Oil price volatility is effective in predicting food price volatility. Or is it?

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The spikes in the prices of internationally traded agricultural commodities and oil in 2008 and 2011 and the associated food inflation have raised concerns about the impact of food price volatility on both consumers and producers across the world.

Understanding food price volatility is important for three main reasons. First, it affects hedging costs of agricultural firms. Second, increased food price volatility affects food security and malnutrition, which is a key concern for policy makers. Third, commodity markets (including food and oil markets) have attracted the interest of financial investors, and as a consequence have become more financialised and thus, more volatile. The increased financialisation has also resulted in the strengthening links between oil and agricultural commodities, both in returns and volatilities. Such links have been stressed by existing literature based on in-sample evidence, yet, there has been no empirical study to suggest whether oil price volatility improves real out-of-sample forecasts of food price volatility.

Thus, given the weight of in-sample evidence from a number of studies pointing to the important role of oil price volatility in commodity price volatility, we utilise out-of-sample forecasting techniques in order to investigate whether oil price volatility has any incremental predictive information with regard to food price volatility.

To do so, we focus on five key food commodities, namely, corn, rough rice, soybeans, sugar #11 and wheat, as well as, the two main crude oil benchmarks, i.e. West Texas Intermediate (WTI) and Brent for the period January, 1990 to March, 2017. In the interest of comparison, we employ predictive models with and without the information from the oil market (i.e., oil volatility). In particular, we initially employ the Heterogenous Autoregressive (HAR) model by Corsi (2009) on monthly volatility, which we augment with oil price volatility (HAR-X). We further enhance our modelling approach by considering a mixed-data sampling model (MIDAS) so to assess whether the incremental predictive information of oil price volatility on monthly food price volatility forecasts can be hidden in higher frequency (i.e. daily oil price volatility, MIDAS-HAR- X). For robustness, we use three volatility measures, namely, realized volatility, price range volatility and realized range volatility. We produce real out-of-sample forecasts for 1- up to 12-months ahead for the period January, 2000 up to March, 2017 (i.e. 207 months)

Our findings suggest that the oil price volatility-enhance models cannot systematically outperform the standard version of the HAR model that excludes information stemming from the oil market. In point of fact, any improvement that occurs in the out-of-sample forecasting of monthly food price volatility, based on the HAR-X or MIDAS-HAR-X models, is sporadic, despite the fact that the in-sample analysis suggested that the performance of the MIDAS-HAR-X models is su-

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perior compared to the standard HAR model. What is more, these findings hold irrespective of the crop, forecast horizon, volatility frequency or the type of oil market that is studied. These findings remain robust to (i) alternative volatility measures (realized volatility, price range volatility and realized range volatility), (ii) forecasting averaging techniques, as well as, (iii) analysis during turbulent periods, such as the food crises of 2007–2009 and 2010–2012, as well as, the oil price collapse in 2014–2016.