423

(b) Phillips & Perron test

	1974Q1–2016Q4		1974Q1–1994Q4		1995Q1–2016Q4	
	$Z(\alpha)$ stat.	p-value	$Z(\alpha)$ stat.	p-value	$Z(\alpha)$ stat.	p-value
$\log(Y)$	-4.102	0.880	-7.106	0.700	-5.800	0.778
$\log(Q)$	-15.068	0.253	-9.872	0.537	-16.677	0.138
$\log(P)$	-9.072	0.595	-7.575	0.673	-7.893	0.655

Notes: Table (a) shows the augmented Dicky-Fuller (ADF) test of logarithm values of world GDP, global oil production and crude oil price for different periods. The number of lags used in the tests is selected using BIC. We perform augmented Dicky-Fuller test with constant. The null hypothesis of the ADF test states that the test series is a unit root. Table (b) shows the Phillips & Perron (PP) test of unit roots. The test regression is estimated with intercept. Four truncation lag parameters are used in the test for the period 1974Q1–2016Q4. Three truncation lag parameters are used in the test for the sub-periods 1974Q1–1994Q4 and 1995Q5–2016Q4. The null hypothesis of the PP test states that the test series is a unit root.