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Energy commodities and U.S. housing: Long-run Price and volatility integration with comparative evidence from non-energy markets

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ABSTRACT

This study investigates long-run price and volatility integration between U.S. regional housing markets and both energy and non-energy commodities. The analysis applies Fourier-augmented Toda–Yamamoto models to examine price transmission and Fourier-augmented causality-in-variance tests to assess volatility spillovers, conditioning commodity indexes on region-specific heating degree days to preserve long-run information while capturing smooth structural changes. After controlling for macroeconomic factors and weather-driven demand, the results show that oil remains integrated with housing prices and that oil-related volatility exhibits widespread, often bidirectional spillovers with housing markets—highlighting the central role of oil as both an input cost and a macro-financial barometer. In contrast, natural gas and coal display little evidence of persistent integration once weather demand and gradual shifts are accounted for, and their volatility spillovers are limited and region-specific. The non-energy results provide a comparative benchmark: industrial metals generate long-run integration in construction-intensive regions, agriculture primarily contributes through volatility associated with household-budget and income channels, and precious metals transmit state-contingent volatility consistent with safe-haven and portfolio behavior. Overall, persistent integration is strongest and most durable for oil, whereas other energy and non-energy commodities display more selective and region-specific linkages. These findings underscore the importance of regional policy on heating-fuel choices and the management of petroleum-linked costs, while offering guidance for investors seeking to hedge oil exposure and construction-input risk in rapidly growing housing markets.

1. Introduction

Dynamics of housing prices shape macroeconomic conditions via consumption, credit, and propagate across regions through migration and investment (Gyourko and Saiz, 2006; Hirata et al., 2013; Taylor, 2007). The post-2020 cycle highlights these links via rapid price appreciation, tight supply, and large swings in mortgage rates coinciding with pronounced shifts in energy and construction-input costs. Housing market valuation responds to borrowing costs, income risks, and input prices, with heterogeneity reflecting climate, industrial structure, and supply constraints (Chiang et al., 2020; Antonakakis and Floros, 2016).

Energy is central to these mechanisms. Prices of oil, gas, and coal impact household budgets through heating and transportation costs. They also affect the costs of housing capital and construction. Financing conditions amplify or dampen these effects (see Chan et al., 2011; Liang et al., 2021; Yunus, 2023). Energy price movements also carry information about global demand, supply disruptions, and policy that shape risk premia (Rehman et al., 2020; Salisu and Gupta, 2021; Nazlioglu et al., 2020). Critically, the building-fuel mix varies with climate; region-specific heating degree days (HDD) shift effective housing costs and can inflate measured housing–energy co-movement if ignored.

Although the impacts of energy commodities on various markets are well documented, non-energy commodities are also expected to play an important role. The literature frequently examines energy and non-

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energy commodities in the same context when evaluating spillovers to other markets, and housing is suspected to exhibit similar dynamics. For example, metals and agriculture co-move with energy and transmit shocks to inflation and financial markets: agricultural and energy prices display sizable pass-through to inflation (Abbas and Lan, 2020); return and volatility connectedness across energy, metals, and agriculture rises in crises (Farid et al., 2022); commodity–equity volatility linkages span energy and non-energy contracts (Creti et al., 2013); energy–agriculture risk transmission is significant (Ji et al., 2018; Luo and Ji, 2018); and fuel–biofuel–agriculture interactions are contemporaneous and asymmetric (Fernandez-Perez et al., 2016). For housing, industrial metals map into construction and replacement costs, while agriculture and precious metals influence household budgets and portfolio rebalancing. Studying energy and non-energy commodities jointly therefore frames housing within the integrated commodity system.

We place regional U.S. housing in this setting while maintaining an energy market focus. Building on evidence of information transmission from oil to housing (Nguyen et al., 2021) and nonlinear tail dependence between regional housing and energy (Stenvall et al., 2022), we move from short-run returns to long-run price integration and separate volatility spillovers from mean dynamics. Methodologically, we augment the causality test of Toda and Yamamoto (1995, hereafter TY) preserving long-run information in levels and the causality-in-variance LM test of Hafner and Herwartz (2006) for volatility spillover with a Fourier approximation to accommodate smooth structural shifts. To limit confounding, we condition commodity indexes on region-specific HDD and include macroeconomic controls commonly used in literature.

Empirical findings provide important insights. First, after controlling for HDD and macro factors, oil prices are still volatility-integrated in the long run with most housing regions and price-integrated with several regions—an effect that persists beyond weather-driven demand. Second, volatility integration between oil and housing is very strong and bidirectional in most regions.

Equally as significant, once we account for the weather-driven demand and allow for smooth structural changes, natural gas and coal are not strongly integrated with regional housing in the long run. This particular finding strikes a direct contrast between the short and long-run integration of the housing market with these energy commodities. While recent literature shows short-run comovement (e.g. Stenvall et al., 2022), the relationship seems to dissipate in the long run. This refinement is economically intuitive: natural gas prices are highly sensitive to degree-days and storage fundamentals, so much of their short-horizon co-movement with housing reflects transitory weather shocks rather than persistent transmission channels—structural and futures-market evidence attributes a large share of gas price variation to temperature and inventories (Mu, 2007; Nick, 2014). Coal, by contrast, enters household budgets mainly indirectly via electricity, and its salience for housing is often local and non-market—for example, coal-to-gas switching and coal-plant closures improve local air quality and raise nearby property values—rather than a broad price-integration mechanism (Rivera, 2022). Our break-robust, HDD-conditioned results therefore complement and refine returns-based evidence that documents impactful energy–housing dependence in the tails (Stenvall et al., 2022): they show that oil retains long-run price and volatility integration with housing, whereas the apparent influence of natural gas and coal largely dissipates once weather demand and regime shifts are taken into account.

Non-energy commodities provide a benchmark that supplements the energy findings: industrial metals transmit to housing prices in manufacturing- and construction-intensive divisions, consistent with a replacement-cost mechanism; agriculture exhibits selective but persistent price transmission and broad two-way volatility connectedness that reflects household-budget and regional-income channels; and precious metals show selective long-run price co-movement and state-contingent volatility spillovers that align with safe-haven and portfolio-rebalancing behavior. Taken together, these results indicate that robust level integration is commodity-specific and strongest for oil—reflecting transport, user-cost, and macro-financial aggregation channels—whereas risk transmits more broadly through both energy and non-energy markets in ways that respect regional energy systems and industrial structure. Assessing energy commodities along with their non-energy counterparts clarifies the mechanisms through which construction inputs and household budgets map into housing dynamics, consistent with recent evidence on cross-commodity connectedness in the commodity complex (Bastianin et al., 2023; Farid et al., 2022).

The findings have important implications for investors and policy makers. For investors, oil-related risk remains material for regional housing exposures even after accounting for weather, while volatility transmitted from industrial metals warrants hedges for construction-cost risk and real-asset portfolios. For policymakers, region-targeted energy-efficiency and heating-fuel policies are warranted in oil-exposed regions, and monitoring input-cost pressures is essential where housing supply expands; conditioning on HDD clarifies where integration reflects economic linkages rather than climate.

2. Hypothesis development and literature review

2.1. *Therotical channels*

Commodity–housing linkages arise through five mechanisms: The income channel, the user-cost and transportation channel, the construction-input channel, the monetary policy channel, and the financialization/portfolio channel. First, commodity booms raise regional incomes in producing areas and erode real disposable income in consuming areas, generating heterogeneous housing responses (Grossman et al., 2019; Killins et al., 2017). Second, energy prices enter household budgets via heating and commuting costs—HDD captures the weather-driven component of energy demand that affects effective housing costs (U.S. Energy Information Administration, 2024a). Third, energy and non-energy commodities (especially industrial metals) raise replacement and building costs, altering supply responsiveness (Bastianin et al., 2023). Fourth, commodity-driven inflation prompts tighter policy, raising mortgage rates and dampening housing demand (Guhathakurta et al., 2020). Fifth, greater financial integration amplifies cross-market information and volatility transmission (Farid et al., 2022).

2.2. *Empirical literature*

A growing literature documents economically meaningful connections between energy prices and housing prices. Using a VAR framework, Nguyen et al. (2021) show that information transmission between oil and housing intensifies in turbulent periods, indicating that energy shocks co-move with housing beyond tranquil states. Regional U.S. evidence aligns with the income channel: Grossman et al. (2019) find that oil price shocks increase house prices in oil-dependent Texas cities with partial pass-through, while effects remain statistically detectable—even if smaller—in less oil-dependent areas. Cross-country comparisons suggest heterogeneity by oil trade status and shock type; Killins et al. (2017) report that demand-driven oil shocks can bolster housing in exporters but supply-driven oil spikes are contractionary, with stronger headwinds for net importers. Together, these studies motivate a regional, mechanism-aware approach to long-run price transmission from energy commodities to housing markets.

Beyond mean relationships, tail co-movements matter for housing risk. Stenvall et al. (2022) analyze nonlinear tail dependence between U. S. regional housing and energy markets in the short term and show that the strength and asymmetry of dependence vary across Census divisions. Their returns- and quantile-based evidence complements our long-run levels perspective: tail dependence at high and low quantiles coexists with persistent price transmission in levels once structural breaks and weather are accounted for. This motivates our use of Fourier-augmented TY tests that preserve long-run information while accommodating all types of structural shifts.

Recent works underscore pervasive return and volatility connectedness across energy, metals, and agriculture. Farid et al. (2022) document time-varying, crisis-amplified connectedness, indicating that common risk factors and information flows propagate across commodity classes. Guhathakurta et al. (2020) report period-specific spillovers between oil and metals/agriculture, with oil and industrial metals acting as net transmitters to other commodity groups. Bastianin et al. (2023) find pronounced connectedness among energy-transition metals and between base and precious metals, highlighting channels through which construction-relevant inputs may affect real activity. In our context, these results justify disaggregating non-energy commodities (agriculture, industrial metals, precious metals) when assessing housing–commodity transmission: industrial metals plausibly link to housing via construction-input costs, whereas agriculture and precious metals predominantly affect volatility through inventory, portfolio, and safe-haven dynamics.

While housing is less liquid than financial assets, its volatility responds to macro-financial uncertainty and commodity shocks. Nguyen et al. (2021) show stronger oil–housing comovement during extremes, consistent with crisis-period risk transmission. The broader connectedness literature (Farid et al., 2022; Guhathakurta et al., 2020; Bastianin et al., 2023) implies that commodity volatility innovations can spill over into real assets. We therefore implement the Fourier-Augmented version of Hafner and Herwartz (2006) LM test for causality-in-variance to establish whether commodity volatility systematically increases housing volatility across regions and commodity classes.

Over long samples, ignoring smooth or abrupt structural changes can bias unit-root and causality inference. Enders and Lee (2012) advocate Fourier approximations to capture low-frequency breaks without prespecifying break dates, and Toda and Yamamoto (1995) show that VAR-in-levels with augmented lags yield valid Wald tests irrespective of integration and cointegration. Our break-robust design combines these insights—Fourier-augmented TY for price transmission and LM variance-causality for volatility—while HDD adjustment mitigates spurious weather-demand effects in energy-sensitive markets (U.S. Energy Information Administration, 2024a).

2.3. Hypotheses

- H1 (Energy price transmission). Energy commodity prices, adjusted for regional HDD, exert a long-run influence on regional housing prices. We expect stronger price transmission from oil than from natural gas or coal, consistent with seasonal demand, income, user-cost, and monetary channels (Nguyen et al., 2021; Grossman et al., 2019).
- H2 (Non-energy price transmission). Non-energy commodity prices transmit to housing in the long run, with heterogeneous effects across sub-classes: industrial metals drive price transmission via construction-input costs, while agriculture and precious metals play a smaller role in prices but are important for volatility comovement (Farid et al., 2022; Bastianin et al., 2023; Guhathakurta et al., 2020).
- H3 (Volatility spillovers). Due to financialization of commodity markets (Gormus et al., 2024; Nazlioglu et al., 2016; Nazlioglu et al., 2020), volatility shocks in commodity markets spill over to housing in a region-, type-, and channel-dependent process.

These hypotheses guide our empirical strategy in the next section, where we describe the data, HDD adjustments, and the implementation of Fourier-augmented TY causality tests and LM volatility causality tests across the nine Census divisions and the national aggregate.

3. Methodology

3.1. Testing for price transmission with structural changes

To investigate price spillover, we utilize a Fourier-augmented transmission model from Nazlioglu et al. (2016, 2019) and Gormus et al. (2018). Their approach is a derivation of the TY transmission model.[2] TY propose to augment VAR(p) with maximum integration (unit root degree) degree of variables, denoted as d, and thus to estimate VAR ($p + d$) model by using level of y_t. The so-called lag-augmented VAR model can be written as

$$y_t = A + B_1 y_{t-1} + \ldots + B_{p+d} y_{t-(p+d)} + e_t. \tag{1}$$

where y_t includes endogenous variables, A is a vector of constants, B = (B_1, …,B_p)' are parameters, e_t is error term, and p is the number of lags. To test for the null of no causality in Granger sense, the null hypothesis of non-causality is based on zero restriction on first p parameters.

given by (H_o:B_1 = ⋯ = B_p = 0). The conventional Wald statistic for testing the null hypothesis, has an asymptotic chi-square distribution with p degrees of freedom.

An issue related to the conventional Wald statistic for testing causality is that it rejects the null hypothesis if a structural break in data is ignored in estimations of VAR model (Ventosa-Santaulària and Vera-Valdés, 2008), and tends to exhibit size distortions arising from not only neglecting structural break but also not properly modelling the breaks (see, Enders and Holt, 2014). Thus, results from a standard Granger causality analysis may have caveats when structural breaks exist or are not properly addressed. In a VAR model, either determining the source of breaks or controlling for them is not an easy task since breaks can be transitionary between variables (Enders and Holt, 2014). The Fourier approximation utilized by Nazlioglu et al. (2016, 2019) and Gormus et al. (2018), based on a variant of Flexible Fourier Form in Gallant (1981), addresses the identification of form of shifts without requiring to know the form, number, and date of breaks in the VAR construct. By benefiting from these extensions in causality analysis, we allow structural shifts in constant term A and use the following Fourier approximation to capture structural shifts as a gradual process

$$\mathrm{A(t)} \cong A_0 + A_1 sin\left(\frac{2\pi kt}{T}\right) + A_2 cos\left(\frac{2\pi kt}{T}\right) \tag{2}$$

where A(t) is now a function of time and denotes any structural shifts in y_t, k is an integer frequency, A_1 and A_2 measures the amplitude and displacement of the frequency, respectively. Substituting eq. (3) into (2) yields

$$y_t = A_0 + A_1 sin\left(\frac{2\pi kt}{T}\right) + A_2 cos\left(\frac{2\pi kt}{T}\right) + B_1 y_{t-1} + \ldots + B_{p+d} y_{t-(p+d)} + u_t \tag{3}$$

and then follow the usual TY approach to testing for price transmission.[3]

3.2. Testing for volatility transmission with structural changes

To investigate volatility spillover, we utilize a Fourier-augmented GARCH model from Nazlioglu et al. (2020a and 2020b). The Lagrange multiplier (LM) volatility spillover test developed by Hafner and Herwartz (2006) is based on GARCH (1,1) specification for series i and j,

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[2] The Toda and Yamamoto (1995) model is a modified version of the conventional approach, suggested by Granger (1969).

[3] In order to save space, we are not including the full derivation and explanations of the model. Interested readers can refer to Nazlioglu et al. (2016, 2019) and Gormus et al. . (2018).

given by.

$$y_{it} = x_{it}'c_i + \varepsilon_{it} \tag{4}$$

$$\sigma_{it}^2 = \omega_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i \sigma_{it-1}^2 \tag{5}$$

where x_{it} is exogenous variables, ε_{it} is error terms that denotes the real-valued information, and σ_{it}^2 is conditional variance. It is assumed that $\omega_i > 0,\ \alpha_i, \beta_i \geq 0$ is for non-negativity of conditional variance, with $\alpha_i + \beta_i < 1$ for finite variance.[4] Then we define.

$$\varepsilon_{it} = \xi_{it}\sqrt{\sigma_{it}^2\left(1 + z_{jt}'\phi\right)}, z_{jt} = \left(\varepsilon_{jt-1}^2, \sigma_{jt-1}^2\right)' \tag{6}$$

where ξ_{it} is standardized residuals of series i. ε_{jt}^2 and σ_{jt}^2 are squared disturbance term and volatility for series j, respectively. The null hypothesis of no-volatility transmission ($H_0 : \phi = 0$) is tested against the alternative hypothesis of volatility transmission ($H_0 : \phi \neq 0$), with the LM statistic.

$$\lambda_{LM} = \frac{1}{4T}\left(\sum_{t=1}^{T}\left(\xi_{it}^2 - 1\right)z_{jt}'\right)V(\theta_i)^{-1}\left(\sum_{t=1}^{T}\left(\xi_{it}^2 - 1\right)z_{jt}\right) \sim \chi_2^2 \tag{7}$$

where $V(\theta_i) = \frac{\kappa}{4T}\left(\sum_{t=1}^{T} z_{jt}z_{jt}' - \sum_{t=1}^{T} z_{jt}x_{it}'\left(\sum_{t=1}^{T} x_{it}x_{it}'\right)^{-1}\sum_{t=1}^{T} x_{it}z_{jt}'\right)$, $\kappa = \frac{1}{T}\sum_{t=1}^{T}\left(\xi_{it}^2 - 1\right)^2$.

If there are structural changes in the conditional variance process in eq. (5), the standard GARCH(1,1) model may be inadequate for capturing long-term volatility dynamics. It is shown that Fourier approximation can mimic structural changes in the conditional variance without prior information regarding numbers, dates, and form of variance shifts. It also may be better suited for financial data that spans long periods wherein multiple structural breaks can occur and may be challenging to pinpoint precisely (see Pascalau et al., 2011; Teterin et al., 2016; Li and Enders, 2018).

To account for structural breaks in volatility transmission analysis, Nazlioglu et al. (2020a and 2020b) employ Fourier approximation that captures any shifts in the volatility process given by

$$\sigma_{it}^2 = \omega_{0i} + \omega_{1i}sin\left(\frac{2\pi k_i t}{T}\right) + \omega_{2i}cos\left(\frac{2\pi k_i t}{T}\right) + \alpha_i \varepsilon_{it-1}^2 + \beta_i \sigma_{it-1}^2. \tag{8}$$

The test statistic in eq. (7) can be obtained based on eq. (8), called as Fourier λ_{LM} ($F\lambda_{LM}$). [5]

4. Data

The data includes multiple time-series across three major markets: housing, energy commodities, and non-energy commodities. In addition, we incorporate regional weather information and macroeconomic indicators as control variables[6]. The housing data are the seasonally adjusted monthly Federal Housing Finance Agency purchase-only indices for each of the nine U.S. Census divisions and the USA combined. Each division index has a base value of 100 beginning in January 1991. The use of purchase-only data ensures underlying housing values are market transaction-based and exclude values assigned only from tax assessment or refinance appraisals. Our sample includes all observations from January 1991 through May 2024. The U.S. Census divisions arranged in this data are East North Central, East South Central, Middle Atlantic, Mountain, New England, Pacific, South Atlantic, West North Central, and West South Central. See Table 1 for the state assignments per division.

We also utilize daily price indexes of WTI (West Texas Intermediate) oil, residential natural gas, biofuel, coal (ICE Newcastle Global Coal), S&P GSCI Agricultural, Industrial Metals, and Precious Metals obtained from the Morningstar database. Regional heating degree days (HDD) are from the U.S. Energy Information Administration, 2024b[7]. 30-year mortgage rate, inflation, U.S. unemployment rate, housing starts, and real disposable income per capita data are obtained from the FRED database.

Table 2 presents descriptive statistics and preliminary diagnostics for the variables used in the empirical analysis. Across commodity groups, dispersion is highest for natural gas and lowest for housing, consistent with the well-documented volatility hierarchy between commodities and real assets. Skewness and excess kurtosis indicate fat-tailed behavior in energy and non-energy indexes, particularly for natural gas and precious metals, whereas housing exhibits comparatively mild departures from normality.

We also test the significance of gradual/smooth structural breaks based on the regression model $y_t = d_0 + d_1 \sin\left(\frac{2\pi kt}{T}\right) + d_2 \cos\left(\frac{2\pi kt}{T}\right) + e_t$ using the F-test (denoted as F*trig*) for the null hypothesis of $d_1 = d_2 = 0$. By employing one frequency, the null hypothesis is rejected at 1 % for all series, supporting the significance of breaks[8]. These findings further

Table 1

States included in the nine U.S. census divisions.

U.S. Census Division	Abbrev.	*States*
East North Central	ENC	Indiana, Illinois, Michigan, Ohio, Wisconsin
East South Central	ESC	Alabama, Kentucky, Mississippi, Tennessee
Middle Atlantic	MA	New Jersey, New York, Pennsylvania
Mountain	MT	Arizona, Colorado, Idaho, New Mexico, Montana, Utah, Nevada, Wyoming
New England	NE	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
Pacific	PF	Alaska, California, Hawaii, Oregon, Washington
South Atlantic	SA	Delaware, DC, Florida, Georgia, Maryland, *N. Carolina*, *S. Carolina*, Virginia, W. Virginia
West North Central	WNC	Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
West South Central	WSC	Arkansas, Louisiana, Oklahoma, Texas
United States	NAT	Aggregate

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[4] Everything that is assumed for the series i hold for series j as well.

[5] In order to save space, we are not including the full derivation and explanations of the model. Interested readers can refer to Nazlioglu et al. (2020a and 2020b)

[6] Stenvall et al. . (2022) focus on short-term interactions between energy commodities and the housing market, incorporating macroeconomic controls such as unemployment, industrial production, interest rate, credit growth, and house price inflation. By contrast, our study examines the long-term price and volatility interactions between housing and both energy and non-energy commodities. Accordingly, we employ a more housing-centered set of controls, including the 30-year mortgage rate, inflation, U.S. unemployment rate, housing starts, and real disposable income per capita. While theirs emphasize broader macroeconomic conditions, ours directly capture the demand, supply, and affordability aspects most relevant for long-term housing market dynamics.

[7] All energy and non-energy commodities are adjusted for heating degree days (HDD) when conducting the price and volatility transmission tests. To ensure the reliability of the inferences, several robustness checks are performed on these adjustments. Details on the methods and corresponding results are provided in the Appendix.

[8] We have also conducted Augmented Dickey and Fuller (1979) unit root tests as well as Enders and Lee (2012b) ADF unit root tests with Fourier approximation (F-ADF). The optimal frequency and lags were determined by Schwarz information criterion for F-ADF by setting maximum number of lags to 5 and of Fourier frequency to 3. The results show the null hypothesis cannot be rejected. All results are available upon request.

Table 2

Descriptive statistics and preliminary tests.

Commodity	Min.	Mean	Max.	SD	S	K	JB		F*trig*	
Energy										
Oil	11.35	51.49	133.88	29.42	0.47	2.09	28.38	***	265.535	***
Gas	5.50	11.25	25.34	4.05	0.69	3.10	31.84	***	82.476	***
Coal	24.00	78.63	467.78	70.47	3.15	15.18	3142.13	***	56.819	***
Non-Energy										
Agriculture	299.61	690.38	1461.00	246.52	0.98	3.85	76.52	***	151.66	***
Indst. Metal	397.20	1098.16	2316.40	520.09	0.37	1.90	29.45	***	198.29	***
Prec.Metal	341.95	1114.82	2634.43	688.18	0.34	1.62	39.73	***	465.83	***
Housing										
ENC	100.00	178.75	349.92	55.29	1.23	4.44	135.97	***	52.049	***
ESC	100.00	189.97	399.96	70.31	1.30	4.41	146.94	***	94.548	***
MA	98.80	185.51	379.64	69.80	0.66	3.13	29.66	***	121.252	***
MT	98.75	253.49	596.80	126.64	1.26	3.97	121.32	***	92.947	***
NE	95.10	196.41	420.57	79.08	0.73	3.38	37.93	***	90.325	***
PF	95.24	212.95	469.12	104.08	0.81	2.89	43.92	***	101.309	***
SA	100.00	202.17	460.20	88.05	1.20	4.12	117.59	***	84.177	***
WNC	100.00	201.56	404.10	72.39	0.92	3.59	63.05	***	97.043	***
WSC	99.58	199.69	421.92	83.30	1.10	3.59	86.61	***	150.835	***
NAT	100.00	198.80	424.72	80.52	1.06	3.75	84.63	***	96.062	***
Macro-Controls										
Mortgage rate	2.65	5.86	9.62	1.77	0.06	1.92	19.77	***	459.13	***
Inflation	−2.10	2.62	9.06	1.58	1.09	6.26	257.46	***	26.14	***
Unemployment	3.40	5.74	14.80	1.77	1.20	4.84	153.50	***	23.79	***
Income	28,593	3928	6150	648	0.17	2.38	8.25	**	198.36	***
Housing starts	3.30	5.81	12.20	1.79	1.13	3.89	98.73	***	19.63	***

Notes: Min. is minimum value, Max. is maximum value, SD is standard deviation, S is Skewness, K is Kurtosis, and JB is Jarque and Bera (1987) normality statistic. F*trig* tests the significance of trigonometric terms in $y_t = d_0 + d_1 \sin\left(\frac{2\pi kt}{T}\right) + d_2 \cos\left(\frac{2\pi kt}{T}\right) + e_t$, for the null of $d_1 = d_2 = 0$ by using $k = 1$ with the usual F-testing procedure. k^* is the Fourier frequency selected by minimizing the sum of squared residuals from OLS estimation of eq. (4) with k∈[1,1.1,1.2…,5]. ***, **, and * indicate statistical significance at 1, 5, and 10 %.

necessitate the methodologies we use that account for all types of structural breaks, including gradual ones.

Fig. 1a and 1b show the relative scaled prices of Aggregate U.S. Housing against energy and non-energy commodities over time. The values have been normalized based on their initial prices in 1991, showing the percentage increase or decrease relative to the starting point.

When we look at the price comparison between housing and energy commodity prices (Fig. 1a), we see that energy commodities had a significant volatility jump starting in late 2007. This high volatility cluster continued until 2016, when oil was the most volatile among the energy commodities. In the meantime, housing price volatility remained in a narrower band where there was a comparatively smaller jump around 2006, and prices have been steadily increasing since 2012. Coal prices tracked along with oil and natural gas until 2020. After that, coal had a significant price increase, peaking in 2022 and then coming down to normal levels (similar to other energy commodities) in 2024. These movements parallel major market events. The global financial crisis of 2007–2008 corresponds to the significant volatility we observe in energy prices. In July 2008, oil prices peaked at around $147 per barrel, and by December 2008, they had plummeted to about $33 per barrel as the financial crisis deepened, illustrating extreme volatility. The subprime mortgage crisis, influenced by an increase in high-risk mortgage lending, led to a rise in defaults starting in 2006, which contributed to the bursting of the housing bubble. The significant price jump in coal corresponds with a post-pandemic economic rebound, causing a demand surge in energy, natural gas shortages, and the Russia-Ukraine conflict, which forced sanctions on Russia and a significant decrease in coal supply. The prices coming back down to normal levels in 2024 can be attributed to increased coal production, importers diversifying suppliers, and a decrease in demand for coal.

The non-energy panel (Fig. 1b) reveals that industrial metals track episodes of elevated construction input costs more closely than agriculture or precious metals, consistent with a replacement-cost channel; agriculture displays cumulative movements aligned with food-price cycles and trade shocks; and precious metals reflect macro-financial conditions and real-rate environments rather than construction cost pressures.

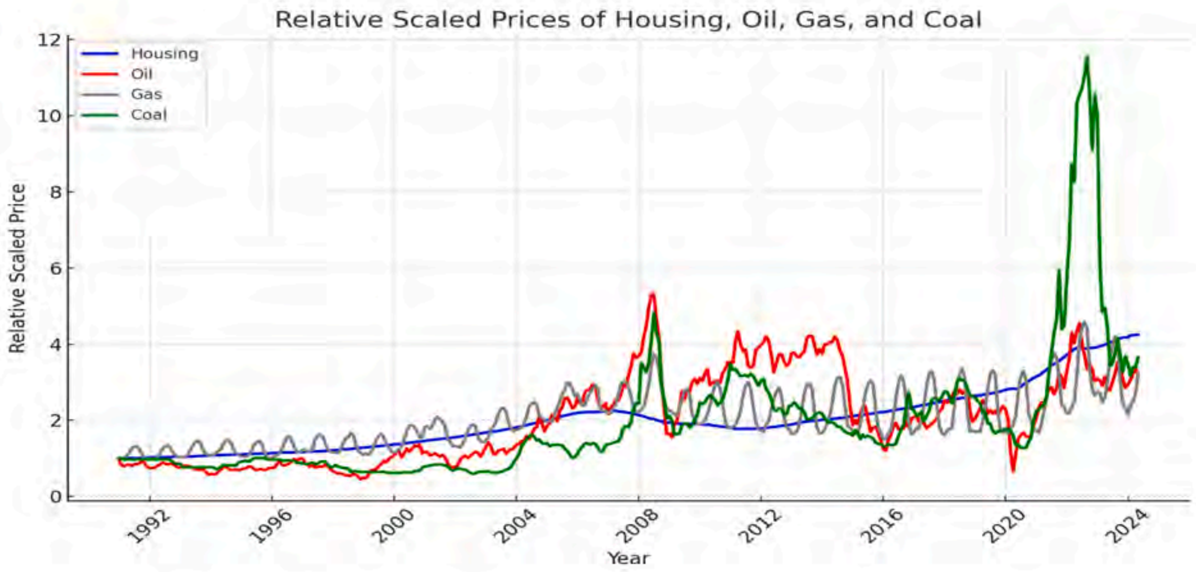
5. Results

5.1. Price transmission in energy commodities

Our transmission analysis starts with oil and the regional housing market (Table 3). We find that there is price transmission from oil to New England, Pacific, West South Central and the aggregate national housing price index. These results can be corresponding to a combination of regional economic structures, dependence on the oil industry, and the unique ways in which oil prices influence local economies.

Table 3 shows economically meaningful but regionally heterogeneous long-run linkages. On the commodity-to-housing direction, transmission is significant for New England (NE), West South Central (WSC), Pacific (PF), and the national aggregate (NAT). These patterns align with well-documented channels: in producer-heavy WSC (Texas, Oklahoma, Louisiana, Arkansas), oil income and employment cycles feed into regional demand and collateral values; the 2010s shale expansion and subsequent busts amplify this mechanism (U.S. Energy Information Administration, 2025a; U.S. Energy Information Administration, 2017a; Nguyen et al., 2021). In NE, the high prevalence of heating-oil households (about 82 % of U.S. heating-oil users reside in the

a: Time Plot of Relative Scaled Prices of Aggregate US Housing, Oil, Gas, and Coal



b: Time Plot of Relative Scaled Prices of Aggregate US Housing, Agriculture, Industrial Metals, and Precious Metals

Fig. 1. a: Time plot of relative scaled prices of aggregate US housing, oil, gas, and coal. b: Time plot of relative scaled prices of aggregate US housing, agriculture, industrial metals, and precious metals.

Northeast) reveals a persistent cost-of-living channel that remains after HDD conditioning, plausibly via transport costs, inflation pass-through, and mortgage-rate responses (U.S. Energy Information Administration, 2024a; Nguyen et al., 2021). In PF, the West Coast's constrained and policy-intensive fuels market (CARB gasoline, capacity reductions, heightened import dependence) embeds oil shocks more durably in household budgets and expectations (California Energy Commission, 2024; U.S. Energy Information Administration, 2024a; Reuters, 2025). At the same time, the housing-to-commodity margin (To Oil) is significant only for East North Central (ENC), consistent with bidirectional information flows documented for oil–housing during turbulent periods (Nguyen et al., 2021): housing prices in the manufacturing belt can proxy shifts in expected activity and mobility that forecast petroleum demand. Absence of significance elsewhere is coherent with the global nature of crude pricing and with regional heterogeneity in exposure; in many divisions, oil shocks are absorbed by commuting patterns,

Table 3
Price transmission with oil.

Region	From Oil		*p*-value	To Oil		p-value
ENC	2.5228		0.1122	3.8499	*	0.0497
ESC	0.8073		0.3689	1.4527		0.2281
MA	0.7307		0.3927	0.2022		0.6529
MT	0.3374		0.5613	0.6972		0.4037
NE	5.6631	**	0.0173	1.6659		0.1968
PF	8.2189	**	0.0417	1.0629		0.7860
SA	0.4624		0.4965	0.6234		0.4298
WNC	0.0063		0.9370	1.2052		0.2723
WSC	6.6696	***	0.0098	0.0539		0.8164
NAT	6.0312	**	0.0141	1.0949		0.2954

Notes: The results are based on Fourier TY approach with single frequency which is based on eq. (3), with one frequency. Maximum lag (p) is set to 12, then optimal p is determined by Schwarz information criterion. p-value is based on the asymptotic chi-square distribution. VAR(p + d) models are estimated with d equal to 1. VAR models include housing price and heating-degree days controlled oil prices for each region as endogenous variables and macroeconomic indicators (30-year mortgage rate, inflation, U.S. unemployment rate, housing starts, and real disposable income per capita) as additional control variables. *, ** and *** represents significance at 10 %, 5 % and 1 % level.

substitution, or policy buffers rather than translating into persistent price integration (Stenvall et al., 2022).

The price-transmission analysis with natural gas provides a different picture (Table 4). The results indicate no statistically significant long-run transmission in either direction across regions. This null result is informative: once commodity prices are conditioned on HDD and the tests accommodate smooth structural breaks, the episodic co-movements between housing and natural gas prices that appear in returns-based evidence (e.g., tail dependence) do not persist as long-run price integration (Stenvall et al., 2022). The finding is consistent with the dominant role of weather and storage in U.S. gas pricing—winter temperatures, inventories relative to the five-year average, and short-run market tightness drive Henry Hub dynamics (U.S. Energy Information Administration, 2023; U.S. Energy Information Administration, 2025b). Recent episodes underscore this mechanism: historically low gas prices in 2023–2024 with record-high storage and unusually warm winters, and subsequent forecasted increases tied to LNG export growth and inventory rebalancing (Reuters, 2024; U.S. Energy Information Administration, 2025b; American Gas Association, 2024). Such transitory weather-storage cycles affect household energy expenditures but wash out in levels-based, break-robust causality tests once HDD is explicitly controlled. The absence of significant housing-to-gas transmission is likewise expected: residential real estate prices are slow-moving aggregates that are unlikely to forecast short-horizon gas fundamentals after controlling for macro factors and weather. Overall, the gas results refine the narrative advanced by returns-based studies by showing that long-run price integration with housing is weak once meteorological and regime effects are separated (Stenvall et al., 2022).

Table 4
Price transmission with natural gas.

Region	From Gas	p-value	To Gas	p-value
ENC	0.1076	0.7429	0.1651	0.6845
ESC	3.3100	0.6523	1.4789	0.9155
MA	0.8556	0.3550	0.0071	0.9330
MT	2.8453	0.7238	1.5251	0.9102
NE	0.8805	0.9716	1.7136	0.8872
PF	2.3202	0.8033	0.6684	0.9847
SA	2.6647	0.7515	4.6131	0.4649
WNC	0.2027	0.6526	1.2336	0.2667
WSC	0.7580	0.8595	3.6380	0.3033
NAT	0.8914	0.3451	0.1088	0.7415

Notes: The results are based on Fourier TY approach with single frequency which is based on eq. (3), with one frequency. Maximum lag (p) is set to 12, then optimal p is determined by Schwarz information criterion. *p*-value is based on the asymptotic chi-square distribution. VAR(p + d) models are estimated with d equal to 1. VAR models include housing price and heating-degree days controlled natural gas prices for each region as endogenous variables and macroeconomic indicators (30-year mortgage rate, inflation, U.S. unemployment rate, housing starts, and real disposable income per capita) as additional control variables. *, ** and *** represents significance at 10 %, 5 % and 1 % level.

Regarding Coal, Table 5 shows very limited, localized effects: coal-to-housing transmission is significant only for the Pacific division (PF). This pattern is historically relevant. During the early part of the sample, PF includes states with legacy coal-fired generation and interconnected wholesale power markets (e.g., Washington's Centralia units and Oregon's Boardman plant), and coal-related electricity cost swings can pass through to household budgets and valuations; both facilities retire during 2020–2025 (U.S. Energy Information Administration, 2025c; Oregon Public Broadcasting, 2020; TransAlta, 2025). As decarbonization and plant retirements reduce coal's salience in the West, long-run integration diminishes elsewhere, which our Fourier-augmented tests capture by allowing smooth structural change. The absence of significant coal transmission in other regions is consistent with coal's structural decline in U.S. energy supply and with the increasing role of gas and renewables in marginal electricity pricing (Reuters, 2024). Taken together with the oil results, the coal evidence emphasizes that energy–housing integration in levels is commodity-specific: where coal matters historically through power prices, we observe transmission; otherwise, persistent integration is scarce. These coal patterns complement returns-based evidence of energy–housing dependence in extreme states (Stenvall et al., 2022) but indicate little enduring price integration once the sample's regime shifts are accommodated.

5.2. *Volatility transmission in energy commodities*

In this part of our study, we concentrate on the volatility interactions between specific energy commodity prices and the housing market. Table 6 presents our results on the oil volatility. The findings indicate widespread, predominantly bidirectional spillovers between oil and regional housing markets. On the commodity-to-housing direction, volatility spillovers are significant for ENC, MA, NE, PF, WNC, WSC, and the national aggregate (NAT). On the housing-to-commodity direction, volatility from housing to oil is significant across all nine divisions and NAT. Economically, these results are consistent with the dual role of oil as both a production input and a financialized macro-financial barometer. Producer-heavy WSC and manufacturing-intensive ENC are exposed to energy-sector capital cycles and demand expectations that

Table 5
Price transmission with coal.

Region	From Coal		p-value	To Coal	p-value
ENC	0.0911		0.7628	0.1578	0.6912
ESC	0.8063		0.3692	0.0155	0.9009
MA	0.3814		0.5369	0.0543	0.8158
MT	0.0013		0.9718	0.0474	0.8277
NE	0.4740		0.4912	0.2742	0.6005
PF	10.4981	**	0.0148	0.5489	0.9080
SA	0.0400		0.8414	0.0943	0.7588
WNC	1.6415		0.2001	2.6296	0.1049
WSC	1.3558		0.2443	0.2362	0.6269
NAT	0.0003		0.9873	0.1483	0.7002

Notes: The results are based on Fourier TY approach with single frequency which is based on eq. (3), with one frequency. Maximum lag (p) is set to 12, then optimal p is determined by Schwarz information criterion. p-value is based on the asymptotic chi-square distribution. VAR(p + d) models are estimated with d equal to 1. VAR models include housing price and heating-degree days controlled coal prices for each region as endogenous variables and macroeconomic indicators (30-year mortgage rate, inflation, U.S. unemployment rate, housing starts, and real disposable income per capita) as additional control variables. *, ** and *** represents significance at 10 %, 5 % and 1 % level.

Table 6

Volatility transmission with oil.

Region	From Oil		*p*-value	To Oil		p-value
ENC	16.0453	***	0.0003	14.0022	***	0.0009
ESC	2.6317		0.2682	14.8809	***	0.0006
MA	9.4717	***	0.0088	12.8263	***	0.0016
MT	2.3648		0.3065	12.6519	***	0.0018
NE	14.5083	***	0.0007	15.0518	***	0.0005
PF	11.5830	***	0.0031	13.0027	***	0.0015
SA	1.5986		0.4496	14.2272	***	0.0008
WNC	5.9287	**	0.0516	13.2907	***	0.0013
WSC	4.7741	*	0.0919	13.5747	***	0.0011
NAT	13.7091	***	0.0011	13.2238	***	0.0013

Notes: The results are based on volatility spillover Fourier *LM* ($F\lambda_{LM}$) statistic from the variance eq. (8), with one frequency. The mean equation is based AR(1) model for the return series. *, ** and *** represents significance at 10 %, 5 % and 1 % level.

Table 7

Volatility transmission with natural gas.

Region	From Gas		*p*-value	To Gas		p-value
ENC	2.2391		0.3264	1.6909		0.4294
ESC	2.9395		0.2300	2.1745		0.3371
MA	3.0226		0.2206	2.5788		0.2754
MT	0.3327		0.8468	5.7375	*	0.0568
NE	2.1442		0.3423	6.9318	**	0.0312
PF	3.5373		0.1706	1.9533		0.3766
SA	4.3656		0.1127	2.2687		0.3216
WNC	4.8636	*	0.0879	1.6925		0.4290
WSC	2.0567		0.3576	0.1250		0.9394
NAT	2.7311		0.2552	3.3434		0.1879

Notes: The results are based on volatility spillover Fourier *LM* ($F\lambda_{LM}$) statistic from the variance eq. (8), with one frequency. The mean equation is based AR(1) model for the return series. *, ** and *** represents significance at 10 %, 5 % and 1 % level.

condition housing volatility and, in turn, propagate to oil (U.S. Energy Information Administration, 2025a; Grossman et al., 2019). In NE and PF, fuel mix, regulatory structure, and supply constraints (heating-oil prevalence in the Northeast; California's CARB fuel specifications, capacity limitations, and import dependence) create an environment where oil price uncertainty permeates household budgets and local risk premia (U.S. Energy Information Administration, 2024a; California Energy Commission, 2024). The near-universal significance of the "To Oil" side aligns with evidence that housing and oil share heightened connectedness during stress episodes, reflecting common financial conditions and risk-sharing channels (Nguyen et al., 2021; Ewing and Malik, 2016). The absence of "From Oil" spillovers in ESC, MT, and SA is plausible: diversified electricity and transportation fuel mixes, lower direct heating-oil reliance, and greater capacity to substitute among energy inputs dampen the translation of oil volatility into local housing risk (Stenvall et al., 2022). Importantly, these volatility findings complement the paper's price-in-levels results: oil exhibits long-run price integration in selected regions, while volatility spillovers are broader and more symmetric, as would be expected when risk shocks transmit more readily than permanent level shifts (Nguyen et al., 2021; Ewing and Malik, 2016).

Although region-specific factors are important, we suspect the main driver of these interactions is related to the financialization of oil markets. Regions with more integrated financial markets may experience greater transmission of volatility due to investor behavior and expectations (Basak and Pavlova, 2016). Housing market volatility can influence investor behavior, leading to shifts in investment portfolios, including commodities like oil. Changes in investment demand for oil futures can increase oil price volatility. Housing markets are significant indicators of economic health. Volatility in housing prices reflects changes in economic conditions, consumer confidence, and investment levels. When housing price volatility increases, it may signal economic uncertainty, leading to fluctuations in oil demand and price volatility.

Regarding the volatility integration with natural gas (Table 7), we find somewhat similar results to our price transmission analysis. Results indicate rare occurrences of spillovers even when we control for HDD. In the commodity-to-housing direction, only WNC exhibits significant reception of gas volatility (at 10 % significance). On the other hand, volatility from housing to gas is significant in MT (at 10 % significance) and NE; other regions and the national aggregate are not significant. Due to the weak and rare statistical significance we observe, it is possible for the findings to be less applicable to interpretation. However, these patterns are still consistent with the regional fundamentals of U.S. natural gas. In WNC, winter demand spikes and exposure to mid-continent pipeline networks make gas volatility particularly sensitive to polar-vortex-type events and storage deviations—uncertainty that can spill into housing via heating expenses and local macro sentiment (U.S. Energy Information Administration, 2023; U.S. Energy Information Administration, 2025b). In NE, well-documented pipeline constraints and a high share of buildings heated by delivered fuels render gas prices and basis volatility particularly reactive to demand shocks, so periods of heightened housing uncertainty can presage volatility on regional gas hubs (U.S. Energy Information Administration, 2022; U.S. Energy Information Administration, 2024a). In MT, several states have meaningful upstream exposure (e.g., Colorado, New Mexico, Wyoming), so cyclical variations in housing activity and credit conditions map into investment cycles that can affect local gas market volatility (U.S. Energy Information Administration, 2025d). The absence of significant spillovers elsewhere coheres with the study's price results: once we remove weather-driven demand via HDD and accommodate all types of structural breaks, natural gas explains little of the persistent housing dynamics, and the volatility channel is concentrated in regions with either infrastructure constraints (NE), pronounced winter severity (WNC), or upstream production linkages (MT). More broadly, the limited footprint of gas volatility relative to oil is consistent with evidence that commodity volatility connectedness varies across classes and tends to intensify only in specific regimes and regions (Farid et al., 2022; Guhathakurta et al., 2020).

In Table 8, we provide our findings about the volatility transmission between coal and the housing market. Results reveal very few coal-to-housing volatility spillovers (in MA, MT and NE) and no significant housing-to-coal spillovers. The "From Coal" significance in MA accords with the region's historical proximity to coal production and coal-fired generation in parts of the PJM footprint; uncertainty in fuel markets can pass through wholesale power prices and, by extension, to household budgets and housing risk (U.S. Energy Information Administration,

Table 8

Volatility transmission with coal.

Region	From Coal		p-value	To Coal		p-value
ENC	4.1197		0.1275	1.5632		0.4577
ESC	0.8288		0.6607	3.6248		0.1633
MA	20.2842	***	0.0000	0.6595		0.7191
MT	8.6447	**	0.0133	0.6783		0.7124
NE	6.6955	**	0.0352	0.5823		0.7474
PF	2.7869		0.2482	1.6232		0.4442
SA	2.2017		0.3326	0.6307		0.7295
WNC	1.0526		0.5908	1.8621		0.3941
WSC	3.8418		0.1465	1.1045		0.5757
NAT	5.3266	*	0.0697	0.6583		0.7195

Notes: The results are based on volatility spillover Fourier *LM* ($F\lambda_{LM}$) statistic from the variance eq. (8), with one frequency. The mean equation is based AR(1) model for the return series. *, ** and *** represents significance at 10 %, 5 % and 1 % level.

2025e). In NE, early-sample coal-fired units—such as Brayton Point (retired 2017)—contribute to a transitional period during which coal market volatility plausibly maps into electricity prices and housing risk premia; the fading role of coal thereafter is appropriately handled by the paper's Fourier augmentation (U.S. Energy Information Administration, 2017b). In MT, the presence of major coal resources (e.g., Powder River Basin in Wyoming) and regional exposure to coal logistics (rail and contractual arrangements) provide a channel from coal market uncertainty to local activity and residential risk (U.S. Energy Information Administration, 2025f). The lack of significant spillovers in other divisions suggests coal's structural decline in the U.S. generation mix and the increasing dominance of gas and renewables in marginal pricing—factors that limit coal volatility's ability to shape broad housing risk outside historically exposed areas (U.S. Energy Information Administration, 2024a). These volatility results dovetail with the price-in-levels evidence that coal plays, at most, a localized role in long-run housing integration, with spillovers concentrated where historical generation assets or fuel supply chains remain salient (Stenvall et al., 2022).

Taken together, the price (Tables 3–5) and volatility (Tables 6–8) results portray a coherent energy–housing nexus that is both commodity-specific and regionally contingent. Oil emerges as the principal financialized commodity with near-universal bidirectional long-run volatility spillovers. This pattern is economically intuitive: beyond direct transport and heating links, oil aggregates global macro-financial information, so oil shocks transmit widely and, reciprocally, housing volatility proxies shifts in domestic demand and credit conditions relevant for oil (Nguyen et al., 2021; Ewing and Malik, 2016). Natural gas, by contrast, displays muted long-run price integration after HDD adjustment but exhibits targeted volatility channels in regions where infrastructure constraints, winter severity, or upstream exposure amplify uncertainty (NE, WNC, MT). Coal demonstrates localized volatility spillovers (MA, MT, NE) consistent with historical generation assets and supply chains; elsewhere, the energy transition and coal's declining marginal role temper both price and volatility transmission. Importantly, there is no contradiction between the price and volatility layers: level integration requires durable channels linking long-run fundamentals, whereas volatility spillovers reflect how information and risk propagate in the short- to medium-run even when levels remain decoupled. The HDD-conditioning step clarifies that the persistence of oil's linkages is not a spurious artifact of weather, while the Fourier-augmented inference ensures that structural change in energy use and policy does not bias causality results. The aggregate message is that energy–housing connectedness in the U.S. is strongest and most generalized for oil, selective for natural gas (concentrated in regions with pronounced climatic and infrastructural features), and localized for coal; this gradient maps cleanly to the economic roles of these fuels in household budgets, industrial structure, and regional energy systems. As such, the empirical findings are internally consistent and align with recent evidence on cross-market connectedness and regime-dependent spillovers in commodity markets (Farid et al., 2022; Guhathakurta et al., 2020), while complementing tail-dependence work that focuses on extremes (Stenvall et al., 2022).

5.3. Price transmission in non-energy commodities

In order to keep cross-commodity connectedness in perspective, we repeat our price transmission analysis with prominent non-energy commodities. Table 9 indicates long-run price transmission from Agriculture into housing in MT, NE, SA, WSC, and NAT, with no significant housing-to-agriculture effects. Interpreted through the paper's break-robust, HDD-conditioned lens, these linkages represent persistent channels whereby agricultural price levels enter household budgets and regional income, ultimately capitalized into house prices. In WSC and MT, agriculture's macro footprint is sizable—Texas leads U.S. production in multiple agricultural categories and cash receipts, and the Mountain division includes farm- and ranch-intensive states—so commodity income cycles plausibly transmit to local housing via employment, migration, and collateral values (USDA-ERS, 2025; Texas NASS, 2023). In NE, the mechanism is suspected to be primarily cost-of-living: food price pass-through to headline inflation and mortgage-rate expectations align with evidence that agricultural and energy commodities materially affect inflation dynamics, especially in high-inflation regimes (Abbas and Lan, 2020). Although we control for inflation in our tests, the results indicate either an interaction outside inflationary pressures or an overreaction/sensitivity to inflation (or expected inflation) that is not captured by the inflation control variable we use. The SA effect is consistent with large, consumption-oriented metros where food and transportation costs shape affordability constraints and thus the user cost of housing. The absence of significant housing-to-agriculture effects is economically coherent: regional house price levels are slow-moving and unlikely to forecast standardized agricultural indices once macro factors are controlled. Importantly, while the number of instances where agriculture is linked to housing is comparable to Oil in Table 3, the economic content differs: agricultural transmission is expenditure/income-driven and region-specific, whereas oil's integration reflects transport and macro-financial channels tied to energy supply and regulation (Nguyen et al., 2021).

Table 10 shows that metals prices transmit to housing in ENC, ESC,

Table 9
Price transmission with agricultural.

Region	From AG		*p*-value	To AG		p-value
ENC	2.1503		0.1425	0.8880		0.3460
ESC	1.6157		0.2037	0.3638		0.5464
MA	0.4904		0.4837	0.0304		0.8615
MT	3.9247	**	0.0476	0.0001		0.9912
NE	3.9956	**	0.0456	0.0408		0.8398
PF	0.2831		0.8680	1.9214		0.3826
SA	3.5207	*	0.0606	0.3279		0.5669
WNC	0.0380		0.8454	0.3158		0.5742
WSC	3.9013	**	0.0482	2.6330		0.1047
NAT	4.2557	**	0.0391	2.0584		0.1514

Notes: The results are based on Fourier TY approach with single frequency which is based on eq. (3), with one frequency. Maximum lag (p) is set to 12, then optimal p is determined by Schwarz information criterion. p-value is based on the asymptotic chi-square distribution. VAR(p + d) models are estimated with d equal to 1. VAR models include housing price and heating-degree days controlled coal prices for each region as endogenous variables and macroeconomic indicators (30-year mortgage rate, inflation, U.S. unemployment rate, housing starts, and real disposable income per capita) as additional control variables. *, ** and *** represents significance at 10 %, 5 % and 1 % level.

Table 10
Price transmission with industrial metals.

Region	From IM		p-value	To IM		p-value
ENC	6.4717	**	0.0110	0.7081		0.4001
ESC	11.0893	***	0.0009	0.8695		0.3511
MA	0.5521		0.4575	0.3436		0.5578
MT	7.7954	**	0.0203	0.5805		0.7481
NE	0.2069		0.6492	0.1810		0.6705
PF	1.7919		0.4082	0.3625		0.8342
SA	2.2987		0.1295	3.8981	**	0.0483
WNC	0.0161		0.8990	0.0044		0.9468
WSC	6.3790	**	0.0115	0.0523		0.8191
NAT	7.6504	***	0.0057	0.6021		0.4378

Notes: The results are based on Fourier TY approach with single frequency which is based on eq. (3), with one frequency. Maximum lag (p) is set to 12, then optimal p is determined by Schwarz information criterion. p-value is based on the asymptotic chi-square distribution. VAR(p + d) models are estimated with d equal to 1. VAR models include housing price and heating-degree days controlled coal prices for each region as endogenous variables and macroeconomic indicators (30-year mortgage rate, inflation, U.S. unemployment rate, housing starts, and real disposable income per capita) as additional control variables. *, ** and *** represents significance at 10 %, 5 % and 1 % level.

MT, WSC, and NAT; conversely, housing transmits to metals only in SA. The directional asymmetry is intuitive. Industrial metals (e.g., copper, steel, aluminum) are core inputs to residential construction and infrastructure; cost shocks therefore embed directly in replacement costs and the user cost of housing. This channel is strongest where manufacturing and construction footprints are large—ENC and ESC contain the U.S. manufacturing belt, while WSC and MT combine robust construction cycles with resource extraction and fabrication capacity (USGS, 2024, 2025; NAHB, 2023). The SA "To Indutrial Metals" effect is consistent with demand pull from rapid housing expansion in southeastern metros, where building cycles can forecast subsequent metals demand and pricing. The pattern accords with recent evidence that metals are central transmitters in commodity networks and that cross-class connectedness intensifies in stress regimes (Bastianin et al., 2023; Farid et al., 2022; Guhathakurta et al., 2020). At the same time, the lack of significance elsewhere underscores the role of local supply chains and sectoral composition: in regions where services dominate or where pipeline and import frictions buffer input costs, long-run price co-movement with metals is weak. These metals results complement the energy commodity findings by isolating a non-energy benchmark for construction-cost channels; oil remains the only energy commodity to display broad long-run price integration after HDD and macro conditioning, whereas metals' influence is region-specific and consistent with input-cost pass-through.

When we evaluate precious metals (Table 11) we find that precious metals price-transmit to housing in ENC, MT, WSC, and NAT, and a housing-to-precious-metals effect in MT. Because precious metals primarily reflect macro-financial risk and real-rate expectations rather than direct input costs, the observed long-run co-movement most likely captures slow-moving market factors affecting housing valuations. The MT bidirectional link is plausible given the division's mining exposure—Nevada alone accounts for roughly 70 %–73 % of U.S. gold output—and the broader commodity orientation of regional activity (USGS, 2023, 2024). The WSC and ENC effects are consistent with financially integrated housing markets in large metro areas where wealth, risk appetite, and mortgage-rate expectations move with safe-haven demand for gold and silver (Akhtaruzzaman et al., 2021; Salisu and Gupta, 2021). The absence of significance elsewhere coheres with the idea that precious metals do not map directly into housing via cost channels and that, once macro factors are controlled, remaining co-movement is selective. These results clarify that non-energy financial commodities mostly transmit through portfolio and expectations channels.

Table 11
Price transmission with precious metals.

Region	From PM		*p*-value	To PM		p-value
ENC	4.9308	**	0.0264	0.1651		0.6845
ESC	0.8487		0.3569	1.7726		0.1831
MA	2.1220		0.1452	0.0012		0.9727
MT	5.8591	*	0.0534	5.7304	*	0.0570
NE	2.1534		0.1423	0.2269		0.6338
PF	2.9582		0.3981	6.0024		0.1115
SA	0.9772		0.3229	0.0058		0.9392
WNC	0.0004		0.9836	0.0987		0.7534
WSC	3.0729	*	0.0796	2.5809		0.1082
NAT	4.0454	**	0.0443	0.0005		0.9818

Notes: The results are based on Fourier TY approach with single frequency which is based on eq. (3), with one frequency. Maximum lag (p) is set to 12, then optimal p is determined by Schwarz information criterion. p-value is based on the asymptotic chi-square distribution. VAR(p + d) models are estimated with d equal to 1. VAR models include housing price and heating-degree days controlled coal prices for each region as endogenous variables and macroeconomic indicators (30-year mortgage rate, inflation, U.S. unemployment rate, housing starts, and real disposable income per capita) as additional control variables. *, ** and *** represents significance at 10 %, 5 % and 1 % level.

5.4. *Volatility transmission in non-energy commodities*

Table 12 reveals asymmetric volatility spillovers between agriculture and the housing market. From Agriculture to housing, volatility transmits significantly in MT, SA, WSC, and NAT; from housing to Agriculture, spillovers are widespread—ENC, ESC, MA, MT, NE, SA, WNC, WSC, and NAT. In agriculture-exposed divisions, weather, inventory, and trade shocks raise uncertainty about food prices, household budgets, and local income—risk that is rapidly capitalized into housing risk premia even when levels are decoupled. The broad housing-to-agriculture spillovers highlight the role of macro-financial conditions: U.S. housing co-moves with aggregate demand, credit cycles, and collateral values; volatility in these fundamentals induces portfolio rebalancing and hedging demand in commodity markets, propagating to agricultural indices (Abbas and Lan, 2020; Farid et al., 2022; Ji et al., 2018). Regionally, the MT/SA/WSC reception aligns with production agriculture and food-processing footprints, while NE's strong "To AG" reflects the sensitivity of distribution margins to demand uncertainty in a high-cost region. Crucially, agriculture does not transmit only risk: Table 9 shows persistent housing price integration in several divisions. Agriculture exhibits both selective long-run price transmission (budget/income channels) and broad volatility connectedness (risk channels), whereas oil's distinctiveness lies in the combination of durable price integration tied to energy-specific mechanisms and near-universal volatility spillovers (Nguyen et al., 2021).

Industrial Metals provide significant spillovers to MA, SA, WNC, WSC, and NAT, and the reverse in ENC, NE, PF, and WNC. Industrial metals are central in construction and manufacturing; uncertainty in these inputs—amplified during tariff cycles and pandemic-era supply bottlenecks—feeds into project timelines, builder margins, and housing risk premia (NAHB, 2023). The WSC and SA reception of metals volatility is consistent with large, growth-intensive housing markets where input-cost uncertainty binds. WNC and MA reflect the manufacturing/agriculture interface in the Midwest and Plains where metals prices influence equipment and building costs. On the outgoing side, housing-to-metals volatility in ENC, NE, PF, and WNC suggests that regional housing uncertainty forecasts construction-related metals demand, consistent with connectedness evidence that metals co-move with macro risk and that spillovers intensify in stress regimes (Bastianin et al., 2023; Farid et al., 2022). The presence of two-way spillovers in WNC, coupled with one-way effects elsewhere, underscores that bidirectional volatility integration emerges where both construction demand and manufacturing supply chains are concentrated. The absence of broader bidirectionality highlights that, unlike oil, metals' volatility transmission is more tied to sectoral channels than to macro-financial aggregation. This complements the price results—where metals deliver region-specific long-run integration (ENC, ESC, MT, WSC)—and

Table 12
Volatility transmission with agricultural.

Region	From AG		p-value	To AG		p-value
ENC	1.4015		0.4962	15.5844	***	0.0004
ESC	1.3334		0.5134	15.8555	***	0.0004
MA	4.4001		0.1108	4.7004	*	0.0954
MT	11.2274	***	0.0036	13.9006	***	0.0010
NE	2.1681		0.3382	7.5547	**	0.0229
PF	3.9164		0.1411	4.5253		0.1041
SA	9.7326	***	0.0077	10.9422	***	0.0042
WNC	3.9645		0.1378	19.2586	***	0.0001
WSC	5.7991	*	0.0550	20.5646	***	0.0000
NAT	8.3239	**	0.0156	6.3363	**	0.0421

Notes: The results are based on volatility spillover Fourier *LM* ($F\lambda_{LM}$) statistic from the variance eq. (8), with one frequency. The mean equation is based AR(1) model for the return series. *, ** and *** represents significance at 10 %, 5 % and 1 % level.

supports the interpretation that industrial metals operate primarily through a replacement-cost mechanism rather than a generalized commodity factor.

Table 14 indicates significant precious-metals to housing spillovers in ESC, SA, WNC, WSC, and NAT, and housing to precious-metals spillovers in ENC, NE, and MT. This pattern is consistent with the safe-haven and portfolio-rebalancing roles of gold and silver: during uncertainty, flows into precious metals reprice risk premia in interest-rate-sensitive assets such as housing, while housing volatility can proxy shifts in aggregate demand and credit risk that feed back into precious metals (Akhtaruzzaman et al., 2021; Elgammal et al., 2021). Importantly, the literature documents that gold's transmitter/receiver status is regime-dependent. In some systems and observation windows, oil (and risk assets) act as net transmitters with gold receiving shocks; in others, gold transmits volatility—particularly around macro stress, policy surprises, or liquidity constraints (Mensi et al., 2021; Arfaoui et al., 2023; Farid et al., 2022). Our HDD-conditioned, break-robust results align with the latter: precious metals transmit volatility to housing in several divisions, while housing feeds back to precious metals in financially deep or mining-exposed regions (ENC, NE, MT). The absence of significance elsewhere coheres with the limited direct input role of precious metals in construction costs; where local portfolios and intermediation are thinner, safe-haven flows do not translate as strongly into housing risk. Thus, the precious-metals evidence refines the energy narrative: although both oil and precious metals are found to be heavily financialized in literature, in the context of the housing market, oil remains to be the commodity with the broadest and most persistent linkages, while precious metals' volatility effects are selective and state-contingent.

5.5. *Summary of results*

The combined evidence across price (Tables 3–5, 9–11) and volatility (Tables 6–8, 12–14) tests establishes a coherent energy–housing nexus in which oil is the dominant and most pervasive energy conduit, while natural gas and coal play, at most, selective roles once weather and regime shifts are properly controlled. In the price layer, after conditioning commodity indexes on heating degree days (HDD) and controlling for macro factors, we observe long-run price integration between oil and several housing regions, with particularly clear effects in divisions that either depend more on petroleum for transport and heating or are more exposed to energy policy and supply structure. By contrast, natural gas and coal do not exhibit strong long-run price integration with regional housing once we purge weather-driven demand and allow for smooth structural breaks, indicating that the apparent co-movements sometimes seen in returns are largely short-horizon and regime-specific rather than permanent. This separation is central: persistent level integration requires durable mechanisms that survive weather and macroeconomic conditioning; for oil, those mechanisms, including user-cost/transport, macro-financial aggregation, and policy/market structure, remain definitive.

Table 13

Volatility transmission with industrial metals.

Region	From IM		*p*-value	To IM		p-value
ENC	4.1205		0.1274	16.0518	***	0.0003
ESC	0.9352		0.6265	2.1180		0.3468
MA	5.1804	*	0.0750	2.5548		0.2788
MT	2.8600		0.2393	3.5581		0.1688
NE	1.9480		0.3776	5.6250	*	0.0601
PF	3.8394		0.1467	5.9593	*	0.0508
SA	29.3043	***	0.0000	4.3501		0.1136
WNC	4.9967	*	0.0822	6.0895	**	0.0476
WSC	12.1089	***	0.0023	2.5675		0.2770
NAT	30.1264	***	0.0000	1.8287		0.4008

Notes: The results are based on volatility spillover Fourier *LM* ($F\lambda_{LM}$) statistic from the variance eq. (8), with one frequency. The mean equation is based AR(1) model for the return series. *, ** and *** represents significance at 10 %, 5 % and 1 % level.

Table 14

Volatility transmission with precious metals.

Region	From PM		*p*-value	To PM		p-value
ENC	3.1710		0.2048	11.1613	***	0.0038
ESC	5.2043	*	0.0741	1.7485		0.4172
MA	2.8240		0.2437	3.2695		0.1950
MT	2.7130		0.2576	5.1172	*	0.0774
NE	1.8987		0.3870	10.0498	***	0.0066
PF	1.2349		0.5393	3.4245		0.1805
SA	31.9427	***	0.0000	0.6083		0.7377
WNC	7.9788	**	0.0185	3.4086		0.1819
WSC	12.9860	***	0.0015	1.8800		0.3906
NAT	20.5612	***	0.0000	1.0314		0.5971

Notes: The results are based on volatility spillover Fourier *LM* ($F\lambda_{LM}$) statistic from the variance eq. (8), with one frequency. The mean equation is based AR(1) model for the return series. *, ** and *** represents significance at 10 %, 5 % and 1 % level.

The volatility layer complements this picture. Oil-related volatility spillovers are broad and largely bidirectional across regions: oil uncertainty propagates to local housing risk premia, and housing volatility (as a proxy for domestic demand, credit, and collateral conditions) feeds back to oil. This near-universal volatility connectedness for oil should be expected if oil aggregates global macro and financial information more than the other fuels. Natural gas volatility is very selective—concentrated in regions with winter severity, infrastructure constraints, or upstream linkages—and coal volatility is rare and localized, consistent with coal's declining marginal role and region-specific legacy assets. These volatility findings are consistent with the price results: where durable level integration is weak (gas, coal), risk can still move episodically along identifiable regional channels.

Non-energy commodities provide a holistic benchmark that sharpens the energy narrative. In the price results, industrial metals transmit to housing in manufacturing- and construction-intensive divisions (e.g., ENC, ESC, MT, WSC) and nationally—evidence for a replacement-cost mechanism. Agriculture shows selective but persistent price transmission (e.g., MT, NE, SA, WSC, NAT), consistent with household-budget and regional-income channels; although similar to oil in instances of impact to housing regions, the interpretation and suspected drivers are economically distinct from oil. Precious metals display price co-movement in a smaller set of divisions (e.g., ENC, MT, WSC, NAT), reflecting macro-financial and real-rate conditions rather than direct input costs. In the volatility results, agriculture sends risk into housing in production- and processing-intensive regions and receives risk from housing broadly—evidence of two-way macro-financial propagation. Industrial metals exhibit two-way volatility links concentrated where construction demand and supply chains are thickest. Precious metals act as state-contingent transmitters and receivers: we see precious-metals-to-housing spillovers in several divisions and housing-to-precious-metals feedback where financial intermediation is deep or mining exposure is salient. These non-energy results serve two identification purposes: they (i) prevent possible cross-commodity spillovers from being misattributed to energy and (ii) help attribute oil's persistence to genuinely energy-specific mechanisms rather than a generic "commodity factor."

Overall, the evidence makes economic sense and is internally consistent. Oil retains persistent price integration and widespread volatility connectedness; natural gas and coal do not show strong long-run integration after HDD and break adjustments, and only display limited volatility channels. Industrial metals matter where construction costs are central; agriculture matters where budgets and regional incomes can hinge on food prices; precious metals matter through portfolio and expectations channels. This hierarchy clarifies the dynamics of the energy–housing nexus while also recognizing the role of non-energy markets in shaping overall integration mechanisms. While oil's pervasive and financialized role remains evident even after accounting for weather-related demand, uncertainty in certain non-energy commodities can be more relevant for specific regions through direct channels than does uncertainty in natural gas or coal in the long run.

6. Conclusion

The empirical results establish a clear hierarchy in the transmission of shocks between commodity markets and regional U.S. housing. After conditioning commodity indexes on region-specific heating degree days and controlling for macroeconomic drivers, long-run price and volatility integration is strong for oil, whereas comparable integration for natural gas and coal is largely absent. This pattern persists when the tests allow for smooth structural breaks, indicating that the co-movement that emerges in short-horizon returns does not translate into persistent linkages for gas and coal once weather-driven demand and regime shifts are purged. Oil's persistence is consistent with transmission channels that operate through transport and user-cost components of housing, as well as through macro-financial aggregation whereby oil prices reflect global demand, risk premia, and policy-driven constraints. Oil-related volatility demonstrates widespread and often bidirectional spillovers with regional housing, consistent with oil's informational role during macro-financial stress and with feedback from local demand and credit conditions to energy markets. By contrast, the institutional and climatic determinants of natural gas pricing—degree-day sensitivity, inventory cycles, and infrastructure—produce episodic co-movement that does not survive a break-robust specification; coal's declining role in generation further limits its capacity to anchor durable integration with housing.

The inclusion of non-energy commodities provides a holistic benchmark that clarifies mechanisms and strengthens inference. Industrial metals generate long-run price integration in manufacturing- and construction-intensive regions and nationally, consistent with a replacement-cost channel that ties input prices to housing valuations. Agriculture produces selective but persistent price integration and broad volatility connectedness, suggesting the role of food prices in household budgets and regional incomes and the sensitivity of agricultural markets to macro-financial conditions. Precious metals exhibit selective price co-movement with housing and state-contingent volatility spillovers, a pattern consistent with safe-haven and portfolio-rebalancing behavior in financially deep regions or in areas with mining exposure. Taken together, these results indicate that durable integration is commodity-specific—strongest for oil, but uncertainty in some non-energy commodity markets can be more relevant for certain regions compared to uncertainty in coal and gas markets in the long run.

The methodological choices are central to these conclusions. Conditioning commodity indexes on region-specific heating degree days removes weather-driven demand from the commodity–housing link, avoiding spurious attribution to climatic variation. The Fourier-augmented Toda–Yamamoto approach retains long-run information in levels and accommodates smooth structural change, a critical feature for samples spanning multiple policy, technology, and market regimes. The Hafner–Herwartz variance-causality framework separates risk transmission from mean dynamics, revealing the distinct reach of volatility shocks.

These findings carry several implications. For policy, the sustained role of oil for regional housing valuations supports investments in transport efficiency, weatherization, and the heating-fuel mix in regions with greater exposure to petroleum-linked costs, and it underscores the value of monitoring fuel-market policy and supply structure when assessing regional housing risk. For investors and risk managers, the evidence recommends explicit hedging of oil-related exposures and the incorporation of industrial-metals risk in markets with rapid construction activity or constrained housing supply; agriculture and precious metals warrant attention as volatility channels that alter short- to medium-run housing risk premia even when levels do not co-move. More broadly, situating regional housing within the context of the overall commodity space is economically intuitive and suggests internally consistent patterns: persistent level integration where fundamental linkages are strong, and broader volatility spillovers where information and risk traverse markets. The analysis thus advances understanding of how energy and commodity shocks permeate regional real-asset valuations and provides a framework for assessing the distribution of housing risk across U.S. regions.

CRediT authorship contribution statement

Alper Gormus: Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization. **Robert Salvino:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Conceptualization. **Saban Nazlioglu:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Ugur Soytas:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization.

Appendix A - Additional robustness checks

We implement the HDD-adjustment robustness tests to all disaggregated commodity inputs used in the paper: Oil, Gas, Coal (energy commodities) and Agriculture, Indst. Metals, Prec. Metals (non-energy commodities). All specifications use monthly data, a constant, and ln(price index) as the dependent variable; HDD remains in levels unless otherwise noted.

Methods Used

Baseline: ln(Index) on HDD (levels).

Alt-1 (transform): ln(Index) on ln(1 + HDD).

Alt-2 (seasonality): ln(Index) on HDD + month-of-year fixed effects (11 dummies).

Alt-3 (outlier-robust): Huber M-estimator, ln(Index) on HDD.

Alt-4 (placebo falsification): ln(Index)_t on HDD_{t + 1} (lead). We also check HDD_{t + 2}.

Alt-5 (stability): sub-sample estimates for 1991–2007, 2008–2019, 2020–present; Chow tests at 2008 and 2020.

A. Energy Commodities (Oil, Gas, Coal) - Min/Median/Max.

Residual correlation vs baseline	Alt-1: ln(1 + HDD)	Alt-2: + Seasonality	Alt-3: Robust (Huber)	Placebo R^2 (Lead HDD)	Chow test *p*-value (2008)	Chow test p-value (2020)
Min	0.955	0.962	1	0.0000	0.0000	0.0000
Median	1	0.993	1	0.0015	0.0000	0.0000
Max	1	1	1	0.1420	0.0000	0.0000

B. Non-Energy Commodities (Agriculture, Indst. Metals, Prec. Metals) - Min/Median/Max.

Residual correlation vs baseline	Alt-1: ln(1 + HDD)	Alt-2: + Seasonality	Alt-3: Robust (Huber)	Placebo R^2 (Lead HDD)	Chow test p-value (2008)	Chow test p-value (2020)
Min	0.999	0.966	1	0.0000	0.0000	0.0000
Median	1	0.991	1	0.0008	0.0000	0.0000
Max	1	1	1	0.0029	0.0000	0.0000

Interpretation & link to main identification

1) The HDD-adjusted commodity series are highly robust to alternative ways of removing weather demand effects. Across both sets, residuals from the baseline, ln(1 + HDD), seasonal-adjusted, and robust specifications are near-identical (median correlations $\geq$0.991).

2) Lead-HDD placebos exhibit negligible explanatory power overall (median $R^2 \approx 0.001$–0.002). For energy/index pairs, some statistical significance appears—consistent with forward-looking price setting in energy markets—yet explanatory power is small. Conclusions from the main analysis are unaffected.

3) Strong evidence of breaks around 2008 and 2020 corroborates the gradual/abrupt shift diagnostics (F-trig) reported in the main text and motivates our use of Fourier-augmented transmission tests.

These checks, along with ADF and F-trig already in the paper, satisfy the robustness request and support the stability of our findings across reasonable weather-adjustment choices.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2025.109007.

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