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Expectations and Speculation in the US Natural Gas Market

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ABSTRACT

This paper aims to assess the role of expectations as a determinant of the real price of natural gas in the US. Three specifications of a structural VAR (SVAR) model are estimated to identify an expectations-driven speculative demand shock. The first includes natural gas inventories, consistently with the theory of storage; the second the risk-adjusted futures spread; the third functional shocks defined as shifts in the entire risk-adjusted natural gas futures term structure. The results of the third model suggest that speculative demand shocks have sizeable effects on the real price of natural gas. A shock decomposition exercise shows that increases in the price of natural gas are driven primarily by changes in the curvature of its futures term structure, which indicates that medium-term expectations or large differences between short- and long-term expectations are the main determinant of increases in the spot price of natural gas. It appears that speculative demand shocks are most relevant for the price of natural gas in the model with functional shocks, where they account for around 40% of its variation.

JEL Classification: D84, G15, Q41, Q43

1 | Introduction

The economics literature has shown great interest in understanding the determinants of energy prices, both in the case of crude oil (Kilian 2009; Kilian and Murphy 2014; Cross et al. 2022) and in the case of natural gas (Wiggins and Etienne 2017; Rubaszek et al. 2021). Apart from standard demand and supply forces, unobservable shifts in expectations about future supply and demand have been identified as important drivers of prices in energy markets. In the oil market, this was formally discussed and empirically tested by Kilian (2009), who identified a precautionary demand shock which captures changes in the price of oil driven by uncertainty about the availability of future oil supplies. This shock can be considered a shift in the conditional variance, rather than the conditional mean, of expected oil supply shortfalls relative to expected demand. Alquist and Kilian (2010) provided a theoretical framework to interpret these findings. Kilian and Murphy (2014) later identified a speculative demand shock through appropriate sign restrictions in an oil market VAR (vector autoregressive) model which included inventories. In contrast to Kilian (2009), their shock represented a shift in first moment expectations. Their work was expanded by Kilian and Lee (2014), who obtained similar results by using different measures of inventories. Cross et al. (2022) then were the first ones to identify both a speculative demand shock and an uncertainty-driven precautionary demand shock separately, and found that oil price fluctuations are determined primarily by the latter. These papers take different approaches to identify unobservable underlying shifts in expectations which can account for price increases.

While the issues mentioned above have been extensively analysed in the case of the oil market, much less evidence is currently available for the natural gas market, despite its growing importance in recent decades. Unlike oil markets, natural gas markets are highly localised; in our case, we focus on the US natural gas market. Existing studies investigate the role of speculative activity by including inventories in a

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structural VAR model of the US natural gas market (Wiggins and Etienne 2017; Rubaszek et al. 2021). While the addition of inventories provides an understanding of the role of speculation in the natural gas market, they tend to represent the realised accumulation of physical natural gas, which can be backward-looking. An alternative way to capture expectations is to consider natural gas futures prices. According to the Theory of Storage, inventories in the physical market are related to futures prices via the convenience yield, where high (low) inventory levels indicate a low (high) convenience yield, which moves futures prices above (below) spot prices (Valenti et al. 2020). From the perspective of precautionary demand, natural gas inventories can also be accumulated in anticipation of adverse future shocks. In practise, speculative and precautionary demand shocks are difficult to disentangle (Cross et al. 2022). An alternative way to capture expectations is to consider natural gas futures prices, which reflect not only financial markets but also forward-looking expectations and therefore provide an interesting alternative to physical inventories. In particular, unlike inventory holders, participants in the futures markets do not need to engage in any activity in the physical markets. Given this nuance, the present study aims to better understand speculative activity in the natural gas markets and add to the existing literature by investigating whether inventories best capture speculative activity and expectations compared to information contained in futures prices and the futures term structure. We identify three different ways to represent speculation. First, we identify a speculative demand shock through an appropriate identification scheme in a baseline SVAR (structural VAR) model, which includes natural gas production, real activity, the real price of natural gas, and natural gas inventories as in Kilian and Murphy (2014). Second, we use the risk-premium adjusted futures spread, namely the percent deviation of the expected future spot price from the actual spot price, which is representative of the convenience yield expressed with the opposite sign (Alquist and Kilian 2010; 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, which includes inventories and differentiates between natural gas flow supply and flow demand shocks, an expectations-driven speculative demand shock, and a residual demand shock, similar to the oil market model by Kilian and Murphy (2014). Next, given the discussion in Baumeister and Kilian (2018) and Valenti (2022), we estimate a SVAR model that contains the risk-adjusted futures spread. We 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, which can be seen as a close approximation of expected future spot prices (Baumeister and Kilian 2018). Finally, we include in the SVAR analysis functional natural gas price shocks, which represent shifts in the entire risk-adjusted natural gas futures term structure. 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). 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. Another extension is provided by Cross et al. (2022), who include an oil market uncertainty measure in their model which allows them to identify a precautionary demand shock separately from a speculative demand one. Their results imply a primary role for precautionary demand shocks in driving real oil price dynamics. Valenti (2022) instead replaces crude oil inventories with the futures spread. The identified financial market shock appears to have played an important role for rising oil prices during the 2003–2008 period. His analysis has two shortcomings. First, contrary to what he claims, the restrictions do not allow for identifying a financial market and a precautionary demand shock respectively. Second, it does not take into account the possible existence of a risk premium which is important to obtain an accurate measure of the expected future spot price.

Baumeister and Kilian (2018) highlight the importance of accounting for the existence of such 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 in 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.

The literature on the natural gas market includes a few studies concerned with understanding market dynamics in the US. Wiggins and Etienne (2017), for instance, estimate a structural VAR model with sign restrictions of the US natural gas market. Supply and demand shocks appear most relevant for explaining movements in the price of natural gas, with speculative demand shocks contributing around 15% to the evolution of the natural gas price. Using a Bayesian SVAR model, Rubaszek et al. (2021) find that market-specific demand shocks are most relevant for US natural gas prices, explaining between 65% and 80% of their movements, compared to supply or inventory shocks, which can account for 10% and 20%, respectively. Rubaszek and Uddin (2020) estimate a Threshold-SVAR model of the US natural gas market and show that the relationship between spot and futures prices is stronger when the level of underground storage is low and that natural gas prices are more responsive to structural shocks when inventory levels are low. While most of these studies include inventories as an important component of the natural gas market, speculative activity remains a sideline rather than a focus of these studies.

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 similar to the oil market model by Kilian and Murphy (2014), who identify a speculative demand shock through appropriate restrictions in a VAR model that includes inventories. 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 of the following form:

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

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 is a measure of real economic activity, 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, price and inventories data. Following Kilian and Murphy (2014) we allow for up to 24 lags in the model.

There are four structural shocks in the model (see Table 1 for a summary). The first shock corresponds to a natural gas flow supply shock, which 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 flow supply shock triggers a predictable increase in the price of natural gas. We impose the restrictions for the flow supply shock dynamically so that they are valid for a response horizon of 12 months. The other three shocks are different types of demand shocks. First, as in the case of an oil flow demand shock in the oil markets, a natural gas flow demand shock increases the real price of natural gas and production in order to satisfy the extra consumption demand. Second, 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 demand shock, inventories increase alongside the price of natural gas. Consequently, natural gas producers are incentivised to increase their production, and real activity 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. The third demand shock is a residual one that captures other factors, such as weather or technology changes, not already incorporated in the first two shocks. Therefore, the response is expected to be positive in the case of the real price and zero in the case of all other variables. This shock is not typically identified in existing SVAR models of the US natural gas market (see, for instance, Wiggins and Etienne 2017). We use a Normal-Inverse-Wishart prior and the algorithm by Arias et al. (2018).

Kilian and Murphy (2012) question the use of posterior median responses to infer the responses to structural shocks in sign-identified VAR models of markets. Specifically, they show that sign restrictions themselves are insufficient to identify demand

TABLE 1 | Sign restrictions in the VAR model with inventories.

	Flow supply shock	Flow demand shock	Speculative demand shock	Residual demand shock
Natural gas production	−	+	+	0
Real activity	−	+	−	0
Real price of natural gas	+	+	+	+
Natural gas inventories			+	0

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

and supply shocks in oil market models. Instead, they suggest combining sign restrictions with empirically plausible bounds on the size of the short-run supply elasticity and the impact response of real activity. In this way, one can obtain a subset of admissible models with qualitatively similar estimates to derive the closest-to-median responses that satisfy all identifying restrictions. This approach is also useful for VAR models of markets other than oil. Following Kilian and Murphy (2014), we impose bounds restrictions on the impact elasticity of natural gas flow demand and supply on the basis of the empirical findings of Hausman and Kellogg (2015). Since the demand elasticity has to be weakly negative, we impose an upper bound of zero and a lower bound of −0.22, which we later replace with −0.40; these values lie in between the long-run elasticities for the US residential and commercial sectors in Hausman and Kellogg (2015). For the short-run supply elasticity, we impose an upper bound of 0.09.

To test whether the VAR model contains sufficient information to provide the correct structural shocks, we follow the testing procedure for nonfundamentalness by Forni and Gambetti (2014). This involves estimating principal components from a large dataset of macroeconomic variables and testing whether the principal components Granger-cause the variables in the VAR model. If the null hypothesis of no Granger causality is rejected, then the variables in the original model are not informationally sufficient. In such a case, one needs to estimate a FAVAR (Factor-augmented VAR) model, which includes some of these factors in addition to the original variables in the VAR model. We use the out-of-sample Granger causality test by Gelper and Croux (2007) with 12 lags and two to ten principal components.

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. However, in the presence of a risk premium, estimates based on the standard futures spread are inaccurate, since only risk-premium adjusted futures prices can be regarded as appropriate representations of expected future spot prices. Baumeister and Kilian (2018) 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. 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. 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). We estimate the model as in (1) but now replace the natural gas inventories with the risk-premium adjusted futures spread. This is obtained by first estimating the time-varying risk premium following the method by Hamilton and Wu (2014) and then subtracting the risk premium from the futures price for a given maturity, which gives us the risk-adjusted futures price or expected future spot price for this maturity. The speculative demand shock represents 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 risk-adjusted futures price from the spot price of natural gas, namely $\omega_t = \frac{F_t - P_t}{P_t}$. Table 2 outlines the full set of restrictions.

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, that is 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 rational expectation of future spot prices for different maturities. We estimate the term structure parameters using the Nelson and Siegel (1987) model:

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

TABLE 2 | Sign restrictions in the VAR with the futures spread.

	Flow supply shock	Flow demand shock	Speculative demand shock	Residual demand shock
Natural gas production	−	+	+	0
Real activity	−	+	−	0
Real price of natural gas	+	+	+	+
Futures spread			+	0

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

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 risk-adjusted futures prices are obtained using the Hamilton and Wu (2014) method before they are included in the Nelson-Siegel model. 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.

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 structure, alongside changes in the level and curvature, we are able to express shifts in speculative 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 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

TABLE 3 | Sign restrictions in the VAR model with functional shocks.

	Flow supply shock	Flow demand shock	Speculative demand shock	Residual demand shock
Natural gas production	−	+	+	0
Real activity	−	+	−	0
Real price of natural gas	+	+	+	+
Functional natural gas price shocks			+	0

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

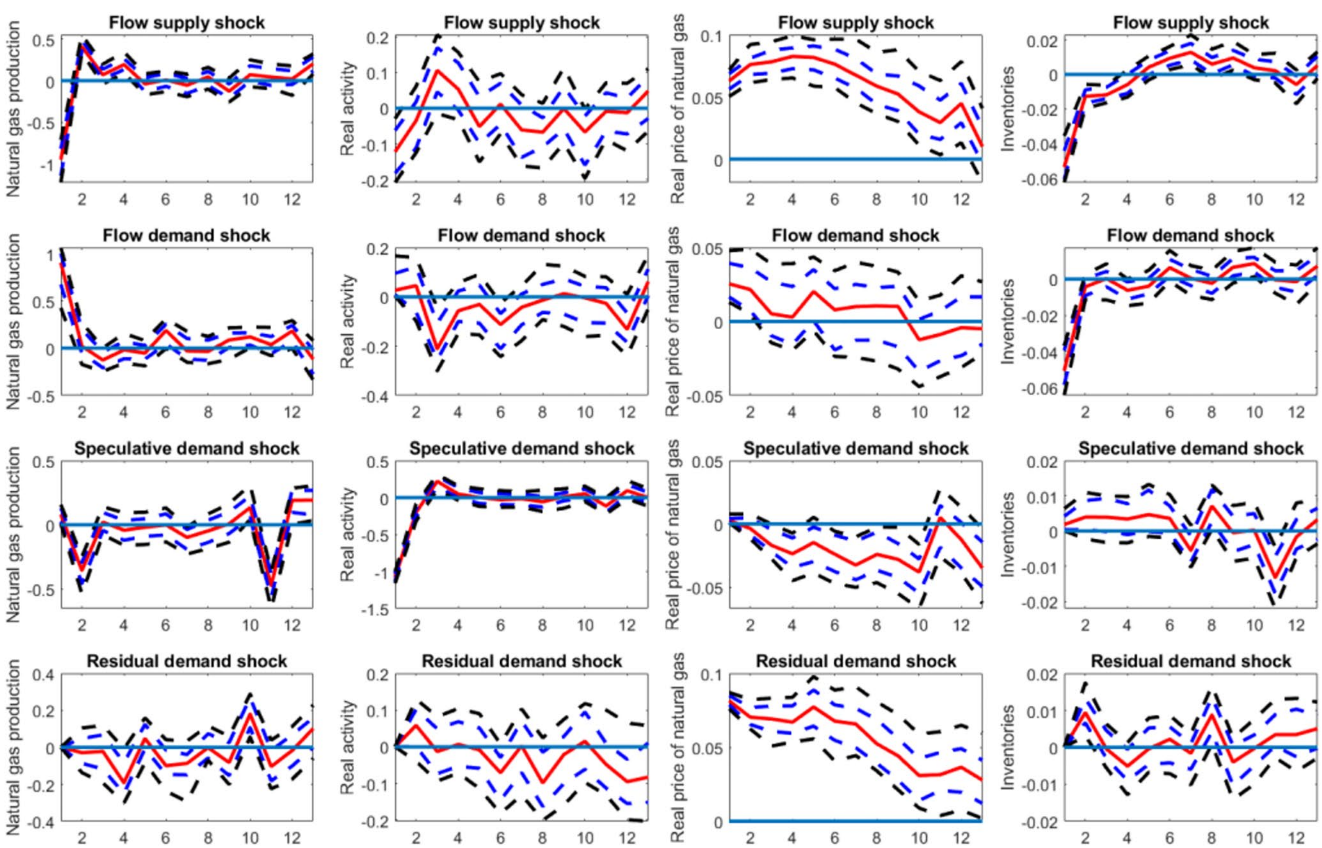

FIGURE 1 | Results from the model with inventories. Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands and the dashed black lines to the 95% error bands. The response of natural gas production is in percent change, that of real activity in standard deviations, that of the real price of natural gas in percent and that of inventories in changes. The impulse horizon is in months. [Colour figure can be viewed at wileyonlinelibrary.com]

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 (2) but now replace the futures spread with the functional natural gas price shocks stemming from the futures markets. The sign restrictions and identified shocks are the same as before and summarised in Table 3. We evaluate the forecast error variance decomposition for the three models presented thus far. Here we use the posterior mean rather than the median, since the latter violates the adding up constraint. 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

We conduct the analysis for the US natural gas market.[2] 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, which enters the model in log levels. Since the spot price is only available since January 1997, the sample period goes from January 1997 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 to 12 months. Specifically, these are NG1-NG12 series obtained from Bloomberg. Natural gas production is the natural gas marketed production for the US obtained from the EIA and is expressed in percentage change. US real activity is measured by the Chicago Fed Real Activity Index (CFNAI). The series for natural gas inventories is the total underground storage volume obtained from the EIA for the US and is expressed in changes. For the nonfundamentalness test and principal components analysis, we use the FRED-MD dataset of macroeconomic variables as well as data on US natural gas exports and consumption obtained from the EIA.

4.2 | Results From the Model With Inventories

Figure 1 shows the results from the model inventories, similar to the Kilian and Murphy (2014) specification. As can be seen, an unexpected natural gas flow supply disruption first reduces production, but the effect is only transitory since after approximately 2 months production increases slightly before it reduces to fluctuating around zero. Real activity also falls on impact but starts increasing after 2 months and then falls again to move around the zero mark for the remainder of the

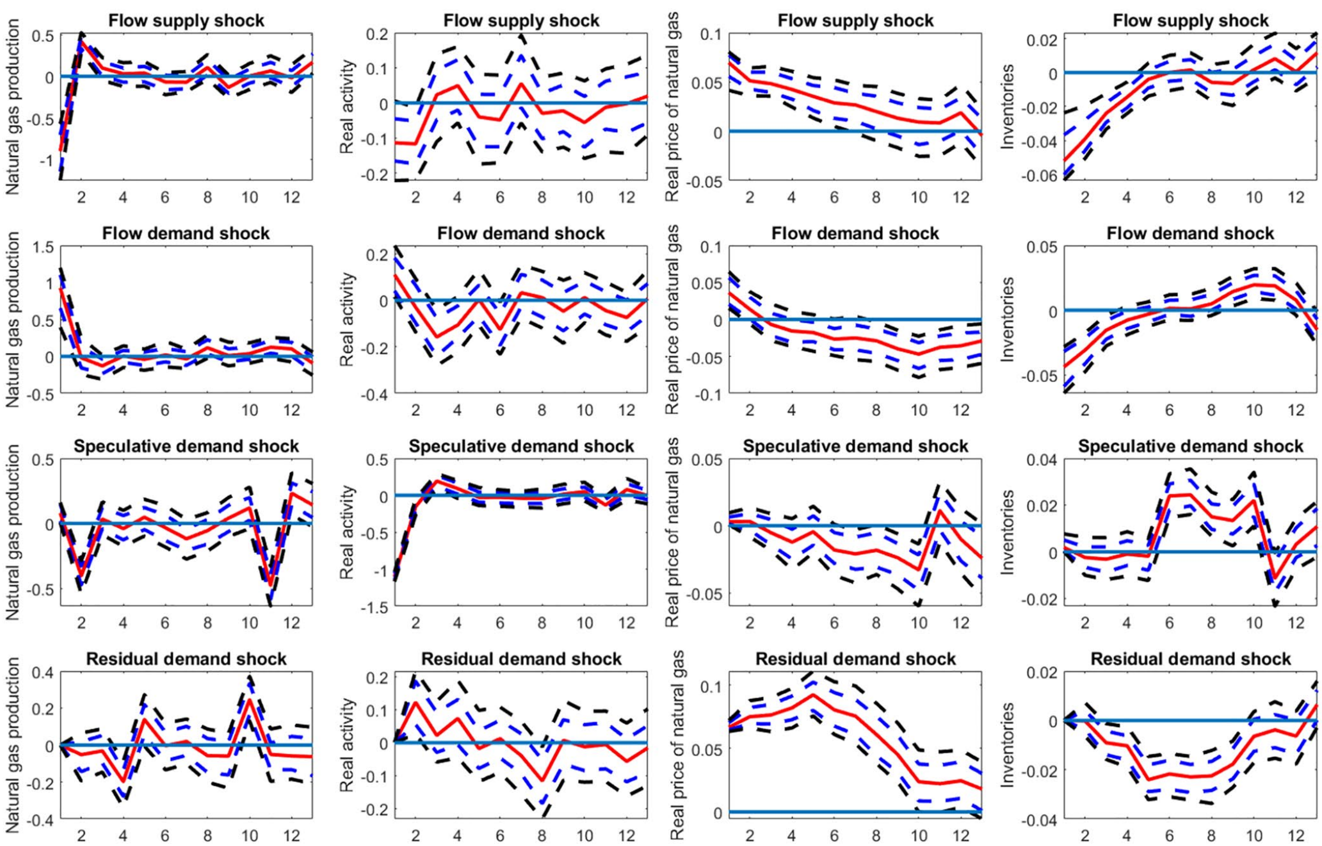

FIGURE 2 | Results from the model with the 3-month futures spread. Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands and the dashed black lines to the 95% error bands. The response of natural gas production is in percent change, that of real activity in standard deviations, that of the real price of natural gas in percent and that of the real spread in points. The impulse horizon is in months. [Colour figure can be viewed at wileyonlinelibrary.com]

horizon. The fluctuations in natural gas production and real activity in response to the shock might be indicative of the more cyclical behaviour of these variables. The effect on the real price of natural gas is positive with a peak around the five-month mark after which it dies out towards the end of the 12-month response horizon. The effect on inventories is negative and temporary, lasting only for around 4 months to smooth consumption. A flow demand shock raises natural gas production initially but the effect dies out after 2 months. Real activity only responds mildly at first, after which it fluctuates close to zero over the response horizon. The real price of natural gas increases for only 4 months after which it moves close to zero. Inventories respond negatively to the flow demand shock, but this effect dies out after 3 months, which suggests that storage is only temporarily drawn down. A speculative demand shock does not affect production much except for two troughs around the two-month and the 11-month marks. The initial negative response of real activity dies out after 3 months. The speculative demand shock seems to affect the real price of natural gas very little at first after which the effect becomes negative over most of the horizon, when the excess inventories are depleted. In response to the residual demand shock, both production and real activity fluctuate around zero for the entire response horizon. The effect on the real price of natural gas is similar to that of a flow supply shock.

In summary, the results from the Kilian-Murphy model lead to two main conclusions. First, the responses of production, real activity, 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 relative to flow supply and residual demand shocks. When we almost double the demand elasticity bound to −0.40, the results are surprisingly similar.

4.3 | Results From the Model With the Futures Spread

In this section we present the results from the model which includes the futures spread instead of inventories. The results of the model with the 3-month futures spread are reported in Figure 2 and are similar to those obtained from the model with inventories in the previous section. Once again, a speculative demand shock has almost no initial effect on the real price of natural gas, in contrast to the residual demand shock which instead increases the real price of natural gas. We also estimate the model for additional maturities of the futures spread, specifically the 6- and 12-month spreads; these results are reported in Appendix A (Figures A1 and A2) and show similar results.

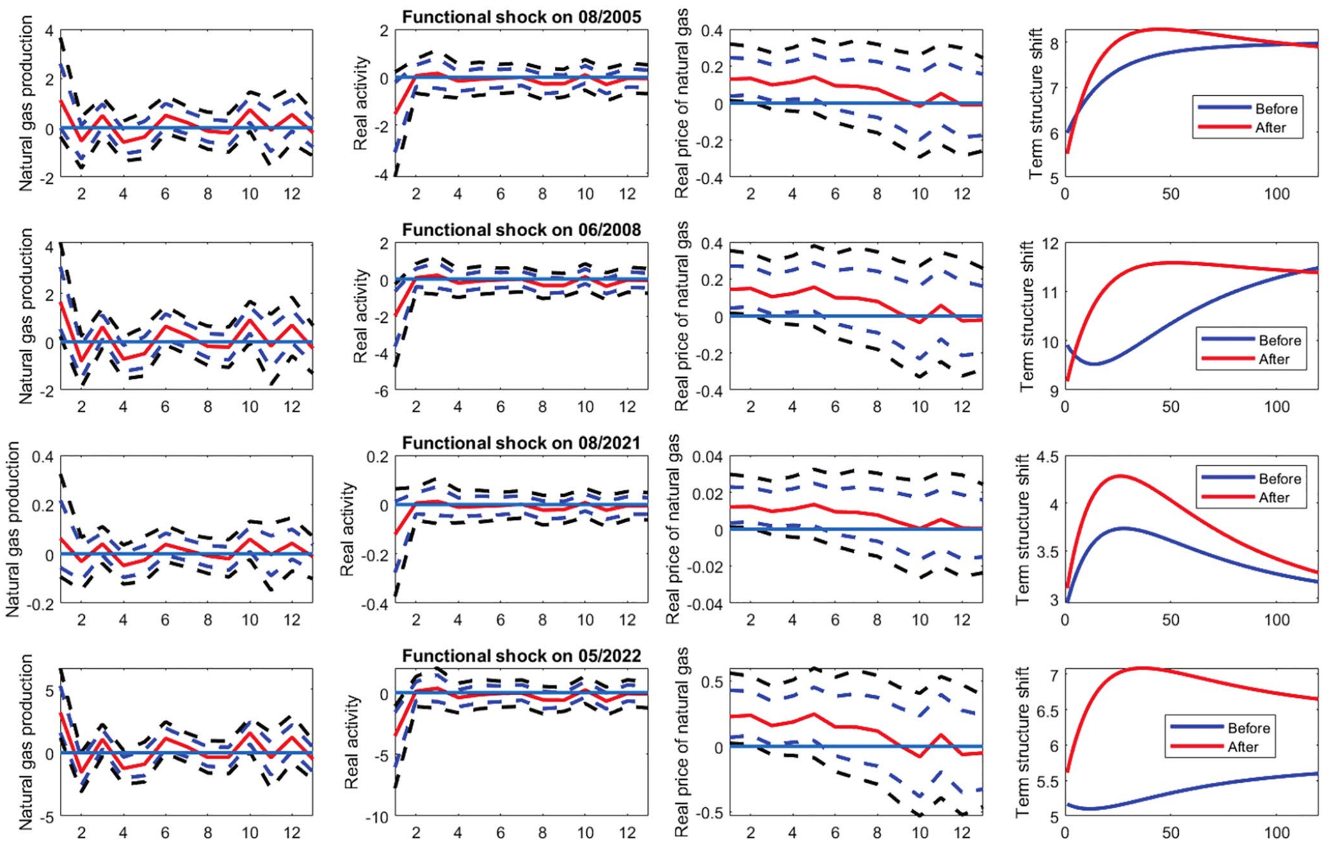

FIGURE 3 | Responses to functional shocks in the model. Structural impulse responses and term structure shifts. In the first four graphs in each row, the solid red lines indicate the closest to median responses from the admissible models, the dashed blue lines correspond to the 68% error bands and the dashed black lines to the 95% error bands. The response of natural gas production is in percent change, that of real activity in standard deviations and that of the real price of natural gas in percent. The impulse horizon is in months. 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. [Colour figure can be viewed at wileyonlinelibrary.com]

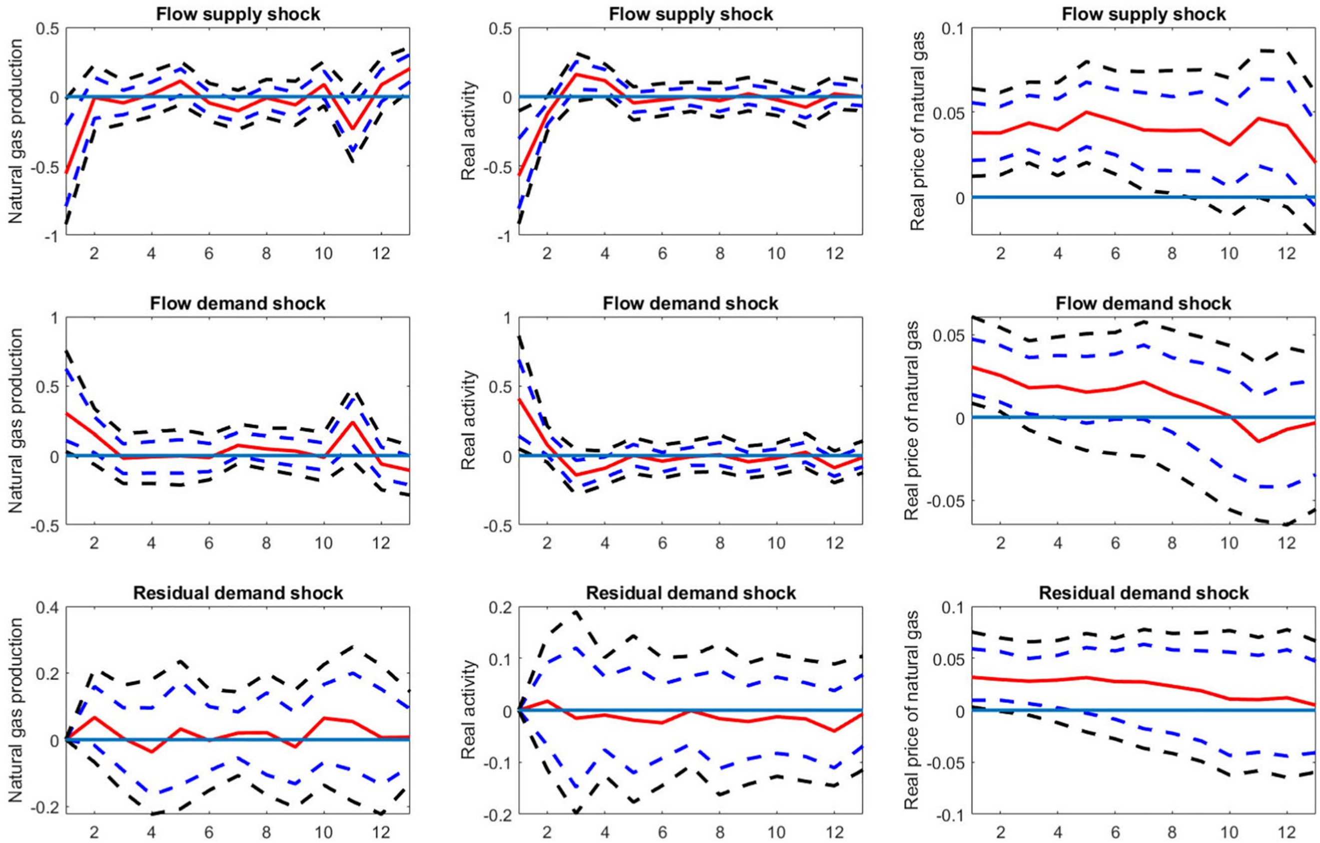

FIGURE 4 | Responses to other shocks in the model. Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands and the dashed black lines to the 95% error bands. The response of natural gas production is in percent change, that of real activity in standard deviations and that of the real price of natural gas in percent. The impulse horizon is in months. [Colour figure can be viewed at wileyonlinelibrary.com]

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

	Flow supply shock	Flow demand shock	Speculative demand shock	Residual demand shock
Model with inventories	0.4550 (0.0102)	0.0533 (0.0025)	0.0420 (0.0076)	0.4498 (0.0135)
Model with 3-month futures spread	0.2531 (0.0702)	0.1101 (0.0305)	0.0265 (0.0073)	0.6103 (0.1693)
Model with 6-month futures spread	0.4375 (0.1213)	0.1012 (0.0281)	0.0233 (0.0065)	0.4379 (0.1215)
Model with 12-month futures spread	0.4960 (0.1376)	0.1483 (0.0411)	0.0294 (0.0082)	0.3263 (0.0905)
Model with functional shocks	0.2714 (0.0753)	0.1207 (0.0335)	0.4070 (0.1129)	0.2009 (0.0557)

Note: 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. Posterior means based on all admissible models. Standard errors in parentheses.

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. Figure 3 shows the responses of each of the variables to the functional shocks on each of those dates. 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 (real activity) is initially

TABLE 5 | Granger causality test results.

	KM model	Valenti model with 3-month spread	Valenti model with 6-month spread	Valenti model with 12-month spread	Functional model
$p=4$	0.00	1.00	0.80	1.00	1.00
$p=6$	0.10	1.00	0.50	0.90	0.90
$p=8$	0.20	1.00	0.70	1.00	0.90
$p=10$	0.10	1.00	0.90	1.00	1.00

Note: p-values of the out-of-sample Granger causality tests for nonfundamentalness. P is the number of principal components.

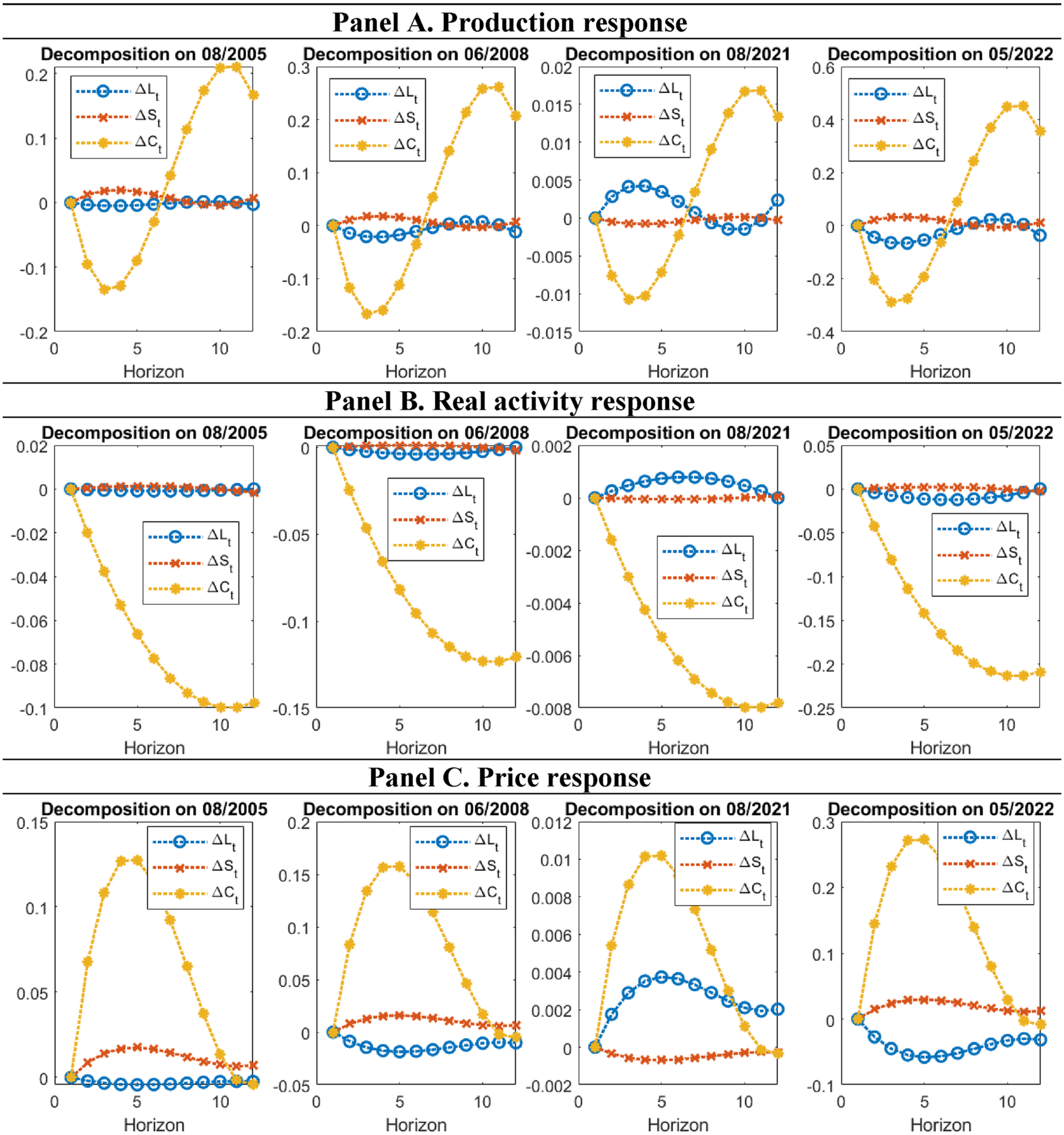

FIGURE 5 | Decomposition of responses to functional shocks in the model. Decomposition of responses to term structure factors. (A) Production response. (B) Real activity response. (C) Price response. [Colour figure can be viewed at wileyonlinelibrary.com]

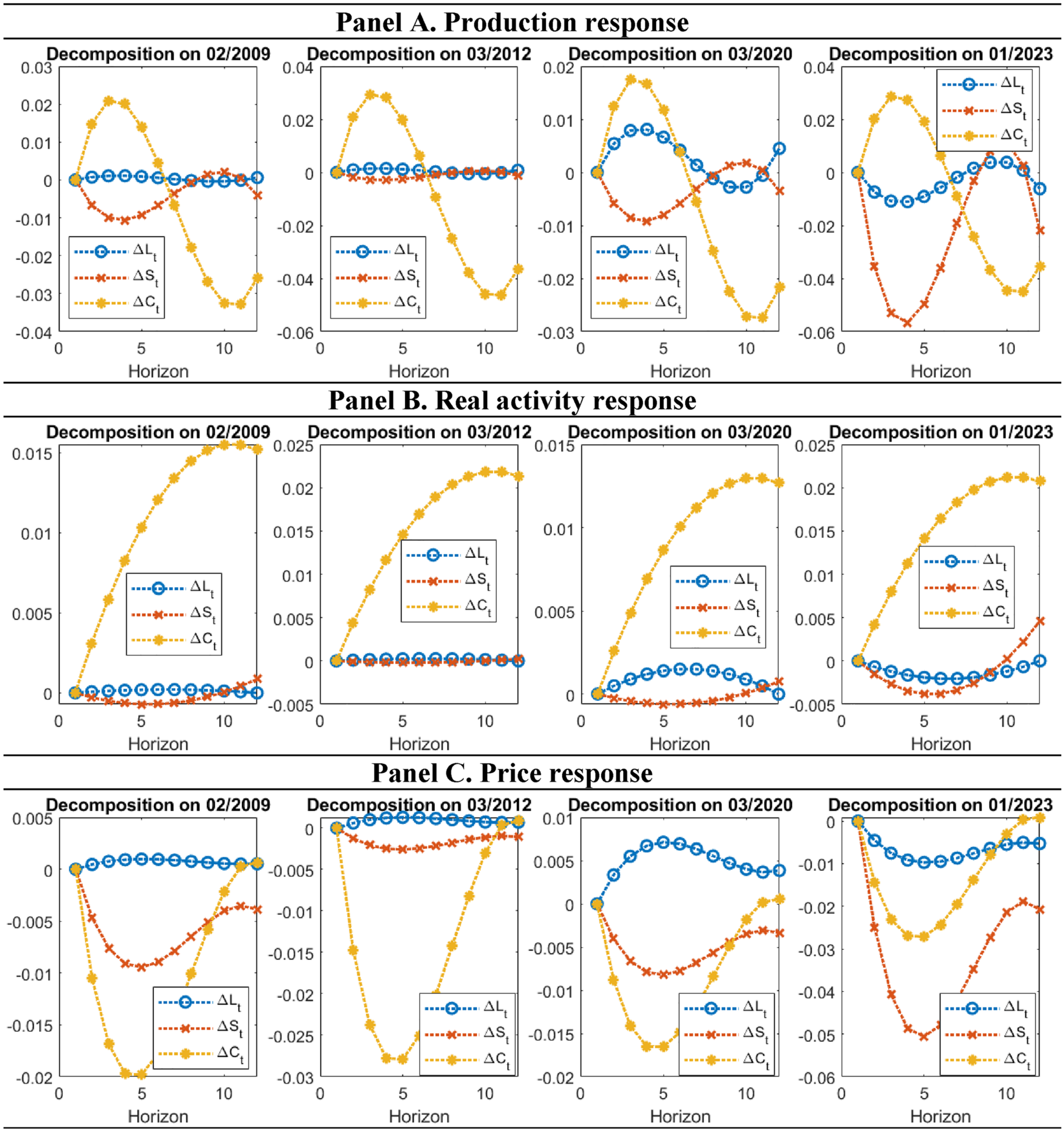

FIGURE 6 | Decomposition of responses to functional shocks during periods of price decreases. Decomposition of responses to term structure factors. (A) Production response. (B) Real activity response. (C) Price response. [Colour figure can be viewed at wileyonlinelibrary.com]

positive (negative) and volatile but short-lived. As one would expect, the real price of natural gas increases on impact, but the effect dies out over the response horizon. The responses of the variables to the other shocks in the model, shown in Figure 4, are similar to those observed for the previous two model specifications, with the exception of the effect of a flow supply shock, which now has a more persistent effect on the real price of natural gas.

Next, we carry out a mean forecast error variance decomposition of the real price of natural gas for the different model specifications considered thus far (see Table 4). The largest contribution for most model specifications is made by the flow supply and residual demand shocks, which jointly explain between 81% and 90% of the fluctuations in the real price of natural gas. Flow demand shocks explain at most 14%. The contribution of speculative demand shocks is small, with the exception of the model with functional shocks, where they explain 40% of fluctuations in the price of natural gas, while flow supply and residual demand shocks jointly now only account for 47% of those. The model with inventories confirms previous findings of the relative importance of supply shocks for the price of natural

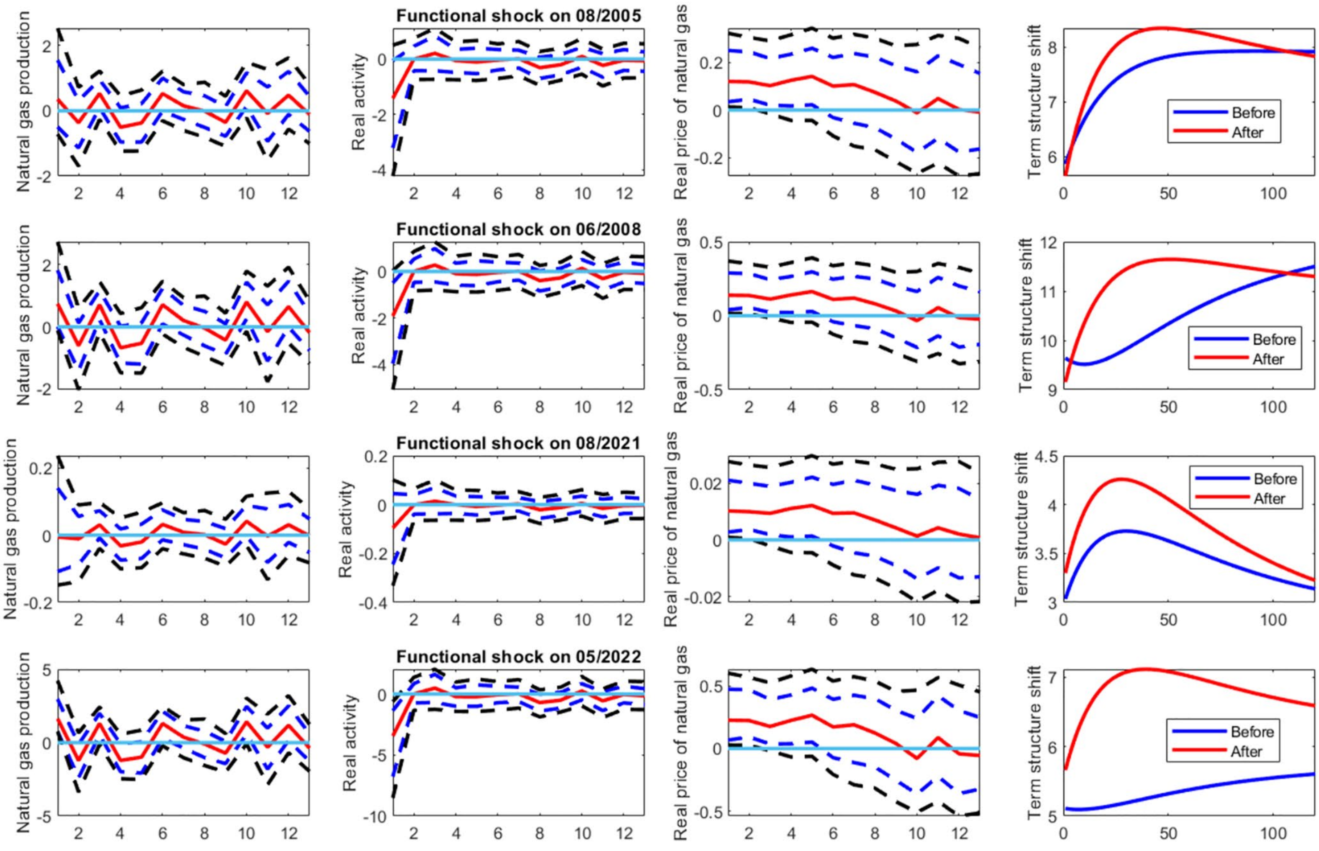

FIGURE 7 | Responses to functional shocks in the model with $\lambda = 0.05$. Structural impulse responses and term structure shifts with decay parameter $\lambda = 0.05$. [Colour figure can be viewed at wileyonlinelibrary.com]

gas, although speculative shocks appear to be less relevant in our case (Wiggins and Etienne 2017). One likely reason for this finding is that we explicitly identify the residual demand shock through sign restrictions. The result that, in the model with functional shocks, speculative shocks are almost twice as important as flow supply shocks is consistent with the evidence reported by Rubaszek et al. (2021).

Table 5 reports the results of the Granger causality tests for non-fundamentalness. In almost all cases, we cannot reject the null hypothesis of no Granger causality, which means that the variables included in the models are informationally sufficient to estimate the structural shocks.

Finally, 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 5 shows that the curvature factor is the main driver of real natural gas prices as well as production and real activity. 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 either medium-term expectations or a significant change between very short-term and very long-term expectations. A more important role of medium-term considerations can be due to seasonal or cyclical factors, such as weather forecasts for intermediate seasons, pipeline disruptions or the availability of storage. Alternatively, a discrepancy between short- and long-term expectations can reflect the different factors relevant at the two horizons; for instance, short-term expectations might respond more to immediate changes in weather while long-term expectations might be informed more by production trends. 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, that is, 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. At the same time, real activity decreased. Producers reacted by lowering production, taking the change in medium-term expectations as a signal of higher prices in the future, but then increasing it towards the middle of the response horizon in order to sell at the higher prices. This behaviour is consistent with theory. These effects are identical for the shocks on all other dates.

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 Figure 6. As can be seen, the observed effects are essentially the opposite of the previously estimated ones. One notable difference is that, in the case of a downward shift in the natural gas futures term structure, the slope factor also seems to be important for the

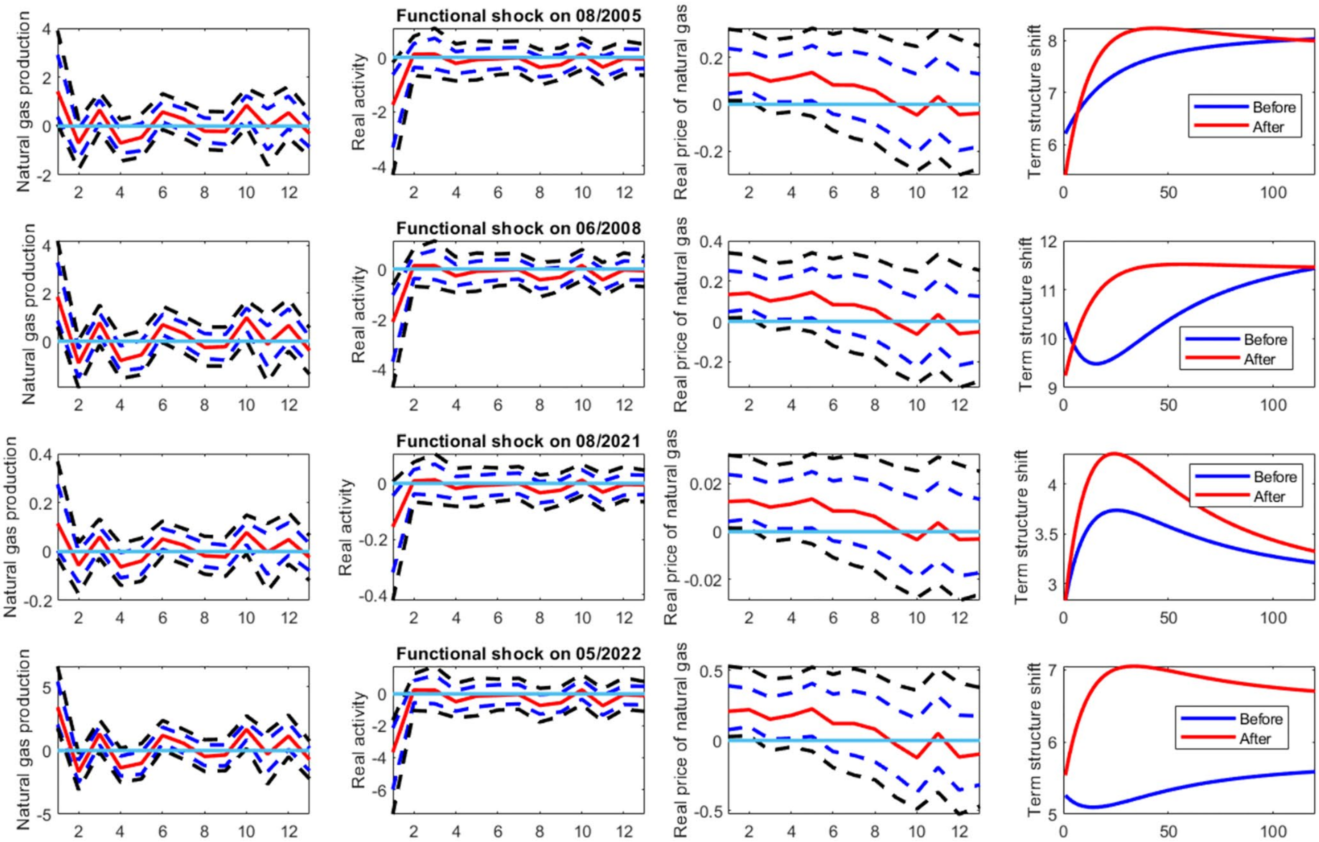

FIGURE 8 | Responses to functional shocks in the model with $\lambda = 0.076$. Structural impulse responses and term structure shifts with decay parameter $\lambda = 0.076$. [Colour figure can be viewed at wileyonlinelibrary.com]

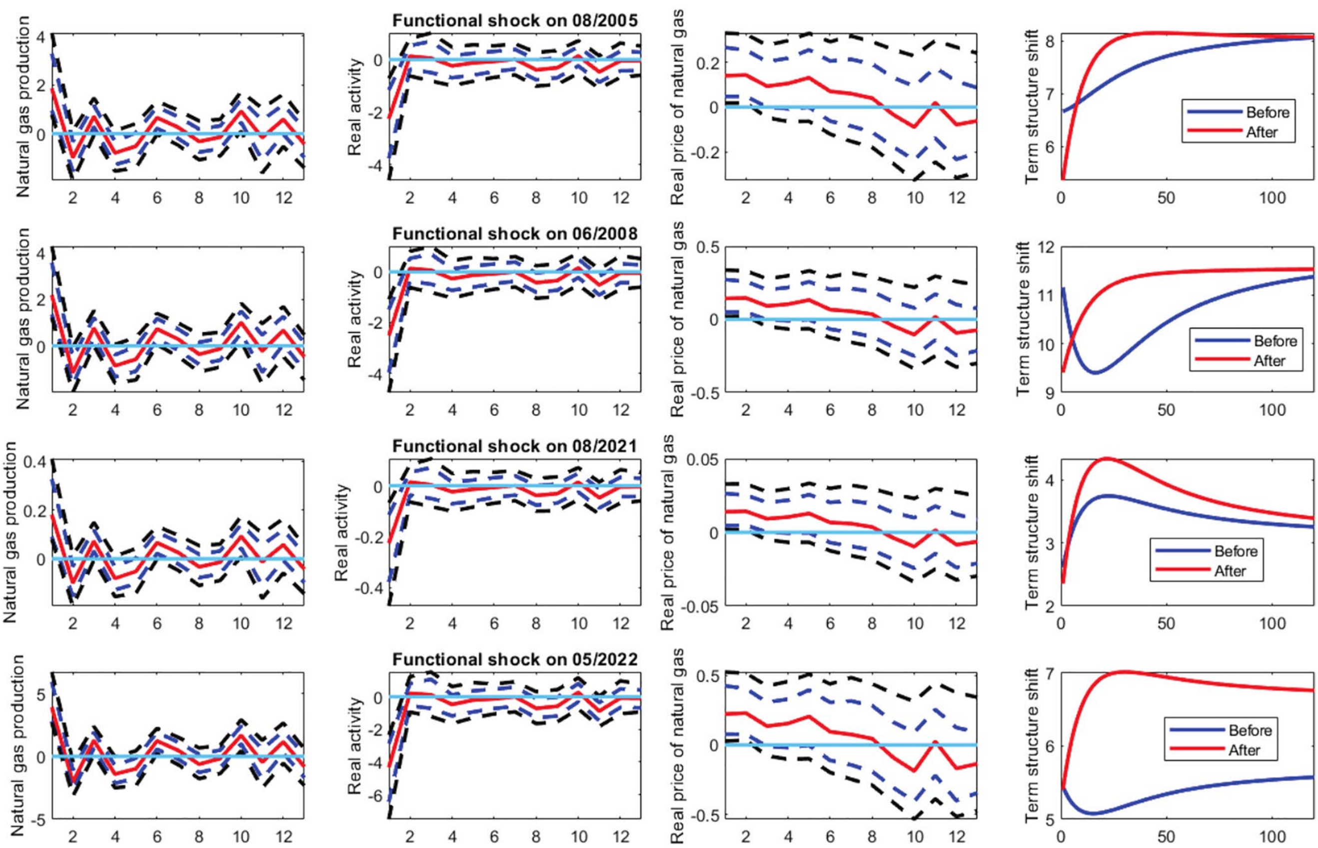

FIGURE 9 | Responses to functional shocks in the model with $\lambda = 010$. Structural impulse responses and term structure shifts with decay parameter $\lambda = 0.10$. [Colour figure can be viewed at wileyonlinelibrary.com]

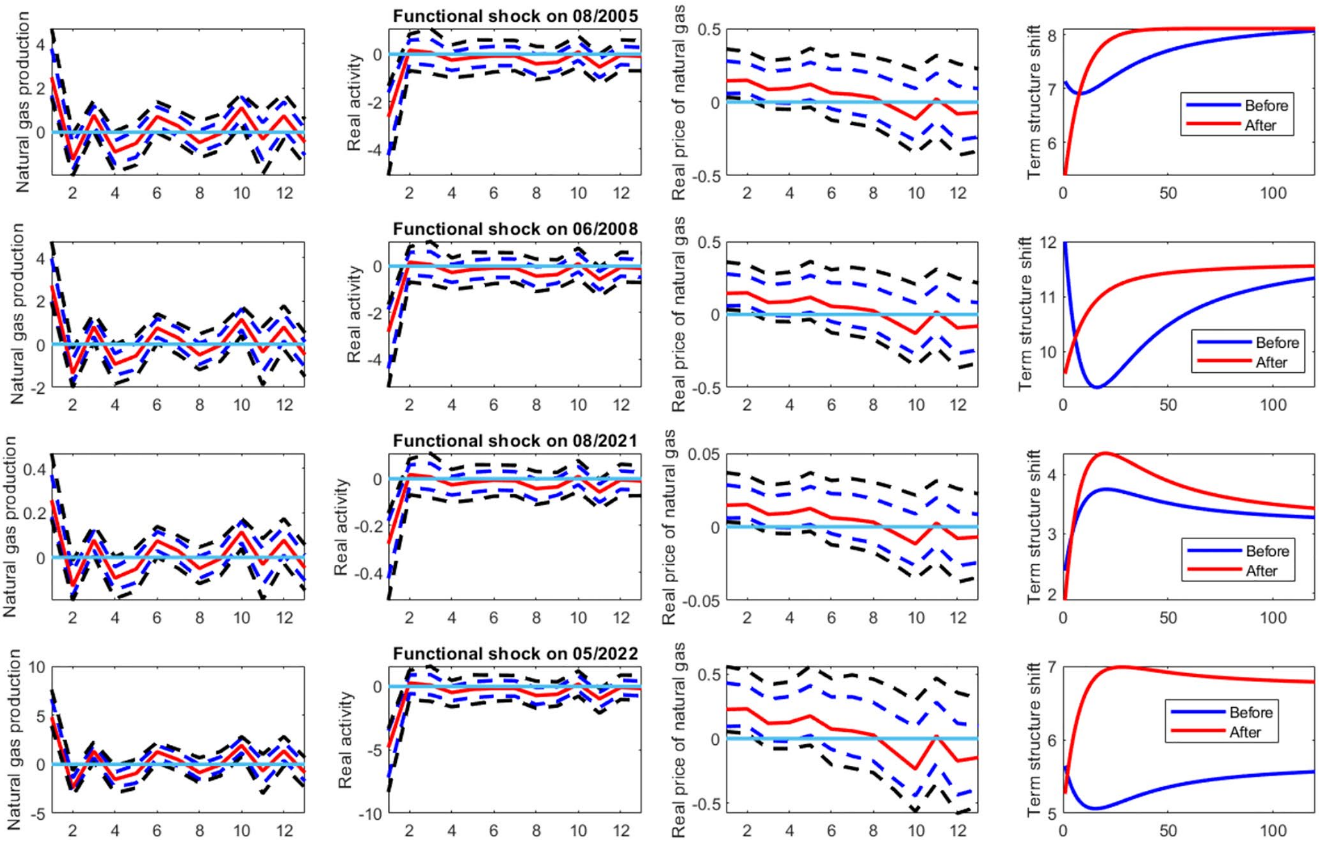

FIGURE 10 | Responses to functional shocks in the model with $\lambda = 0.12$. Structural impulse responses and term structure shifts with decay parameter $\lambda = 0.12$. [Colour figure can be viewed at wileyonlinelibrary.com]

responses of the price and production of natural gas to the functional shocks.

The findings from the three specifications provide some important insights into the features of expectations in the US natural gas market. First, it appears that natural gas futures markets contain important information about expectations, suggesting that forward-looking expectations are relatively more informative about natural gas spot prices than physical market imbalances. This finding adds an information dimension to the existing natural gas literature, which recently reported that speculative shocks are an important determinant of natural gas prices (Rubaszek and Uddin 2020; Rubaszek et al. 2021). Second, it is not forward-looking expectations related to any one individual maturity but the entire term structure that matters, medium-term expectations being particularly important and short- and long-term expectations being significantly different. This indicates that the anticipation of market fundamental movements several months down the line constitutes the most important part of speculative activity. Short-term movements might be very noisy or considered temporary, while long-term ones might represent more structural market changes. The importance of medium-term expectations indicates that the market is not overly speculative in relation to either very immediate developments or very distant structural changes, but rather to a large discrepancy between the two. For policymakers and market participants, this information is relevant to gauge which futures price movements can be used as leading indicators of price and fundamental changes in the physical markets.

4.5 | Sensitivity to the Decay Parameter

In this section we test the sensitivity of our results to variation in the decay parameter λ in the term structure model. The parameter determines the maturity at which the curvature peaks, that is the location of the hump. Our baseline λ value of 0.0609 corresponds to a curvature loading peak at 30 months. For robustness we consider different values of λ which correspond to curvature peaks at different maturities, namely 0.05, corresponding to a peak at 36 months (3 years), 0.076 for a peak at 24 months (2 years), 0.10 for a peak at 18 months (1.5 years) and 0.12 for a peak at 15 months (1 year and a quarter). Curvature peaks towards the longer end of the term structure are less suitable for the case of natural gas due to its high liquidity and constrained storage capacity. Lambda values relating to short term curvature peaks should therefore more accurately capture market dynamics and speculative activity. The results from the models with the alternative lambda values are reported in Figures 7–10. As can be seen, a lower value of the decay parameter of 0.05 seems to be less suitable as it generates many insignificant responses of production and real activity to the functional shocks, although the response of the price of natural gas is not very different compared to the previous results. A higher value on the other hand generates very similar results to the baseline model, suggesting robustness of our results with respect to the value of lambda.

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. The first identifies a speculative demand shock in a model which includes inventories; the second incorporates instead the risk-adjusted 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, in the model with inventories, the real price of natural gas seems to respond less to speculative demand shocks 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 flow demand shocks. Second, in the model with functional shocks, the speculative demand shock seems to have sizeable 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 supply forces in driving spot prices. Third, increases in the spot price of natural gas are primarily driven by the curvature factor of the natural gas term structure, which suggests that in this case the price responds either to medium-term expectations about future price developments or large differences between short- and long-term expectations, while decreases are driven also by the slope factor. Fourth, the forecast error variation decomposition indicates that the speculative demand shock in the model with functional shocks, which represents shifts in the expected future price of natural gas, is able to explain around 40% 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 in the model with functional shocks. Finally, unlike in empirical studies of the oil market, we find less evidence for a large role played by flow demand shocks in the natural gas markets. Instead, flow supply shocks appear to be the main driver of natural gas price fluctuations, together with speculative demand shocks, in the model with functional shocks.

Our findings pose some challenges to policymakers. First, the greater importance of flow supply shocks compared to demand shocks for the price of natural gas makes policy interventions difficult. Second, medium-term expectation changes can put considerable pressures on spot natural gas prices (as seen in the model with functional shocks). This sizeable effect of speculative shocks on the real price of natural gas needs to be monitored, so that it does not spill over to other prices.

Data Availability Statement

The data that support the findings of this study are openly available in the US Energy Information Authority at https://www.eia.gov.

Endnotes

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

[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.

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Appendix A

Results of Valenti Models With Different Maturities

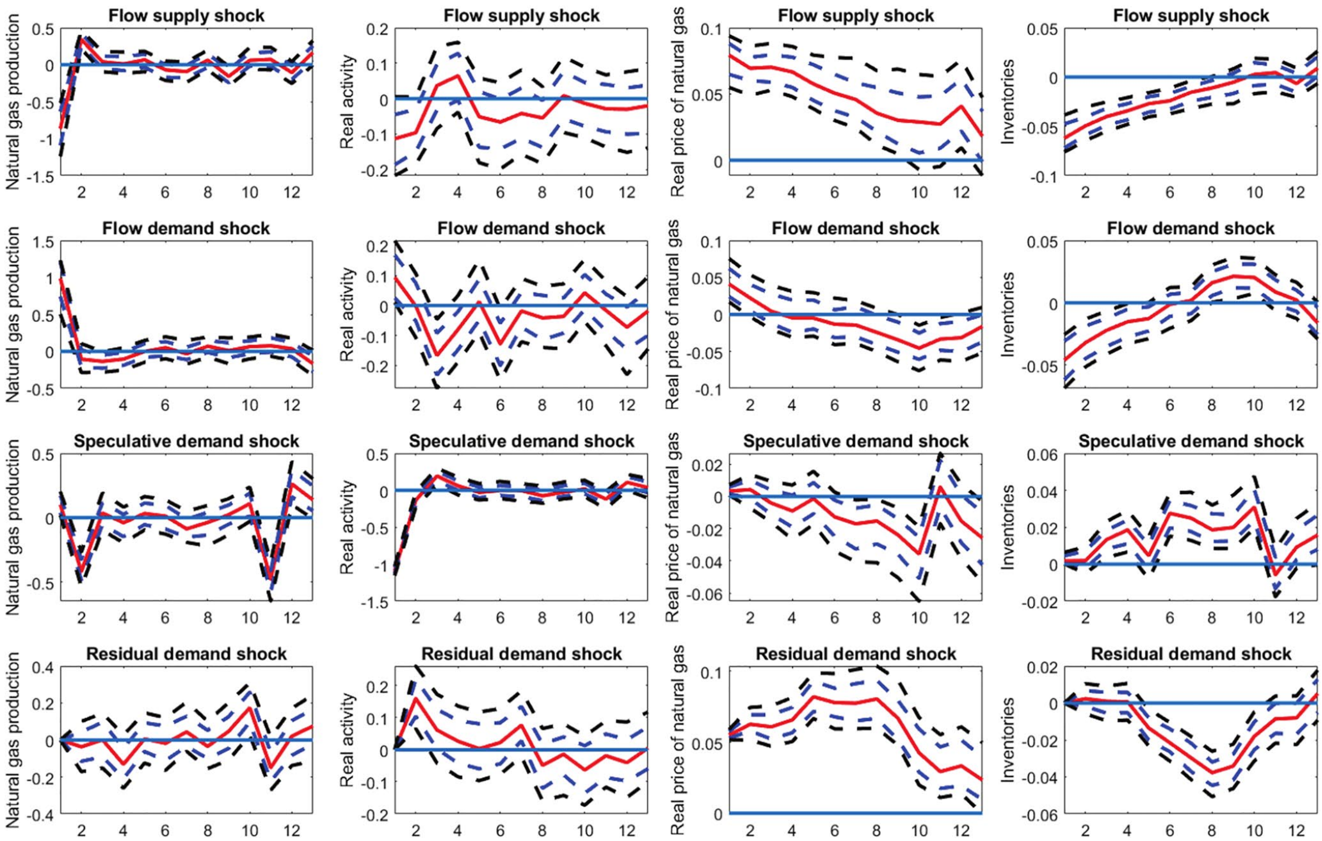

FIGURE A1 | Results from the Valenti model with the 6-months futures spread. Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands and the dashed black lines to the 95% error bands. The response of natural gas production is in percent change, that of real activity in standard deviations, that of the real price of natural gas in percent and that of the real spread in points. The impulse horizon is in months. [Colour figure can be viewed at wileyonlinelibrary.com]

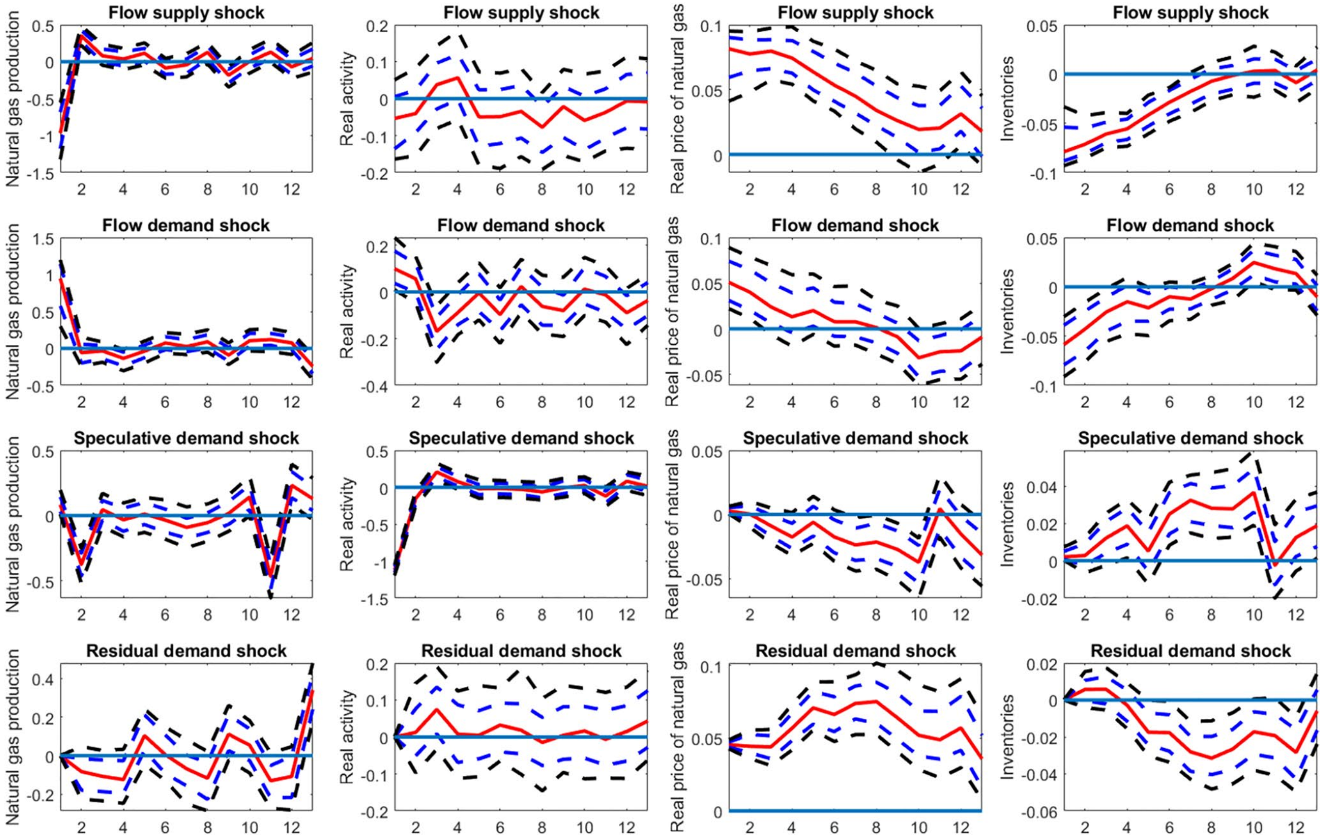

FIGURE A2 | Results from the Valenti model with the 12-months futures spread. Structural impulse responses. The solid red lines indicate the closest to median responses from the admissible models. The dashed blue lines correspond to the 68% error bands and the dashed black lines to the 95% error bands. The response of natural gas production is in percent change, that of real activity in standard deviations, that of the real price of natural gas in percent and that of the real spread in points. The impulse horizon is in months. [Colour figure can be viewed at wileyonlinelibrary.com]