Nowcasting Transaction-Based House Price Indices Using Web-Scraped Listings and MIDAS Regression

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Motivation

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Investigate if online real-estate list-price data can be used to reduce the time gap and improve house price measurement

Contribution

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1) Compile hedonic price indices for both list and transaction data using 16 years of micro-level list and transaction data for Warsaw and Poznan

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2) Use MIDAS regression to nowcast property prices and show timely list-price indices can provide early and reliable signals of transaction-price dynamics

Timeline of the transaction process for Warsaw

Micro-level dataset for two Polish cities

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Use a unique property database with 16 years of micro-level transaction and list price data for two major Polish cities

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Without adjustment this would result in over-representation of expensive or atypical properties in the list-price dataset

Summary of micro-dataset before and after cleaning

	Listings		Transactions	
	Raw	Cleaned	Raw	Cleaned
Warsaw				
Mean price (per m^2)	10,675	10,446	9,564	9,832
Mean area (m^2)	62	60	54	53
Mean age (years)	31	32	34	34
Observations	1,674,796	760,273	162,015	154,729
Poznan				
Mean price (per m^2)	6,404	6,935	6,239	6,264
Mean area (m^2)	58	57	51	51
Mean age (years)	34	36	41	41
Observations	338,164	133,026	50,891	44,384

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RTD hedonic models incorporate property characteristics and time dummies for consecutive period with a fixed window length (both one year)

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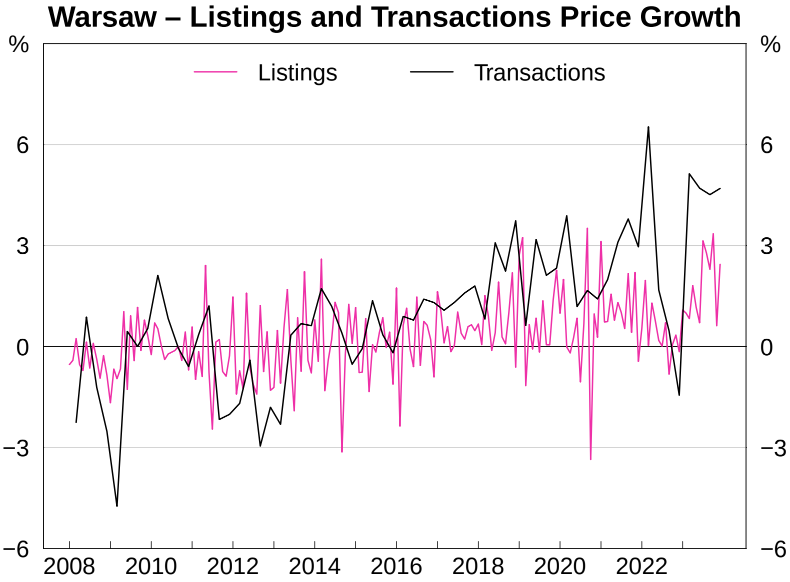
Use hedonic rolling-time-dummy (RTD) method to compile residential property price indices for Warsaw and Poznan

RTD hedonic models incorporate property characteristics and time dummies for consecutive period with a fixed window length (both one year)

When new data is available, window is rolled forward and hedonic model is re-estimated



Warsaw – Listings and Transactions Price Growth
%
%
Listings
Transactions
6
3
0
−3
−6
6
3
0
−3
−6
2008
2010
2012
2014
2016
2018
2020
2022

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Leads to potential loss of high frequency information

Alternative is **MI**xed **DA**ta **S**ampling (MIDAS) regression

- Exploits *all* high frequency information in highly parsimonious way

State-space models also feasible, but MIDAS models shown to perform as well in forecasting and much easier to implement

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Allows dependent and explanatory variables of time series regressions to be sampled at different frequencies:

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$$y_t = \beta_0 + \alpha(L)\, y_t + \beta_1 \mathcal{W}\left(L^{1/m};\theta\right) x_t^m + \varepsilon_t \tag{1}$$

where $\alpha(L)$ is a lag polynomial, $\mathcal{W}\left(L^{1/m};\theta\right) = \sum_{k=0}^{K} W(k;\theta)\, L^{1/m}$ and $L^{1/m}$ is a lag operator such that $L^{1/m} x_t^m = x_{t-1/m}^m$ with m indicating the higher sampling frequency

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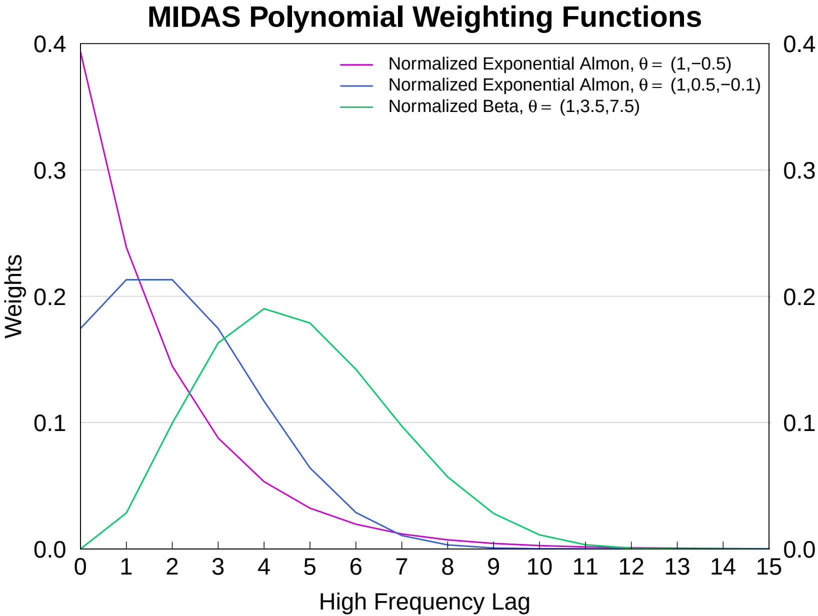
Specifications for $\mathcal{W}$ include: Normalised Exponential Almon and Normalised Beta

Data Frequency Alignment

Example: Simple MIDAS model assuming only monthly data in the current quarter has explanatory power (i.e. $K = 3$):

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_T \end{bmatrix} = \begin{bmatrix} 1 & x_3 & x_2 & x_1 \\ 1 & x_6 & x_5 & x_4 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{3T} & x_{3T-1} & x_{3T-2} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_T \end{bmatrix}$$

Note: if y_t is of length T then x_t must be of length $m \times T$


MIDAS Polynomial Weighting Functions
Normalized Exponential Almon, θ = (1,−0.5)
Normalized Exponential Almon, θ = (1,0.5,−0.1)
Normalized Beta, θ = (1,3.5,7.5)
Weights
High Frequency Lag
0.0
0.1
0.2
0.3
0.4
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15

Specifying MIDAS models

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1) Suitable functional constraint (i.e. $\mathcal{W}$)

2) Appropriate maximum lag order (i.e. K)

Can address both issues together using an information criterion, such as BIC, to select best model in terms of parameter restriction and lag order

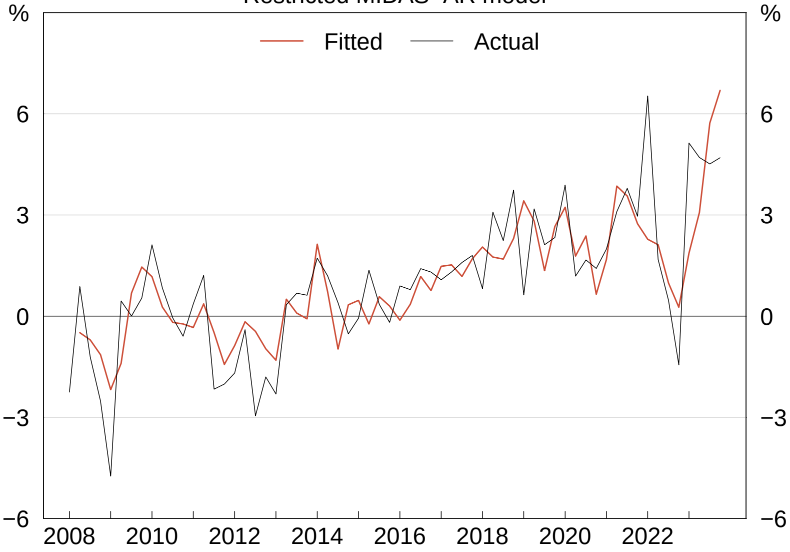
Warsaw: MIDAS model comparisons

	Normalised Exponential Almon				Normalised Beta		Unrestricted MIDAS	
	$j = 2$		$j = 3$		$j = 3$			
Lag K	BIC	p-value	BIC	p-value	BIC	p-value	BIC	p-value
0:2	**236.21**	**0.54**	239.90	0.00	252.33	0.00	239.90	–
0:3	**228.76**	**0.71**	232.14	0.93	250.62	0.00	236.28	–
0:4	**231.93**	**0.28**	232.13	0.66	243.60	0.00	239.82	–
0:5	<u>**225.89**</u>	<u>**0.25**</u>	227.78	0.27	241.91	0.00	238.03	–

Notes: p-value is for test of null hypothesis that the restrictions on the MIDAS regression coefficients implied by the polynomial weighting function are valid. Failure to reject the null implies the functional restrictions are supported by the data. Bold values denote best model per lag. A bold and underline value denote best overall model.

Warsaw – Transacted Prices and Fitted Prices

Restricted MIDAS−AR model



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Only consider current quarter predictions of quarterly transaction price growth

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For each quarter can produce **four predictions** of current quarter transaction price growth as new monthly list-price series are produced:

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1) **FC** in $t - 2/3$ (i.e. month 1 in quarter t) includes data up to $t - 1$ (last month of previous quarter)

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1) **FC** in $t-2/3$ (i.e. month 1 in quarter t) includes data up to $t-1$ (last month of previous quarter)
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3) **M2** in t (month 3) includes data up to $t-1/3$
4) **M3** in $t+1/3$ (month 1 in quarter $t+1$) includes data up to t

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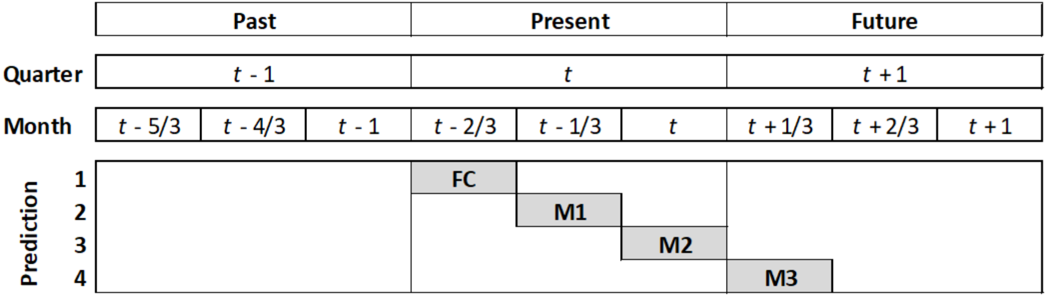
3) **M2** in t (month 3) includes data up to $t - 1/3$
4) **M3** in $t + 1/3$ (month 1 in quarter $t + 1$) includes data up to t

R-MIDAS models differ in number of coefficients to estimate for each prediction but include a lag of y_t and use the Normalised Exponential Almon weighting function

Timeline of nowcasting transaction-price growth



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Goal: Predict current quarter transaction price growth

- Rolling window (i.e. fixed 8-year window) and recursive estimation (i.e. expanding window)
- Training sample: 2008:Q1–2015:Q4
- Evaluation sample: 2016:Q1–2023:Q4

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Use range statistic (T_R), with $\alpha = 10\%$, and compute p-value via a stationary bootstrap (bloc length 8 quarters and 5,000 replications)

Results: Warsaw – rolling window

	AR(1)	MA(1)	AR(2)	ARMA(1,1)	FC	M1	M2	M3	QA
				Past 3-years					
RMSE	2.51	2.47	2.72	2.68	2.33	**2.19**	2.75	2.76	2.68
(90%)$\mathcal{M}$						$*$			
p-value	0.00	0.04	0.00	0.00	0.04	1.00	0.00	0.00	0.00
				Past 5-years					
RMSE	2.18	2.18	2.27	2.25	2.13	**1.90**	2.26	2.27	2.19
(90%)$\mathcal{M}$						$*$			
p-value	0.05	0.05	0.05	0.05	0.05	1.00	0.05	0.05	0.05
				Full sample					
RMSE	1.87	1.96	1.92	1.90	1.82	**1.57**	1.95	1.91	1.89
(90%)$\mathcal{M}$						$*$			
p-value	0.01	0.01	0.01	0.01	0.01	1.00	0.01	0.01	0.01

Notes: Rolling window estimation begins in 2016:Q1 with window length of 32 quarters. Full sample: 2016:Q1–2023:Q1. Bold values denote best model(s) for each horizon

Results: Warsaw – recursive

	AR(1)	MA(1)	AR(2)	ARMA(1,1)	FC	M1	M2	M3	QA
				Past 3-years					
RMSE	2.60	2.86	2.63	2.64	2.50	2.22	2.00	2.00	**1.99**
(90%)$\mathcal{M}$							$*$	$*$	$*$
p-value	0.01	0.00	0.01	0.01	0.01	0.01	0.21	0.21	1.00
				Past 5-years					
RMSE	2.25	2.50	2.22	2.22	2.16	1.98	2.12	**1.80**	**1.80**
(90%)$\mathcal{M}$	$*$		$*$	$*$	$*$	$*$	$*$	$*$	$*$
p-value	0.14	0.00	0.14	0.14	0.14	0.19	0.14	0.76	1.00
				Full sample					
RMSE	1.96	2.22	1.92	1.92	1.82	1.62	1.74	1.55	**1.51**
(90%)$\mathcal{M}$			$*$	$*$	$*$	$*$	$*$	$*$	$*$
p-value	0.03	0.00	0.26	0.27	0.27	0.48	0.31	0.57	1.00

Notes: Recursive estimation begins in 2016:Q1 with initial sample length of 32 quarters. Full sample: 2016:Q1–2023:Q4. Bold values denote best model(s) for each horizon

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Employ MIDAS regression to nowcast quarterly transaction-price growth using monthly list-price indices and achieve more accurate predictions than traditional ARMA models

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Drawing on 16 years of micro-level data from Warsaw and Poznan construct quality-adjusted list and transaction price indices using hedonic rolling time dummy method

Employ MIDAS regression to nowcast quarterly transaction-price growth using monthly list-price indices and achieve more accurate predictions than traditional ARMA models

Results confirm list-price indices provide a timely indication to future movements in transaction-price indices

Spares

Constructing hedonic price indices – details

Assuming the first period in the window is t, the semi-log hedonic model is:

$$\ln(p_{\tau n}) = \sum_{c=1}^{C} \beta_c z_{\tau n} + \sum_{s=t+1}^{t+m} \delta_s d_{\tau sn} + \varepsilon_{\tau n} \qquad (2)$$

where $p_{\tau n}$ is price of property n in period τ, $z_{\tau n}$ are the property characteristics while $d_{\tau sn}$ is a dummy variable equal to 1 when $\tau = s$ and 0 otherwise

From (2) obtain the price index as:

$$\frac{P_{t+m}}{P_{t+m-1}} = \frac{\exp\left(\hat{\delta}^{t}_{t+m}\right)}{\exp\left(\hat{\delta}^{t}_{t+m-1}\right)} \qquad (3)$$

where P_{t+m-1} and P_{t+m} denote the level of the price index in periods $t+m-1$ and $t+m$ while $\hat{\delta}^{t}_{t+m-1}$ and $\hat{\delta}^{t}_{t+m}$ are the estimated coefficients of the last two time dummies

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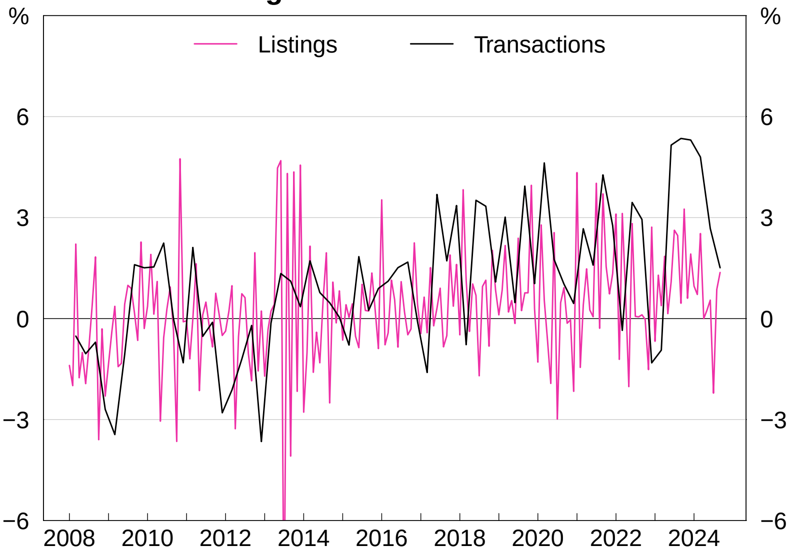
Overall price index starting in $t = 1$ is calculated by chaining all the pairwise price indices together as follows:

$$\frac{P_{t+m}}{P_1} = \prod_{\tau=1}^{t-m} \left[\frac{\exp\left(\hat{\delta}^{\tau}_{\tau+m}\right)}{\exp\left(\hat{\delta}^{\tau}_{\tau+m-1}\right)} \right] \tag{4}$$

Poznan – Listings and Transactions Price Growth



Poznan: MIDAS model comparisons

	Normalised Exponential Almon				Normalised Beta		Unrestricted MIDAS	
	$j = 2$		$j = 3$		$j = 3$			
Lag K	BIC	p-value	BIC	p-value	BIC	p-value	BIC	p-value
0:2	**285.50**	**0.87**	289.66	0.00	293.32	0.00	289.66	–
0:3	**277.10**	**0.54**	280.35	0.54	282.53	0.11	284.28	–
0:4	277.10	0.01	292.16	0.00	**275.13**	**0.00**	276.86	–
0:5	274.11	0.00	**<u>268.68</u>**	**<u>0.64</u>**	269.18	0.34	280.04	–

Note: p-value is for test of null hypothesis that the restrictions on the MIDAS regression coefficients implied by the polynomial weighting function are valid. Failure to reject the null implies the functional restrictions are supported by the data. Bold values denote best model per lag. A bold and underline value denote best overall model.

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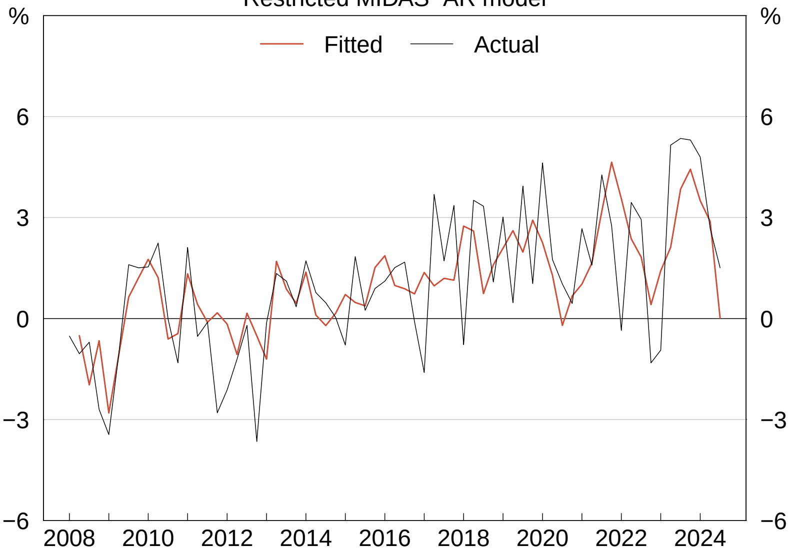
Restricted MIDAS−AR model



Results: Poznan – rolling window

	AR(1)	MA(1)	AR(2)	ARMA(1,1)	FC	M1	M2	M3	QA
				Past 3-years					
RMSE	2.61	2.63	2.84	2.69	2.63	**2.43**	2.52	2.74	2.68
(90%) $\mathcal{M}$	$*$	$*$				$*$	$*$		$*$
p-value	0.21	0.27	0.01	0.03	0.09	1.00	0.27	0.09	0.27
				Past 5-years					
RMSE	2.33	2.35	2.42	2.34	2.30	**2.09**	2.24	2.50	2.34
(90%) $\mathcal{M}$						$*$			
p-value	0.05	0.03	0.03	0.03	0.03	1.00	0.05	0.00	0.05
				Full sample					
RMSE	2.33	2.34	2.34	2.27	2.29	**2.20**	2.33	2.47	2.33
(90%) $\mathcal{M}$	$*$	$*$	$*$	$*$	$*$	$*$	$*$		$*$
p-value	0.55	0.24	0.38	0.55	0.55	1.00	0.24	0.04	0.24

Notes: Rolling window estimation using the extended dataset begins in 2016:Q3 with window length of 34 quarters. Full sample: 2016:Q3–2024:Q3. Bold values denote best model(s) for each horizon

Results: Poznan – recursive

	AR(1)	MA(1)	AR(2)	ARMA(1,1)	FC	M1	M2	M3	QA
				Past 3-years					
RMSE	2.45	2.54	2.67	2.58	2.28	2.13	2.20	**2.03**	2.08
(90%)$\mathcal{M}$	*	*		*	*	*	*	*	*
p-value	0.29	0.29	0.05	0.16	0.29	0.64	0.46	1.00	0.64
				Past 5-years					
RMSE	2.28	2.38	2.34	2.29	2.11	**1.88**	2.05	1.89	1.89
(90%)$\mathcal{M}$			*	*	*	*	*	*	*
p-value	0.05	0.06	0.16	0.16	0.16	1.00	0.16	0.90	0.90
				Full sample					
RMSE	2.32	2.40	2.32	2.29	2.19	**1.98**	2.21	2.09	2.03
(90%)$\mathcal{M}$			*	*	*	*	*	*	*
p-value	0.03	0.02	0.15	0.15	0.15	1.00	0.15	0.56	0.56

Notes: Recursive estimation using the extended dataset begins in 2016:Q3 with initial sample length of 34 quarters. Full sample: 2016:Q3–2024:Q3. Bold values denote best model(s) for each horizon