Nonlinear Macroeconomic Effects in CRE Vacancy Forecast Models

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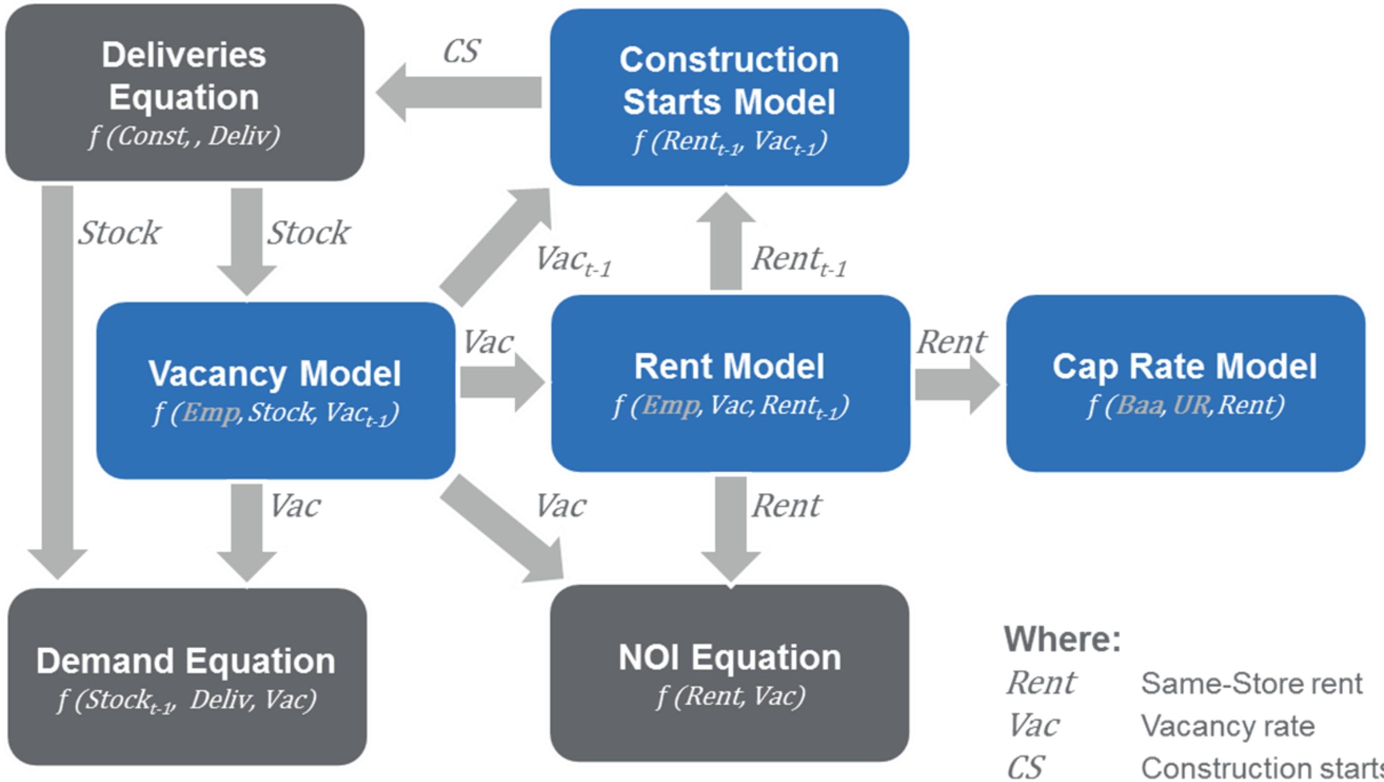
Introduction

- Can we better incorporate business cycles into vacancy forecast models?

- Overview of CoStar's metro forecast models
- Potential nonlinear transformations of macroeconomic variables
- Results of vacancy forecast models with additional variables

CoStar Metro Forecast Model



Denotes econometric model

Denotes mathematical equation

Bolded grey text indicates exogenous economic or capital market forecasts

Where:

Rent	Same-Store rent
Vac	Vacancy rate
CS	Construction starts
Const	Construction underway
Deliv	Construction completions
Emp	Total employment
Stock	Total stock
Baa	Baa yield
UR	Unemployment rate

Regression Equations

Stock

$$CS_t = f(\Delta R_{t-1}, V_{t-1}) \tag{1}$$

where CS_t is construction starts, ΔR_{t-1} is lagged first difference of log rent, V_{t-1} is lagged vacancy.

Rent

$$R_t = f(O_{t-1}, E_t) \tag{10}$$

$$\Delta R_t = f(\Delta O_{t-1}, \Delta E_{t-1}, \hat{r}_{t-1}) \tag{11}$$

where R_t is log rent, O_{t-1} is lagged log occupancy, E_t is log employment, ΔR_t is first difference of log rent, ΔO_{t-1} is lagged first difference of log occupancy, ΔE_{t-1} is lagged first difference of log employment, and $\hat{r}_{t-1}$ is the lagged predicted residual from Equation 10.

Vacancy

$$V_t = f(\Delta E_t) \tag{5}$$

$$\Delta V_t = f(\Delta^2 E_{t-1}, \Delta S_{t-1}, \hat{v}_{t-1}) \tag{6}$$

where V_t is log vacancy, ΔE_t is first difference of log employment, ΔV_t is first difference of log vacancy, $\Delta^2 E_{t-1}$ is lagged second difference of log employment, ΔS_{t-1} is lagged first difference of log stock, and $\hat{v}_{t-1}$ is the lagged predicted residual from Equation 5.

Cap Rate

$$\Delta Y_t = f(\Delta I_{t-1}, \Delta U_t, \Delta^2 R_{t-1}) \tag{16}$$

where ΔY_t is first difference of log cap rate, ΔI_{t-1} is lagged first difference of log Baa corporate bond yield, ΔU_t is first difference of unemployment rate, and $\Delta^2 R_{t-1}$ is lagged second difference of log rent.

Linear Transformations

Table 1: Typical Independent Variable Transformations

Equation	Description
X_t	No transformation
$X_t - X_{t-k}$	First difference
$X_t/X_{t-k} - 1$	Percentage change or growth rate
$ln(X_t)$	Natural logarithm
$ln(X_t) - ln(X_{t-k})$	First difference of natural logarithm

Additional Nonlinear Transformations

Table 2: Nonlinear Independent Variable Transformations

Equation	Description
X_t^2	Squared
X_t^3	Cubed
$P(R_t)$	Probability of recession
$P(R_{t,i})$	Probability of recession by metro
R_t	Recession dummy

Probability of Recession Binary Logistic Regression

$$\mathrm{P}(R_t) = \Lambda\left(X\beta + \varepsilon\right) \quad \text{where } \Lambda(x) = \frac{\mathrm{e}^x}{1 + \mathrm{e}^x} \tag{1}$$

Where $\mathrm{P}(R_t)$ is the probability of R_t, X is the independent variable matrix including first difference log national employment, β is the vector of coefficient estimates, ε is the error term, and $\Lambda(x)$ is logistic cumulative distribution function.

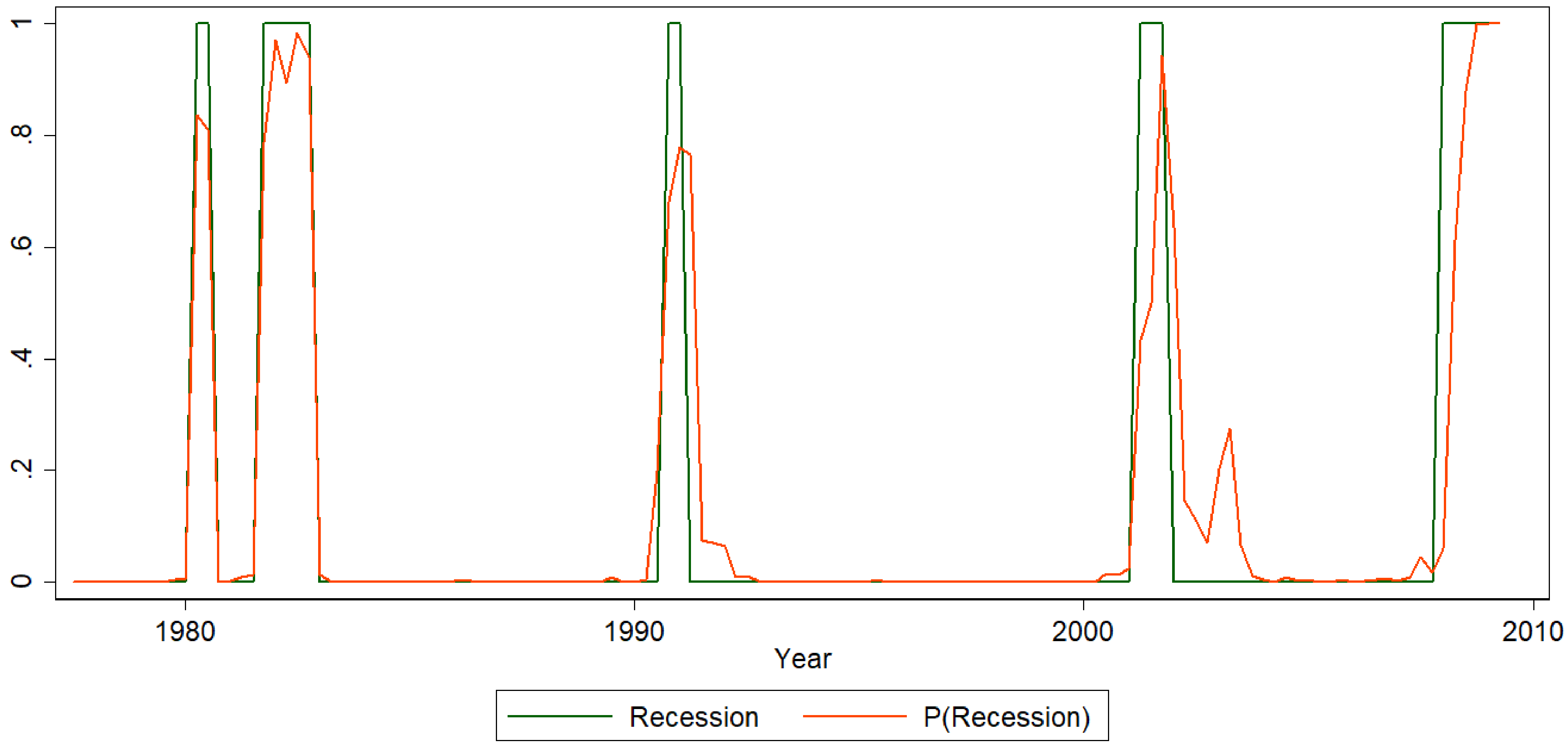
Recession Model Estimation Results

Table 3: Estimation Results for Recession Model

	Coefficient
Constant	-2.5014
	(-3.24)
Employment	-871.0072
	(-3.91)
N	137
Pseudo R^2	0.7555
Sensitivity	0.8889
Specificity	0.9748
AUC	0.9860

The t statistics are shown in parenthesis.

Recession Model Fitted Values



Baseline Vacancy Forecast Model

$$\Delta V_t = \beta_0 + \beta_1 \Delta E_{t-1} + \beta_2 \Delta S_{t-1} + \varepsilon \tag{2}$$

Where V_t is first difference log vacancy, ΔE_{t-1} is lagged second difference log employment, ΔS_{t-1} is lagged first difference log stock, and ε is the error term. Equation 2 is estimated using ordinary least squares, and $\beta_0 \ldots \beta_n$ represent the coefficient estimates.

Additional Independent Variables

Table 4: Additional Independent Variables

Equation	Description
$(\Delta E_{t-1})^2$	Squared Employment Growth
$(\Delta E_{t-1})^3$	Cubed Employment Growth
R_t	Recession dummy
$P(R_t)$	Probability of recession
$P(R_{t,i})$	Probability of recession by metro

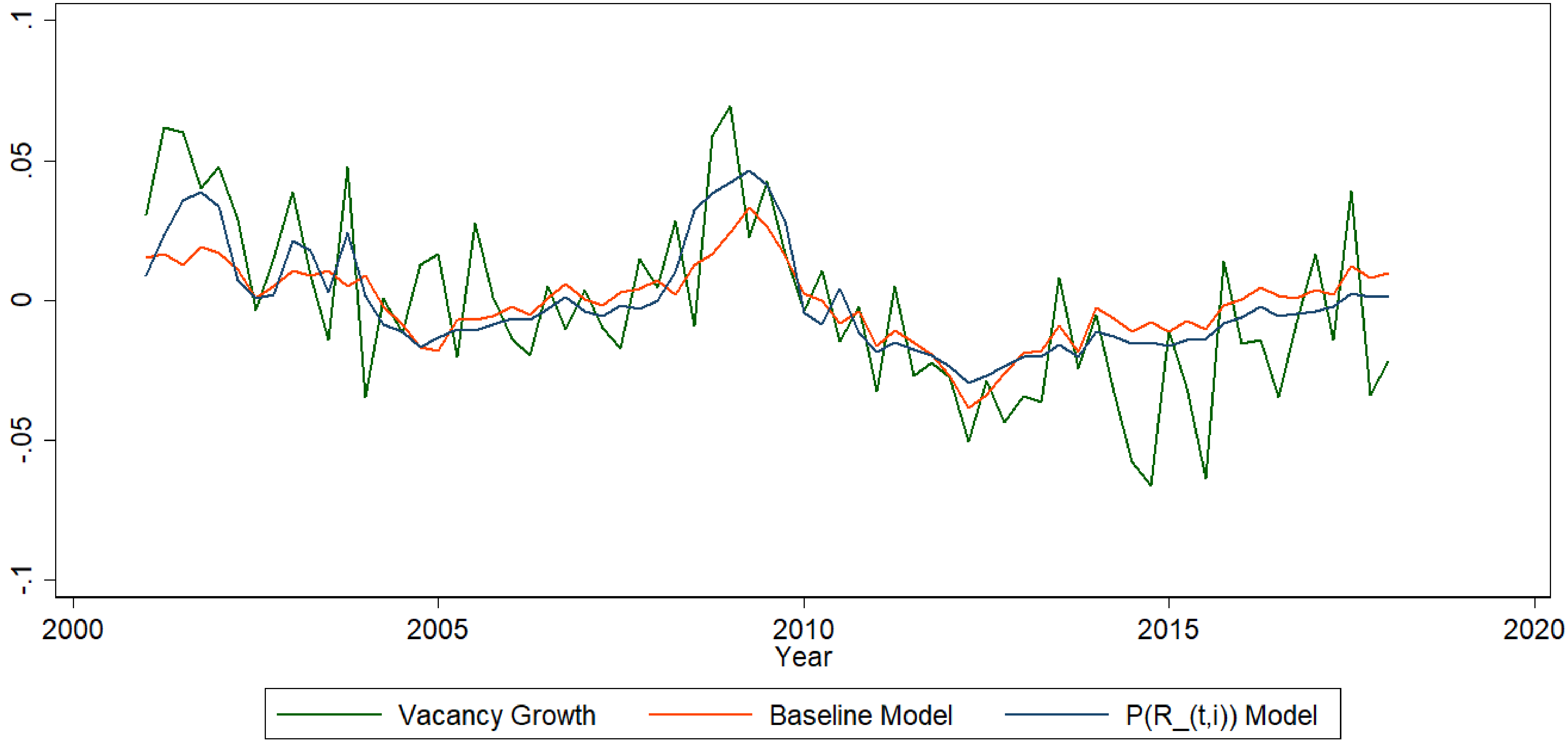
Vacancy Forecast Model Estimation Results

Table 5: Estimation Results for Vacancy Models

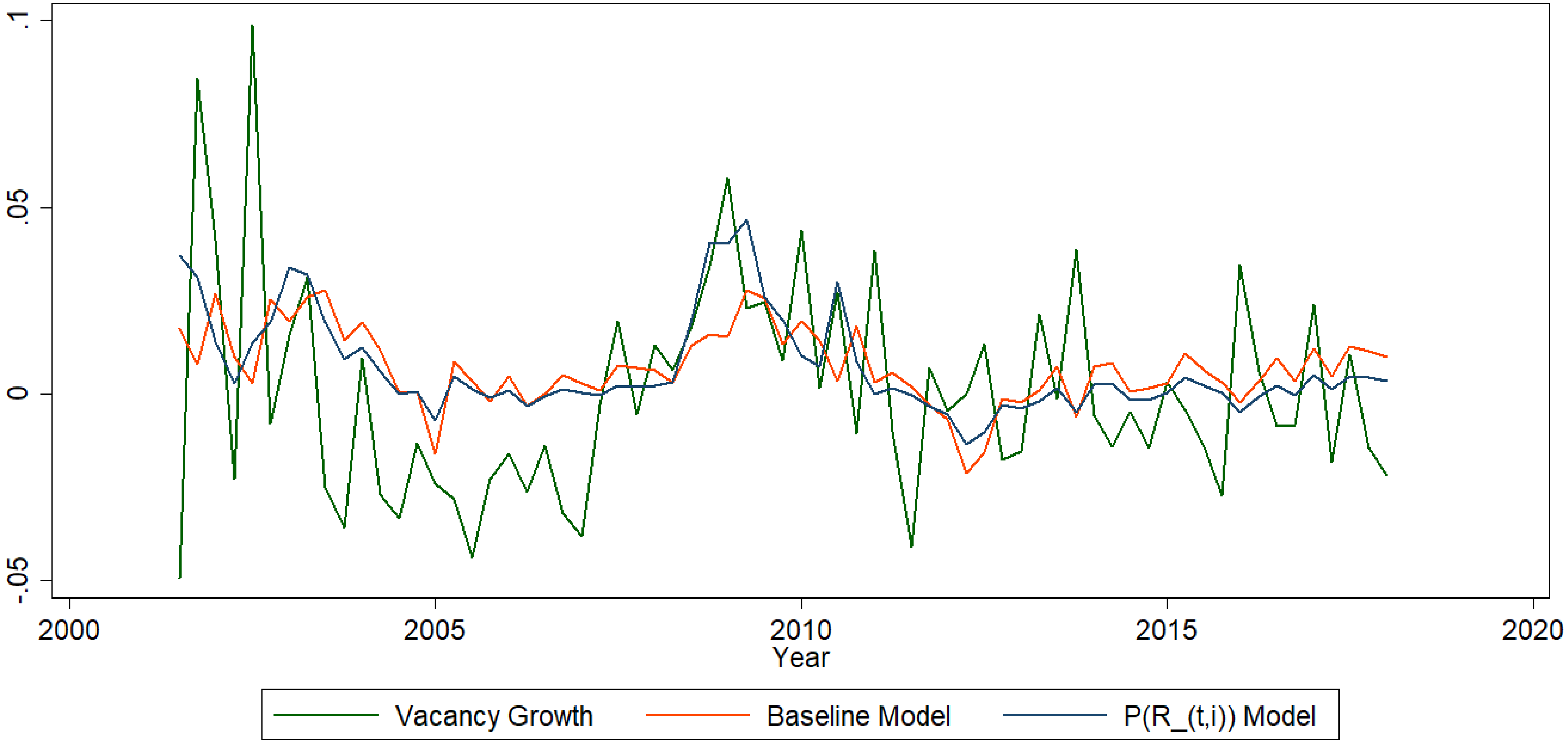
	Baseline	$(\Delta E_{t-1})^2$	$(\Delta E_{t-1})^3$	$P(R_t)$	$P(R_{t,i})$	R_t
Constant	-0.0114	-0.0146	-0.0111	-0.0157	-0.0164	-0.0136
	(-14.18)	(-17.29)	(-13.85)	(-18.88)	(-19.70)	(-17.02)
ΔE_{t-1}	-1.2024	-1.1689	-1.4600	-0.6590	-0.6208	-0.8823
	(-24.23)	(-23.66)	(-19.90)	(-11.29)	(-10.73)	(-17.00)
ΔS_{t-1}	0.8435	0.8378	0.8251	0.7918	0.7797	0.7190
	(15.98)	(15.98)	(15.61)	(15.19)	(14.99)	(13.72)
Additional Variable		27.5448	474.1052	0.0344	0.0343	0.0294
		(11.76)	(4.76)	(17.08)	(18.71)	(18.32)
N	10,579	10,579	10,579	10,579	10,579	10,579
R^2	0.1071	0.1178	0.1096	0.1319	**0.1387**	0.1367
MAE	0.03493	0.03442	0.03491	0.03420	**0.03415**	0.03428
RMSE	0.05055	0.05022	0.05050	0.04986	**0.04972**	0.04976
VIF	1.12	1.08	1.96	1.43	1.41	1.20

The t statistics are shown in parentheses. The highest R^2 and lowest MAE and RMSE values are highlighted in bold.

Chicago Industrial In-Sample Fitted Values



New York Office In-Sample Fitted Values



Out-of-Sample Results (2008Q1-2012Q4)

Table 6: Out-of-Sample Results (2008Q1-2012Q4)

	Baseline	$(\Delta E_{t-1})^2$	$(\Delta E_{t-1})^3$	$P(R_t)$	$P(R_{t,i})$	R_t
N	3,691	3,691	3,691	3,691	3,691	3,691
MAE	0.03422	0.03489	0.03494	0.03605	**0.03347**	0.03495
RMSE	0.04589	0.04674	0.04545	0.04771	**0.04479**	0.04641

The lowest MAE and RMSE values are highlighted in bold.

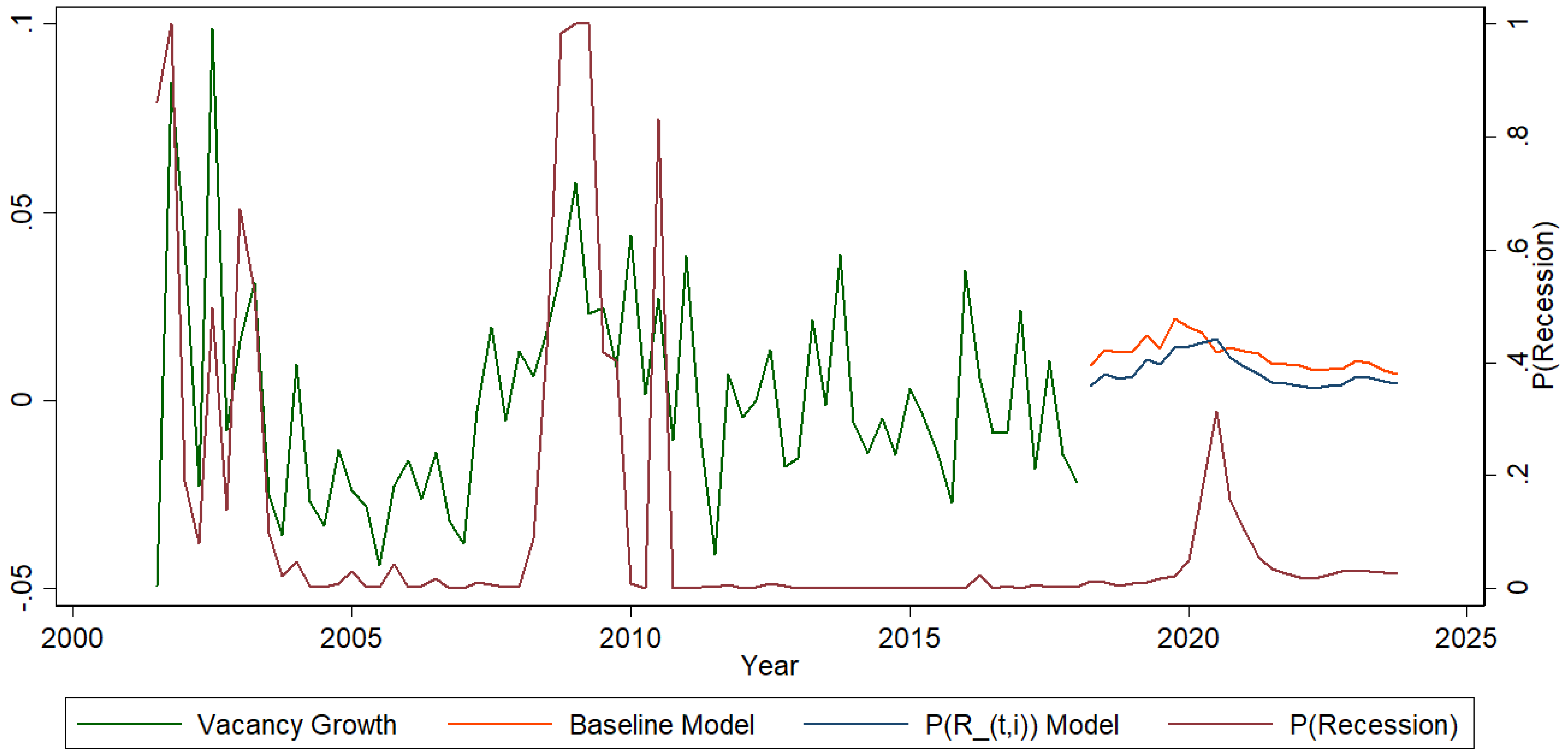
Out-of-Sample Results (2013Q1-2017Q4)

Table 7: Out-of-Sample Results (2013Q1-2017Q4)

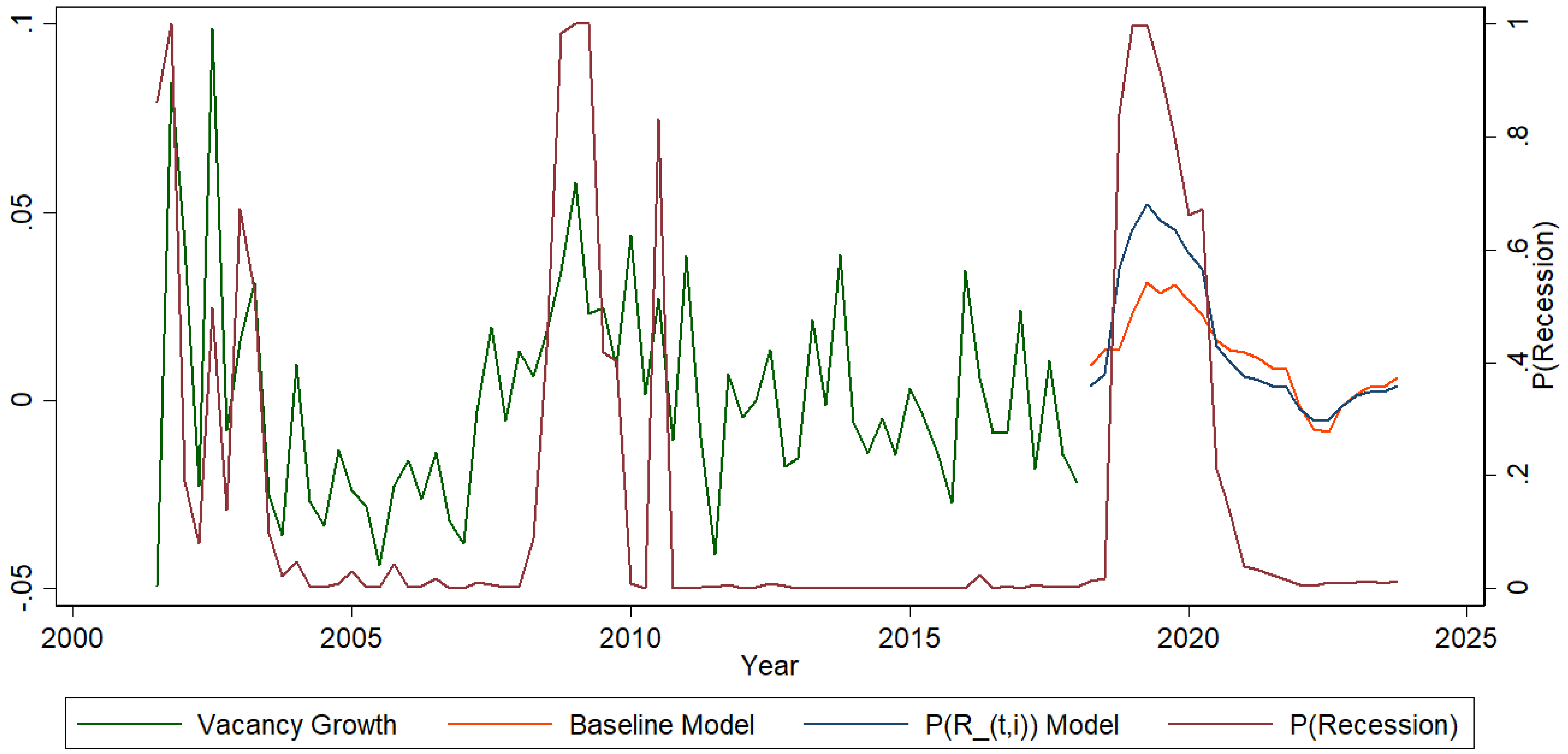
	Baseline	$(\Delta E_{t-1})^2$	$(\Delta E_{t-1})^3$	$P(R_t)$	$P(R_{t,i})$	R_t
N	7,051	7,051	7,051	7,051	7,051	7,051
MAE	0.03948	0.03859	0.03947	0.03795	**0.03757**	0.03829
RMSE	0.05412	0.05332	0.05412	0.05274	**0.05249**	0.05302

The lowest MAE and RMSE values are highlighted in bold.

New York Office Base Case Forecast



New York Office Recession Forecast



Conclusion

- Examined a baseline vacancy forecast model and compared it to five other models with additional variables
- Looked at in-sample and out-of-sample results
- The addition of nonlinearly transformed variables improved the fit of the baseline vacancy model
    - In particular, the addition of the fitted values from a recession model using metro employment as its independent variable
    - Even though employment was already a factor
- Underscores that the real world is complex and nonlinear
- Demonstrates a practical method to factor business cycles into vacancy forecast models

Future Research

- Add nonlinear macroeconomic effects to other CRE forecast models
- Additional nonlinear transformations of the employment variable, or of other variables
- Separate property type or metro models

Questions or Comments?

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