Oil Fundamental Value and the Business Cycles

Daniel Cuzzi†

Abstract

This paper explores equilibrium conditions within the oil market. Departing from the common assumption of no relationship in variable levels, my study provides robust evidence supporting a cointegrating relationship among real oil prices, global industrial production, and oil production. I use Hamilton (2021) data on global industrial production and disentangle the dynamics between OPEC and non-OPEC supply. Equilibrium is restored with oil price and non-OPEC supply adjustments. I show that deviations from the fundamental value gradually diminish as real prices converge. The cointegration error explains 35% of oil returns at a 24-month horizon, 75% higher than the same measure generated by performing the Hamilton Filter. Short-term forecasts generated from the Vector VECM outperform random walk by over 15% in RMSE reduction. These findings underscore the significance of the market clearing adjustments in the oil price dynamics.

JEL classifications: *C5,G12,Q41*
Keywords: *Oil Price Forecasting, Cointegration Analysis, OPEC oil production*

†Graduate School of Economics and Finance FGV-Rio, Brazil

1 Introduction

As oil became a primary input in the global economy, a substantial body of literature emerged, exploring its economic drivers and the consequential impacts on macro variables. The empirical approach commonly adopted involves taking the natural logarithms and the first difference to analyze oil returns and other stationary variables within a system. The underlying assumption posits no relationship in the levels of these variables. However, this approach overlooks the dynamic effect of long-term equilibrium on the system, introducing potential bias. This paper aims to contribute to the current discussions on equilibrium relationships, as works such as He et al. (2010) and Lardic and Mignon (2006).

I present evidence supporting the presence of a cointegrating relationship among real oil prices, global industrial production, and oil production, separating *OPEC* from *non-OPEC* supply. The referenced studies He et al. (2010); Lardic and Mignon (2006) employ *gdp* and the *freight index* proposed by Kilian (2009) as monthly economic activity trackers with a control for global oil production. Following Baumeister and Hamilton (2019), I utilize the Global Industrial Production Index, encompassing OECD plus 6 countries, including China[1]. As indicated by Hamilton (2021), industrial production is likely the most effective monthly tracker of the dynamics of economic activity. I employ this index also to capture the levels of global industrial production as key information for broad oil demand. Additionally, I distinguish between the dynamics of OPEC's and non-OPEC oil production, acknowledging their distinct data-generating processes, as reflected in their different trends Baumeister and Hamilton (2023). Results are supportive of this separation due to their distinct role in equilibrium.

Studies highlight demand shocks as the primary source of short-term unpredictability. Kilian (2009) attributes 80 to 90% of oil return explanatory power to business cycle shocks identified as innovations in the freight index, controlling for global oil production in a SVAR identification. Additionally, Issler et al. (2014) advocates for a low short-term supply elasticity, presenting an industrial firm scenario where increased demand prompts optimal decisions to elevate production, constrained by short-term supply rigidity. In line, Kumar and Mallick (2023) finds zero short-run supply elasticity. In essence, the overarching findings suggest that short-term fluctuations stem from business cycle sur-

[1]Details are provided in the Data section

prises, with their impact more pronounced on prices than quantities. These influences gradually diminish as real prices converge towards their fundamental level.

The distance to equilibrium explains the medium-term trajectory of oil prices, achieving an explanatory power of 35% at a 24-month horizon, with evidence of a full return to the estimated long-term trend. The medium-term prediction generated by the Hamilton Filter produces lower bias then the historical mean[2] but still biased as the fundamental value produces unbiased estimates to the medium-term real oil price. Short-term oil price forecasts from the implied VECM model surpass random walk by over 15% in RMSE reduction. My findings present robust evidence of heterogeneity in the supply side. Notably, Cartel production exhibits in equilibrium a positive long-term correlation with oil prices, while the reverse holds true for non-OPEC or Rest of the World (RoW) producers. Furthermore, my evidence suggests that, in conjunction with oil prices, non-OPEC production also contributes to reestablishing market equilibrium.

The consideration of disequilibrium proves pivotal in comprehending oil price and market dynamics. These findings highlight the importance of interpretation and forecasting models to incorporate the error correction mechanism. It becomes particularly relevant when the instrument is correlated with market disequilibrium. In the next section, I describe the dataset, followed by the presentation of the model in the subsequent section including the equilibrium condition, statistical implications and cointegrating relation estimates. In the fourth section I explore out-of-sample properties presenting estimates of medium-term and short-term oil price forecasting. In the fifth I conclude.

2 Data

I utilized monthly data spanning from January 1993 to May 2023. The oil-price data was sourced from the FRED database of the St. Louis Federal Reserve and specifically comprises the global price of West Texas Intermediate (WTI) crude oil. I obtain the real oil price after deflating the nominal price using the US Consumer Price Index (CPI), also retrieved from the FRED database.

Additionally, I incorporated the Global Industrial Production index, following the approach by Hamilton Baumeister and Hamilton (2019). These series are seasonally

[2]This assumption would be reasonable if real oil prices were stationary, as a substantial portion of the literature assumes; however, it does not provide mean return properties. Their explanatory powers are similar, approaching 20%, close to half of the fundamental value performance

adjusted and serve as a robust proxy for global economic activity and combine OECD Industrial production with Brazil, China, India, Indonesia, Russia, and South Africa. The level of industrial production reflects a substantial demand for oil, making it a reliable indicator of aggregate demand. For data on oil production, I accessed information from the US Energy Information Administration open data.

Figure 1: The Industrial Production Index by Baumeister and Hamilton (2019) and the real oil price log levels in the top and 9month moving average in the bottom.

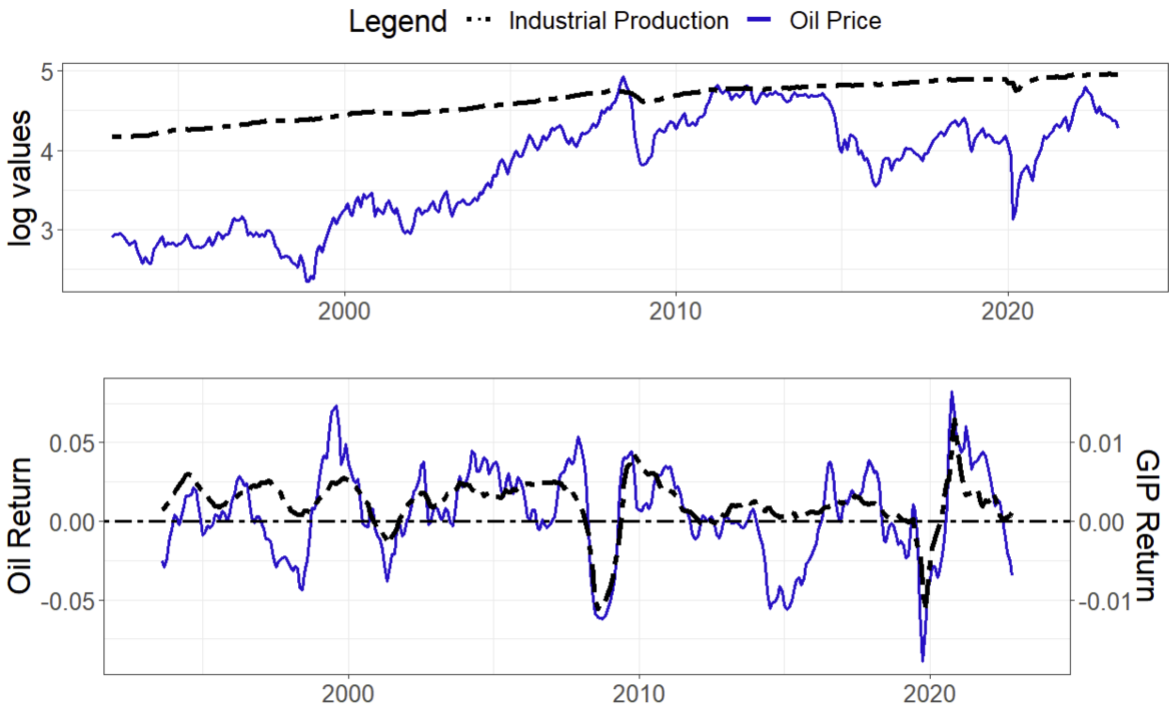
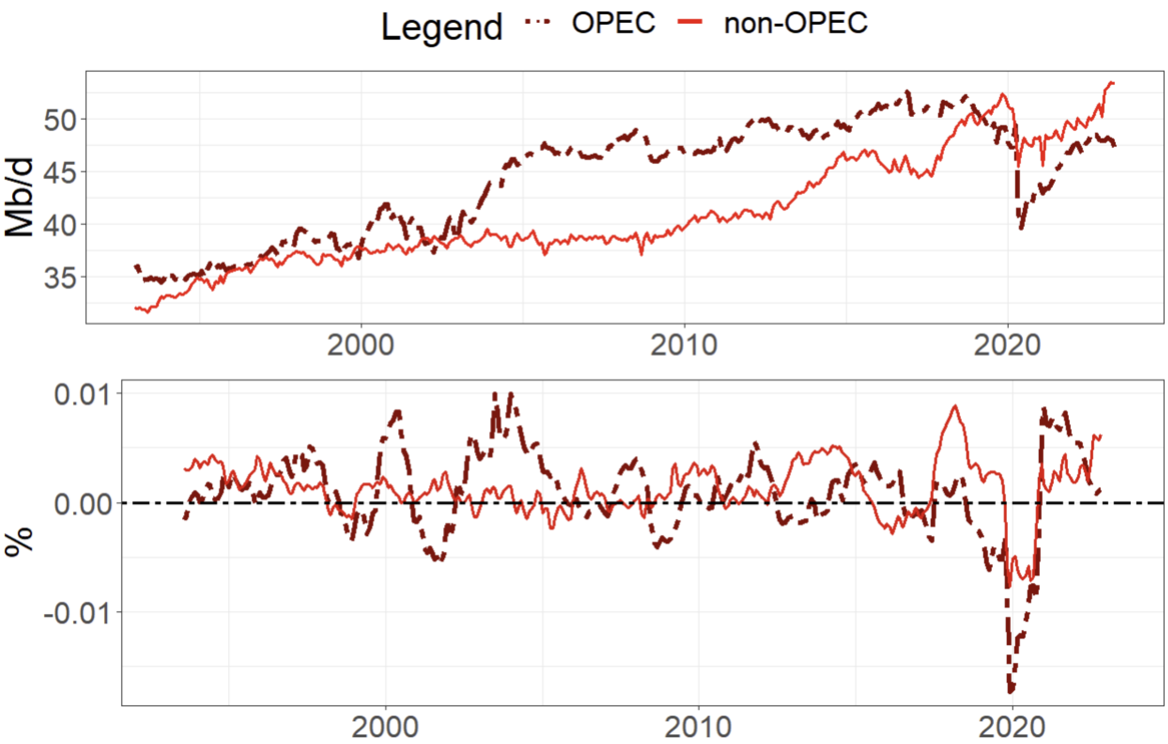


Figure 2: Level of OPEC and non-OPEC production in millions of barrels per day and the 9-month moving average of the return of the series.



3 The Oil Price Fundamental Value

Given levels of global industrial production and global oil supply, there is an equilibrium price that balances the market. A price that would occur in the absence of second moment shocks, so deviations[3] from this equilibrium are transitory. Baumeister and Hamilton (2019) provide a global industrial production index, which I utilize to track global demand for oil. Their work also demonstrates that industrial production is arguably the most effective monthly economic activity tracker. Supply is disaggregated into *OPEC* production and *non-OPEC* production to capture heterogeneity in the data-generating process, aligning with expectations based on market structure and empirical evidence Baumeister and Hamilton (2023).

When the oil price diverges from its fundamental value, as determined by oil supply and demand, this divergence has a short-term impact on price. Prices eventually adjust to balance supply and demand over time, a mechanism confirmed in the empirical analysis.

[3]According to the literature, most of the short-term fluctuations are given by business cycle shocks and exert cyclical pressure on prices while supply remains constrained. So I expect the disequilibrium to be linked to business cycles.

Let $y_t = (p_t, ip_t, q^O, q^r)$ representing the natural logarithms of the real oil price, OPEC and non-OPEC oil production, and global industrial production, respectively. The equilibrium condition is expressed as:

$$p_t = \beta_1 ip_t + \beta_2 q_t^o + \beta_3 q_t^r + e_t^c \tag{1}$$

It is noteworthy that $\beta' y_t = e_t^c$, where $\beta = (1, -\beta_1, -\beta_2, -\beta_3)$, is stationary with an expected value of zero. The fundamental value corresponds to the expected value of the real oil price given supply and demand: $p_t^* = \beta_1 ip_t + \beta_2 q_t^o + \beta_3 q_t^r$. This relationship is detailed in the empirical section and the appendix, stating:

$$p_t - p_t^* = e_t^c \sim \mathcal{I}(0)$$

Consistent with the arguments advanced by Cogley (2002) in studying inflation convergence, later applied by Burger et al. (2022) in capital flows applications, if $\mathbb{E}_t[p_{t+h^*}] = p_t^*$, where h is a medium-term horizon over which we anticipate the real oil price will converge to its fundamental level, subtracting both sides by p_t yields:

$$\mathbb{E}_t[p_{t+h}] - p_t = -p_t + p_t^*$$

Rewriting and using the definition $\mathbb{E}_t[p_{t+h}] = p_{t+h} + e_{t+h}$, obtaining:

$$p_{t+h} - p_t = -\left(p_t - p_t^*\right) + u_{t+h}$$

Considering $\alpha_{0,h} = 0$ and $\alpha_{1,h} = -1$, this expression is equivalent to:

$$p_{t+h} - p_t = \alpha_{0,h} + \alpha_{1,h}\left(p_t + p_t^*\right) + u_{t+h}$$

Leading us to the following specification:

$$\sum_{1 \le i \le h} \Delta p_{t+i} = \alpha_{0,h} + \alpha_{1,h} e_t^c + u_{t+h} \tag{2}$$

The cointegration error appears on the right-hand side, explaining the cumulative returns. We can estimate this in an OLS estimation by replicating the local projection h periods ahead. Equation (2) parallels the analysis conducted by Cogley (2002) on inflation and Burger et al. (2022) on capital flows. It suggests that if the relationship holds, the gap between expected real oil prices h periods ahead and current real oil prices is the negative of today's difference between p_t and p_t^*.

$$\mathbb{E}\left[\sum_{1\leq i\leq h} \Delta p_{t+i}\right] = -e_t^c \tag{3}$$

I test whether deviations of current real oil prices from the natural level are inversely related to subsequent changes in real oil prices. Cogley (2002) emphasized that $\alpha_{0,h}$ should equal zero; otherwise, p_t^* would be biased. However, the focus is primarily on $\alpha_{1,h}$ following Burger et al. (2022). If p^* reflects real oil prices' long-term trend, we obtain $\alpha_{1,h} = -1$ for medium-run horizons. A $\alpha_{1,h} = -1$ estimate implies that the gap between real oil prices and p^* represents its transitory component, and real oil prices are expected to converge to p^* in h periods.

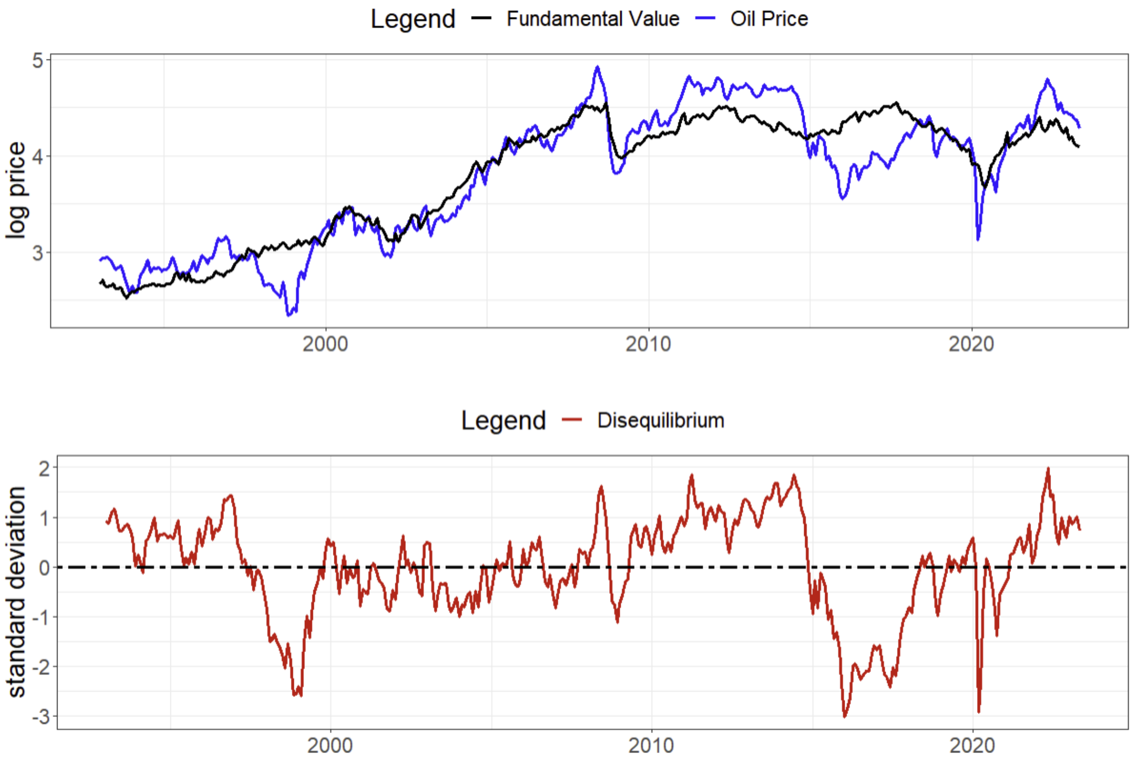
3.1 Cointegration Estimates

I model the real price of oil in the OPEC production, non-OPEC production, and global industrial production.[4]. With a single common trend cointegrating relation can be estimated, this with OLS obtaining super-consistent parameter estimates was found to be 1. A percent increase in non-OPEC production is associated in equilibrium[5] with -3.15% lower real oil prices. A percent increase in OPEC production is associated with 2% higher prices. And 1% higher industrial production level is associated with 3.1% higher prices. This holds in equilibrium.

[4]I employed well-established tests such as those proposed by Engle and Granger (1987), Phillips and Perron (1988) to test for unit roots. Additionally, I applied the Johansen Procedure (Johansen (1991); Johansen (1995)) to estimate the cointegration rank (r) and the cointegrating vectors and the cointegrating relation. Results presented in the Appendix Tables 2, 4 and 5.

[5]Regression tables in the Appendix.

Figure 3: In the left side the fundamental value estimated using equation 1 and the real oil price. The right side the disequilibrium, the stationary error generated by the model.



4 Out of Sample Results

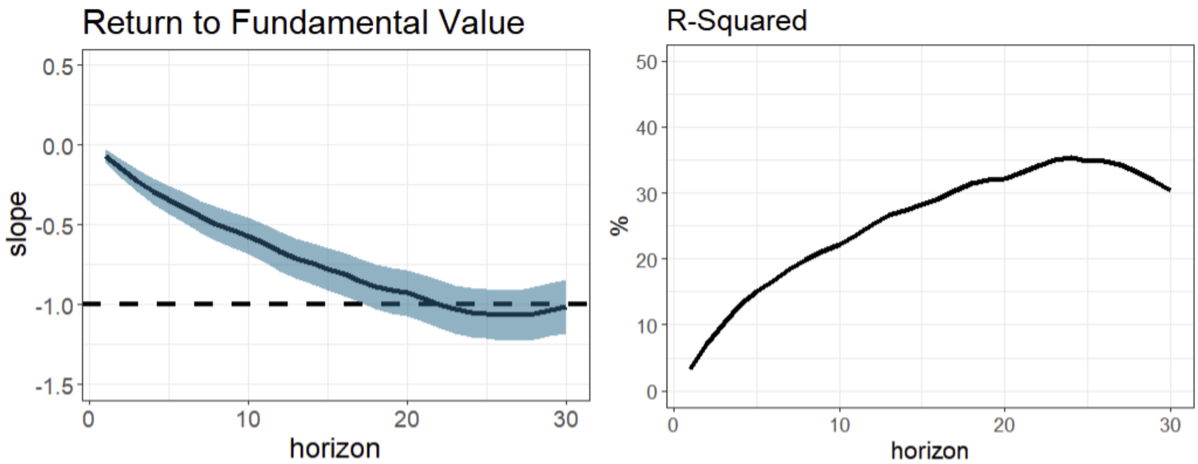
There is a widely shared understanding oil prices oil can significantly impact the global economy. Central banks and market analysts recognize the importance of the oil price as a crucial variable, relevant for evaluating the risks associated with macroeconomic developments. I assess the explanatory capability of the fundamental value through the cointegrating error, comparing my results with benchmarks such as the Hamilton Filter. Additionally, I present the forecasting performance of the VECM implied by the equilibrium condition. My model outperforms random walk at a 1-month horizon price forecast.

4.1 On The Explanatory Power of p^*

The fundamental level represents the expected oil price or the value in the absence of volatility. Utilizing an equilibrium measure, my objective is to enhance predictions as stationary shocks fade. Conducting the Cogley (2002) test in line with Burger et al. (2022) for horizons ranging from 1 to 30 months ($h = 1, \ldots, 30$), I estimate Equation

(2)[6]. Note that this analysis is out of sample, utilizing the period t gap between the actual real oil price and the predetermined p^* to predict the h period-ahead change in oil returns. The proximity of $\alpha_{1,h}$ to -1 serves as a summary measure of the model's performance.

Figure 4: Estimates of equation 2. Forecast horizon going from 1 to 30. In the left-hand side, I have the slope of the model with 95% bounds. I can interpret it as a share of mean return which is complete in the case of cointegration in which I cannot reject -1 for α_h for the twentieth month on. R-squared of the models on the right-hand side



My findings indicate that the mean return occurs over an average period of two years, which intriguingly aligns with results obtained for other economic variables, such as real exchange rates (Rossi (2013)) and capital flows (Burger et al. (2022)). Results suggest that convergence is fully archived, and the disequilibrium of the oil price to my fundamental measure vanishes in around 2 years.

Benchmark Estimates: I perform medium-term forecasting, the same exercise for the fundamental value but using the Hamilton Filter, following the author's suggestion by filtering two years of cycles, a practice consistent with my findings. This filter is known to perform well as a trend tracker[7]. and this historical average. The Hamilton Filter proposed in Hamilton (2018) is a long-term tracker of the variable of interest; it

[6]
$$\sum_{1\leq i\leq h} \Delta p_{t+i} = \alpha_{0,h} + \alpha_{1,h} e_t^c + e_{t+h}$$

[7]The specification is given by: Hamilton (2018)

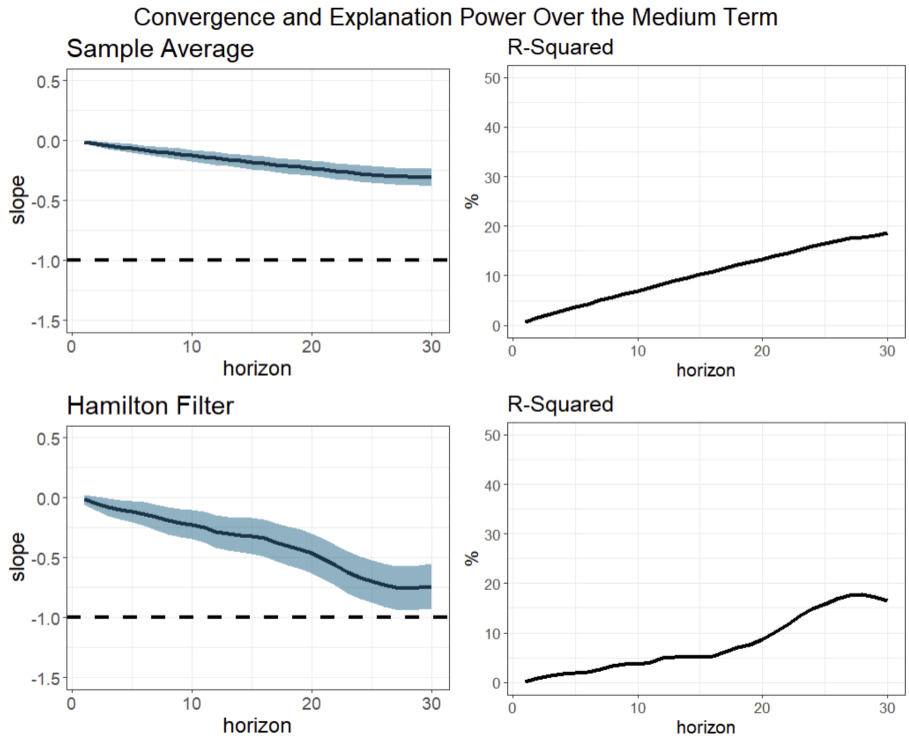
$$p_{t+h} = \phi_1 p_{t-1} + \phi_2 p_{t-2} + \phi_3 p_{t-3} + \phi_4 p_{t-4} + e_t$$

In my case, the result is quite similar to a random walk forecast because the estimated coefficient ϕ_1 is close to one.

eliminates the cycle which is based on the trend and cycle decomposition idea put forth by Beveridge and Nelson (1981). Burger et al. (2022) show that the Hamilton Filter has the same performance for capital flow forecast compared to their equilibrium measure. Also, some papers in the oil market assume that the oil price is stationary[8] and if this is true, its historical mean would also be a natural forecaster because all shocks vanish along the cycle and converge towards the historical mean.

$$\sum_{1\leq i\leq h} \Delta p_{t+i} = \alpha_h \left(p_t - \hat{p}_t\right) + e_{t+h} \tag{4}$$

Figure 5: Estimates of equation (2) considering the forecaster sample average, Hamilton Filter. Forecast horizon going from 1 to 30.



4.2 Dynamic Estimates

Short-term predictability and outperformance against random walk can be found in Alquist et al. (2013) for the 3-month horizon using oil futures. Baumeister and Kilian (2012) presents nowcasting models using macroeconomic aggregates that perform well in the short-run yet the enhancement of predictability against the random walk diminishes as the horizon extends beyond 1 year.

[8]as I the evidence I presented in the last section that there is no return to the historical mean.

Here I present results related to the VECM estimation, in which I model variables of the system using the disequilibrium and lag of the variables, results in Table 1. The significant variables to forecast oil price return in the next month are the return to equilibrium through e^c_{t-1} and a negative parameter reflecting the mean return property, momentum via the positive parameter associated with the lagged oil return, also industrial production lags, positive for the 2nd and negative by the fourth month, and at least OPEC production with 5 lags. Note that non-OPEC oil production does not appear to be statistically significant for the oil price dynamics directly, but its level is important through the cointegrating error with dynamic implications. Interestingly, the opposite is also true. Non-OPEC production growth does not respond to oil return for any lag, but the level of oil prices is relevant through the cointegrating error in explaining their oil supply decisions.

Table 1: VECM Model Coefficients with Standard Errors

	Δp_t		Δq^{OPEC}_t		Δq^{RoW}_t		Δip_t	
	Coef	(SE)	Coef	(SE)	Coef	(SE)	Coef	(SE)
e^c_{t-1}	-0.0697^{***}	(0.0220)	0.0019	(0.0029)	0.0059**	(0.0027)	0.0013	(0.0017)
Intercept	-0.0045	(0.0060)	-0.0015^{***}	(0.0008)	0.0017**	(0.0007)	0.0018***	(0.0005)
Δp_{t-1}	0.1550**	(0.0563)	-0.0249^{***}	(0.0074)	0.0016	(0.0069)	0.0326***	(0.0044)
Δp_{t-2}	-0.0305	(0.0617)	0.0257***	(0.0081)	0.0102	(0.0076)	0.0043	(0.0048)
Δp_{t-3}	-0.0991	(0.0619)	0.0021	(0.0081)	0.0027	(0.0076)	0.0002	(0.0048)
Δp_{t-4}	-0.0838	(0.0618)	0.0117	(0.0081)	0.0053	(0.0076)	-0.0045	(0.0048)
Δp_{t-5}	0.0244	(0.0614)	0.0018	(0.0081)	-0.0085	(0.0075)	0.0006	(0.0048)
Δp_{t-6}	0.0241	(0.0611)	0.0057	(0.0080)	0.0070	(0.0075)	-0.0007	(0.0048)
Δq^{OPEC}_{t-1}	-0.4299	(0.4198)	-0.0522	(0.0553)	-0.0744	(0.0515)	-0.0659^{**}	(0.0328)
Δq^{OPEC}_{t-2}	-0.3581	(0.4233)	-0.0867	(0.0557)	0.0129	(0.0520)	-0.0837^{**}	(0.0330)
Δq^{OPEC}_{t-3}	0.3776	(0.4212)	-0.1326^{*}	(0.0555)	-0.0206	(0.0517)	0.0230	(0.0329)
Δq^{OPEC}_{t-4}	0.3240	(0.4205)	0.1225**	(0.0554)	0.0635	(0.0516)	0.0285	(0.0328)
Δq^{OPEC}_{t-5}	-0.7263^{*}	(0.4131)	-0.0680	(0.0544)	0.0838*	(0.0507)	-0.0431	(0.0322)
Δq^{OPEC}_{t-6}	0.0107	(0.3563)	0.0759	(0.0469)	-0.1072^{**}	(0.0437)	-0.0313	(0.0278)
Δq^{RoW}_{t-1}	-0.4817	(0.4654)	0.0364	(0.0613)	-0.2059^{***}	(0.0571)	0.0002	(0.0363)
Δq^{RoW}_{t-2}	0.2144	(0.4748)	-0.0036	(0.0625)	-0.1224	(0.0583)	-0.0676	(0.0371)
Δq^{RoW}_{t-3}	0.2769	(0.4788)	0.1536**	(0.0631)	0.0089	(0.0588)	-0.0128	(0.0374)
Δq^{RoW}_{t-4}	-0.1871	(0.4805)	0.0147	(0.0633)	0.1058*	(0.0590)	-0.0166	(0.0375)
Δq^{RoW}_{t-5}	-0.0281	(0.4867)	-0.0190	(0.0641)	-0.0740	(0.0597)	-0.0814^{***}	(0.0380)
Δq^{RoW}_{t-6}	-0.2575	(0.4662)	0.0125	(0.0614)	-0.0705	(0.0572)	-0.0242	(0.0364)
Δip_{t-1}	0.3652	(0.7156)	0.7020***	(0.0942)	0.2380***	(0.0878)	0.0631	(0.0559)
Δip_{t-2}	3.2303***	(0.7680)	0.1838***	(0.1011)	-0.0071	(0.0943)	0.0739	(0.0599)
Δip_{t-3}	0.4687	(0.7927)	-0.2647^{**}	(0.1044)	-0.0584	(0.0973)	0.2457***	(0.0619)
Δip_{t-4}	-1.3993^{*}	(0.8113)	0.2029*	(0.1068)	0.1170	(0.0996)	-0.0341	(0.0633)
Δip_{t-5}	0.5807	(0.8117)	-0.0232	(0.1069)	-0.1302	(0.0996)	-0.0707	(0.0633)
Δip_{t-6}	1.1755	(0.7659)	0.1882*	(0.1009)	-0.0595	(0.0940)	0.0378	(0.0598)

The oil return responds to lagged oil price disequilibrium with a relevant contribution to close the equilibrium gap. But also, non-OPEC oil production increases, contributing to the maintenance of the long-term relationship. Interestingly, these oil producers present no relationship with oil prices, unlike the other share of production delivered by OPEC members. The evidence I present means that the gap is closed with an adjustment of oil prices and also a correction of RoW oil production. If the price is above the fundamental level, we should expect the price to fall and non-OPEC members to increase production, on average. This result is relevant to highlight the importance of disequilibrium in explaining the market dynamics.

Oil Price 1-month Forecasting: The short-term oil price forecasts generated by the implied Vector Error Correction Model (VECM) demonstrate a significant improvement of 15% in Root Mean Square Error (RMSE)[9] reduction compared to a random walk. Figure 6 visually illustrates the performance differences.

Notably, during intervals when the cointegrating error approaches zero and volatility remains low, such as the period between 2000 and 2006 before the commodities super cycle and the financial crisis, the model outperforms the random walk by 22%, representing a substantial 46% improvement over the entire sample period. From the mid to late 2001s until 2004, oil prices consistently remained below the fundamental level, as reflected in positive returns over a 24-month moving average. In contrast, during periods with the highest disequilibrium levels, such as 1996/7 and throughout 2013-2017, the random walk outperforms the forecast generated by the VECM model. This nuanced performance pattern highlights the sensitivity of forecasting accuracy to varying market conditions.

5 Conclusion

The interplay between oil prices and macroeconomic variables has been a focal point of economic research, reflecting the role of oil as a primary input in the global economy. The empirical approach commonly adopted involves taking the natural logarithms and the first difference to analyze oil returns and other stationary variables within a system. The underlying assumption posits no relationship in the levels of these variables. However, this approach overlooks the dynamic effect of long-term equilibrium on the system

I present evidence supporting the presence of a cointegrating relationship among real oil prices, global industrial production, and oil production, separating *OPEC* from *non-OPEC* supply, shedding light on their distinct roles in maintaining market equilibrium. We find that non-OPEC oil production and oil price responds to the disequilibrium contributing to restore the long-term relationship.

Explaining medium-term trajectory of oil prices with the introduction of an equilib-

[9] I compute the MSE ratio. Out statistic that compares model results with random walk performance, the benchmark, in the denominator $r = \frac{\sum_{1\leq t\leq T} e_t^2}{\sum_{1\leq t\leq T} \Delta p_t^2}$

rium measure, represented by the distance to the fundamental value, explains 35% of cumulative returns in oil prices over a 24-month horizon outperforming the Hamilton Filter. Short-term forecasts generated from the implied Vector Error Correction Model (VECM) outperform random walk by over 15% in RMSE reduction. These findings underscore the significance of the market clearing adjustments in the oil price dynamics.

References

ALQUIST, R., L. KILIAN, AND R. J. VIGFUSSON (2013): "Forecasting the price of oil," in *Handbook of economic forecasting*, Elsevier, vol. 2, 427–507.

BAUMEISTER, C. AND J. D. HAMILTON (2019): "Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks," *American Economic Review*, 109, 1873–1910.

——— (2023): "A Full-Information Approach to Granular Instrumental Variables," .

BAUMEISTER, C. AND L. KILIAN (2012): "Real-time forecasts of the real price of oil," *Journal of business & economic statistics*, 30, 326–336.

BEVERIDGE, S. AND C. R. NELSON (1981): "A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the 'business cycle'," *Journal of Monetary economics*, 7, 151–174.

BURGER, J. D., F. E. WARNOCK, AND V. C. WARNOCK (2022): "A natural level of capital flows," *Journal of Monetary Economics*, 130, 1–16.

COGLEY, T. (2002): "A simple adaptive measure of core inflation," *Journal of money, credit and banking*, 94–113.

ENGLE, R. F. AND C. W. GRANGER (1987): "Co-integration and error correction: representation, estimation, and testing," *Econometrica: journal of the Econometric Society*, 251–276.

HAMILTON, J. D. (2018): "Why you should never use the Hodrick-Prescott filter," *Review of Economics and Statistics*, 100, 831–843.

——— (2021): "Measuring global economic activity," *Journal of Applied Econometrics*, 36, 293–303.

HE, Y., S. WANG, AND K. K. LAI (2010): "Global economic activity and crude oil prices: A cointegration analysis," *Energy Economics*, 32, 868–876.

ISSLER, J. V., C. RODRIGUES, AND R. BURJACK (2014): "Using common features to understand the behavior of metal-commodity prices and forecast them at different horizons," *Journal of International Money and Finance*, 42, 310–335.

Johansen, S. (1991): "Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models," *Econometrica: journal of the Econometric Society*, 1551–1580.

——— (1995): "A stastistical analysis of cointegration for I (2) variables," *Econometric theory*, 11, 25–59.

Kilian, L. (2009): "Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market," *American Economic Review*, 99, 1053–1069.

Kumar, A. and S. Mallick (2023): "Oil price dynamics in times of uncertainty: Revisiting the role of demand and supply shocks," *Energy Economics*, 107152.

Lardic, S. and V. Mignon (2006): "The impact of oil prices on GDP in European countries: An empirical investigation based on asymmetric cointegration," *Energy policy*, 34, 3910–3915.

Phillips, P. C. and P. Perron (1988): "Testing for a unit root in time series regression," *biometrika*, 75, 335–346.

Rossi, B. (2013): "Exchange rate predictability," *Journal of economic literature*, 51, 1063–1119.

6 Appendix

6.1 Other Tables and Figures

Table 2: Estimates of equation 1. Cointegration Results with and without constant for the sample period. Includes estimation prior to COVID-19 Crisis.

	Real oil price			
	1993.1 - 2019.12		1993.1 - 2023.5	
	(1)	(2)	(3)	(4)
non-OPEC oil production	−3.147***	−4.904***	−3.624***	−5.397***
	(0.160)	(0.306)	(0.218)	(0.332)
OPEC oil production	2.137***	0.486*	2.702***	−0.452
	(0.158)	(0.291)	(0.233)	(0.513)
Global Industrial Production	3.097***	4.786***	2.880***	5.533***
	(0.079)	(0.266)	(0.096)	(0.401)
Constant		28.477***		40.280***
		(4.311)		(5.933)
Observations	365	365	324	324
R^2	0.995	0.865	0.995	0.876
Residual Std. Error	0.268 (df = 362)	0.253 (df = 361)	0.264 (df = 321)	0.247 (df = 320)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3: Phillips Perron Unit Root Tests: Null Hypothesis $\sim \mathcal{I}(1)$. Unit root rejected only for the cointegrating error.

Variable	Test Type	Dickey-Fuller Statistic	Truncation Lag Parameter	p-value
Real oil price	trend + Constant	-2.2446	5	0.4737
	Constant	-10.511	5	0.5218
Global Industrial Production	trend + Constant	-2.3551	5	0.4271
	Constant	-10.353	5	0.5306
non-OPEC oil production	trend + Constant	-2.7987	5	0.2398
	Constant	-16.476	5	0.1879
OPEC oil production	trend + Constant	-1.6545	5	0.7228
	Constant	-6.6099	5	0.7402
cointegrating error	trend + Constant	-3.6019	5	0.03306
	Constant	-25.027	5	0.02331

Table 4: Johansen-Procedure Results

Test type	maximal eigenvalue statistic (lambda max)			
Eigenvalues (lambda)	7.51×10^{-2}	2.86×10^{-2}	1.36×10^{-2}	6.79×10^{-5}
Values of test statistic				
$r \leq 3$	0.02	6.50	8.18	11.65
$r \leq 2$	4.93	12.91	14.90	19.19
$r \leq 1$	10.43	18.90	21.07	25.75
$r = 0$	28.02	24.78	27.14	32.14

Eigenvectors, normalised to the first column:

$p.l6$	$IP.l6$	$qo.l6$	$qr.l6$
1.000000	1.000000	1.000000	1.000000
-8.733102	1.493193	2.908142	-43.25432
2.967797	-6.987179	4.098141	176.03707
9.238079	-1.524810	-2.373724	-143.54532

Weights W: (Loading matrix)

	$p.l6$	$IP.l6$	$qo.l6$	$qr.l6$
$p.d$	-0.0876206695	-0.0135247015	-1.426572e-03	1.095987e-05
$IP.d$	0.0010317195	0.0007068792	-4.943768e-04	1.503619e-06
$qo.d$	-0.0042339066	0.0037826198	-7.295645e-05	-4.383487e-06
$qr.d$	-0.0002671818	0.0040843775	2.341826e-04	3.626812e-06

Figure 6: Forecasting oil prices one step ahead using VECM, depicting the forecasting errors and comparing them with the random walk, where errors are represented by the return. In the top plot 24 month moving average is computed to get smoothed information. And in the squared errors are 3month moving average.

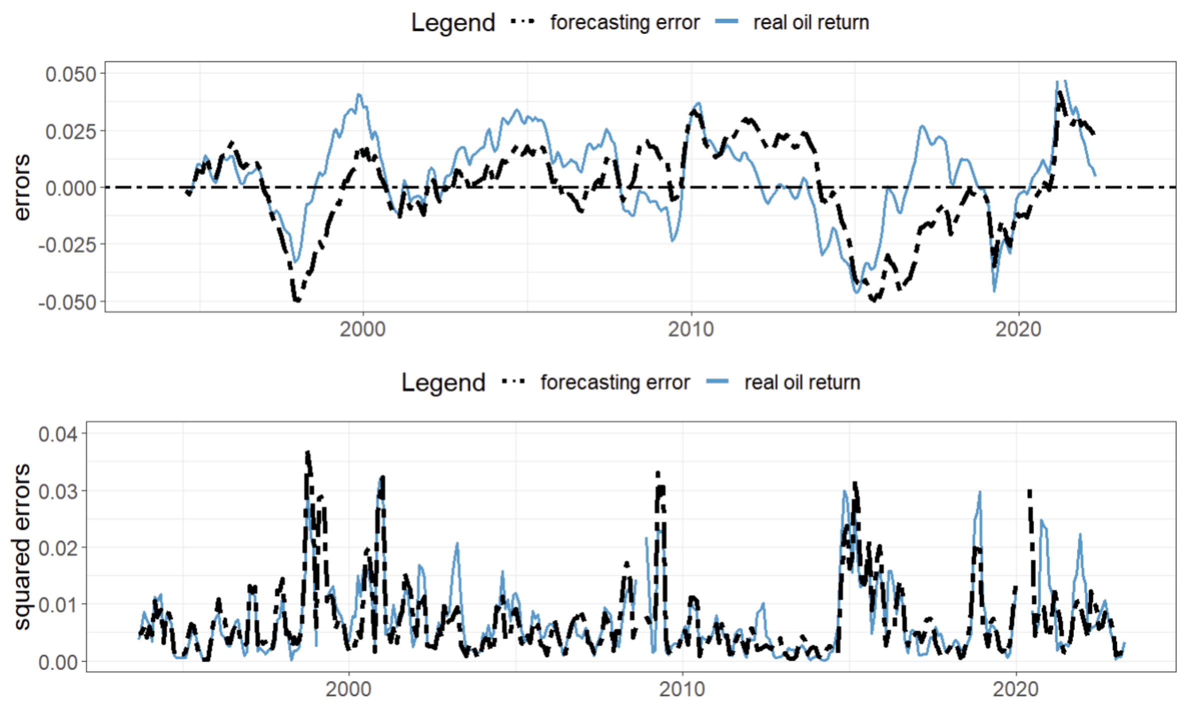


Figure 7: Cointegrating error 12 month moving average and the 24 month moving average of oil returns. In this figure we can visualize the cointegrating error anticipating negatively the 24-step ahead real oil price cumulative returns.

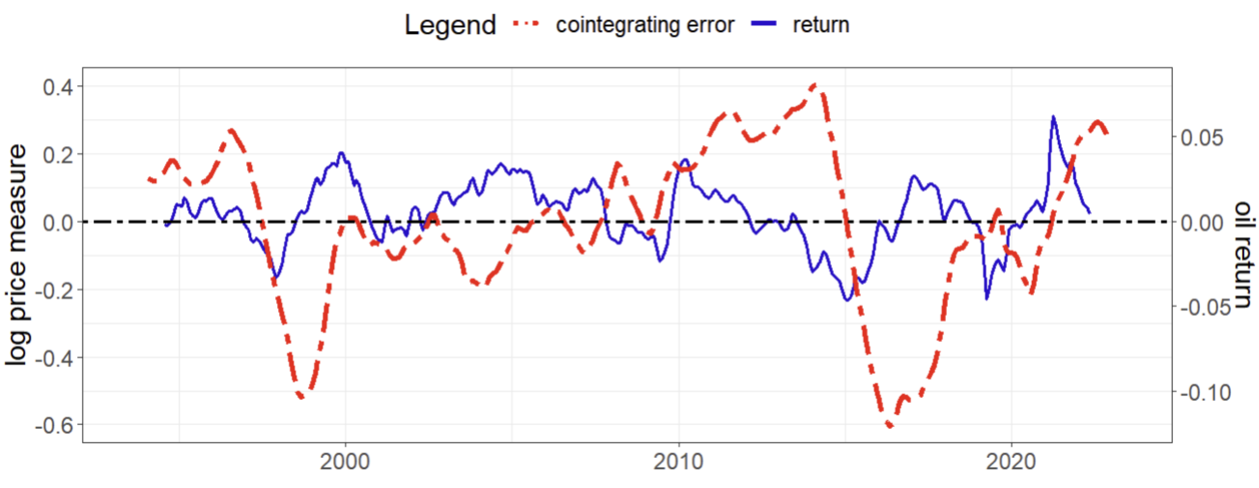


Table 5: MSE Ratios for Different Periods. The first line is the whole sample and than is computed over 36 months.

Start Date	**End Date**	**MSE Ratio**
1993-01-01	2023-05-01	**0.8442**
1993-01-01	1996-01-01	**1.0819**
1997-01-01	2000-01-01	**0.9347**
2001-01-01	2004-01-01	**0.7653**
2005-01-01	2008-01-01	**0.9119**
2009-01-01	2012-01-01	**0.8647**
2013-01-01	2016-01-01	**1.0484**
2017-01-01	2020-01-01	**0.6662**
2020-01-01	2023-05-01	**0.7932**