What Happens in Vegas Doesn't Always Stay in Vegas:

The Dynamics of House Prices and Foreclosure Rates Across Space and Time

Hua Kiefer

Federal Deposit Insurance Corporation

Len Kiefer

Freddie Mac

Diana Wei

Office of the Comptroller of the Currency

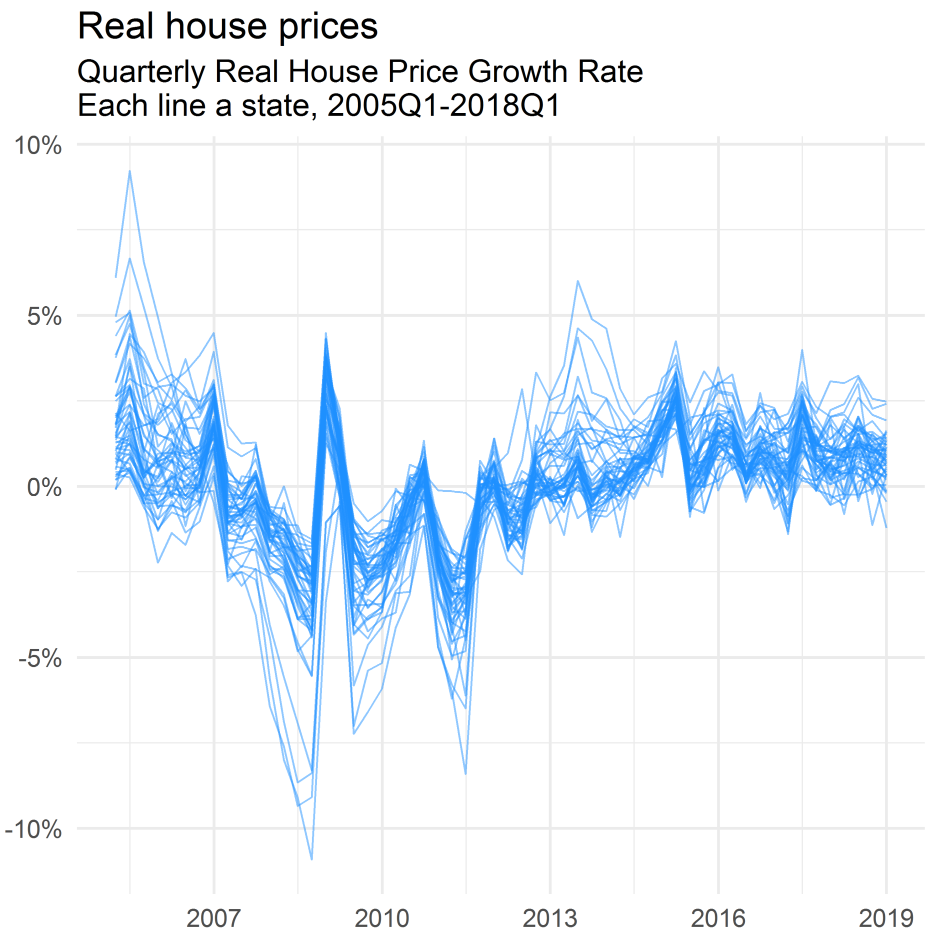
2019-05-23

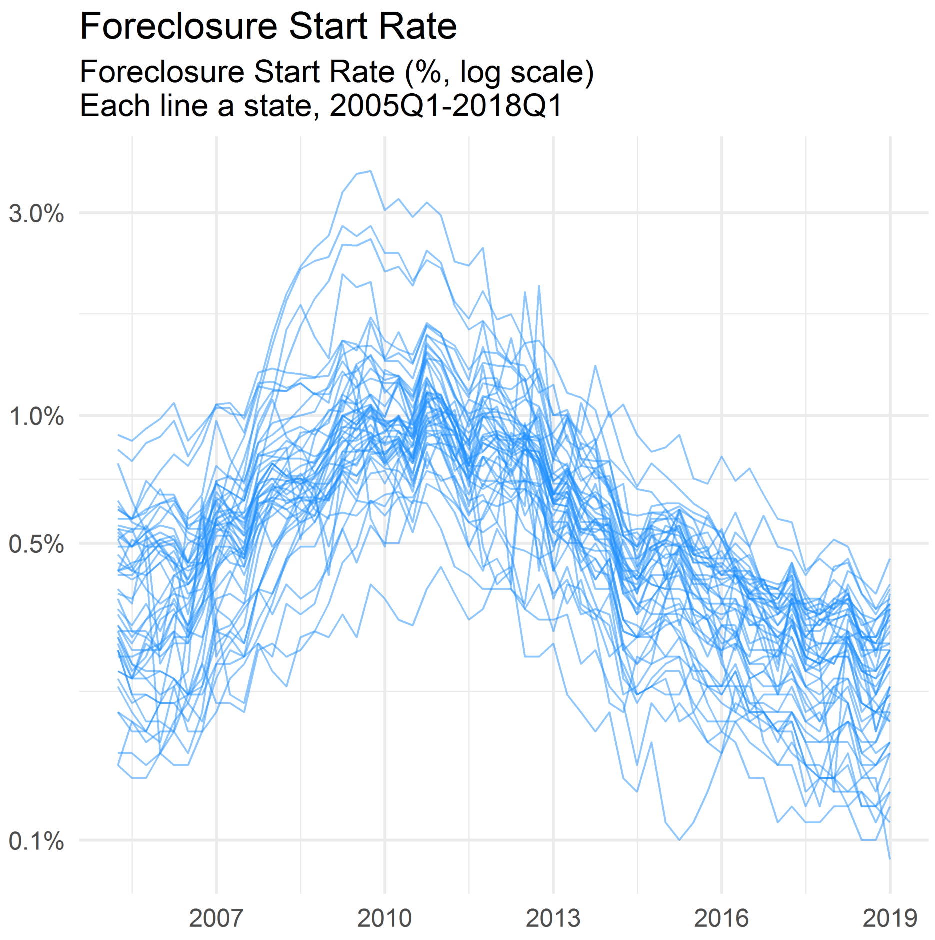
The views expressed in this paper are those of the authors alone and do not reflect those of The Federal Deposit Insurance Corporation, the Office of the Comptroller of the Currency, and Freddie Mac.

Our Contribution

- Specify a Dynamic Spatial Simultaneous Equation System panel model at quarter/state level that
  - Allows simultaneous movement in house prices and foreclosure rates
  - Captures dynamics over time and space
- Identify instruments for house prices and foreclosure rates
- Show that at the state level, there is am amplification mechanism for foreclosure rates
  - Foreclosure shocks have a large and persistent impact on house prices
  - Shocks to housing markets propagate to nearby states
  - A one standard deviations increase in Nevada foreclosure rate leads to
    - 8% decline in Nevada real house prices after 8 quarters
    - 3% decline in California real house prices after 8 quarters

(1) Introduction





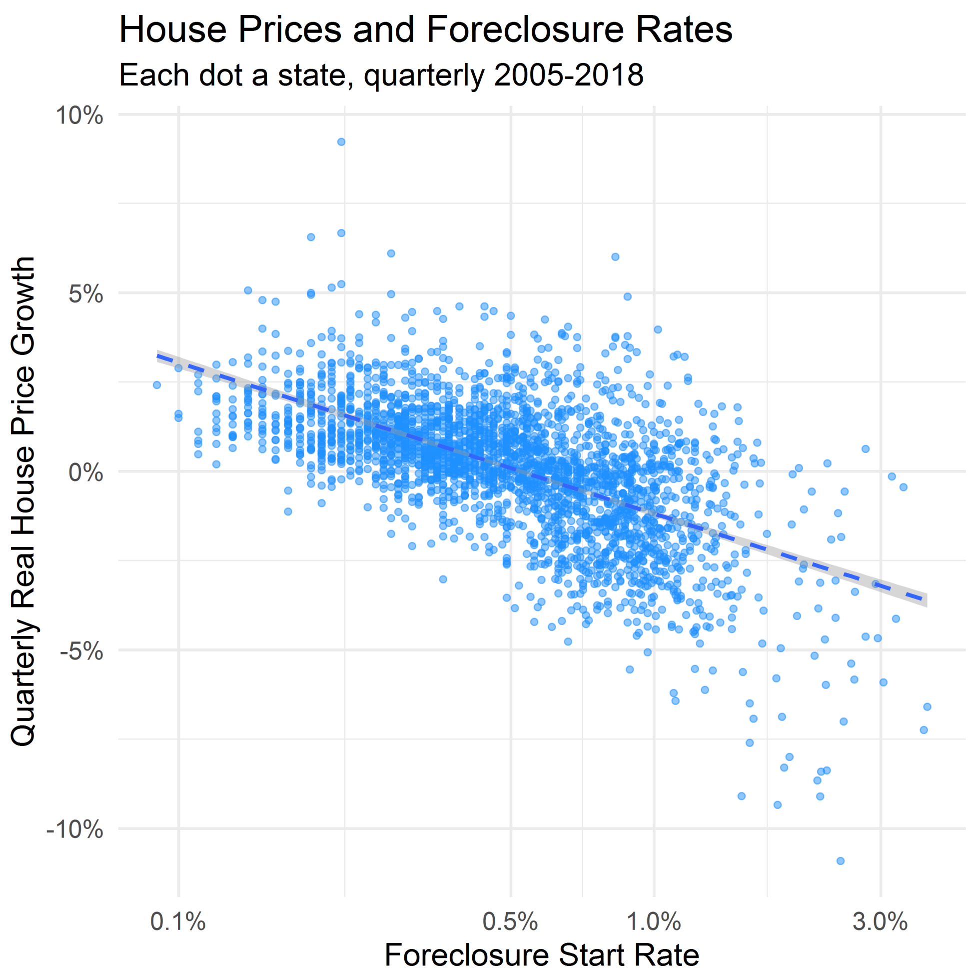
@lenkiefer What Happens in Vegas Doesn't Always Stay in Vegas

House prices and foreclosure rates are negatively correlated

Do high foreclosure rates cause lower house prices?

Or do lower house prices drive foreclosure rates up?

Why not both?



Higher house prices drive foreclosure rates lower

- Theory
    - Foster and Van Order (1984) option-based model
- Empirics
    - Bajari, Chu, Park (2008)
    - Foote, Gerardi, Willen (2008)
    - Guiso, Zingales (2013)

Higher foreclosure rates drive house prices lower

- Foreclosure discount of 20% or more (own property)
    - Carroll, Clauretie, Neill(1997)
    - Clauretie and Daneshvary (2009)
    - Harding, Rosenblatt, Yao (2009)
- How about spillovers?
    - After controlling for simultaneity/reverse causality the foreclosure impact on nearby house prices declines to less than 2 percent
        - Campbell, Giglio, Pathak (2011)
        - Hartley (2014)
        - Gerardi, Rosenblatt, Willen (2015)

Two contrasting studies

Foreclosure rates have a large and persistent impact on house prices

- Mian, Trebbi, Sufi (2015)
  - Use variation in state foreclosure laws as I.V.
  - Examine variations in prices around state borders
  - Zipcode level house prices

1 standard deviation increase in foreclosure rate leads to 8-12% decline in house prices over nine quarters

Foreclosure rates only have a small impact on house prices

- Calomiris, Longhofer, Miles (2013)
  - Fully model the dynamics of house prices, forclosures and other variables
  - Estimate a state Panel Vector AutoRegression (PVAR)
  - PVAR assumes all variables are endogenous
  - Identifies impact via recursive identification scheme

1 standard deviation increase in foreclosure rate leads to 2.7% decline in house prices over nine quarters

Spoilers

- Mian, Trebbi, Sufi (2015, hereafter MTS)

  1 standard deviation increase in foreclosure rate leads to 8-12% decline in house prices over nine quarters

- Calomiris, Longhofer, Miles (2013, hereafter CLM)

  1 standard deviation increase in foreclosure rate leads to 2.7% decline in house prices over nine quarters

- Our Result

  1 standard deviation increase in foreclosure rate leads to 7.7% decline in real house prices over nine quarters

(2) Econometric Models

(2.1) Model 1

Panel Vector AutoRegression (PVAR)

Panel Vector AutoRegression (PVAR)

$$Y_{n2}^*(t) = \sum_{j=1}^{p} Y_{n2}^*(t-j)P_j + d' \otimes l_n + C + U_{n2}^*(t),$$

Panel Vector AutoRegression (PVAR)

$$Y^*_{n2}(t) = \sum_{j=1}^{p} Y^*_{n2}(t-j)P_j + d' \otimes l_n + C + U^*_{n2}(t),$$

- $Y^*_{n2}(t)$ are dependent variables

Panel Vector AutoRegression (PVAR)

$$Y^*_{n2}(t) = \sum_{j=1}^{p} Y^*_{n2}(t-j)P_j + d' \otimes l_n + C + U^*_{n2}(t),$$

- $Y^*_{n2}(t)$ are dependent variables
- $Y^*_{n2}(t-j)P_j$ are time lags effects

Panel Vector AutoRegression (PVAR)

$$Y^*_{n2}(t) = \sum_{j=1}^{p} Y^*_{n2}(t-j)P_j + d' \otimes l_n + C + U^*_{n2}(t),$$

- $Y^*_{n2}(t)$ are dependent variables
- $Y^*_{n2}(t-j)P_j$ are time lags effects
- $d' \otimes l_n$ are state fixed effects

Panel Vector AutoRegression (PVAR)

$$Y_{n2}^*(t) = \sum_{j=1}^{p} Y_{n2}^*(t-j)P_j + d' \otimes l_n + C + U_{n2}^*(t),$$

- $Y_{n2}^*(t)$ are dependent variables
- $Y_{n2}^*(t-j)P_j$ are time lags effects
- $d' \otimes l_n$ are state fixed effects
- C constant (normalized so $\sum_{i=1}^{n} c_{1,i} = 0$)

Panel Vector AutoRegression (PVAR)

$$Y^*_{n2}(t) = \sum_{j=1}^{p} Y^*_{n2}(t-j)P_j + d' \otimes l_n + C + U^*_{n2}(t),$$

- $Y^*_{n2}(t)$ are dependent variables
- $Y^*_{n2}(t-j)P_j$ are time lags effects
- $d' \otimes l_n$ are state fixed effects
- C constant (normalized so $\sum_{i=1}^{n} c_{1,i} = 0$)
- $U^*_{n2}(t)$ disturbance term

FOD operation

- Forward Orthogonal Difference (FOD) removes the fixed effects, constant
- e.g. for house prices the transformation is (13a, 13b from text):

$$y_{l,i}(t) = \left(\frac{T-p-t}{T-p-t+1} \right)^{\frac{1}{2}} \left[y^*_{l,i}(t) - \frac{1}{T-p-t} \sum_{h=t+1}^{T-p} y^*_{l,i}(h) \right]$$

$$y_{l,i}(t-1) = \left(\frac{T-p-t}{T-p-t+1} \right)^{\frac{1}{2}} \left[y^*_{l,i}(t-1) - \frac{1}{T-p-t} \sum_{h=t}^{T-p-1} y^*_{l,i}(h) \right]$$

- After FOD transformation, y_{t-1} depends on observations not only at $t-1$, but also those in future time periods, so it become endogenous

Panel Vector AutoRegression (PVAR)

FOD operation removes constant, fixed effects

After FOD operation the equation can be written as:

$$Y_{nm,\mathcal{T}} = \sum_{j=1}^{p} Y_{nm,\mathcal{T}}^{(-j)} P_j + U_{nm,\mathcal{T}}$$

but $Y_{nm,\mathcal{T}}^{(-j)}$ is no longer exogenous, so can't estimate with Ordinary Least Squares.

Can estimate with GMM

Use R package panelvar

(2.2) Model 2

Dynamic Spatial Simultaneous Equation System

Dynamic Spatial Simultaneous Equation System

The DSSES introduces two additional effects compared to the PVAR

$$Y_{n2}(t)\Gamma = W_n Y_{n2}(t)\Psi + \sum_{j=1}^{p} Y_{n2}(t-j)P_j + X_n(t)\Pi + U_{n2}(t)$$

- Γ: Simultaneous cross effect
- Ψ: Contemporaneous spillover effect

Dynamic Spatial Simultaneous Equation System

House Price Equation:

$$y_{1,i}(t) = -\gamma_{12} y_{2,i}(t) + \psi_{11} W_n Y_{1,n2}(t) + \sum_{j=1}^{p} \rho_{j,11} y_{1,i}(t-j) +$$

$$\sum_{j=1}^{p} \rho_{j,12} y_{2,i}(t-j) + x'_{1,i}(t) \pi_{\cdot 1} + u_{1,i}(t),$$

Foreclosure Equation:

$$y_{2,i}(t) = -\gamma_{21} y_{1,i}(t) + \psi_{22} W_n Y_{2,n2}(t) + \sum_{j=1}^{p} \rho_{j,22} y_{2,i}(t-j) +$$

$$\sum_{j=1}^{p} \rho_{j,21} y_{1,i}(t-j) + x'_{2,i}(t) \pi_{\cdot 2} + u_{2,i}(t)$$

Dynamic Spatial Simultaneous Equation System

House Price Equation:

$$y_{1,i}(t) = -\gamma_{12} y_{2,i}(t) + \psi_{11} W_n Y_{1,n2}(t) + \sum_{j=1}^{p} \rho_{j,11} y_{1,i}(t-j) +$$

$$\sum_{j=1}^{p} \rho_{j,12} y_{2,i}(t-j) + x'_{1,i}(t)\pi_{\cdot 1} + u_{1,i}(t),$$

- $y_{1,i}(t)$ is real house price growth (quarterly log difference HPI)
- $y_{2,i}(t)$ is log foreclosure rate
- $W_n Y_{1,n2}(t)$ is weighted average of neighbors' real house price growth
- $y_{1,i}(t-j)$ is lagged real house price growth
- $y_{2,i}(t-j)$ is lagged log foreclosure rate
- $x'_{1,i}(t)$ are predetermined control variables

Dynamic Spatial Simultaneous Equation System

Foreclosure Equation:

$$y_{2,i}(t) = -\gamma_{21} y_{1,i}(t) + \psi_{22} W_n Y_{2,n2}(t) + \sum_{j=1}^{p} \rho_{j,22} y_{2,i}(t-j) +$$

$$\sum_{j=1}^{p} \rho_{j,21} y_{1,i}(t-j) + x'_{2,i}(t)\pi_{\cdot 2} + u_{2,i}(t),$$

- $y_{2,i}(t)$ is log foreclosure rate
- $y_{1,i}(t)$ is real house price growth (quarterly log difference HPI)
- $W_n Y_{2,n2}(t)$ is weighted average of neighbors' log foreclosure rate
- $y_{2,i}(t-j)$ is lagged log foreclosure rate
- $y_{1,i}(t-j)$ is lagged real house price growth
- $x'_{2,i}(t)$ are predetermined control variables

Dynamic Spatial Simultaneous Equation System

- We estimate with a 3SLS approach, which requires instruments
- Following Lee and Yang (2018) we construct our I.V. matrix as

$$\mathcal{G}_n(t) = \begin{bmatrix} Y^*_{n2}(t-p) & W_n Y^*_{n2}(t-p) & W_n^2 Y^*_{n2}(t-p) & X_n(t) & W_n X_n(t) & W_n^2 X_n(t) \end{bmatrix}$$

Dynamic Spatial Simultaneous Equation System

- We estimate with a 3SLS approach, which requires instruments
- Following Lee and Yang (2018) we construct our I.V. matrix as

$$\mathcal{G}_n(t) = \left[Y^*_{n2}(t-p) \quad W_n Y^*_{n2}(t-p) \quad W_n^2 Y^*_{n2}(t-p) \quad X_n(t) \quad W_n X_n(t) \quad W_n^2 X_n(t) \right]$$

- $Y^*_{n2}(t-p)$ are non-transformed endogenous variables

Dynamic Spatial Simultaneous Equation System

- We estimate with a 3SLS approach, which requires instruments
- Following Lee and Yang (2018) we construct our I.V. matrix as

$$\mathcal{G}_n(t) = \begin{bmatrix} Y^*_{n2}(t-p) & W_n Y^*_{n2}(t-p) & W_n^2 Y^*_{n2}(t-p) & X_n(t) & W_n X_n(t) & W_n^2 X_n(t) \end{bmatrix}$$

- $Y^*_{n2}(t-p)$ are non-transformed endogenous variables
- $X_n(t)$ are predetermined variables

Dynamic Spatial Simultaneous Equation System

- We estimate with a 3SLS approach, which requires instruments
- Following Lee and Yang (2018) we construct our I.V. matrix as

$$\mathcal{G}_n(t) = \left[Y^*_{n2}(t-p) \quad W_n Y^*_{n2}(t-p) \quad W_n^2 Y^*_{n2}(t-p) \quad X_n(t) \quad W_n X_n(t) \quad W_n^2 X_n(t) \right]$$

- $Y^*_{n2}(t-p)$ are non-transformed endogenous variables
- $X_n(t)$ are predetermined variables
- W_n and W_n^2 are first and second order spatial lag terms

Dynamic Spatial Simultaneous Equation System

- First estimate with 2SLS

$$\hat{\theta}^{\mathcal{G}}_{l,2sls} = (Z'_{l,n,\mathcal{T}} P^{\mathcal{G}} Z_{l,n,\mathcal{T}})^{-1} Z'_{l,n,\mathcal{T}} P^{\mathcal{G}} y_{l,n2,\mathcal{T}}$$

- With asymptotic distribution

$$\sqrt{n\mathcal{T}}(\hat{\theta}^{\mathcal{G}}_{l,2sls} - \theta_l) \xrightarrow{d} N\Big(0, plim_{n\to\infty}\Big[\frac{\sigma_l}{n\mathcal{T}}(Z'_{l,n,\mathcal{T}} P^{\mathcal{G}} Z_{l,n,\mathcal{T}})\Big]^{-1}\Big),$$

Dynamic Spatial Simultaneous Equation System

- Estimate 3SLS

$$\hat{\theta}^{\mathcal{G}}_{3sls} = [\widehat{Z}'_{n,\mathcal{T}}(\widehat{\Sigma}^{-1} \otimes I_{n,\mathcal{T}})Z_{n,\mathcal{T}}]^{-1}\widehat{Z}'_{n,\mathcal{T}}(\widehat{\Sigma}^{-1} \otimes I_{n,\mathcal{T}})y_{n2,\mathcal{T}}$$

- With components of $\widehat{\Sigma}$ estimated by the the 2SLS estimator
- With asymptotic distribution

$$\sqrt{n\mathcal{T}}(\hat{\theta}^{\mathcal{G}}_{3sls} - \theta) \xrightarrow{d} N\Big(0, plim_{n\to\infty}\frac{1}{n\mathcal{T}}[\widehat{Z}'_{n,\mathcal{T}}(\Sigma^{-1} \otimes I_{n,\mathcal{T}})\widehat{Z}_{n,\mathcal{T}}]^{-1})\Big),$$

Dynamic Spatial Simultaneous Equation System

We can write the DSSES as (Equation 10):

$$\Phi y^*_{n2}(t) = \mathcal{P} y^*_{n2}(t-1) + r^*(t) + u^*_{n2}(t)$$

$$\Phi = \begin{bmatrix} I_n - \psi_{11} W_n & \gamma_{12} I_n \\ \gamma_{21} I_n & I_n - \psi_{22} W_n \end{bmatrix}$$

$$\mathcal{P} = \begin{bmatrix} \rho_{11} I_n & \rho_{12} I_n \\ \rho_{21} I_n & \rho_{22} I_n \end{bmatrix}$$

- $y^*_{n2}(t)$ dependent variables
- $r^*(t)$ predetermined variables, intercept, fixed effects
- $u^*_{n2}(t)$ shocks

Inverting Equation 10 yields Equation 11

$$y^*_{n2}(t) = \Phi^{-1} \mathcal{P} y^*_{n2}(t-1) + \Phi^{-1} r^*(t) + \Phi^{-1} u^*_{n2}(t)$$

(3) Data

Data

- Our estimation window covers 2005Q1-2018Q1
  - 13.25 years (53 quarters)
- Dependent Variables
  - Quarterly log difference in Real (inflation-adjusted) house prices
    - FHFA All-Transactions House Price Index
    - Deflated by BLS- CPIU: All Items less Shelter
  - Log foreclosure start rate (% of loans starting foreclosure)
    - MBA National Deliquency Survey
- We require instruments for house prices and foreclosure rates.
- We also include additional controls to account for economic and general housing market conditions

Natural population growth as an I.V. for house prices

- To quantify the causal effect of house prices on foreclosures, we use the quarterly change in the growth rate of natural population (i.e., Δ(births - deaths)/population) as our instrument
  - Population growth reflects housing demand and is an important variable in many models of house prices
  - When population growth increases, household formation rates tend to rise, driving up housing demand
  - Natural population growth captures lower frequency movements in population reflecting demographic profile of state and less likely to be correlated with contempraneous shocks

ARM reset rate as an I.V. for Foreclosures

- We focus on the loans experiencing a rate increase during their initial rate reset using Black Knight's McDash 1^{st} lien data
- We derive two indicators for our ARM reset calculation
  - First, we create a variable capturing the date when a reset hits
    - An ARM reset is flagged at the introductory expiration date or when the first principle and insurant (P\&I) payment amount changes, whichever comes first
  - Then, we compare the scheduled P&I payment from the current month with that of the previous month to identify whether the rate increases at the reset day
  - Compute the percent of outstanding loans in a state that experience a payment shock that quarter

Control variables

- We also include three other variables to help control for economic factors
- Lag of quarterly log difference of each:
    - nonfarm payroll employment
    - per capita income
    - single-family housing permits
- Treat as
    - PVAR: Endogenous
    - DSSES: Predetermined

Summary Statistics

dlrhpi: quarterly log difference in real house price index

lfcl: log foreclosure start rate

dnpopg: quarterly change in the growth rate of natural population (Δ (births - deaths)/population)

log_arm: log of proportion of active loans experiencing positive payment shock due to ARM reset

dlemp_lag1: 1-quarter lag in quarterly log difference in nonfarm payroll employment

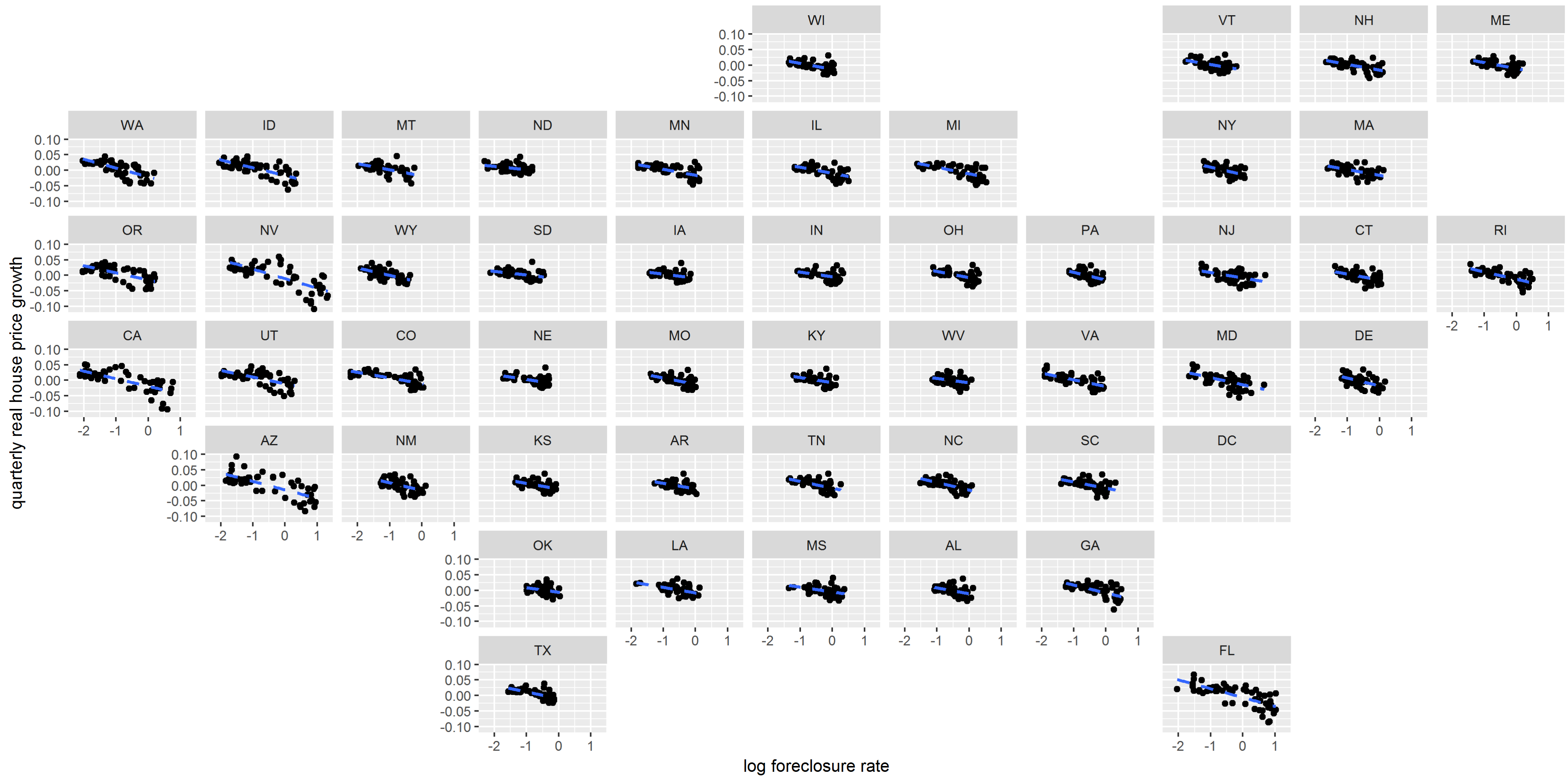
dlperm_lag1: 1-quarter lag in quarterly log difference in single-family building permits

dlpinc_lag1: 1-quarter lag in quarterly log difference in per capita income

Summary Statistics (2005Q1-2018Q1)

var	mean	sd	min	max	n
Dependent Variables					
dlrhpi	0.00	0.02	-0.11	0.09	2544
lfcl	-0.65	0.59	-2.30	1.32	2544
I.V.s					
dnpopg	0.00	0.00	-0.01	0.01	2544
log_arm	-7.24	0.84	-9.26	-4.12	2544
Predetermined Variables					
dlemp_lag1	0.00	0.01	-0.07	0.03	2544
dlperm_lag1	-0.01	0.18	-2.47	2.64	2544
dlpinc_lag1	0.00	0.01	-0.10	0.12	2544

House Prices and Foreclosure Rates



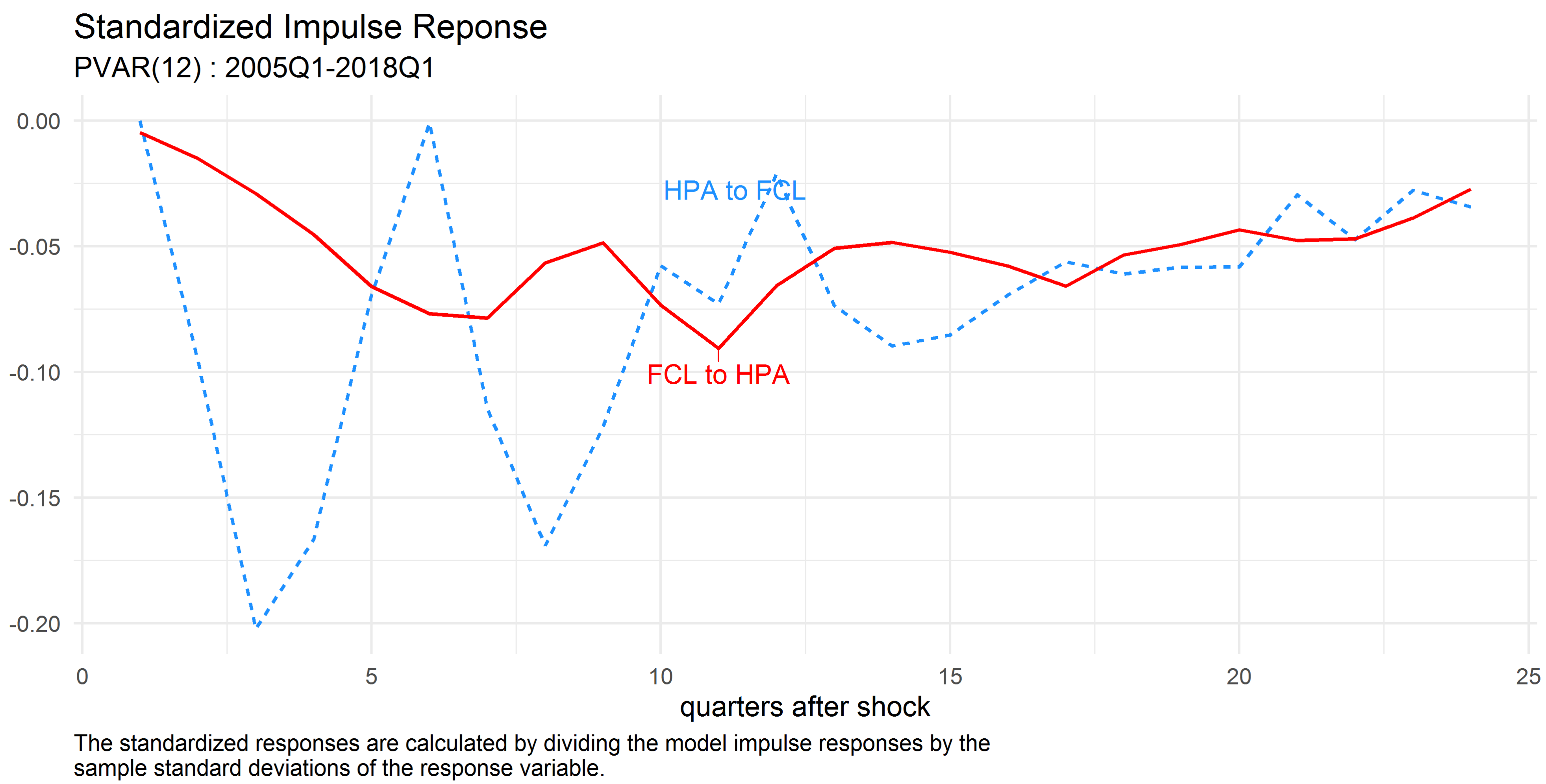
(4) Empirical Results

(4.1) Panel Vector AutoRegression (PVAR)

$$Y_{nm,\mathcal{T}} = \sum_{j=1}^{p} Y_{nm,\mathcal{T}}^{(-j)} P_j + U_{nm,\mathcal{T}}$$

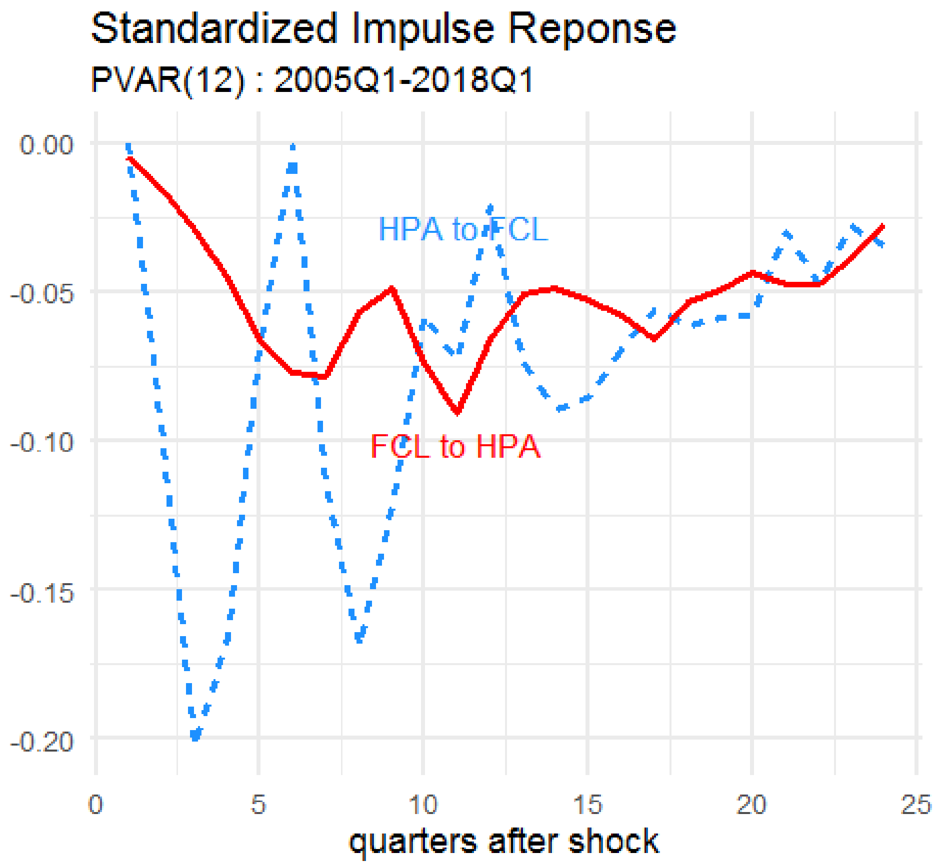
- Estimate with GMM (setting $p = 12$)
    - Estimation yields $5x12 = 60$ coefficients
        - Table in paper
    - Easier to consider aggregations
- Compute Impulse Response Function
- Compute Forecast Error Variance Decomposition
    - The proportion of forecast variance in variable j accounted for by exogenous shocks to variable k

PVAR(12): 2005Q1-2018Q1



PVAR(12): 2005Q1-2018Q1

- Standardized Impulse response of real house price growth (HPA) to log foreclosure (FCL) similar to FCL to HPA
  - CLM find the cumulative 24-quarter HPA to FCL response 79% larger than FCL to HPA
  - We find the cumulative HPA to FCL response 44% larger than FCL to HPA
  - The volatility of foreclosure shocks greater in our period (2005Q1-2018Q1) compared to CLM (1981-2009)



The standardized responses are calculated by dividing the model impulse responses by the sample standard deviations of the response variable.

Forecast Error Variance Decompositions PVAR(12): 2005Q1-2018Q1

Employment

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.808	0.013	0.087	0.081	0.011
8	0.521	0.022	0.186	0.235	0.036
24	0.488	0.032	0.219	0.213	0.048

Per capita income

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.053	0.916	0.012	0.016	0.003
8	0.102	0.836	0.013	0.042	0.008
24	0.106	0.740	0.050	0.066	0.038

Single-Family Permits

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.055	0.007	0.893	0.044	0.002
8	0.054	0.009	0.864	0.051	0.021
24	0.057	0.019	0.829	0.066	0.030

Real House Prices

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.040	0.039	0.038	0.718	0.166
8	0.051	0.034	0.046	0.651	0.218
24	0.084	0.043	0.175	0.471	0.228

Foreclosure

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.004	0.003	0.031	0.029	0.933
8	0.007	0.004	0.132	0.091	0.766
24	0.007	0.012	0.307	0.073	0.601

Forecast Error Variance Decompositions PVAR(12): 2005Q1-2018Q1 Response to House Price shocks

Employment

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.808	0.013	0.087	0.081	0.011
8	0.521	0.022	0.186	0.235	0.036
24	0.488	0.032	0.219	0.213	0.048

Per capita income

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.053	0.916	0.012	0.016	0.003
8	0.102	0.836	0.013	0.042	0.008
24	0.106	0.740	0.050	0.066	0.038

Single-Family Permits

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.055	0.007	0.893	0.044	0.002
8	0.054	0.009	0.864	0.051	0.021
24	0.057	0.019	0.829	0.066	0.030

Real House Prices

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.040	0.039	0.038	0.718	0.166
8	0.051	0.034	0.046	0.651	0.218
24	0.084	0.043	0.175	0.471	0.228

Foreclosure

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.004	0.003	0.031	0.029	0.933
8	0.007	0.004	0.132	0.091	0.766
24	0.007	0.012	0.307	0.073	0.601

Forecast Error Variance Decompositions PVAR(12): 2005Q1-2018Q1 Response to Foreclosure shocks

Employment

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.808	0.013	0.087	0.081	0.011
8	0.521	0.022	0.186	0.235	0.036
24	0.488	0.032	0.219	0.213	0.048

Per capita income

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.053	0.916	0.012	0.016	0.003
8	0.102	0.836	0.013	0.042	0.008
24	0.106	0.740	0.050	0.066	0.038

Single-Family Permits

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.055	0.007	0.893	0.044	0.002
8	0.054	0.009	0.864	0.051	0.021
24	0.057	0.019	0.829	0.066	0.030

Real House Prices

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.040	0.039	0.038	0.718	0.166
8	0.051	0.034	0.046	0.651	0.218
24	0.084	0.043	0.175	0.471	0.228

Foreclosure

horizon	dlemp	dlpinc	dlperm	dlrhpi	lfcl
4	0.004	0.003	0.031	0.029	0.933
8	0.007	0.004	0.132	0.091	0.766
24	0.007	0.012	0.307	0.073	0.601

PVAR Discussion

- PVAR leaves some potential insights on the table
    - Recursive identification imposes some strong restrictions on cross equation effects
    - Doesn't allow for states to influence one another

(4.2) Dynamic Spatial Simultaneous Equation System

(4.2) Dynamic Spatial Simultaneous Equation System

DSSES Estimation: HPA equation

	Beta 3SLS	Std Error	t value	Pvalue
HPA: FCLonHPA (current)	-0.054	0.005	-11.194	0.000
HPA: Spatial_lag	0.444	0.038	11.831	0.000
HPA: owntimelag1	0.228	0.046	4.934	0.000
HPA: cross_FCLlag1	0.050	0.005	10.467	0.000
HPA: Gamma1_dnpopg	0.352	0.194	1.818	0.035
HPA: Gamma1_dlemp_lag1	0.459	0.057	8.063	0.000
HPA: Gamma1_dlpinc_lag1	-0.085	0.021	-4.133	0.000
HPA: Gamma1_dlperm_lag1	-0.002	0.001	-1.755	0.040

DSSES Estimation: FCL equation

	Beta 3SLS	Std Error	t value	Pvalue
FCL: HPAonFCL (current)	-6.684	0.730	-9.161	0.000
FCL: Spatial_lag	-0.044	0.028	-1.539	0.062
FCL: crossHPAlag1	1.212	0.742	1.634	0.051
FCL: owntimelag1	0.932	0.035	27.002	0.000
FCL: Gamma2_log_arm	0.010	0.005	1.774	0.038
FCL: Gamma2_dlemp_lag1	2.699	1.030	2.620	0.004
FCL: Gamma2_dlpinc_lag1	-0.689	0.326	-2.110	0.017
FCL: Gamma2_dlperm_lag1	-0.076	0.020	-3.900	0.000

(4.2) Dynamic Spatial Simultaneous Equation System Cross lag

DSSES Estimation: HPA equation

	Beta 3SLS	Std Error	t value	Pvalue
HPA: FCLonHPA (current)	-0.054	0.005	-11.194	0.000
HPA: Spatial_lag	0.444	0.038	11.831	0.000
HPA: owntimelag1	0.228	0.046	4.934	0.000
HPA: cross_FCLlag1	0.050	0.005	10.467	0.000
HPA: Gamma1_dnpopg	0.352	0.194	1.818	0.035
HPA: Gamma1_dlemp_lag1	0.459	0.057	8.063	0.000
HPA: Gamma1_dlpinc_lag1	-0.085	0.021	-4.133	0.000
HPA: Gamma1_dlperm_lag1	-0.002	0.001	-1.755	0.040

DSSES Estimation: FCL equation

	Beta 3SLS	Std Error	t value	Pvalue
FCL: HPAonFCL (current)	-6.684	0.730	-9.161	0.000
FCL: Spatial_lag	-0.044	0.028	-1.539	0.062
FCL: crossHPAlag1	1.212	0.742	1.634	0.051
FCL: owntimelag1	0.932	0.035	27.002	0.000
FCL: Gamma2_log_arm	0.010	0.005	1.774	0.038
FCL: Gamma2_dlemp_lag1	2.699	1.030	2.620	0.004
FCL: Gamma2_dlpinc_lag1	-0.689	0.326	-2.110	0.017
FCL: Gamma2_dlperm_lag1	-0.076	0.020	-3.900	0.000

(4.2) Dynamic Spatial Simultaneous Equation System Spatial lag

DSSES Estimation: HPA equation

	Beta 3SLS	Std Error	t value	Pvalue
HPA: FCLonHPA (current)	-0.054	0.005	-11.194	0.000
HPA: Spatial_lag	0.444	0.038	11.831	0.000
HPA: owntimelag1	0.228	0.046	4.934	0.000
HPA: cross_FCLlag1	0.050	0.005	10.467	0.000
HPA: Gamma1_dnpopg	0.352	0.194	1.818	0.035
HPA: Gamma1_dlemp_lag1	0.459	0.057	8.063	0.000
HPA: Gamma1_dlpinc_lag1	-0.085	0.021	-4.133	0.000
HPA: Gamma1_dlperm_lag1	-0.002	0.001	-1.755	0.040

DSSES Estimation: FCL equation

	Beta 3SLS	Std Error	t value	Pvalue
FCL: HPAonFCL (current)	-6.684	0.730	-9.161	0.000
FCL: Spatial_lag	-0.044	0.028	-1.539	0.062
FCL: crossHPAlag1	1.212	0.742	1.634	0.051
FCL: owntimelag1	0.932	0.035	27.002	0.000
FCL: Gamma2_log_arm	0.010	0.005	1.774	0.038
FCL: Gamma2_dlemp_lag1	2.699	1.030	2.620	0.004
FCL: Gamma2_dlpinc_lag1	-0.689	0.326	-2.110	0.017
FCL: Gamma2_dlperm_lag1	-0.076	0.020	-3.900	0.000

(4.2) Dynamic Spatial Simultaneous Equation System Time lag

DSSES Estimation: HPA equation

	Beta 3SLS	Std Error	t value	Pvalue
HPA: FCLonHPA (current)	-0.054	0.005	-11.194	0.000
HPA: Spatial_lag	0.444	0.038	11.831	0.000
HPA: owntimelag1	0.228	0.046	4.934	0.000
HPA: cross_FCLlag1	0.050	0.005	10.467	0.000
HPA: Gamma1_dnpopg	0.352	0.194	1.818	0.035
HPA: Gamma1_dlemp_lag1	0.459	0.057	8.063	0.000
HPA: Gamma1_dlpinc_lag1	-0.085	0.021	-4.133	0.000
HPA: Gamma1_dlperm_lag1	-0.002	0.001	-1.755	0.040

DSSES Estimation: FCL equation

	Beta 3SLS	Std Error	t value	Pvalue
FCL: HPAonFCL (current)	-6.684	0.730	-9.161	0.000
FCL: Spatial_lag	-0.044	0.028	-1.539	0.062
FCL: crossHPAlag1	1.212	0.742	1.634	0.051
FCL: owntimelag1	0.932	0.035	27.002	0.000
FCL: Gamma2_log_arm	0.010	0.005	1.774	0.038
FCL: Gamma2_dlemp_lag1	2.699	1.030	2.620	0.004
FCL: Gamma2_dlpinc_lag1	-0.689	0.326	-2.110	0.017
FCL: Gamma2_dlperm_lag1	-0.076	0.020	-3.900	0.000

(4.2) Dynamic Spatial Simultaneous Equation System I.V.

DSSES Estimation: HPA equation

	Beta 3SLS	Std Error	t value	Pvalue
HPA: FCLonHPA (current)	-0.054	0.005	-11.194	0.000
HPA: Spatial_lag	0.444	0.038	11.831	0.000
HPA: owntimelag1	0.228	0.046	4.934	0.000
HPA: cross_FCLlag1	0.050	0.005	10.467	0.000
HPA: Gamma1_dnpopg	0.352	0.194	1.818	0.035
HPA: Gamma1_dlemp_lag1	0.459	0.057	8.063	0.000
HPA: Gamma1_dlpinc_lag1	-0.085	0.021	-4.133	0.000
HPA: Gamma1_dlperm_lag1	-0.002	0.001	-1.755	0.040

DSSES Estimation: FCL equation

	Beta 3SLS	Std Error	t value	Pvalue
FCL: HPAonFCL (current)	-6.684	0.730	-9.161	0.000
FCL: Spatial_lag	-0.044	0.028	-1.539	0.062
FCL: crossHPAlag1	1.212	0.742	1.634	0.051
FCL: owntimelag1	0.932	0.035	27.002	0.000
FCL: Gamma2_log_arm	0.010	0.005	1.774	0.038
FCL: Gamma2_dlemp_lag1	2.699	1.030	2.620	0.004
FCL: Gamma2_dlpinc_lag1	-0.689	0.326	-2.110	0.017
FCL: Gamma2_dlperm_lag1	-0.076	0.020	-3.900	0.000

(4.2) Dynamic Spatial Simultaneous Equation System

- Given the coefficients we can plug into Equation 11:

$$y^*_{n2}(t) = \Phi^{-1}\mathcal{P}y^*_{n2}(t-1) + \Phi^{-1}r^*(t) + \Phi^{-1}u^*_{n2}(t)$$

- Short-run Response to a 1 sd shock (average of all 48 states):
  - 1 sd house price shock after 1 quarter
    - increases house prices 2%
    - decreases the foreclosure rate 13%
  - 1 sd foreclosure shock after 1 quarter
    - decreases house prices 1.6%
    - increases the foreclosure rate 27%
- The long-run cumulative response in the level of house prices to a 1 sd
  - house price shock is a 2.6% increase in house prices
  - foreclosure shock is a 2.0% decrease in house prices

(4.2) Dynamic Spatial Simultaneous Equation System

Impulse response functions for 1 std shock to Nevada (NV)

Cumulative House Price to House Price Shock

horizon	AZ	CA	ID	NV	OR	UT
4	0.011	0.016	0.010	0.032	0.014	0.009
8	0.009	0.014	0.009	0.031	0.012	0.008
24	0.006	0.008	0.005	0.026	0.007	0.005

Foreclosure to House Price Shock

horizon	AZ	CA	ID	NV	OR	UT
4	-0.043	-0.062	-0.040	-0.141	-0.056	-0.036
8	-0.018	-0.026	-0.016	-0.092	-0.023	-0.015
24	0.005	0.008	0.004	-0.023	0.006	0.004

Cumulative House Price to Foreclosure Shock

horizon	AZ	CA	ID	NV	OR	UT
4	-0.007	-0.011	-0.007	-0.025	-0.010	-0.006
8	-0.005	-0.008	-0.005	-0.023	-0.007	-0.004
24	-0.001	-0.002	-0.001	-0.019	-0.002	-0.001

Foreclosure to Foreclosure Shock

horizon	AZ	CA	ID	NV	OR	UT
4	0.024	0.034	0.023	0.244	0.032	0.021
8	-0.001	-0.004	-0.001	0.170	-0.001	-0.001
24	-0.013	-0.021	-0.012	0.056	-0.017	-0.011

(4.2) Dynamic Spatial Simultaneous Equation System

Impulse response functions for a a std shock to Nevada (NV)

Cumulative House Price to House Price Shock

horizon	AZ	CA	ID	NV	OR	UT
4	0.011	0.016	0.010	0.032	0.014	0.009
8	0.009	0.014	0.009	0.031	0.012	0.008
24	0.006	0.008	0.005	0.026	0.007	0.005

Foreclosure to House Price Shock

horizon	AZ	CA	ID	NV	OR	UT
4	-0.043	-0.062	-0.040	-0.141	-0.056	-0.036
8	-0.018	-0.026	-0.016	-0.092	-0.023	-0.015
24	0.005	0.008	0.004	-0.023	0.006	0.004

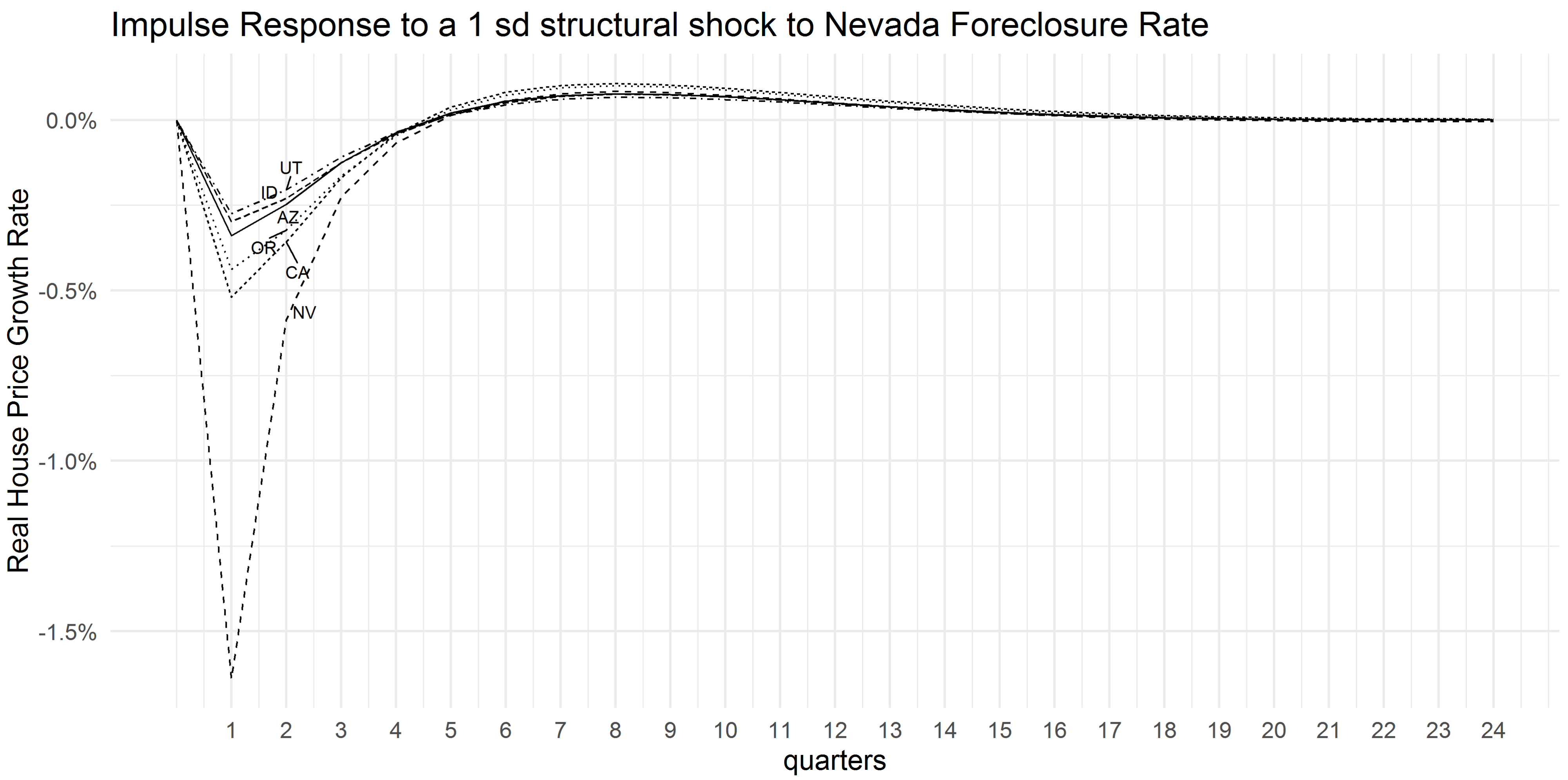
Cumulative House Price to Foreclosure Shock

horizon	AZ	CA	ID	NV	OR	UT
4	-0.007	-0.011	-0.007	-0.025	-0.010	-0.006
8	-0.005	-0.008	-0.005	-0.023	-0.007	-0.004
24	-0.001	-0.002	-0.001	-0.019	-0.002	-0.001

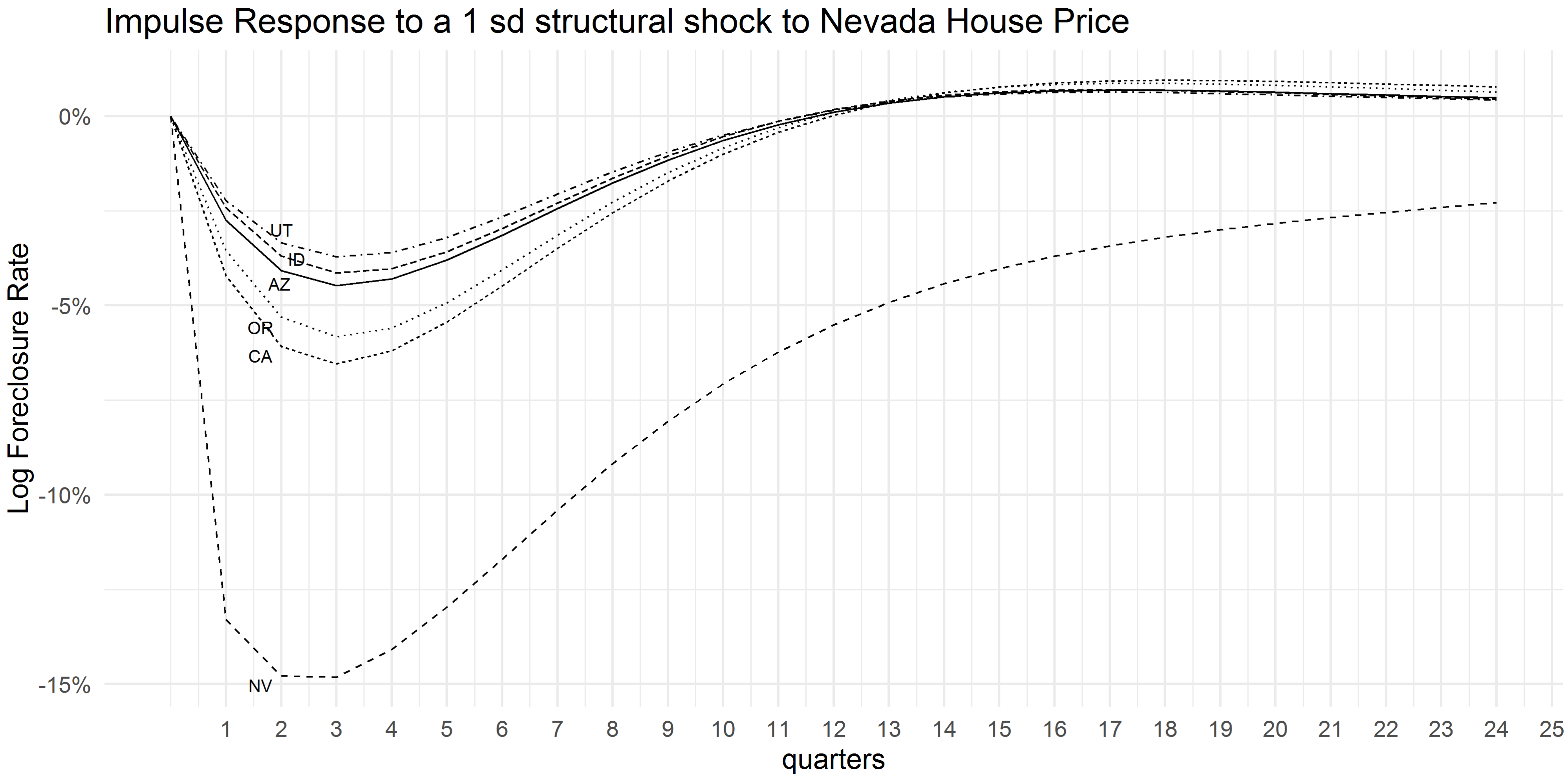
Foreclosure to Foreclosure Shock

horizon	AZ	CA	ID	NV	OR	UT
4	0.024	0.034	0.023	0.244	0.032	0.021
8	-0.001	-0.004	-0.001	0.170	-0.001	-0.001
24	-0.013	-0.021	-0.012	0.056	-0.017	-0.011

(4.2) Dynamic Spatial Simultaneous Equation System



(4.2) Dynamic Spatial Simultaneous Equation System



(5) Conclusion

- Specified a Dynamic Spatial Simultaneous Equation System panel model at quarter/state level that
  - Allows simultaneous movement in house prices and foreclosure rates
  - Captures dynamics over time and space
- Identified instruments for house prices and foreclosure rates
- Showed that at the state level, there is am amplification mechanism for foreclosure rates
  - Foreclosure shocks have a large and persistent impact on house prices
  - Shocks to housing markets propagate to nearby states
  - A one standard deviations increase in Nevada foreclosure rate leads to
    - 8% decline in Nevada real house prices after 8 quarters
    - 3% decline in California real house prices after 8 quarters