The first-difference of industrial production is modeled as an autoregressive moving average (ARMA) process:

$$\varphi(L)\Delta IP_t = \theta(L)\epsilon_t + \mu$$ (1)

where $\varphi$ and $\theta$ are polynomials in the lag operator $L$, and $\mu$ is a constant term. The best-fit specification was chosen...
Table 1. Estimation Results

|                  | GARCH without ΔPC | GARCH with ΔPC |
|------------------|-------------------|----------------|
| β₀               | 0.00001**         | 0.00002**      |
| β₁               | 0.31714**         | 0.32168**      |
| β₂               | 0.30262**         | 0.20205*       |
| ρ                | -----             | -0.00021*      |
| SD of dep. variable | 0.00662         | 0.00662        |
| Adj. R-squared   | 0.12177           | 0.13913        |
| AIC              | -7.52012          | -7.55288       |
| SSR              | 0.00904           | 0.00886        |

GARCH: \( h_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}^2 + \rho \Delta PC_{t-1} \)

Mean: \( \mu_t = \mu + \rho \Delta PC_t \)

Note: *, ** indicate significance at the 5 and 1 percent level, respectively. Error distribution in the reported results is assumed to be Gaussian; however, results are robust to a variety of alternatives including Student’s t and Generalized Error.

based on an inspection of the autocorrelation functions and Box-Jenkins techniques. The determined model has an ARMA(2, 1) specification. Consistent with previous findings (Ewing & Thompson, 2008), the Lagrange multiplier statistic (Engle, 1982) indicated the presence of ARCH effects in the first-difference of industrial production. Accordingly, the mean and variance of industrial production were estimated simultaneously using the method of maximum likelihood. The variance equation for the GARCH(1, 1) model is given by:

\[ h_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}^2 + \rho \Delta PC_{t-1} \quad (2) \]

where conditional variance of \( \varepsilon_t \) with respect to the information set \( \Omega_{t-1} \) is given by \( V(\varepsilon_t | \Omega_{t-1}) = h_t^2 \). \( \beta_0, \beta_1 \) and \( \beta_2 \) are constant non-negative parameters and \( \beta_1 + \beta_2 < 1 \) measures volatility persistence. The restrictions on the parameters prevent negative variances and ensure that the process is covariance stationary with positive and finite variance, \( \frac{\beta_1}{1-\beta_1-\rho} > 0 \) (Bollerslev, 1986). Equation (3) is estimated in order to examine how changes in crude oil pipeline capacity impact the volatility dynamics of industrial production growth.

\[ h_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}^2 + \rho \Delta PC_{t-1} \quad (3) \]

The results from estimating the GARCH models with and without changes in PC are presented in Table 1. In both models, the estimated coefficients on the ARCH and GARCH terms are statistically significant and, therefore, volatility can be predicted in the presence of time-varying volatility. Also, in both cases the models are shown to be covariance stationary, that is, \( \frac{\beta_1}{1-\beta_1-\rho} > 0 \).

As noted above, \( \beta_1 + \beta_2 \) shows the degree of volatility persistence. Compared to the model without accounting for pipeline capacity, the results from the GARCH model with changes in pipeline capacity show a nearly 16% reduction in volatility persistence. From a macroeconomic standpoint this suggests a reduction in the length and/or magnitude of business cycles when considering how long volatility (a measure of cycle) lasts. Put differently, if a standardized shock would otherwise increase volatility for a period of one year (i.e., the volatility takes one year to dissipate), then a one percent increase in pipeline capacity would reduce the extent of the shock or the time it persists by nearly two full months. Further, the effect that pipeline capacity has on economic stability is shown by the negative and signifi-

Figure 1: Pipeline capacity and industrial production

Note: This plots the natural log of US industrial production and natural log of crude oil pipeline capacity over time.

3. Concluding Remarks

Crude oil pipeline infrastructure has been shown to benefit the economy in terms of increases in jobs, output, value added, and government revenues. However, evidence as to the possible benefit of increased economic stability of pipelines has not been examined. This study documents two important findings regarding crude oil pipelines. First, the results indicate that volatility persistence of industrial production is lower with pipeline capacity included in the GARCH model than when it is excluded. As such, changes in pipeline capacity are seen to shorten the length of the business cycle. Second, including pipeline capacity in the GARCH model reduces the volatility of industrial production. Improvements in economic stability provide for a more robust, resilient and sustainable economy. Overall, the findings support the critical role that crude oil pipeline plays in...
the US economy.

Acknowledgement

This research was supported by a grant from ExxonMobil Pipeline Company. All opinions expressed herein are strictly those of the author. The author would like to thank the Editor and Reviewers of Energy RESEARCH LETTERS for their valuable feedback.
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