



Department of Economics and Finance

Working Paper No. 2412

Economics and Finance Working Paper Series

Christina Anderl and Guglielmo Maria Caporale

Expectations and Speculation in the Natural Gas
Markets

September 2024

<http://www.brunel.ac.uk/economics>

Expectations and Speculation in the Natural Gas Markets

Christina Anderl

London South Bank University

Guglielmo Maria Caporale

Brunel University London

September 2024

Abstract

This paper aims to assess the role of expectations as a determinant of the real price of natural gas. To measure expectations-driven speculative demand three approaches are followed, which are based respectively on using natural gas inventories consistently with the theory of storage (Kilian and Murphy, 2014), the futures spread (Valenti, 2022), and functional shocks defined as shifts in the entire risk-adjusted natural gas futures term structure (Inoue and Rossi, 2021). Three specifications of a structural VAR (SVAR) model are then estimated based on each of those approaches in turn. The results suggest that expectations, especially when measured as functional shocks, lead to strong and persistent increases in the real price of natural gas. A shock decomposition exercise shows that the price of natural gas responds primarily to changes in the curvature of its futures term structure, which indicates that medium-term expectations are the main driver of permanent increases in the spot price of natural gas. Further, the functional natural gas price shocks seem to account for around half of the variation in the real price of natural gas.

Keywords: Natural gas price, expectations, speculation, inventories, functional shocks, structural VAR (SVAR)

JEL Classification: D84, G15, Q41, Q43

Corresponding author: Professor Guglielmo Maria Caporale, Department of Economics and Finance, Brunel University London, Uxbridge, UB8 3PH, UK. Email: Guglielmo-Maria.Caporale@brunel.ac.uk; <https://orcid.org/0000-0002-0144-4135>

1. Introduction

The financialisation of commodity markets in recent decades has led to the acceptance of commodity derivatives as financial assets by a wide range of market participants (Fattouh et al., 2013). It is often argued that increased financialisation has introduced speculative activity which reflects the expectations of forward-looking agents and might account for large increases in spot prices in the physical markets for commodities. The majority of studies on this topic mainly focus on the market for crude oil, some of them reporting that speculation in the futures markets is an important determinant of spot prices (Juvenal and Petrella, 2015; Valenti, 2022), while others report opposite results (Baumeister and Hamilton, 2019). Hardly any evidence is currently available for the natural gas market, despite its growing importance in recent decades.

This study aims to fill this gap in the literature by assessing the importance for the price of natural gas of shocks stemming from the natural gas futures markets relative to that of supply and demand shocks in the physical markets. Similarly to oil markets, natural gas markets have become increasingly financialised, which makes it important to investigate the role of expectations and speculative pressures in this market (Kilian and Murphy, 2014). We examine this expectations-driven component of the price of natural gas in three ways. First, we control for speculative demand shocks through natural gas inventories as in Kilian and Murphy (2014). Second, we use the futures spread, which is the percent deviation of the futures price from the spot price and is representative of the convenience yield expressed with the opposite sign (Valenti, 2022). Third, we model natural gas price expectations using functional shocks derived from the risk-premium adjusted natural gas futures term structure (Inoue and Rossi, 2021).

The analysis involves three steps. To start with, we estimate a structural vector autoregressive model (SVAR) model of the natural gas market and differentiate between physical natural gas supply and demand shocks and an expectations-driven speculative demand shock stemming from natural gas inventories, as in the oil market model by Kilian and Murphy (2014). Next, we estimate a SVAR model as in Valenti (2022) which contains the futures spread and allows one to differentiate between a precautionary demand shock and a financial market shock. Finally, we include in the SVAR analysis functional natural gas price shocks which represent shifts in the entire natural gas futures term structure. To construct them we first use the model by Hamilton and Wu (2014) to account for the existence of a time-varying risk premium and obtain the risk-adjusted natural gas futures prices at all maturities, which can be seen as a close approximation of expected future spot prices. Then we calculate the functional shocks

following the method of Inoue and Rossi (2021); these can be interpreted as changes in expectations about the natural gas markets at all maturity horizons simultaneously. According to the theoretical models of storage, such expectations present in the futures markets should also be reflected in spot prices. These functional shocks are then included in the natural gas SVAR model to represent the speculative component.

The remainder of the paper is organised as follows. Section 2 briefly reviews the literature on expectations and speculation in both the crude oil and natural gas markets, Section 3 outlines the empirical framework, Section 4 presents the empirical results, and Section 5 concludes.

2. Literature Review

The literature analysing the natural gas market, and in particular expectations based on natural gas futures, is relatively new, as most previous papers had focused instead on the price of oil and oil futures. However, some important insights concerning the natural gas market can also be gained from those studies.

Most contributions examining speculation in the oil markets are based on the Masters hypothesis according to which higher futures prices are a signal of expectations of rising spot prices, which should increase the demand for inventories (Fattouh et al., 2013). Hamilton (2009) suggests that if futures prices increase because of speculation, then spot prices should increase as well because of inventory arbitrage. In such a case, financial speculation in the futures markets can be a key determinant of the spot price in the physical market, provided that the price elasticity of demand is perfectly inelastic. Lombardi and Van Robays (2011) estimate a structural VAR model to separate fundamental shocks to oil demand and supply from non-fundamental financial shocks represented by oil futures prices. Their results suggest an important role of financial investors in the futures markets for the short-run destabilisation of the spot price of oil.

One of the most important studies on expectations and speculation in the oil market is due to Kilian and Murphy (2014), who estimate a structural VAR model of the oil market which includes above-ground inventories and sign restrictions that allow them to quantify the effects of a speculative demand shock on the real price of oil. They deliberately exclude any

information from the oil futures market since arbitrage implies that any speculative or expectational changes in those markets should be reflected in a change in inventories in the physical market. In fact they cannot find any evidence of Granger-causality from the futures spread to the other variables in the model and thus conclude that indeed oil inventories already include all relevant information concerning expectations within the oil market. If there was speculation in the futures market, given the arbitrage condition, it would have caused speculative demand for inventories to shift. Kilian and Lee (2014) do some robustness checks for the results presented by Kilian and Murphy (2014) by using different proxies of crude oil inventories. Juvenal and Petrella (2015) estimate a factor-augmented VAR model to obtain measures of speculation in addition to standard physical oil market shocks. Speculative shocks are found to be the most important determinant of the price of oil, second only to demand shocks. Valenti (2022) instead replaces crude oil inventories with the futures spread, which is considered an important measure of forward-looking expectations. The identified financial market shock appears to have played an important role for rising oil prices during the 2003-2008 period.

Baumeister and Kilian (2014) highlight the importance of accounting for the existence of a risk premium in futures markets and advocate the method by Hamilton and Wu (2014) to model a time-varying risk premium. Valenti et al. (2020) include a measure of the time-varying risk premium into a SVAR model of the oil market and find that risk premium shocks are significant drivers of the price of oil only during the 2003-2008 period. The Hamilton and Wu (2014) approach has previously been used to construct measures of the expectations component of crude oil futures (Anderl and Caporale, 2024), but has not yet been applied in the case of natural gas futures.

Within the literature specific to the natural gas markets, several studies are concerned with the integration of physical and futures markets. For instance, Chinn et al. (2005) find that 3- and 6-month natural gas futures are biased predictors of future spot prices of natural gas. Chiou-Wei et al. (2014) study the behaviour of spot and futures prices around announcements related to natural gas storage and report that first futures prices react to surprises about natural gas storage and only subsequently information flows to the spot market. Ghoddusi (2016) reports that futures prices Granger-cause physical natural gas prices, which is in contrast to previous findings concerning the crude oil markets. Using a vector error correction model (VECM), he shows that shocks to natural gas futures prices have persistent effects on natural gas prices in

the physical markets. Taking a different perspective on speculation, Manera et al. (2016) use a GARCH (1,1) model to measure futures price volatility which include different available measures of speculative activity. They find that speculation measured by different indices does not destabilise natural gas prices. Wang et al. (2019) employ dynamic model averaging for the US natural gas markets and apart from demand and supply shocks identify financial market variables representing speculation as the main driver of natural gas spot prices, while the importance of oil prices appears to have fallen over time. It is noteworthy that the evidence regarding speculation in the natural gas markets is mainly based on studies of natural gas futures rather than the theory of storage as in the case of the oil markets.

3. Empirical Framework

3.1 The natural gas market model with inventories

Expectations in the natural gas markets can be measured in different ways; we consider three of them in particular. The first is due to Kilian and Murphy (2014), who identify speculative inventory demand shocks through appropriate restrictions in a VAR framework. These represent unobservable shifts in the expectations about future demand and supply of natural gas. Therefore, in the first instance, we estimate a structural VAR model similar to the one by Kilian and Murphy (2014) but for the natural gas market. This takes the following form:

$$B_0 y_t = \sum_{i=1}^{24} B_i y_{t-i} + \varepsilon_t \quad (1)$$

where $y_t = [\Delta q_t, \Delta p_t, \Delta c_t, \Delta s_t]$, q_t is global natural gas production, p_t is the spot price of natural gas, c_t measures the demand for natural gas, either through real economic activity or natural gas consumption directly, and s_t stands for natural gas inventories. Note that the natural gas market, like other energy markets, is subject to strong seasonal trends due to weather, demand and storage level seasonalities which affect the price. We remove seasonal variation by seasonally adjusting the production, consumption and inventories data. Following Kilian and Murphy (2014) we allow for up to 24 lags in the model.

We also use the same set of sign restrictions as in their study (see Table 1 for a summary). A physical natural gas supply shock, similarly to an oil flow supply shock, is given by any

unanticipated shift in the natural gas supply curve that results in opposite movements of natural gas production and the real price of natural gas. The effect on inventories is ambiguous since they are either depleted in an effort to smooth consumption, or may increase since the negative supply shock triggers a predictable increase in the price of natural gas. As in the case of an oil flow demand shock in the oil markets, a physical natural gas demand shock increases the real price of natural gas and production in order to satisfy the extra consumption demand. A speculative demand shock can arise from either the possibility of a sudden shortage in future natural gas production or expectations of higher future demand for natural gas. In response to a speculative or inventory demand shock, inventories increase alongside the price of natural gas. Consequently, natural gas producers are incentivised to increase their production and consumption declines. In the Kilian and Murphy (2014) model a speculator is anyone who buys the commodity not for current, but future consumption; thus the speculative demand shock captures expectations about future market developments. We impose the restrictions for the physical supply shock dynamically so that they are valid for a response horizon of 12 months. We also impose bounds restrictions on the impact elasticity of natural gas demand. Since this has to be weakly negative on average over the sample we impose an upper bound of zero, but not a lower bound, since there is no consensus in the empirical literature on the size of the demand elasticity of natural gas (Havranek et al., 2012; Liddle et al., 2020). For the short-run supply elasticity we impose an upper bound of 0.025. We use a Normal-Inverse-Wishart prior and the algorithm by Rubio-Ramirez et al. (2010).

Table 1. Sign restrictions in the VAR model with inventories

	Physical natural gas supply shock	Physical natural gas demand shock	Speculative demand shock
Natural gas production	–	+	+
Natural gas consumption	–	+	–
Real price of natural gas	+	+	+
Natural gas inventories			+

Notes: Sign restrictions with (+) indicating a positive response to the shock and (–) indicating a negative response.

3.2 The natural gas market model with the futures spread

Another way to represent expectations in the natural gas market is by using the futures spread. In the context of the oil market, Kilian and Murphy (2014) argue for the exclusion of the futures spread or any oil futures price data from their model; the rationale is that, given the existence of arbitrage, any speculation in the futures markets should be reflected in the physical markets

through a shift in inventories. Valenti (2022) on the other hand shows that forward-looking expectations can be inferred from futures markets, represented by the futures spread. We aim to test for this in the context of the natural gas markets as outlined below.

If futures prices contain important information about spot prices, their omission results in a bias in favour of a stronger role of demand and supply factors for spot price movements (Zagaglia, 2010). Hamilton (2009) highlights a fundamental aspect of the Master’s hypothesis, which specifies that, if futures prices are driven by speculation, spot prices have to move accordingly. In fact, previous evidence by Ghodduzi (2016) suggests that futures prices Granger-cause physical prices in the natural gas market and that shocks to futures prices have persistent effects on physical prices. We estimate the model as in (1) but now replace the natural gas inventories with the futures spread. This allows us to identify one additional shock (see Table 2). The precautionary demand shock takes the form of a rightward shift in the natural gas demand curve along the supply curve which is driven by higher demand for storage. The financial market shock instead is an accumulation of natural gas inventories which is triggered by rising futures prices. The futures spread ω_t is calculated as the percent deviation of the futures price from the spot price of natural gas, namely $\omega_t = \frac{F_t - P_t}{P_t}$, which is why the signs are opposite.

Table 2. Sign restrictions in the VAR with the futures spread

	Physical natural gas supply shock	Physical natural gas demand shock	Precautionary demand shock	Financial market shock
Natural gas production	–	+	+	
Natural gas consumption	–	+	–	
Real price of natural gas	+	+	+	+
Futures spread	–	–	–	+

Notes: Sign restrictions with (+) indicating a positive response to the shock and (–) indicating a negative response.

One limitation of the analysis discussed in this section is that the futures spread relates only to one futures contract maturity at any one time. While we can repeat the analysis using different maturities, we cannot examine simultaneous changes at different maturities. For this reason, next we model expectations in the natural gas markets by estimating functional shocks, i.e. shifts in the entire natural gas futures term structure, as explained in the following section.

3.3 The natural gas futures term structure

We estimate the functional natural gas price expectations shocks from the natural gas futures term structure. To this end we first account for the existence of a time-varying risk premium in order to obtain measures of the expected future spot prices for different maturities. Baumeister and Kilian (2014) suggest to use the method by Hamilton and Wu (2014) to estimate the time-varying risk premium. This approach is based on an affine factor structure to obtain the risk-adjusted futures prices which are measures of the expected future spot prices. We then estimate the term structure parameters using the Nelson-Siegel (1987) model:

$$f_t(\tau) = L_t + \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau}\right) S_t + \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right) C_t, \quad \lambda > 0 \quad (2)$$

where $f_t(\tau)$ is the risk-adjusted futures price for natural gas at time t for maturity τ and L_t , S_t and C_t are the level, slope and curvature factors of the term structure, respectively. The factor λ measures the relative contribution of the slope and curvature factors to the term structure compared to that of the level factor.¹ We follow the method by Inoue and Rossi (2021) for the construction of functional shocks, which captures shifts in all three term structure factors simultaneously. The risk premium is the difference between the futures price and the expected future spot price, which are the returns that compensate speculators for taking on the exposure of another party to fluctuations in the commodity price. This means that accounting for a time-varying risk premium allows one to obtain a measure of market expectations of the future spot price. If the risk premium falls and the cost of hedging decreases, the spot price of natural gas increases, since producers should be more willing to hold inventories (Acharya et al., 2013). In this respect, the natural gas futures markets can provide insurance against any expected future supply and demand disruptions, which serves more or less the same purpose as accumulating inventories.

Moreover, functional shocks have the advantage of capturing changes in expectations across several maturity horizons. By simply including the futures spread, one cannot account for the depth of information about expectational changes contained in the futures markets. For instance, the slope of the futures term structure is often regarded as a proxy for the level of inventories (Basu and Miffre, 2013). By specifically modelling changes in the slope of the term

¹ Following Diebold and Li (2006), we calibrate λ as 0.0609.

structure, alongside changes in the level and curvature, we are able to express shifts in inventory demand directly from the futures markets. Because of arbitrage changes in the term structure should be representative of those in physical inventories and therefore affect the physical spot price of natural gas in a similar manner. An inversion of the term structure, for example, might indicate a tightening of inventories (Sanders and Irwin, 2017). The fact that the shocks are *functional*, rather than scalar, captures important structural and expectational dynamics across the entire maturity dimension and thus can be informative for the degree of speculative activity at short, medium and long horizons.

3.4 The natural gas market model with functional shocks

As a next step we estimate a model similar to the one in (1) but explicitly account for natural gas price expectations by including the functional natural gas price shocks stemming from the futures markets. With the inclusion of the functional natural gas price shocks, we now impose the sign restrictions suggested by Juvenal and Petrella (2015) and summarised in Table 3.

Table 3. Sign restrictions in the VAR model with functional shocks

	Physical natural gas supply shock	Physical natural gas demand shock	Inventory demand shock	Functional natural gas price shock
Natural gas production	–	+	+	–
Natural gas consumption	–	+	–	
Real price of natural gas	+	+	+	+
Natural gas inventories	–		+	+
Functional natural gas price shocks				+

Notes: Sign restrictions with (+) indicating a positive response to the shock and (–) indicating a negative response.

We impose a positive response of the price of natural gas and natural gas inventories and a negative response of natural gas production to the functional shocks. As discussed in Hamilton (2009), financial speculation affects the expected future spot price, which in turn can change the incentives faced by producers of the commodity. Therefore, if the expected future spot price increases, producers in the physical market will hold back natural gas production in the present period in anticipation of receiving a higher price on future deliveries. Consequently, production will fall and inventories will increase. No restriction is placed on the response of natural gas consumption, since there are several possible mechanisms which can affect the demand for natural gas with different signs, as outlined in Juvenal and Petrella (2015). Here, the inventory

demand shock is identical to the speculative demand shock in the Kilian and Murphy (2014) model. Finally, we also assess the relative contribution of the individual term structure factors to the response of the price of natural gas to the functional shocks by doing a shock decomposition exercise.

4. Data and Empirical Results

4.1 Data Description

The sample period goes from January 2000 to July 2024. For the construction of the functional shocks we use Henry Hub natural gas futures which are representative of the American market for maturities from 1 month to 12 months.² Specifically, these are NG1-NG12 series obtained from Bloomberg. Henry Hub natural gas spot prices have been obtained from the US Energy Information Administration (EIA) and deflated by the US consumer price index provided by the OECD to calculate the real spot price. For the construction of the futures spread, we consider three maturities, namely the 3-month, the 6-month and the 12-month futures contracts. Natural gas production is the natural gas marketed production obtained from the EIA for the US, which is the largest global natural gas producer, and is expressed in percentage change. We consider two measures of demand for natural gas. One is a direct measure of natural gas consumption which is obtained from FRED and represents consumption demand for natural gas directly; it is expressed in its percentage change. The second measure is the index of global real economy activity by Kilian (2009), which is commonly used in the oil market literature and is more representative of overall global demand. The series for natural gas inventories is the total underground storage volume obtained from the EIA for the US and scaled by the OECD petroleum stocks to US stocks³ and is expressed in changes. Note that in the oil market literature US inventory data is commonly used as a proxy for global inventories in the absence of a direct measure for the latter.

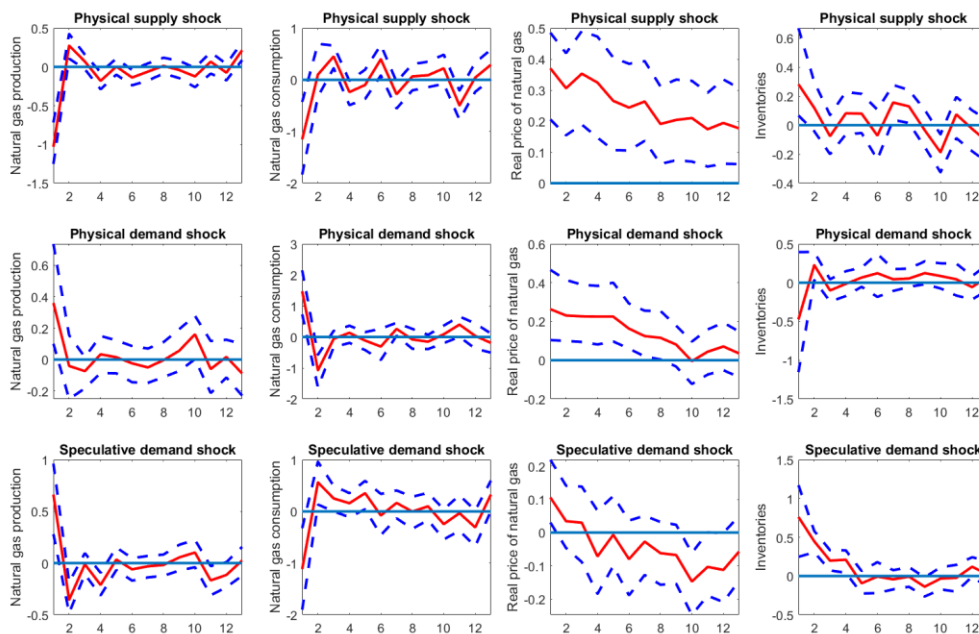
² Ideally one would conduct this type of analysis by region, given that there are regional variations in the spot and futures prices between the North American, European and Asian markets. However, for the latter two, the futures markets have only recently become more relevant in the case of natural gas, with some maturities only trading after 2012 or even 2015. Therefore there is little reason to believe speculation has been significant in these markets. Likewise, regional data on production and inventories of natural gas are not easily available, making a regional analysis difficult at present.

³ This measure contains petroleum and other liquid fuels comprising crude oil, unfinished oils, refined products and natural gas plant liquids. In the absence of any direct measure of OECD or global natural gas inventories, this is the closest approximation we can obtain.

4.2 Results from the Kilian-Murphy model

Figure 1 shows the results from the model based on the Kilian and Murphy (2014) specification. As can be seen, an unexpected natural gas supply disruption reduces production and consumption, but this effect is only transitory. The effect on the real price of natural gas, however, is more persistent over the response horizon. The response of the price of natural gas to a physical demand shock dies out within 12 months. A speculative demand shock seems to affect the real price of natural gas positively at first, but the effect becomes negative after 4 months, when the excess inventories are depleted. Inventories respond only very little to both supply and demand shocks, which suggests that storage is only temporarily accumulated or drawn down to smooth production and consumption.

Figure 1. Results from the Kilian-Murphy model with consumption

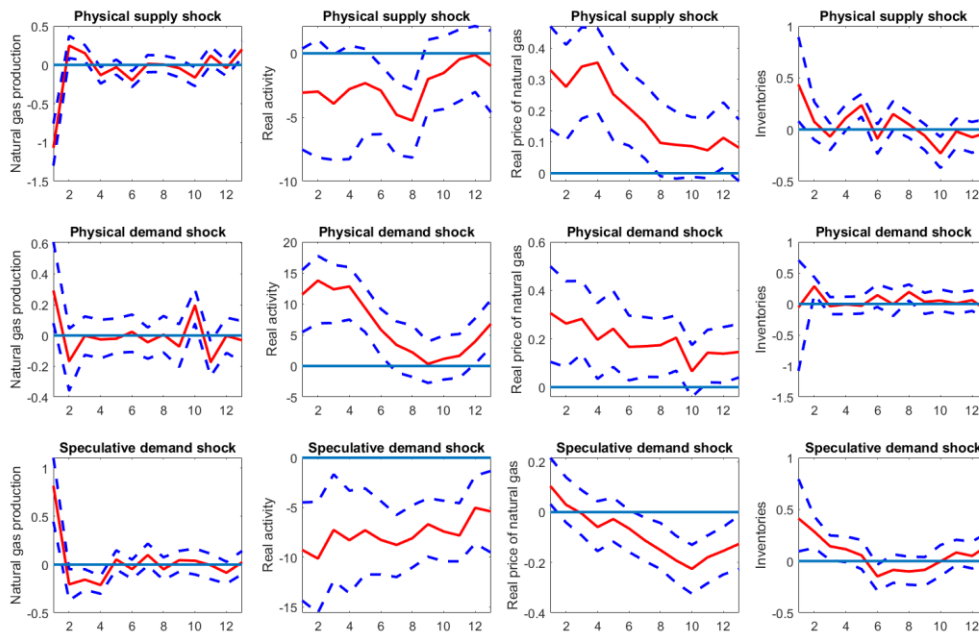


Notes: Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands.

Figure 2 shows the results from the same model, but now with real activity instead of natural gas consumption as the demand variable. The results are almost identical. The main difference is that a speculative demand shock seems to affect real activity more strongly and persistently than natural gas consumption. In summary, the results from the Kilian-Murphy model lead to two main conclusions. First, the responses of production, consumption and inventories to any of the shocks are only transitory. Second, speculative demand shocks, which capture forward-

looking expectations in the model, seem to provide little explanation for increases in the spot price of natural gas.

Figure 2. Results from the Kilian-Murphy model with real activity



Notes: Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands.

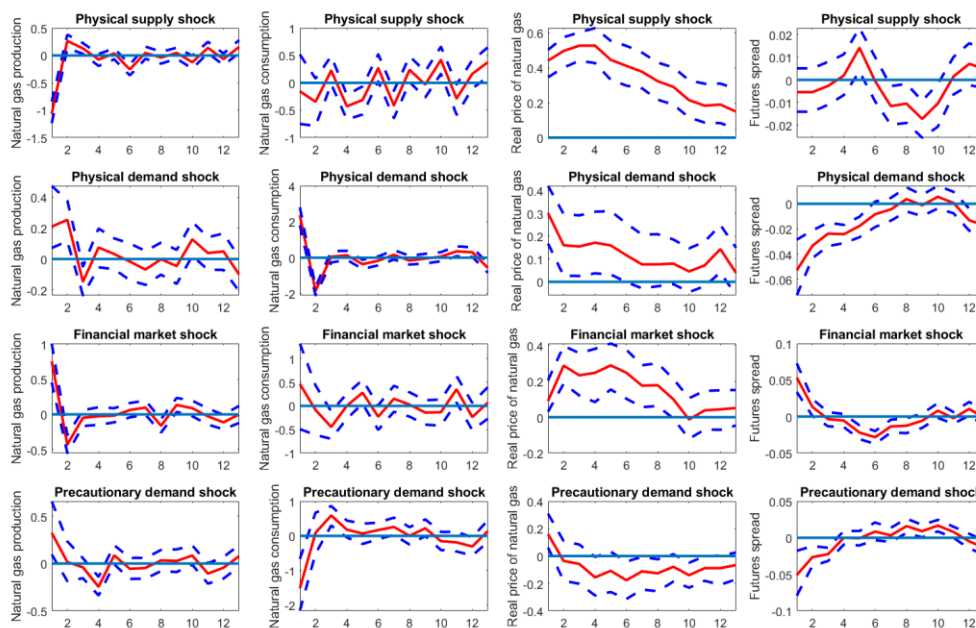
Kilian and Murphy (2014) found that in the oil market demand forces and speculative shocks are the main drivers of the price of oil. The same does not hold for the natural gas market. The forecast error variance decomposition suggests that in the model with consumption 34% of the variation in the real price of natural gas can be attributed to a physical supply shock, 14% to a physical demand shock and only 6% to a speculative demand shock, while the residual shock captures the remaining 46%. In the model with real activity, 27% of fluctuation in the real price of natural gas is due to a physical supply shock, 24% to a physical demand shock, 12% to a speculative demand shock and 37% to the residual shock. These findings suggest that the total variation in the price of natural gas is not fully captured by the shocks identified in the model and that there are other factors driving the price of natural gas.

4.3 Results from the Valenti model

In this section we present the results from the Valenti model which includes the futures spread instead of inventories and distinguishes between a precautionary demand shock and a financial

market shock. The results of the model with the 3-months futures spread are reported in Figures 3 and 4 for consumption and real activity respectively, and are similar to those obtained from the Kilian-Murphy model. An unexpected financial market shock increases the real price of natural gas as well as production on impact. The subsequent fall in production reflects the incentive producers have to increase natural gas inventories with the hope to sell them at a higher price in the future; this mechanism further raises the price of natural gas. The response of the futures spread to a precautionary demand shock is negative as expected, but small. The precautionary demand shock has a similar effect on the real price of natural gas as the speculative demand shock in the previous model. Our findings are broadly similar to those obtained by Valenti (2022) for the oil market, with the exception of a less persistent effect of the financial market shocks on the spot price in our case.

Figure 3. Results from the Valenti model with consumption and the 3-months futures spread

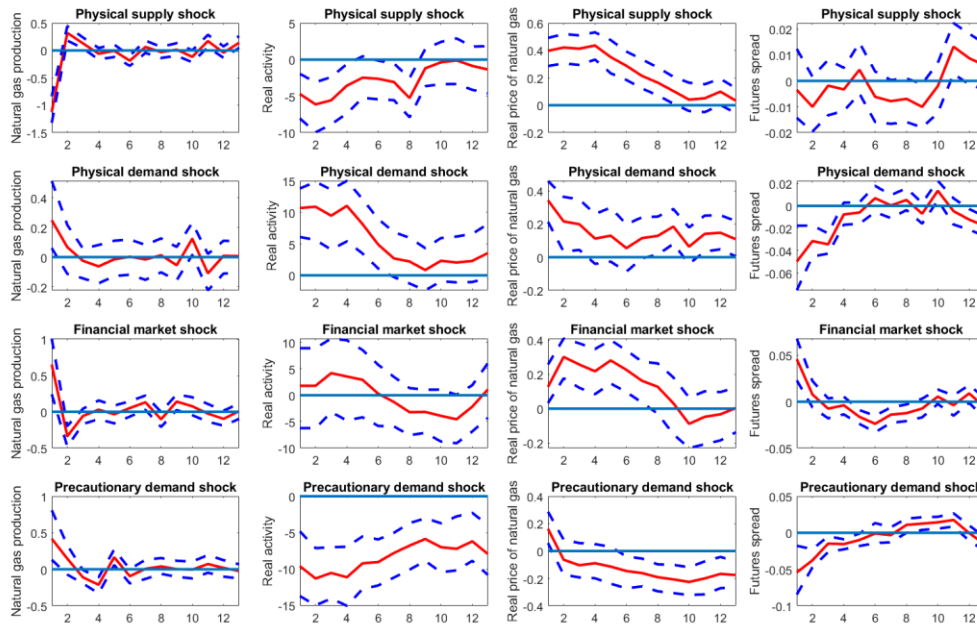


Notes: Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands.

We also estimate the model for additional maturities of the futures spread, specifically the 6-month and 12-month spreads; these results are reported in Appendix A. A forecast error variance decomposition suggests that there are substantial differences in the contribution of each shock to the variation in the real price of natural gas (see Table 4). Specifically, the share of natural gas price fluctuations explained by the individual shocks differs quite substantially

depending on the maturity in the futures spread and whether demand is measured by real activity or natural gas consumption. However, the financial market shock is able to capture more of the variation in the price than the inventory demand shock in the Kilian-Murphy model. These differences motivate the estimation of a model which is able to capture changes in natural gas futures prices at all maturity horizons simultaneously.

Figure 4. Results from the Valenti model with real activity and the 3-months futures spread



Notes: Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands.

Table 4. Forecast error variance decomposition of the real price of natural gas

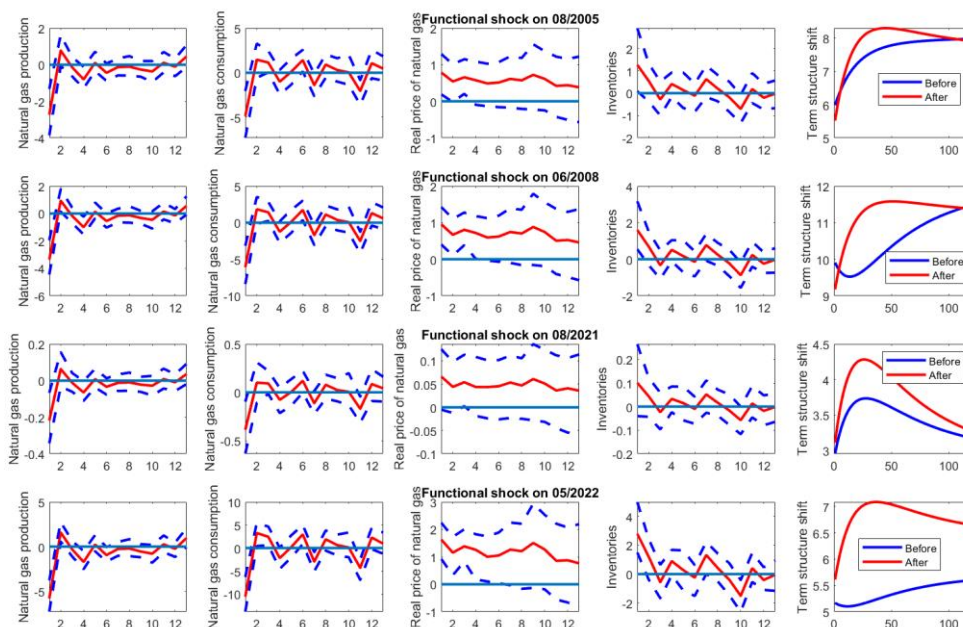
	Supply shock	Demand shock	Financial shock	Precautionary demand shock
Valenti 3-months model with consumption	63%	11%	16%	10%
Valenti 6-months model with consumption	62%	16%	12%	10%
Valenti 12-months model with consumption	58%	26%	6%	11%
Valenti 3-months model with real activity	42%	18%	21%	18%
Valenti 6-months model with real activity	38%	25%	17%	20%
Valenti 12-months model with real activity	38%	36%	9%	16%

Notes: Forecast error variance decomposition of the variation in the real price of natural gas to the identified shocks for different specifications of the Valenti model.

4.4 Results from the model with functional natural gas price shocks

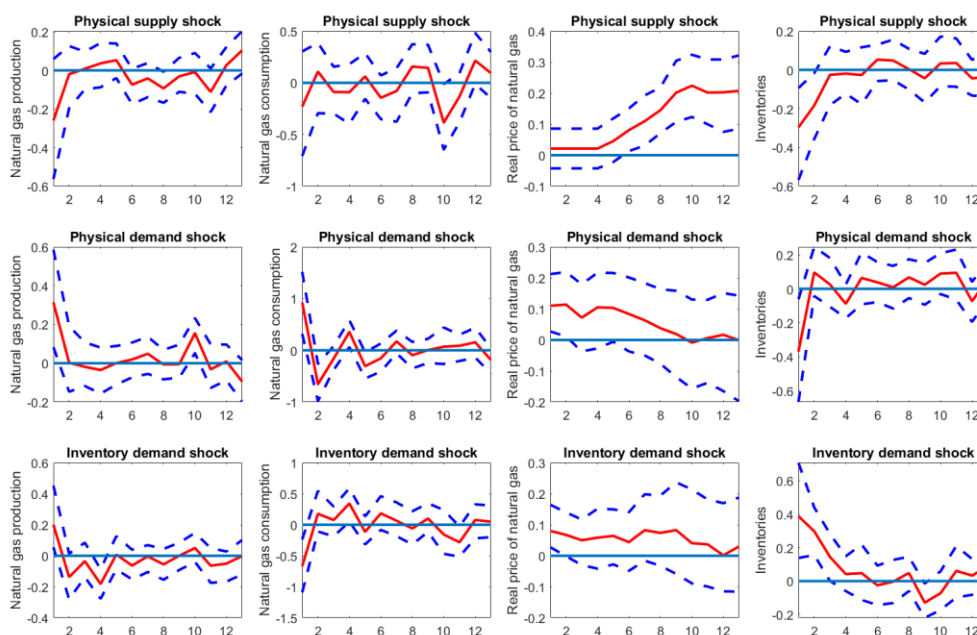
In this section we report the results of the model including the functional natural gas price shocks. One can easily use them to examine individual events during which natural gas prices were rising. We consider four important ones, namely Hurricane Katrina in August 2005, the period in June 2008 shortly before the financial crisis, the period of low temperatures in August 2021 and that in May 2022, shortly after the Russian invasion of Ukraine. Figures 5 and 7 show the responses of each of the variables to the functional shocks on each of those dates for the models including consumption and real activity respectively. In the former case functional shocks seem to have led to an upward shift in the term structure, especially at medium horizons, which results in a more humped shape of the natural gas term structure. The response of production and consumption is initially negative and short-lived in the former case, but more volatile in the latter. As one would expect, the real price of natural gas increases on impact and the effect is persistent over the response horizon. Inventories also increase initially but fluctuate subsequently. The responses of the variables to the other shocks in the model, shown in Figure 6, are similar but suggest that supply shocks have increasingly positive effects on the real price of natural gas.

Figure 5. Responses to functional shocks in the model with consumption



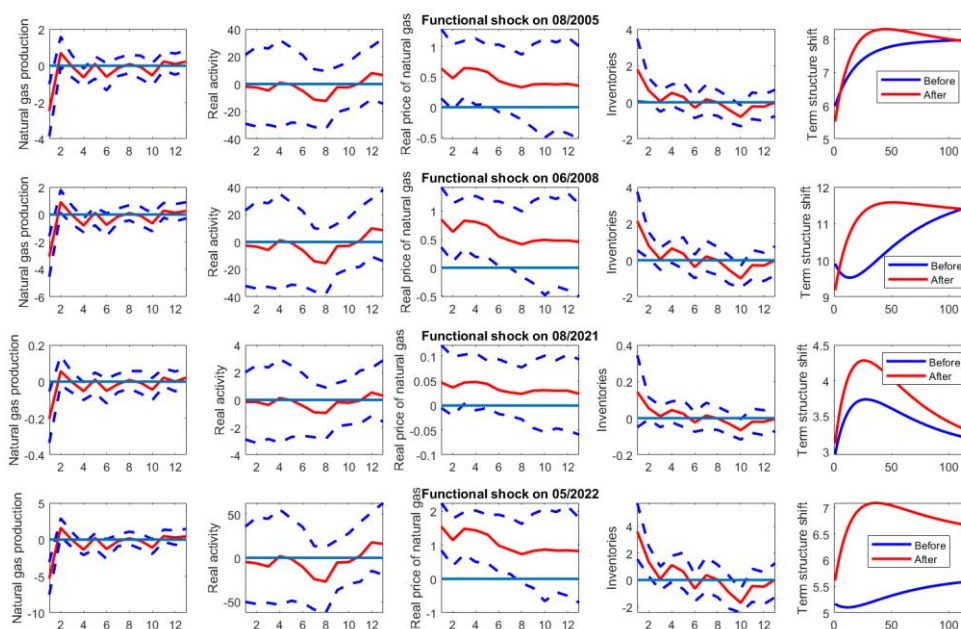
Notes: Structural impulse responses and term structure shifts. In the first four graphs in each row, the solid red lines indicate the closest to median responses from the admissible models and the dashed blue lines correspond to the 68% error bands. In the last graph in each row the solid blue line indicates the term structure before the shock and the solid red line the term structure after the shock.

Figure 6. Responses to other shocks in the model with consumption



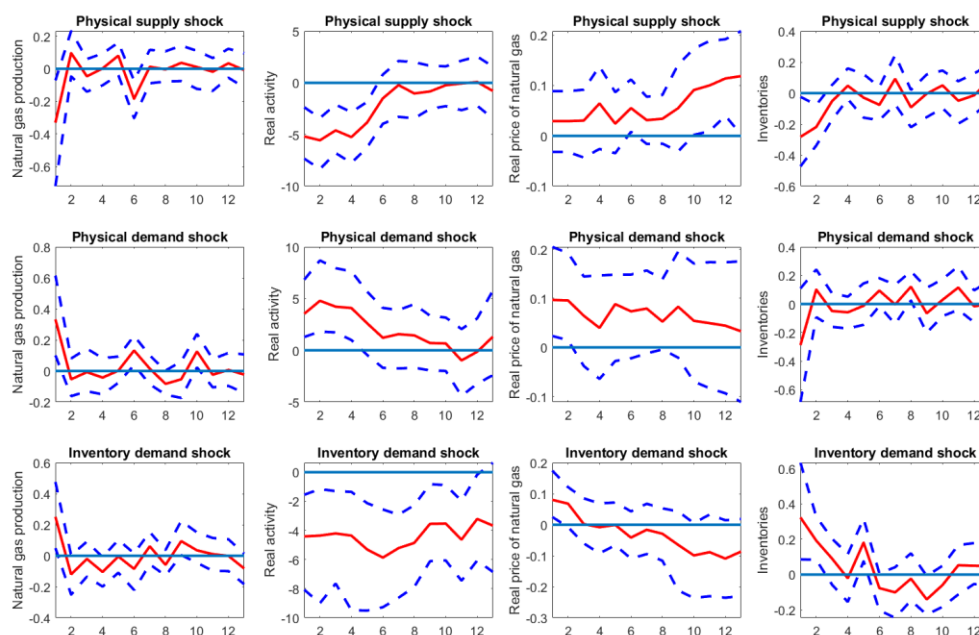
Notes: Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands.

Figure 7. Responses to functional shocks in the model with real activity



Notes: Structural impulse responses and term structure shifts. In the first four graphs in each row, the solid red lines indicate the closest to median responses from the admissible models and the dashed blue lines correspond to the 68% error bands. In the last graph in each row the solid blue line indicates the term structure before the shock and the solid red line the term structure after the shock.

Figure 8. Responses to other shocks in the model with real activity



Notes: Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands.

The results of the model with real activity (see Figure 7) are almost identical, with the exception of real activity itself, which does not seem to respond much to the functional shocks. The responses to the other shocks (see Figure 8) are similar to those obtained from the Kilian-Murphy model. Compared to the previous models a notable difference is again the increasing effect of a supply shock on the real price of natural gas.

The forecast error variance decomposition suggests that in the model with consumption 18% of the variation in the real price of natural gas can be attributed to a physical supply shock, 12% to a physical demand shock, 8% to an inventory demand shock, 47% to the functional natural gas price shocks, and the remainder to the residual shock. In the model with real activity only 8% of the variation in the real price of natural gas is due to a physical supply shock and 11% to a physical demand shock. The inventory demand shock now accounts for 9% and the functional shocks for 58% of fluctuations in the real price of natural gas, while 15% of them are due to the residual shock. Since consumption captures demand for natural gas specifically and real activity global demand generally, it is not surprising that shocks to the former are able to explain more of the variation in the real price of natural gas.

Next, we perform a shock decomposition exercise of the responses of all variables to the functional shocks on the four dates previously specified; this allows us to assess which term structure factor made the largest contribution. Figure 9 shows the results of the model with natural gas consumption. It can be seen that the curvature factor is the main driver of real natural gas prices as well production, consumption and inventory changes. This suggests that the physical natural gas markets are primarily driven by medium-term expectations about developments in the natural gas market, since a change in the curvature factor is associated with changes to medium-term expectations. During the shock in October 2005, the curvature factor increased, which resulted in a steepening of the term structure by increasing the size of its hump at medium horizons, i.e. expectations of medium-term prices increased relative to short- and long-term ones. The price response was positive and the market moved into contango making it worthwhile to hold inventories – these increased immediately in response to the change in the curvature factor and were then sold forward for delivery at medium horizons, which is when they started falling again. Producers reacted by lowering production, taking the change in medium-term expectations as a sign of higher prices in the future, but then increasing it towards the end of the response horizon in order to sell at the higher prices. The behaviour of production and inventories is consistent with theory. Consumption increased, which suggests that the information channel operates most strongly here, and that producers interpret the rising medium-term futures prices as a signal of a strengthening market (Sockin and Xiong, 2013). These effects are identical for the shocks on all other dates. In all cases, the price response is persistent while the responses of all other variables are only transitory, suggesting that speculative shocks stemming from the futures markets can permanently raise prices in the physical markets.

Figure 10 reports the shock decomposition for the model with real activity. The main difference is that real activity responds negatively to the curvature factor change, in contrast to the positive response of natural gas consumption found previously. These results are more in line with a stronger cost channel. For comparison we also focus on some periods during which the spot price of natural gas decreased to assess whether this was caused by a fall in the curvature factor and medium-term expectations. These results are reported in Figures B1 and B2 in Appendix B. As can be seen, the observed effects are essentially the opposite to the previously estimated ones: in all cases, medium-term price expectations decrease relative to short- and long-term

ones; and the spot price in the physical market falls alongside consumption and inventories while production increases.

Figure 9. Decomposition of responses to functional shocks in the model with consumption

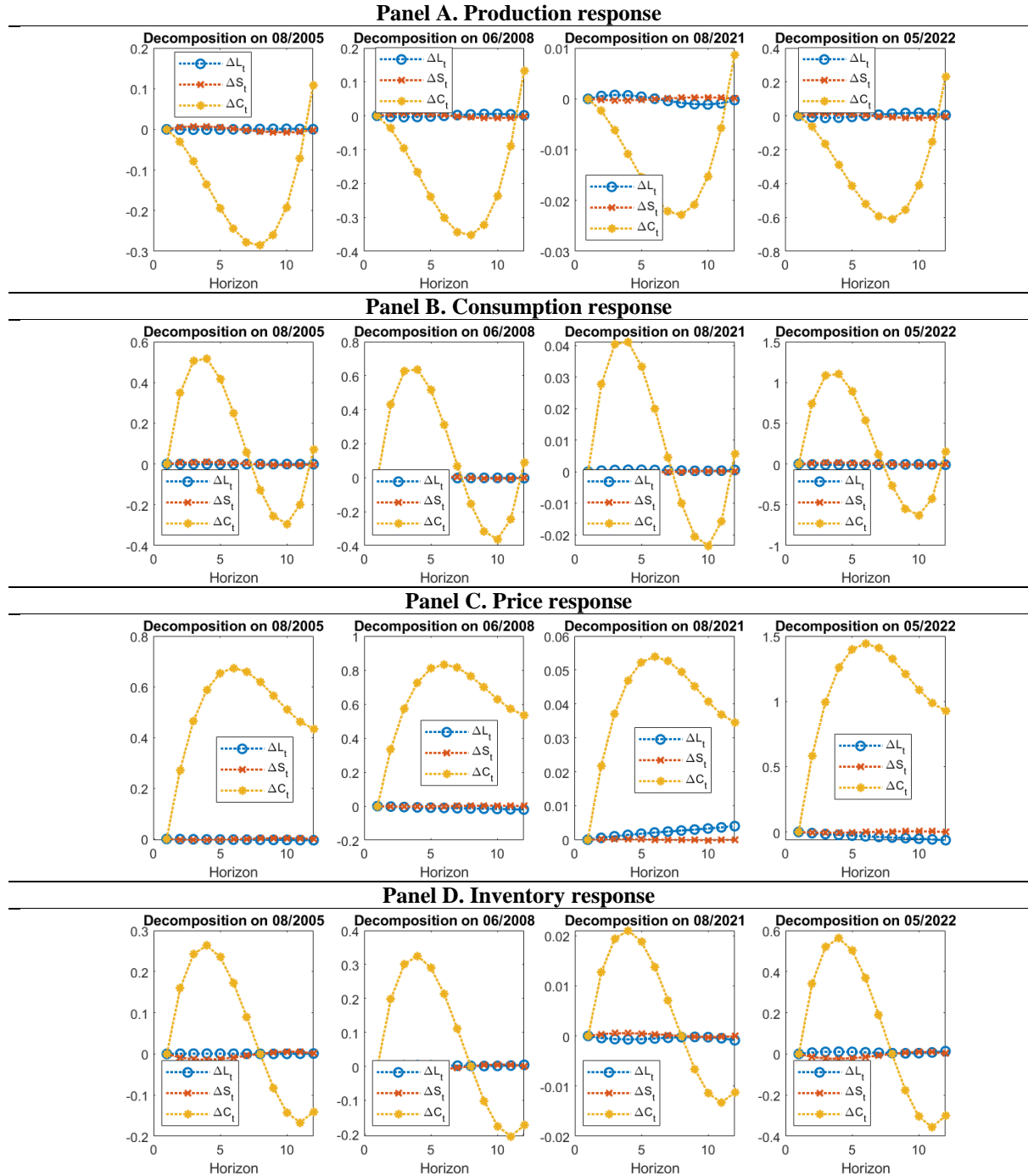
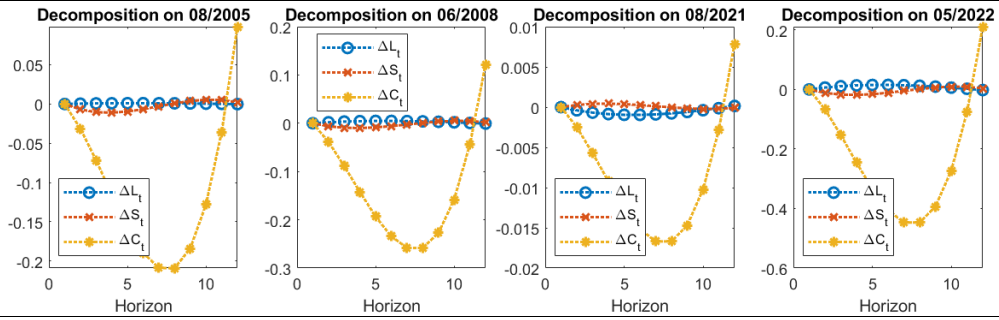
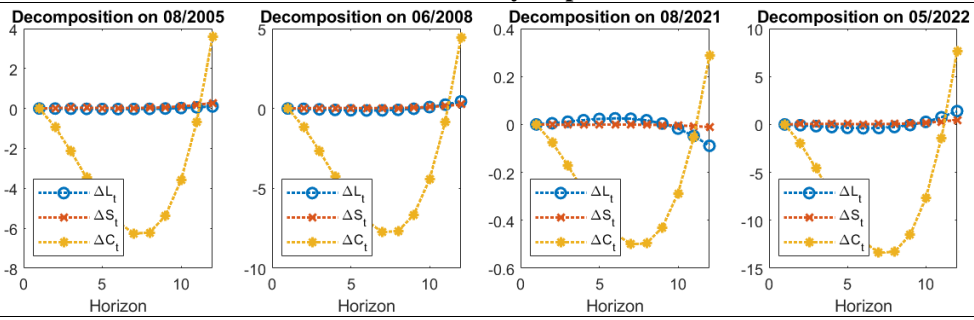


Figure 10. Decomposition of responses to functional shocks in the model with real activity

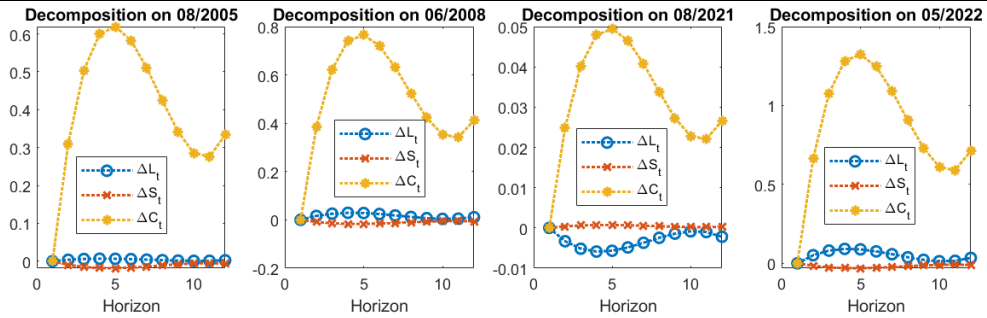
Panel A. Production response



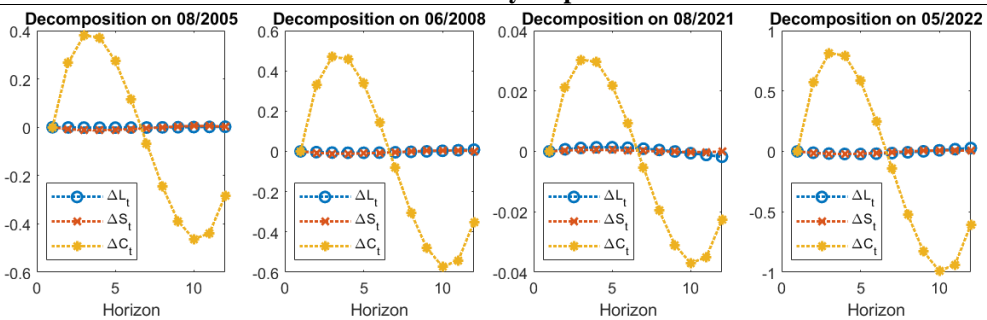
Panel B. Real activity response



Panel C. Price response

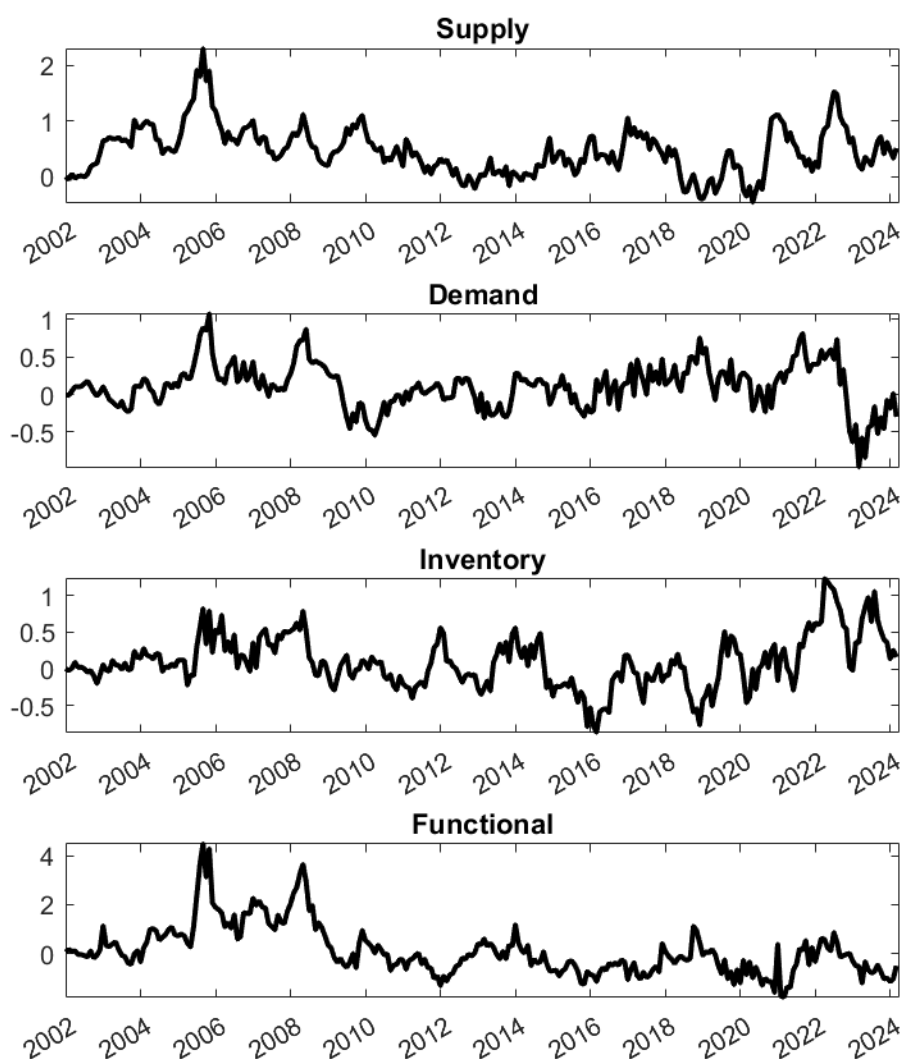


Panel D. Inventory response



Notes: Decomposition of responses to term structure factors.

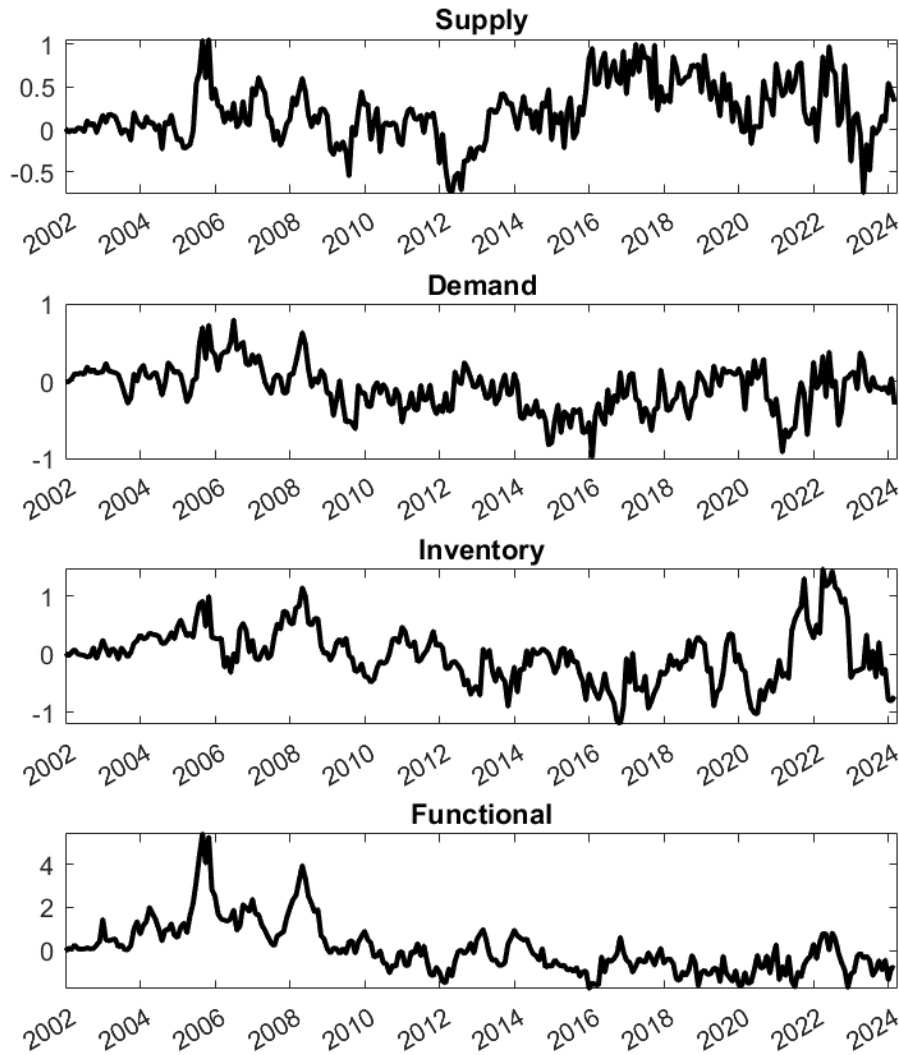
Figure 11. Historical decomposition of the price of natural gas in the model with consumption



Notes: Historical decomposition of the real price of natural gas.

Figures 11 and 12 present the historical decomposition of the real price of natural gas for the various shocks identified in the models with consumption and real activity respectively. It appears that natural gas supply and the functional shocks were the main drivers of natural gas price increases during several periods, which is consistent with our previous findings regarding their persistent effects on the physical price of natural gas. Finally, in the model with real activity, supply shocks seem to play a much more important role in recent years.

Figure 12. Historical decomposition of the price of natural gas in the model with real activity



Notes: Historical decomposition of the real price of natural gas.

5. Conclusions

This paper aims to provide some new insights into the drivers of the real price of natural gas with a specific focus on the role of expectations and speculation in the natural gas markets. For this purpose, three different SVAR specifications have been considered, two of which have previously been estimated in the literature in the case of the oil market. The first follows the Kilian and Murphy (2014) model focusing on speculative demand arising from changes in

inventories; the second the Valenti (2022) model incorporating instead the futures spread; the third introduces functional shocks derived from the risk-adjusted natural gas futures term structure to represent expectations (Inoue and Rossi, 2021).

The results can be summarised as follows. First, the real price of natural gas seems to respond less to speculative activity and expectations reflected in inventory changes than previously found in the case of the oil market, where speculative shocks are the main determinant of the real price of oil, followed by demand shocks. Second, the functional natural gas price expectations shocks have persistent effects on the spot price of natural gas. Therefore the omission of futures prices from natural gas market models might result in overestimating the role of demand and supply factors in driving spot prices. Third, the spot price of natural gas is primarily driven by the curvature factor of the natural gas term structure, which suggests that it responds to medium-term expectations about future price developments. Fourth, the historical and forecast error variation decompositions suggest that the functional shocks, which represent shifts in the expected future price of natural gas, are able to explain around half of the movements in the real price of natural gas. This means that the expectations-driven component of the natural gas price is well-explained by the functional shocks. Finally, unlike in empirical studies of the oil market, we find less evidence for a large role played by demand shocks in the natural gas markets. Instead, natural gas production, together with speculative activity represented by the functional shocks, appear to be the main drivers of natural gas price fluctuations. These findings appear robust to using different measures of demand.

On the whole, our evidence suggests a higher degree of integration between physical and futures markets in the case of natural gas relative to crude oil. This poses some challenges to policymakers. First, the greater importance of supply shocks compared to demand shocks for the price of natural gas makes policy interventions difficult. Second, by affecting the incentives faced by producers in the natural gas markets, speculators can put considerable pressures on prices. This effect as well as the persistent effects of speculative shocks on the real price of natural gas need to be monitored so that they do not become embedded or spill over to other prices.

References

- Acharya, V.V., Lochstoer, L.A. and Ramadorai, T., 2013. Limits to arbitrage and hedging: Evidence from commodity markets. *Journal of Financial Economics*, 109(2), pp.441-465.
- Anderl, C. and Caporale, G.M., 2024. Functional Oil Price Expectations Shocks and Inflation. *Journal of Futures Markets*.
- Basu, D. and Miffre, J., 2013. Capturing the risk premium of commodity futures: The role of hedging pressure. *Journal of Banking & Finance*, 37(7), pp.2652-2664.
- Baumeister, C. and Hamilton, J.D., 2019. Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. *American Economic Review*, 109(5), pp.1873-1910.
- Baumeister, C. and Kilian, L., 2014. A General Approach to Recovering Market Expectations from Futures Prices with an Application to Crude Oil. *CEPR Discussion Paper*, No. DP10162.
- Chinn, M.D., LeBlanc, M. and Coibion, O., 2005. The predictive content of energy futures: an update on petroleum, natural gas, heating oil and gasoline. *NBER Working Paper*, No. 11033.
- Chiou-Wei, S.Z., Linn, S.C. and Zhu, Z., 2014. The response of US natural gas futures and spot prices to storage change surprises: Fundamental information and the effect of escalating physical gas production. *Journal of International Money and Finance*, 42, pp.156-173.
- Diebold, F.X. and Li, C., 2006. Forecasting the term structure of government bond yields. *Journal of Econometrics*, 130(2), pp.337-364.
- Fattouh, B., Kilian, L. and Mahadeva, L., 2013. The role of speculation in oil markets: What have we learned so far?. *The Energy Journal*, 34(3), pp.7-33.
- Ghoddusi, H., 2016. Integration of physical and futures prices in the US natural gas market. *Energy Economics*, 56, pp.229-238.
- Hamilton, J.D., 2009. Causes and Consequences of the Oil Shock of 2007-08, *National Bureau of Economic Research*, Working paper No. w15002.
- Hamilton, J.D. and Wu, J.C., 2014. Risk premia in crude oil futures prices. *Journal of International Money and Finance*, 42, pp.9-37.

Havranek, T., Irsova, Z. and Janda, K., 2012. Demand for gasoline is more price-inelastic than commonly thought. *Energy Economics*, 34(1), pp.201-207.

Inoue, A. and Rossi, B., 2021. A new approach to measuring economic policy shocks, with an application to conventional and unconventional monetary policy. *Quantitative Economics*, 12(4), pp.1085-1138.

Juvenal, L. and Petrella, I., 2015. Speculation in the oil market. *Journal of Applied Econometrics*, 30(4), pp.621-649.

Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99(3), pp.1053-1069.

Kilian, L. and Lee, T.K., 2014. Quantifying the speculative component in the real price of oil: The role of global oil inventories. *Journal of International Money and Finance*, 42, pp.71-87.

Kilian, L. and Murphy, D.P., 2014. The role of inventories and speculative trading in the global market for crude oil. *Journal of Applied Econometrics*, 29(3), pp.454-478.

Liddle, B., Smyth, R. and Zhang, X., 2020. Time-varying income and price elasticities for energy demand: Evidence from a middle-income panel. *Energy Economics*, 86, p.104681.

Lombardi, M. J. and Van Robays, I., 2011. Do Financial Investors Destabilize the Oil Price? *European Central Bank Working Paper*, No 1346.

Manera, M., Nicolini, M. and Vignati, I., 2016. Modelling futures price volatility in energy markets: Is there a role for financial speculation?. *Energy Economics*, 53, pp.220-229.

Nelson, C.R. and Siegel, A.F., 1987. Parsimonious modeling of yield curves. *Journal of Business*, pp.473-489.

Rubio-Ramirez, J.F., Waggoner, D.F. and Zha, T., 2010. Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies*, 77(2), pp.665-696.

Sanders, D.R. and Irwin, S.H., 2017. Bubbles, froth and facts: Another look at the Masters Hypothesis in commodity futures markets. *Journal of Agricultural Economics*, 68(2), pp.345-365.

Sockin M. and Xiong, W., 2013. *Feedback effects of commodity futures prices*. Working Paper. Princeton University.

Valenti, D., 2022. Modelling the Global Price of Oil: Is there any Role for the Oil Futures-spot Spread?. *The Energy Journal*, 43(2), pp.41-66.

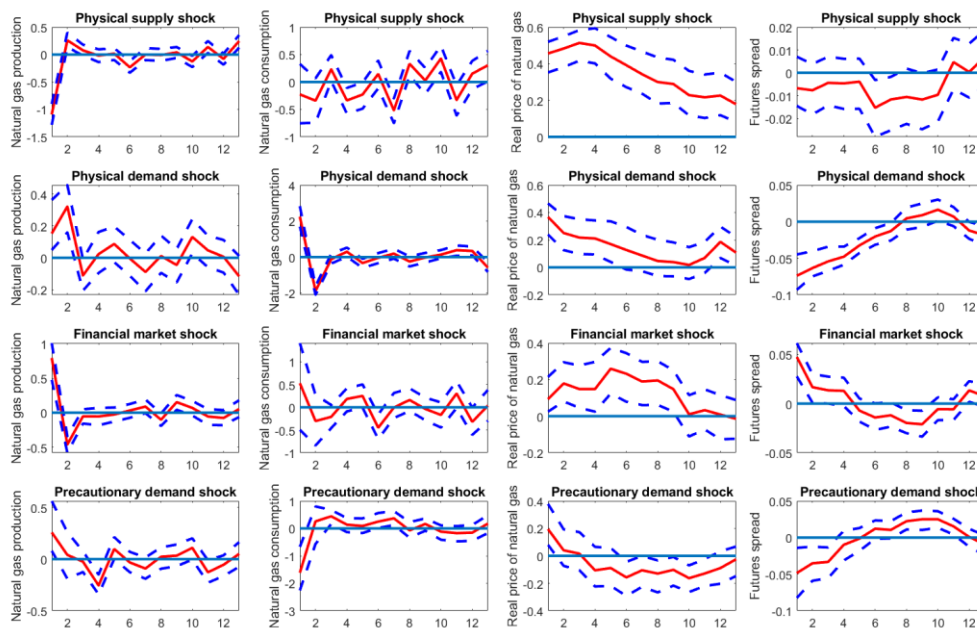
Valenti, D., Manera, M. and Sbuely, A., 2020. Interpreting the oil risk premium: Do oil price shocks matter?. *Energy Economics*, 91, p.104906.

Wang, T., Zhang, D. and Broadstock, D.C., 2019. Financialization, fundamentals, and the time-varying determinants of US natural gas prices. *Energy Economics*, 80, pp.707-719.

Zagaglia, P., 2010. Macroeconomic factors and oil futures prices: a data-rich model. *Energy Economics*, 32(2), pp.409-417.

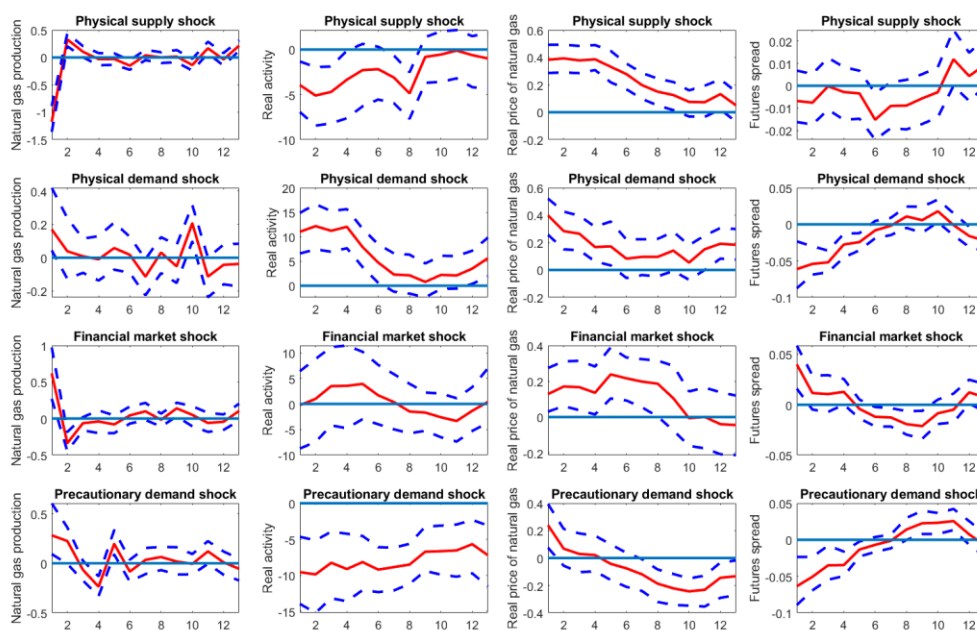
Appendix A. Results of Valenti models with different maturities

Figure A1. Results from the Valenti model with consumption and the 6-months futures spread



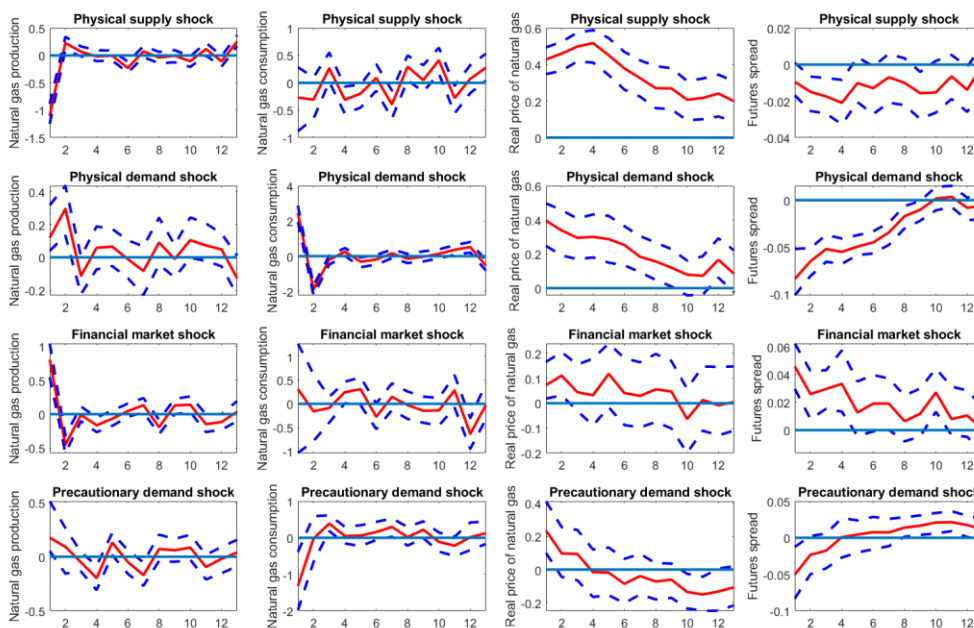
Notes: Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands.

Figure A2. Results from the Valenti model with real activity and the 6-months futures spread



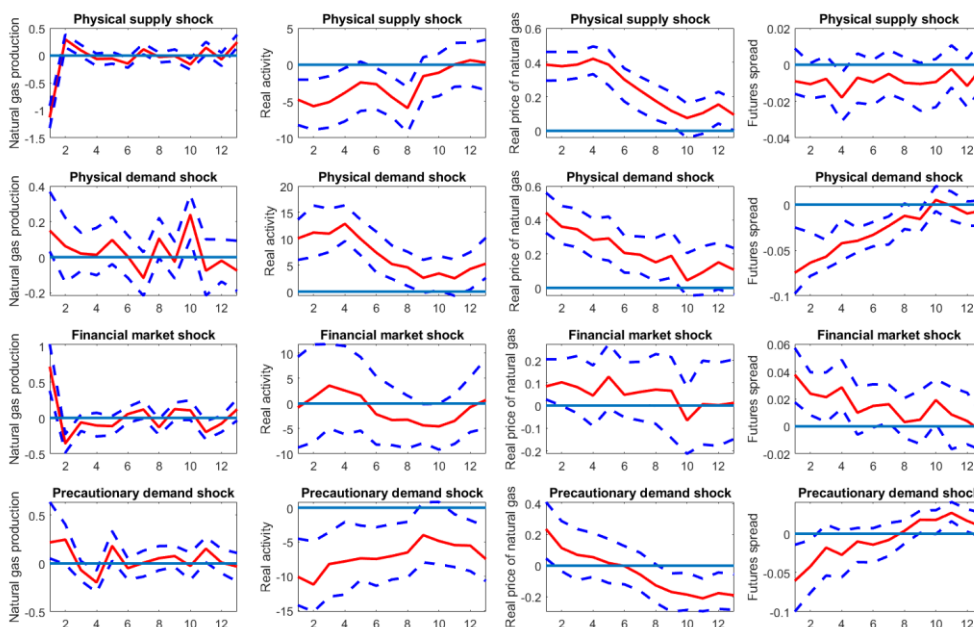
Notes: Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands.

Figure A3. Results from the Valenti model with consumption and the 12-months futures spread



Notes: Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands.

Figure A4. Results from the Valenti model with real activity and the 12-months futures spread



Notes: Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands.

Appendix B. Shock decomposition results for price decreases

Figure B1. Decomposition of responses to functional shocks in the model with consumption during periods of price decreases

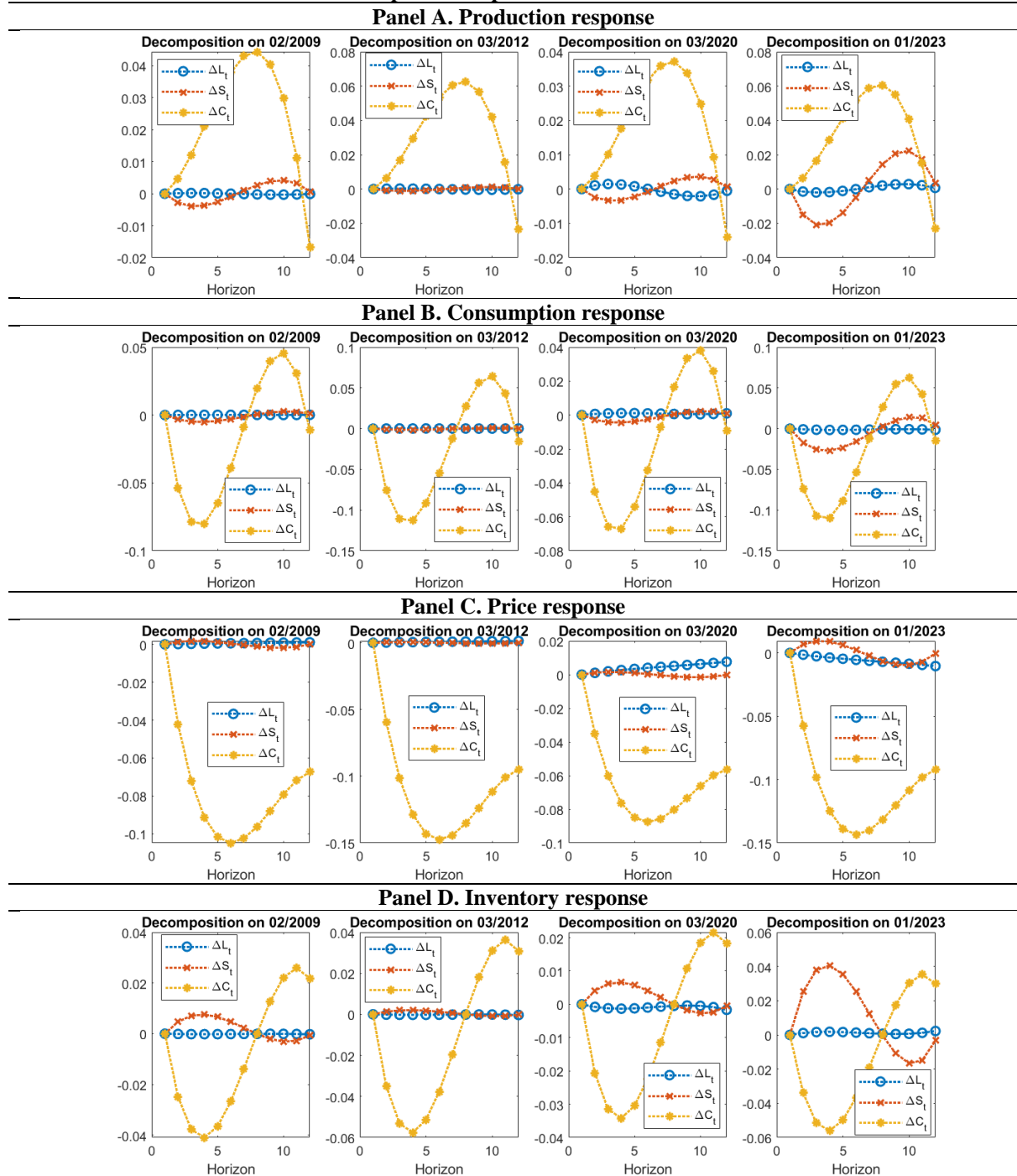
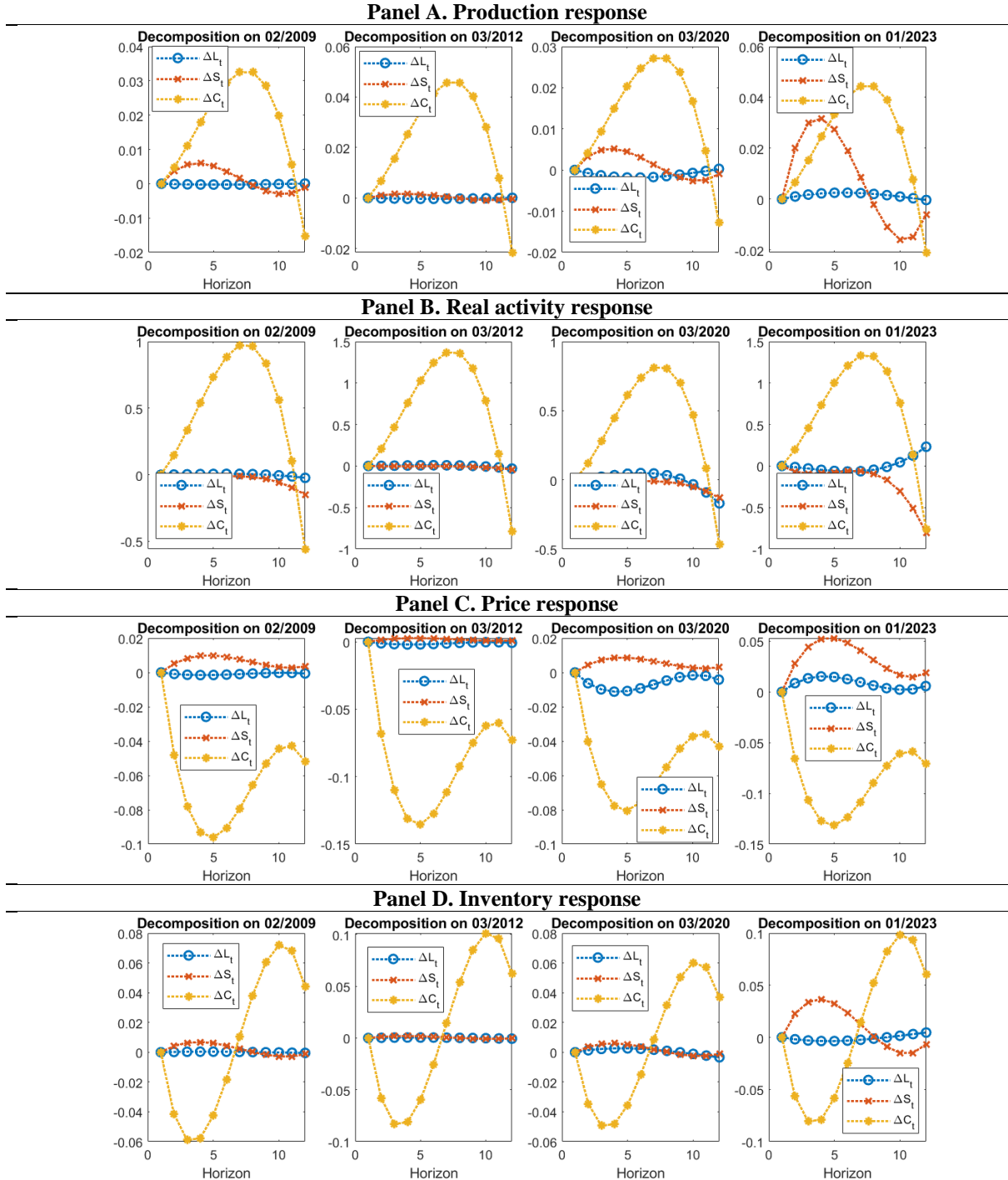


Figure B2. Decomposition of responses to functional shocks in the model with real activity during periods of price decreases



Notes: Decomposition of responses to term structure factors.