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What Happens in Vegas Doesn't Always Stay in Vegas: The Dynamics of House Prices and Foreclosure Rates Across Space and Time

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Abstract

This paper identifies instruments for house prices and foreclosure rates and estimates a Dynamic Spatial Simultaneous Equation System (DSSES) to investigate the dynamics of them across space and time. Shocks to the foreclosure rate in one state not only affect house prices in that state but also the foreclosure rates and house prices in nearby states. When it comes to the housing market, what happens in Vegas doesn't always stay in Vegas. A one standard deviation foreclosure shock leads to a 2 percent decline in real house prices over the long run.

JEL Classification: C33, C36, R31

Keywords: Simultaneous Equation, Dynamic Panel, Spatial Spillover, House Price, Foreclosure

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1 Introduction

In the aftermath of the global financial crisis, the U.S. housing market experienced its worst years since the Great Depression. House prices declined more than 25 percent year-over-year and foreclosure start rates rose more than 3 percentage points in Nevada. Other states experienced large, though less extreme declines in house prices and increases in foreclosure rates.

The U.S. government took unprecedented steps to stabilize the housing market and the macroeconomy. The Federal Reserve launched a massive program of quantitative easing, purchasing approximately $1.8 trillion of agency mortgage-backed securities and agency debt that helped lower mortgage interest rates. In addition, Congress passed the Housing and Economic Recovery Act (HERA) that appropriated considerable funds to help stabilize the U.S. housing market, including substantial tax credits to first-time home buyers that were later extended to all home buyers. HERA also established the Neighborhood Stabilization Program to help communities that suffered from foreclosures and abandonment, which was later renewed by the American Recovery and Reinvestment Act of 2009. In early 2009, the Obama Administration launched the Making Home Affordable program to help struggling homeowners avoid foreclosure through two key initiatives administered by the Federal Housing Finance Agency (FHFA): the Home Affordable Modification Program (HAMP) and the Home Affordable Refinance Program (HARP).

These government programs were created based on the belief that subsidizing housing markets would help stabilize the U.S. housing market and that reducing foreclosures would help stabilize house prices. However, empirical evidence to date is limited with respect to the dynamic relationship between house prices and foreclosures. It is widely accepted in the literature that foreclosures influence house prices mostly through two channels: the disamenity effect of foreclosed properties and the fire sale-induced supply effect. Few studies, however, focus on quantifying the aggregate effect of foreclosures on house prices in a macro setting.

We identified two relevant studies examining the impact of foreclosures on house prices at the state level. However, the findings from these studies differ in the estimated impact of foreclosure rates on house prices. Mian et al., 2015 (referred to hereafter as MST) find that foreclosures led to a large decline in house prices following the recent crisis. Specifically, a 4.3 percentage point increase in the foreclosure rate (a one standard deviation of foreclosures per homeowner from 2008 to 2009) leads to an 8 to 12 percent relative drop in house price growth over a nine-quarter time horizon between fourth quarter 2007 and first quarter 2010. Calomiris et al., 2013 (referred to hereafter as CLM) find that foreclosures have a much smaller impact on house prices based on a Panel Vector Auto Regression (PVAR) using data from 1981 through 2009: a foreclosure shock that results in a two-year increase in the foreclosure rate of 4.3 percentage points leads to a 2.7 percent cumulative decline in house prices over a nine-quarter period. CLM compare the long-term (more than six years) impact of prices on foreclosures against that of foreclosures on prices and find that price shocks are 79 percent larger than foreclosure shocks. CLM conclude that the dominant effect of the house price and foreclosure joint movement comes from price shocks instead of foreclosure shocks, and suggest that the preponderance of the effect of foreclosures on house prices can be explained by the firesale-induced increase of supply.

We note that although the models in both MST and CLM allow for interactions between house prices and foreclosure, they isolate each state and restrict these interactions to within states. However, if house prices or foreclosures are spatially correlated, such restrictions ignore the potential amplification effect owing to spillovers and therefore likely underestimate the impact of foreclosure rates on house prices, and vice versa.

In this paper, we provide causal evidence on house prices and foreclosures under a dynamic panel framework: the Dynamic Spatial Simultaneous Equations System (DSSES). Our structural approach allows for spatial interaction and joint movement of house prices and foreclosures. The reinforcement between the spatial spillover mechanism and the joint movement behavior provides an amplification channel for the transmission of a shock across both time and space. The ideal instruments that help to disentangle the causal effect between house prices and foreclosures are those correlated with one but not both of these variables. In this paper, we introduce two novel instruments meeting such criteria: the adjustable-rate mortgage (ARM) reset rate and the change in the natural population growth rate.

The ARM reset rate is defined as the proportion of mortgages within a state that experiences a payment shock as ARMs reach the end of their introductory period and the interest rate resets upward.[1] The ARM reset rate serves as an instrument for foreclosure rate. Higher monthly payments resulting from an upward ARM interest rate reset can lead to more foreclosures. Supervisory guidance from financial institution regulators [2] discusses the negative impact of ARM reset and encourages mortgage servicers to take advantage of various government programs and work constructively with borrowers subject to ARM reset risk. The high correlation of foreclosure and payment shock suggests that ARM reset rate is a natural instrument for foreclosure rate in studying the causal effect of foreclosures and house prices. ARM reset is determined by the mortgage's contractual terms at the time of origination. For example, the rate of a 3/27 ARM will be reset three

[1] We find two empirical papers utilizing a similar concept in identifying the linkage between foreclosures and house prices. Both Gupta, 2019 and Makridis and Ohlrogge, 2018 approach the causal effect measurement issue from a micro standpoint by exploiting the loan-level interest rate variation due to an ARM reset in their two-stage estimations. Our work differs from these two studies in that our ARM reset instrument measures the proportion of adjustable-rate mortgages within a state that experience an upward payment change due to ARM reset.

[2] See, for example, OCC Bulletin 2007-14, Statement on Working with Mortgage Borrowers, https://www2.occ.gov/news-issuances/bulletins/2007/bulletin-2007-14.html; and former Chair of the Federal Deposit Insurance Corporation, Sheila Bair's congressional testimony on Accelerating Loan Modifications, Improving Foreclosure Prevention and Enhancing Enforcement before the Financial Services Committee; U.S. House Of Representatives; 2128 Rayburn House Office Building December 6, 2007, https://www.fdic.gov/news/news/speeches/archives/2007/chairman/spdec0607.html.

years after its origination, and a 2/28 ARM will be reset two years after origination. Also, whether the subsequent payment will go up or down after an ARM reset is determined by the previous introductory rate, the prevailing market rate to which the mortgage is indexed, and the margin specified in the mortgage contract. It is unlikely that an ARM reset is correlated with current house price shocks, since the tenor of the introductory rate is usually selected by the borrower and likely based on their perception of future expected income, especially for sophisticated borrowers.

To instrument house prices, we use an indicator of housing demand: the change in the natural population growth rate defined as the quarterly change in births minus deaths divided by the population in the state. This indicator captures housing demand shocks through population growth and is less likely to be correlated with house price shocks than the pure population growth rate. The population growth rate in a state is affected by migration patterns, which themselves partially reflect economic trends, especially job growth.

Three sources of endogeneity exist in our DSSES: (1) the endogenous own time-lagged effect after Helmert's transformation,[3] (2) the endogenous joint movement of house prices and foreclosures, and (3) the endogenous spillover effect of house prices and foreclosures. To address these sources of endogeneity, we adapt the finite moments instrument variable (FMIV) method designed for a single equation setting in Lee and Yu, 2014 to our simultaneous equations system. This finite moments IV-based estimator allows us to arrive at a consistent estimator in the presence of multiple sources of endogeneity. We apply the three stage least squares (3SLS) estimator in Yang and Lee, 2018[4] to address the additional complications in our DSSES. Each of our structural equations in the simultaneous equations system satisfies the sufficient and necessary rank and order conditions specified in the Proposition 1 of Yang and Lee, 2018,[5] suggesting all of the structural parameters

[3]To address location and time fixed-effects in a dynamic panel model where the dependent variable is a function of its own time-lagged term, we adopt Helmert's transformation for all the variables on both sides of our equation. The transformed own time-lagged term becomes correlated with the residual and thus can no longer be treated as a pre-determined variable. See Section 3 for more details.

[4]The consistency of the quasi maximum likelihood method in Yang and Lee, 2018 relies on the assumption of large T to avoid handling the initial observation problem, and its asymptotic distribution depends on the growth rate of N and T (i.e., $(N-1)/T^3 \to 0$). Because the T in our empirical analysis is not much larger relatively to N, we chose the 3SLS over the QML for this paper.

[5]Yang and Lee, 2018 articulate the sufficient and necessary conditions for identifying the coefficients of each structural equation in their Proposition 1. The rank condition requires the rank of a matrix representing all exclusive coefficient restrictions for the given equation to be equal to the total number of equations in the system minus one. The order condition requires that the number of all the excluded parameters of the given equation is no less than the total number of equations in the system minus one. It is worth noting that although spatial lag and FOD-transformed own time lag are endogenous from a statistical perspective, it is appropriate to regard both of them as "exogenous" variables for the purpose of counting excluded variables in a structural model. Therefore, extending a first order time lag equation as specified in Yang and Lee, 2018 to a more general specification as our DSSES with p time lags ($p \geqslant 2$) will not change our identification conclusion.

in our system are identifiable. Our estimated results also meet their stable condition,[6] indicating that our system is stable across both space and time.

Shocks to the foreclosure rate in one state not only affect house prices in that state, but also the foreclosure rates and house prices in nearby states. When it comes to the housing market, what happens in Vegas doesn't always stay in Vegas. Estimation results from our DSSES show that a one standard deviation of foreclosure shock leads to a short-run real house price decline of 1.6 percent and a 2 percent decline in real house prices over the long run. A one standard deviation shock to real house prices lowers the foreclosure rate 13 percent in the short run. We also find significant spatial spillovers in both house prices and foreclosure rates across states. For example, four quarters after a one standard deviation shock to Nevada's foreclosure rate, the real house price in California declines a cumulative 1 percent.

2 Literature Review

This paper relates to several streams of literature. First, we contribute to the literature of spatial spillovers. Neighborhood spatial spillovers have been explored extensively in the recent urban and real estate economics literature. However, most of these studies focus only on house prices (see, among others, Se Can and Megbolugbe, 1997; Basu and Thibodeau, 1998; Pace et al., 1998; LeSage and Pace, 2004; Clauretie and Daneshvary, 2009; Kiefer, 2011). These studies suggest the existence of spatial interdependence of house prices in a neighborhood. Anselin and Lozano-Gracia, 2009, and Fingleton and Le Gallo, 2008 suggest that spatially correlated house prices can be due to an omission of spatially autocorrelated regressors and displaced demand and supply effects. Omitted variables are almost inevitable in modeling house prices owing to the uniqueness of location, which is an important determinant of property value. If common characteristics that influence housing values exist in the neighborhood, but are omitted from the model specification (e.g., accessibility of shopping centers/parks, exposure to traffic noise, proximity to a major employment center), prices of nearby houses tend to serve as proxies of these omitted neighborhood effects. Residential appraisals often rely on sales comparables to determine the value of a property in a housing transaction. The widely used Sales Comparison Approach is essentially a weighted average of sales comparables in the vicinity of the subject property. The argument of displaced demand and supply effects is also intuitive: high prices discourage demand. If the price in a local area is high, the quantity demanded should decrease. Thus, demand from this location will be displaced into a nearby location, suggesting a positive relationship between local demand and nearby prices. The same argument holds for the supply function: a high price in a local area will attract supply

[6] To have a nonexplosive system either in time and space, the aggregated effects of spatial spillovers, serial correlations, and cross effects cannot be too large. More specifically, the sufficient but not necessary condition defined by Yang and Lee, 2018 requires the total effect to be less than one for row-normalized spatial weight matrices.

from nearby places, suggesting a negative relationship between local supply and nearby prices. In equilibrium where demand equals supply, the displaced demand and supply effects translate into a positive spatial relationship of nearby house prices.

Studies on spillovers of mortgage defaults and foreclosures are rather limited. The existing research shows that a borrower's default risk is affected by the household/loan characteristics of surrounding properties (see, among others, Goodstein et al., 2011; Agarwal et al., 2012; Zhu and Pace, 2014). However, the models in these studies do not directly relate the borrower's default decision to that of their neighbors to fully capture the spillover effect of mortgage defaults and, thus, likely underestimate the impact. Towe and Lawley, 2013 establish the connection between a homeowner's default decision and their observations of neighbors' time-lagged default decisions and explain it as a result of social interaction behaviors. Chomsisengphet et al., 2018 further this line of work by providing empirical evidence of spatial spillovers in homeowners' mortgage default decisions in terms of both time-lagged and contemporaneous effects.

The spillover literature discussed above emphasizes the spatial neighborhood effect as a local phenomenon. The spatially interacted neighborhood is usually defined as a planned community within a city (e.g, Clauretie and Daneshvary, 2009), a county (e.g., Se Can and Megbolugbe, 1997; Towe and Lawley, 2013; Chomsisengphet et al., 2018; LeSage and Pace, 2004; Kiefer, 2011), or a Metropolitan Statistical Area (e.g., Basu and Thibodeau, 1998). The "local" characteristic of price or foreclosure spillovers makes sense because the location feature of a house is unique and one of the main determinants of its value. However, we are interested in testing whether this type of local neighborhood effect persists in our aggregated state-level data as a collective outcome.

It is interesting to examine whether these local spillovers will be filtered out entirely when data are aggregated to a higher geographic level. In other words, are these local spatial spillover effects still observable at the state level? Intuitively, the joint movements of house prices and foreclosures within the same geographic boundary reinforce each other (i.e., spatial unit i's house price moves together with spatial unit i's foreclosure) and help fuel the ripple effects of house prices and foreclosures, which could result in a nontrivial impact on a spatial unit far from the origin of a shock. Meanwhile, the spatial spillover transmission mechanism provides an amplification channel for price to respond to a foreclosure shock within the same spatial unit.

By connecting the limited studies on the quantification of the causal effect between foreclosures and house prices at the macro level to the micro-based spillover literature, our results shed light on the extent to which spatial spillovers enhance the joint movement of house prices and foreclosures and motivate the wide range of federal programs targeting stressed borrowers.

In addition, our work contributes to a growing literature on the causal linkage between house prices and foreclosures. Accurately measuring the price impact of foreclosures is not a simple task, owing to the reverse causality issue: house prices can affect foreclosure rates, and vice versa. Strong instruments such as those we propose in this paper-ARM reset rate and change in the natural population growth rate-are useful for overcoming this identification difficulty.

The causality direction can move from house prices to foreclosures. The option-based model in Foster and Van Order, 1984 suggests that a put option (i.e., mortgage default) is in the money when house prices fall. Falling house prices shrink homeowners' equity. For homeowners with thin equity to start with (i.e., low or no down payment mortgages), a sharp drop in house prices like we saw during the recent crisis can easily push borrowers underwater (e.g., negative equity), which is a necessary (but not sufficient) condition for mortgage default. While the literature on the default impact of declining house prices is still immature (especially in terms of accurately quantifying the price externality), existing studies have suggested that house price changes play a significant role in homeowners' default decisions (e.g., among others, Bajari et al., 2008; Foote et al., 2008; Guiso et al., 2013).

The opposite causality direction is equally plausible. Foreclosed properties are usually sold at a discount either because of their below-average physical condition or the stigma effect that arises simply because these properties have been involved in foreclosure proceedings. The literature has suggested a 20 percent or higher discount associated with the sale of foreclosed properties (e.g., among others, Clauretie and Daneshvary, 2009; Carroll et al., 1997; Harding et al., 2009; Campbell et al., 2011). Besides the discount of a property due to its foreclosure status, the negative price impact of a distressed property is found in forms of externality, through either a disamenity channel (deferred maintenance or attracting crime owing to vacancy) or a supply channel (foreclosed properties add to the local house inventory available for sale). Both put downward pressure on nearby house prices.

A large literature focuses on disentangling these causality flows and examining the magnitude of the foreclosure externality on house prices. Recent studies have emphasized the importance of controlling for reverse causality to accurately measure the price impact of foreclosures. For example, to address the simultaneity issue, Harding et al., 2009 adopt a repeat sales approach; Campbell et al., 2011 and Hartley, 2014 use a difference-in-difference identification strategy in their hedonic estimations; Mian et al., 2015 use an instrument variable capturing the differences in state foreclosure laws (i.e., judicial vs. non-judicial); and Gerardi et al., 2015 include triple-interaction fixed effects (i.e., times of initial and subsequent sales and geographic location) in their repeat sales specification. The consensus in the literature is that the foreclosure spillovers on nearby house prices are less than 2 percent after properly controlling for the simultaneity issue in the estimation procedure.[7] These empirical studies have focused on "controlling" for the reverse causality of house prices on foreclosure rates by including and excluding variables representing housing quality and housing supply.

Though the potential for simultaneous movement of house prices and foreclosures is widely rec-

[7]Owing to its relatively small effect, we leave out the cross spillovers between house prices and foreclosures across spatial units from our already complicated model specification.

ognized, few studies have focused explicitly on modeling the co-movement pattern. The exception is the CLM study, which examines the simultaneous relationship between house prices and foreclosures and compares the magnitudes of price and foreclosure externality. CLM use a five-equation PVAR consisting of house price appreciation and foreclosure rates in addition to three macroeconomic indicators: employment growth rates, permits, and home sales. Their findings suggest that causality indeed exists in both directions. However, the cumulative impact (over six years) that prices have on foreclosures is 79 percent larger than the impact of foreclosures on prices. As a result, the strong connection between house prices and foreclosures mainly reflects the house price impact on foreclosure activities rather than the other way around.

By allowing for spatial autocorrelation and contemporaneous interactions between house prices and foreclosures, our empirical results of long-run analysis suggest the cumulative response to a standardized shock is only 36 percent larger for house prices on foreclosures than for foreclosures on house prices, which stands in contrast to CLM's claim of 79 percent. A shock to the foreclosure equation in our estimated DSSES that increases the foreclosure rate by one standard deviation after eight quarters decreases the real house price by 7.9 percent over that same period, which is in line with MST's findings of an 8 to 12 percent decline in prices over nine quarters in response to a similar shock.

The rest of the paper is organized as follows: Section 3 presents two alternative econometric specifications, the PVAR and the DSSES, and their estimation methodologies. Section 4 describes the data and summary statistics and discusses our instrumental variables. Section 5 discusses our empirical results. Section 6 concludes.

3 Econometric Model

In this section, we start with a PVAR commonly used in dynamic panel studies. Then we present a DSSES. Our DSSES differs from the conventional PVAR approaches of house price and foreclosure panel data modeling in two ways: the simultaneous equations system allows for a *simultaneous-cross effect* between house prices and foreclosures, and the spatial lags in the system introduce a *contemporaneous-spillover effect* of house prices and foreclosures. The DSSES emphasizes the amplification mechanism arising from the intertwined cross-effect dynamics and spatial spillovers of house prices and foreclosures.

3.1 Panel Vector Auto Regression

As explained in Canova and Ciccarelli, 2013, "PVARs have the same structure as VAR models, in the sense that all variables are assumed to be endogenous and interdependent, but a cross sectional dimension is added to the representation." Our PVAR consists of m equations with house prices and foreclosures as two of the m endogenous variables. The model also includes the individual time lags and location fixed effects, as well as the interaction of the endogenous variables but with time lags, or *time-lagged-cross effects*. When n denotes the total number of spatial units, m denotes the total number of equations, and T denotes the total number time periods, the PVAR system at time period $t(\forall t = 1, 2, \cdots, T-p)$ can be written as

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

and the lth equation $(\forall l = 1, 2, \cdots, m)$ in the system can be expressed as,

$$y^*_{l,nm}(t) = \sum_{j=1}^{p} Y^*_{nm}(t-j)\rho_{j,\cdot l} + d_l \otimes l_n + c_{\cdot l} + u^*_{l,nm}(t). \tag{1b}$$

The dependent variable, $Y^*_{nm}(t) = [y^*_{1,nm}(t), y^*_{2,nm}(t), \cdots, y^*_{m,nm}(t)]$, with each column representing one endogenous variable (e.g., house prices, foreclosures, etc.), is an $n\times m$ matrix. Similarly, $Y^*_{nm}(t-j) = [y^*_{1,nm}(t-j), y^*_{2,nm}(t-j), \cdots, y^*_{m,nm}(t-j)]$ is an $n \times m$ matrix representing the time-lagged dependent variables to the jth order. $U^*_{nm}(t) = [u^*_{1,nm}(t), u^*_{2,nm}(t), \cdots, u^*_{m,nm}(t)]$ is the disturbance term. We assume the errors are i.i.d. across space and time.[8] P_j is a $m \times m$ matrix with the diagonal elements capturing the own time-lagged effect from j periods ago, and the off-diagonal elements denoting the cross time-lagged effect from j periods ago. We use $\rho_{j,\cdot l}$ to denote the lth column of P_j. C and d are, respectively, an $n \times m$ matrix of location fixed effects[9] and an m-dimensional column vector of intercepts, while l_n is an $n\times 1$ vector of ones and $\otimes$ denotes the kronecker product. $c_{\cdot l}$ represents the lth column of C and d_l is the lth element of d.

It is well known that in a dynamic panel, the fixed-effects estimator is consistent only to the extent that the time dimension of the panel (T) is large. We apply the forward orthogonal difference (FOD) transformation (i.e., Helmert's transformation) to each variable input of Equation (1) to remove the fixed effects.[10] The FOD transformation eliminates both the intercepts and location fixed effects from Equation (1) and reduces the total observations from $mn(T-p)$ to $mn(T-p-1)$. Let $\mathcal{T} = T-p-1$ to simplify the notation, after stacking observations from all $\mathcal{T}$ time periods, the equations system can be written as

$$Y_{nm,\mathcal{T}} = \sum_{j=1}^{p} Y^{(-j)}_{nm,\mathcal{T}} P_j + U_{nm,\mathcal{T}}, \tag{2}$$

where the superscript $(-j)$ of $Y^{(-j)}_{nm,\mathcal{T}}$ indicates the value of the variable is lagged by j periods. To consistently estimate Equation (2), restrictions are typically imposed on the coefficient matrices P_js to make the variance of $Y_{nm,\mathcal{T}}$ bounded and to make sure that P_js exists.

[8] PVAR estimation usually does not require zero correlations across equations.

[9] To avoid perfect collinearity, we impose a normalization condition of $\sum_{i=1}^{n} c_{1,i} = 0$.

[10] See Appendix A for details of the operation of FOD.

3.2 Dynamic Spatial Simultaneous Equations System

The PVAR takes into account interactions between house prices and foreclosures but assumes that the cross effect happens with time lags. There are reasons to believe, however, that this assumption may be unrealistic. For example, if foreclosure rates respond quickly to price changes, our house price and foreclosure measures may be simultaneously determined, denoted by *simultaneous-cross effect*. To allow for such a possibility, we need a system allowing for simultaneously determined dependent variables. We introduce a DSSES in this section to address not only the simultaneous-cross effect but also the *contemporaneous-spillover effect* to fully account for the interactive dynamics of house prices and foreclosures and their spatial transmission mechanism. More specifically, we adopt the format of the widely used spatial autoregressive (SAR) model from Cliff and Ord, 1973 in each time period and for the house price and foreclosure equations to capture the contemporaneous-spillover effect. These two panel SAR models are then built into a simultaneous equations system to allow for the simultaneous-cross effect. The FOD transformed functions consist of both types of simultaneity and have the form of [11]

$$Y_{n2}(t)\Gamma = W_n Y_{n2}(t)\Psi + \sum_{j=1}^{p} Y_{n2}(t-j)P_j + X_n(t)\Pi + U_{n2}(t), \tag{3a}$$

and the lth equation ($\forall l = 1, 2$) in the system is expressed as,

$$y_{l,n2}(t) = -Y_{n2}(t)\gamma_{\cdot l} + W_n Y_{n2}(t)\psi_{\cdot l} + \sum_{j=1}^{p} Y_{n2}(t-j)\rho_{j,\cdot l} + X_{l,n}(t)\pi_{\cdot l} + u_{l,n2}(t), \tag{3b}$$

for $t = 1, 2, ..., \mathcal{T}$. The dependent variable, $Y_{n2}(t) = [y_{1,n2}(t), y_{2,n2}(t)]$, with the first column, $y_{1,n2}(t) = [y_{1,1}(t), \cdots, y_{1,n}(t)]'$ representing the FOD-transformed dependent variable in the house price equation and the second column, $y_{2,n2}(t) = [y_{2,1}(t), \cdots, y_{2,n}(t)]'$ representing the FOD-transformed dependent variable in the foreclosure equation, is an $n \times 2$ matrix. Γ is a 2×2 matrix with ones at the main diagonal. Its off-diagonal elements capture the simultaneous-cross effect (in a negative term). W_n is a time-invariant $n \times n$ weight matrix of known constants,[12] whose ijth entry is w_{ij}, and Ψ is the corresponding spatial autoregressive coefficient matrix with zeros for off-diagonal elements. $X_n(t) = X_{1,n}(t) \cup X_{2,n}(t)$, is the FOD-transformed exogenous variable with dimension of $n \times k$ (with x variables appearing in both equations counted for once only to avoid perfect multicollinearity, so $k \leqslant (k_1 + k_2)$), and $U_{n2}(t) = [u_{1,n2}(t), u_{2,n2}(t)]$ is the FOD-transformed disturbance term. Π is a $k \times 2$ coefficient matrix for exogenous regressors, and P_j is a 2×2 matrix for $j = 1, ...p$, with the diagonal elements capturing the own time-lagged effects

[11] Instead of a total number of m equations in the PVAR system, the DSSES consists of two equations only: the house price equation and the foreclosure equation. It also includes xs as exogenous variables.

[12] We are assuming that the system involves only one weight matrix. This assumption is made for ease of presentation but also seems to be the typical specification in applied work. Our results can be generalized in a straightforward way in which each spatially lagged variable depends upon a weight matrix that is unique to that variable.

and off-diagonal elements capturing the time-lagged cross effects. If $j \geqslant 2$, Equation (3a) becomes a high order dynamic model. We use $-\gamma_{\cdot l}$, $\psi_{\cdot l}$, $\rho_{j,\cdot l}$, and $\pi_{\cdot l}$ to denote the lth column of the corresponding parameter matrices in Equation (3b).

Equation (3) falls under the general form of spatial dynamic panel simultaneous equations models described in Yang and Lee, 2018.[13] Besides the previously discussed endogeneity arriving from the FOD-transformed own time lag (i.e., represented by the nonzero diagonal elements of P_j) as in the PVAR, two new sources of endogeneity exist: the simultaneous-cross effect represented by the nonzero off-diagonal elements in Γ and the contemporaneous-spillover effect represented by the nonzero diagonal elements of Ψ (i.e., often referred to as spatial lag in the spatial literature). We adopt the 3SLS estimation strategy in Yang and Lee, 2018, which is an extension of the finite moments instrument variable (FMIV) method proposed in Lee and Yu, 2014. Our IV matrix is then defined as

$$\mathcal{G}_n(t) = \Big[Y^*_{n2}(t-p) \quad W_n Y^*_{n2}(t-p) \quad W^2_n Y^*_{n2}(t-p) \quad X_n(t) \quad W_n X_n(t) \quad W^2_n X_n(t), \Big] \tag{4}$$

where the exogenous variables (i.e., $X_n(t)$) and predetermined variables (i.e., $Y^*_{n2}(t-p)$) are raised to first and second spatial orders (i.e., pre-multiplied by W_n and W^2_n) to address the contemporaneous spillover. The IV matrix, $\mathcal{G}_n(t)$, is not equation specific, because $X_n(t) = X_{1,n}(t) \cup X_{2,n}(t)$ represents the complete set of exogenous variables of the system and $Y^*_{n2}(t-p)$ reflects all the predetermined variables of the system. Using this IV matrix, we first derive the 2SLS estimate of each of the lth equation from Equation (3b) and then explore the information in the cross-equation variance-covariance matrix to arrive at our 3SLS estimate. Step-by-step details of how we apply the FMIV from Lee and Yu, 2014 and the 3SLS estimator from Yang and Lee, 2018 on the estimation of Equation (3) are summarized in Appendix B.

In our DSSES, contemporaneous-spillover effects serve as an amplification channel enhancing the feedback between house prices and foreclosures. To understand how these spillover effects matter in terms of amplifying the transmission of a structural shock, we used the estimated parameters to compute the impulse response to a structural shock by rearranging Equation (3b) to express $y_{l,n2}(t)$ as a function of its history, the exogenous variables, and structural innovations.

4 Data and Summary Statistics

We use data for the lower 48 contiguous U.S. states, omitting the District of Columbia.

[13] The general form in Yang and Lee, 2018 allows for a four-way channel of spatial spillovers: contemporaneous, time-lagged, within-equation, and cross-equation. Our DSSES specification omits the time-lagged and cross-equation spillover terms.

4.1 House Price and Foreclosure

We use quarterly data. For house prices, we are interested in the real (inflation-adjusted) quarterly log difference in house prices (denoted by HPA). We use the FHFA seasonally adjusted all-transactions price index to measure nominal prices and deflate it by the U.S. Bureau of Labor Statistics Consumer Price Index for all items less shelter.

For foreclosure rates, we use the natural log of the state-level foreclosure start rates as estimated by the Mortgage Bankers Association's National Delinquency Survey. Our foreclosure rate measures the percentage of all active borrowers that start a foreclosure (i.e., foreclosure start) in a quarter (denoted by FCL).

4.2 Neighborhood Specification

We construct the weight matrix of Equation (3), W_n as an adjacency matrix by setting the weight element, w_{ij}, equal to $1/c_i$ if i and j border to each other, where c_i is the number of i's adjacent neighbors, and zero otherwise. Our adjacency weight matrix thus describes the pairwise proximity of our observation units.

To test the robustness of our model, we estimate Equation (3) using alternative specifications of the weight matrix. The alternative weight matrices and the corresponding results are described in Section 5.4.

4.3 Instrumental Variables

To distinguish the impact of foreclosures on house prices from that of house prices on foreclosures in the DSSES, our 3SLS estimator calls for valid IVs for addressing the endogeneity arising from FOD-transformed own time-lags, contemporaneous-spillover effect, and simultaneous-cross effect in each of the lth equation. As described in Equation (4), the building block, $X_n(t)$ in the IV matrix consists of two types of exogenous variables: those excluded from the lth equation and those included in the lth equation. The main challenge comes from identifying the appropriate variables meeting such exclusion criteria. In other words, we need economic variables that are correlated with house prices but not correlated with foreclosures, and vice versa.

4.3.1 ARM Reset as an Instrument for Foreclosures

To quantify the causal effect of foreclosures on house prices, we propose a novel instrument by leveraging the space and time variations of the number of ARMs that are hit by their contractual interest rate reset clock. Specifically, we calculate the number of ARMs encountering upward rate reset as a share of the total number of active loans in a given month for a given state and use it as the exclusion restriction for identifying the house price equation.

ARMs were quite popular during the housing boom years of 2003 to 2006, as they offered borrowers low initial payments. ARMs often have low introductory rates (i.e., teaser rates) that help entice borrowers and increase the marketability of ARMs over fixed-rate mortgages (FRMs). ARM products typically involve two phases: (1) an introductory period during which the interest rate is fixed and (2) a period during which the rate is periodically moved to reflect prevailing market rates. An ARM contract has several key features. It defines the length of the introductory period, in which the interest rate is fixed; a selected market index (e.g., LIBOR, TBill, Prime rate), which is used to reset rates in the second phase; the margin, or the spread between the index rate and the reset rate; and the floors and caps, which determine the maximum and minimum amount the rate may move either for one reset period or for the life of the loan.

The introductory rate is temporary and typically ranges from three to ten years. At the end of the introductory period, the borrower is confronted with the fluctuation of interest rate and its frequent reset. ARMs indeed carry a financial risk for borrowers and, therefore, borrowers tend to convert their ARMs to FRMs or refinance into new ARMs before the rate reset date, provided the prevailing market rate is favorable. ARM borrowers who are unable to refinance before the end of the introductory period are often those who experience rising market rates, those with a less-than-perfect credit rating[14], those in a weak equity position, or all of above.[15] These ARM borrowers are more likely to encounter difficulty repaying their mortgage if the rate resets higher.

A hot housing market might attract more ARM borrowers because of the low initial payments. It is reasonable to believe that the number of ARMs originated might be correlated with house prices at the time of loan origination. However, we do not expect that the number of ARMs that reset in the future is directly correlated with future house prices, unless the correlation is through the foreclosure channel. This is an important point that supports the validity of our instrument. It is likely that ARMs were more heavily used in areas with rapid house price appreciation and deterioration in average credit quality. Thus, the share of ARMs originated would be a potentially poor instrument. However, for reasons argued above, the share of ARM borrowers experiencing a

[14]It is also possible that lenders could have tightened credit standards when they anticipated a decline in future house prices, which would have prevented borrowers from taking advantage of the prevailing market rate and refinancing into a more favorable loan term. Borrowers affected by such lender behavior were usually subprime borrowers who were believed to build up the latent risk of the recent crisis. These subprime borrowers were obviously vulnerable to a rate increase.

[15]One could argue that a borrower might have experienced declining market rates and therefore anticipated the rate would further decline at the ARM reset date. So, the borrower would not mind moving into the second phase of the ARM instead of refinancing out of it. However, if the market rate is trending down, from a theoretical perspective, the borrower may often be better off refinancing into a new ARM with a more favorable term instead of waiting for the expiration of the existing ARM. From an empirical perspective however, this scenario is not possible on a large scale owing to frictions (e.g., refinance cost). This is especially the case when the market rate has dropped significantly over a long enough period (e.g., the post-crisis time), as borrowers qualified for loan refinancing would have already refinanced.

reset in any particular period is unlikely to be influenced by the current period's house price shocks. Our identification requires that the ARM reset variable be uncorrelated only with contemporaneous shocks, not past house price shocks.

We focus on loans that had a rate increase during their initial rate reset period using Black Knight's McDash first lien data.[16] 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 end of the introductory period or when the first principal and interest (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 on the reset day.[17]

The McDash database contains historical monthly loan-level information for more than 180 million mortgages; from 2005 ro 2018, the McDash data covered between 52 and 70 percent of the U.S. mortgage market. When aggregated across states and time, the average reset rate is 0.19 percent and the average reset rate with higher payment is 0.11 percent. The number remains roughly the same across states. For example, California has an average reset rate of 0.22 percent, and 0.13 percent of borrowers are paying higher payments upon reset. Similarly, Texas has an average reset rate of 0.18 percent, and 0.09 percent of borrowers are paying higher payments upon reset. But these rates fluctuate significantly across time.

4.3.2 Natural Population Growth as an Instrument 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. In markets with elastic housing supply, the impact of increased population will, over time, be mitigated by expansion of the housing supply. However, many markets in the United States have inelastic housing supply. Moreover, housing is long-lasting and thus inelastic with respect to negative shocks. The housing supply does not simply shrink when housing demand contracts. Rather, vacancy rates tend to rise and house price growth suffers.

[16] Black Knight's McDash data provide loan-level information collected from residential mortgage servicers on loans securitized by government agencies and non-agencies as well as loans held in portfolio. The McDash data provide loan origination information and payment performance tracking records over time. See https://www.blackknightinc.com/what-we-do/data-services/ for details.

[17] Because our ARM reset measure is used to proximate the number of borrowers who are likely to experience a payment shock and subsequently fall behind on their payments, we are mainly interested in tracking as our base population ARM borrowers who have not yet defaulted before a rate reset. To alleviate the potential data pollution from those defaulted borrowers, we drop loans from our sample when a delinquency (i.e., 90DPD) occurs. In other words, these ever-delinquent loans are still counted as active loans before they become delinquent. Loans that have been modified at any time are excluded from our data sample if modification occurs before the reset date.

State population growth by itself, however, is not a suitable candidate instrument because of the migration that occurs across states. Areas with robust job growth tend to have higher population growth rates, as a booming economy attracts workers. For example, during the energy boom from 2007 to 2014, North Dakota experienced a large influx of workers and the resident population increased sharply. Because this migration flow is likely correlated with the same shocks that drive foreclosure rates, we use the quarterly change in the natural population growth rate to control for demand shocks that are largely uncorrelated with economic conditions. The natural population growth rate is defined as births minus deaths divided by population. While some correlation may exist between economic conditions and fertility/mortality, the impact is much smaller, likely with considerable lags; thus, most of the cross-state variation in natural population rates is likely uncorrelated with state economic conditions.

4.4 Summary Statistics

Our estimation window covers first quarter 2005 to first quarter 2018, a period of 13.25 years (53 quarters). In addition to the instruments described above, we include other controls to account for economic and general housing market conditions. These controls are nonfarm payroll employment, per capita income, and single-family housing permits. For each of these controls, we take the quarterly log difference in the variable. Summary statistics and variable definitions are shown in Table 1.

Table 1: Summary Statistics (2005Q1-2018Q1)

Variable	**Mean**	**Std**	**Min**	**Max**	**Obs**
Employ	0.002	0.006	-0.066	0.03	2544
Permit	-0.012	0.176	-2.466	2.641	2544
Income	0.003	0.013	-0.095	0.12	2544
HPA	0	0.019	-0.109	0.092	2544
Pop	0	0.001	-0.007	0.007	2544
FCL	-0.646	0.592	-2.303	1.324	2544
ARMreset	-7.236	0.842	-9.261	-4.125	2544

Employ:	1 quarter lag of log difference in nonfarm payroll employment
Permit:	1 quarter lag of log difference in single-family housing permits
Income:	1 quarter lag of log difference in per capita income
HPA:	log difference in real house price index
Pop:	quarterly difference in the natural population growth rate (births - deaths)/population
FCL:	log of foreclosure start rate
ARMreset:	log of arm reset share

5 Estimation Results

In this section, we estimate the causal effect between house prices and foreclosures for the PVAR and the DSSES. Based on these estimates, we compute the short-run and long-run cross effects and discuss the different outcomes from these two model specifications.

5.1 PVAR

Our main result involves the DSSES described in Section 3.2. However, before we proceed to the more complicated dynamics embedded in the DSSES, it is useful to consider the results of the PVAR discussed in Section 3.1. The PVAR approach provides a useful benchmark and allows us to compare our results directly to previous literature, particularly CLM who also use a PVAR.

The PVAR treats all variables as endogenous and estimates a reduced form equation. It then identifies structural innovations through a chosen strategy. The most common approach, and the one used by CLM, is a recursive identification strategy, which requires that variables only respond contemporaneously to innovations in variables ordered ahead of that equation. Thus, the first variable in the system is assumed to respond only to itself. The second variable responds to the first and itself, and so on, until the last variable in the system responds to innovations in all other equations. Table 10 in Appendix C presents the estimation results for a PVAR(12).

The coefficients of the PVAR are difficult to interpret, so it is useful to consider summary statistics. One useful statistic is the forecast error variance decomposition, which estimates the proportion of variation at a given time horizon that is attributable to innovations in one of the variables.

The first panel of Table 2 presents estimates for the proportion of forecast errors for employment attributable to various innovations at horizons of 4, 8, and 24 quarters. For the employment variable, more than 80 percent of the variation in the four-quarter window is due to innovations in the employment equation. The foreclosure rate contributes only a small amount, slightly more than 1 percent. At the end of 24 quarters, innovations in the foreclosure equation contribute less that 5 percent of the variation. Note that for each of the first three variables (employment, per capita income, and permits), innovations in the foreclosure equation contribute less than 5 percent, even out to 24 quarters.

The fourth panel of Table 2, which shows the house price response to shocks, is of key interest. This measure tells us the proportion of real house price variation that can be attributed to innovations in each variable. We find that innovations in the foreclosure equation account for between 16.6 and 22.8 percent of the variation in house prices. This is notably higher than the results in the CLM study, which finds that foreclosure innovations explain only about 5 percent of the variation. Our PVAR includes different variables, but that is not the main reason for the divergence. Indeed, if we include the same variables as in CLM, we still would see a divergence between our results and

Table 2: Forecast Error Variance Decomposition

FEVD: Employment Response to Shocks (2005-2018)					
Horizon	**Employ**	**Income**	**Permit**	**HPA**	**FCL**
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
FEVD: Per capita income Response to Shocks (2005-2018)					
Horizon	**Employ**	**Income**	**Permit**	**HPA**	**FCL**
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	0.74	0.05	0.066	0.038
FEVD: Single-Family Permits Response to Shocks (2005-2018)					
Horizon	**Employ**	**Income**	**Permit**	**HPA**	**FCL**
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	0.03
FEVD: House Price Response to Shocks (2005-2018)					
Horizon	**Employ**	**Income**	**Permit**	**HPA**	**FCL**
4	0.04	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
FEVD: Foreclosure Response to Shocks (2005-2018)					
Horizon	**Employ**	**Income**	**Permit**	**HPA**	**FCL**
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

CLM's.

The main reason for the divergence is the sample selection period. CLM estimate their PVAR on data from 1981 to 2009. This period excludes much of the long recovery in housing markets following the Great Recession. While shorter, our sample period (first quarter 2005 to first quarter 2018) extends beyond the Great Recession and into the recent housing recovery. The foreclosure rate was much higher and more volatile during that time than during the period studied by CLM. Also, our sample allows us to trace the dynamic linkages between house prices and foreclosure rates during periods when foreclosure start rates spiked and subsequently fell.

5.2 DSSES

The PVAR does not fully exploit the information contained in the state data. In particular, it does not take advantage of possible spatial autocorrelation. It seems unlikely that innovations in one state would have no impact on outcomes in a neighboring state. To help control for possible spatial autocorrelation and to allow for contemporaneous interactions between foreclosure starts and house prices, we estimate the DSSES model described in Equation (3). We use the instrumental variables described in Section 4.3 to identify the contemporaneous impact of a foreclosure innovation on house prices, and vice versa.

We chose to limit our estimation to a single time lag (i.e., $p = 1$) for each equation. While the estimation is straightforward to include additional lags in the specification, the results become more difficult to interpret. The inclusion of a single time lag (own and cross equation) along with a spatial lag provides a sufficiently rich model of the state house price and foreclosure rate interactions. For an easy cross-reference, we rewrite Equation (3) for $p = 1$ (to simplify the notations, we omit the subscript of p from the coefficients of ρs and replace p by 1 for the time index of time-lagged ys) below

$$y_{1,i}(t) = -\gamma_{12}y_{2,i}(t) + \psi_{11}W_n Y_{1,n2}(t) + \rho_{11}y_{1,i}(t-1) + \rho_{12}y_{2,i}(t-1) + x'_{1,i}(t)\pi_{\cdot 1} + u_{1,i}(t), \quad (5a)$$

and

$$y_{2,i}(t) = -\gamma_{21}y_{1,i}(t) + \psi_{22}W_n Y_{2,n2}(t) + 1\rho_{22}y_{2,i}(t-1) + \rho_{21}y_{1,i}(t-1) + x'_{2,i}(t)\pi_{\cdot 2} + u_{2,i}(t), \quad (5b)$$

for $t = 1, 2, \cdots, \mathcal{T}$ and $i = 1, 2, \cdots, n$. We treat employment, per capita income, and permits as predetermined variables and include them with a time lag of a single quarter. Table 3 presents our main results corresponding to Equation (5).

Our DSSES includes two equations: the real house price growth rate equation (referred to as HPA equation) and the log foreclosure rate equation (referred to as FCL equation).

Table 3: DSSES Estimation - State Adjacency Weights

	Beta 3SLS	**Std Error**	**t-value**	**p-value**
HPA: FCL ($-\gamma_{12}$)	-0.054	0.005	-11.194	0
*HPA: W*HPA* (ψ_{11})	0.444	0.038	11.831	0
HPA: HPA_lag1 (ρ_{11})	0.228	0.046	4.934	0
HPA: FCL_lag1 (ρ_{12})	0.05	0.005	10.467	0
HPA: Pop ($\pi_{.1}$)	0.352	0.194	1.818	0.035
HPA: Employ ($\pi_{.1}$)	0.459	0.057	8.063	0
HPA: Income ($\pi_{.1}$)	-0.085	0.021	-4.133	0
HPA: Permit ($\pi_{.1}$)	-0.002	0.001	-1.755	0.04
FCL: HPA ($-\gamma_{21}$)	-6.684	0.73	-9.161	0
*FCL: W*FCL* (ψ_{22})	-0.044	0.028	-1.539	0.062
FCL: HPA_lag1 (ρ_{21})	1.212	0.742	1.634	0.051
FCL: FCL_lag1 (ρ_{22})	0.932	0.035	27.002	0
FCL: ARMreset ($\pi_{.2}$)	0.01	0.005	1.774	0.038
FCL: Employ ($\pi_{.2}$)	2.699	1.03	2.62	0.004
FCL: Income ($\pi_{.2}$)	-0.689	0.326	-2.11	0.017
FCL: Permit ($\pi_{.2}$)	-0.076	0.02	-3.9	0

HPA:	HPA equation
FCL:	FCL equation
*W*HPA:*	spatial lag in the HPA equation
*W*FCL:*	spatial lag in the FCL equation
HPA_lag1:	1 quarter time lag of HPA
FCL_lag1:	1 quarter time lag of FCL

5.2.1 House Price Equation

Our results indicate that a 1 percent increase in the foreclosure rate ceteris paribus reduces real house prices by 5.4 basis points. The effect is dampened by the positive coefficient on the cross lag,ρ_{12}, which nearly equals the contemporaneous coefficient, $-\gamma_{12}$. It reflects the fact that over the long run, foreclosure innovations should have limited impact on the level of real house prices.

We find a significant positive coefficient on the spatial lag of 0.444. This implies that a 1 percent increase in the average of neighboring states' house prices leads to a 0.444 percent increase in a state's house prices. We also see an own time-lagged effect of 0.228, implying house price innovations are persistent. The IV for house prices, Pop, has a small but statistically significant coefficient of 0.352. This implies that a 1 percentage point increase in the state's natural population growth rate leads to a 0.352 percent increase in real house prices.

The control variables, Employ, Income, and Permit, are significant drivers of house prices, though their signs are difficult to interpret in isolation owing to considerable collinearity between the three variables. For example, employment growth has a positive coefficient while per capita income has a negative coefficient. However, employment is unlikely to increase without affecting per capita income. When we estimate the model with only one of the predetermined variables, the signs are as expected (positive), but our ability to identify the contemporaneous impact of foreclosure shocks is reduced.

5.2.2 Foreclosure Equation

We find a large and significant negative coefficient on HPA, indicating an increase in house prices lowers the foreclosure start rate as economic theory would suggest.

The spatial autoregressive coefficient, ψ_{22}, in the foreclosure equation is small but statistically significant. The interpretation of this negative spatial coefficient is not straightforward, but it is important to remember that we have estimated a complex dynamic equation system. Results in Section 5.2.3 provide additional insight for FCL responses to FCL shocks.

Considerable persistence exists in the foreclosure equation with an own time-lagged effect of 0.932. This implies that four quarters following a shock, more than three-quarters of the effect ($0.932^4 = 0.7545$) remains. The cross lag of HPA on FCL, ρ_{21}, has an opposite sign to the contemporaneous impact of HPA on FCL, $-\gamma_{21}$, indicating some dampening over time.

Our instrument $\mathsf{ARMreset}$ has a statistically significant impact on the foreclosure rate. A 1 percent increase in the share of mortgage loans that experience a payment shock results in a 1 basis point increase in the foreclosure rate. That effect may seem economically small, but the standard deviation of our $\mathsf{ARMreset}$ indicator is 0.842, indicating that a typical shock to $\mathsf{ARMreset}$ raises the foreclosure rate by 0.842 percent.

As in the HPA equation, interpreting the control variables individually is difficult, but we see statistically significant impacts from each control.

5.2.3 Short-Run and Long-Run Analysis

Even though the DSSES results are easier to inspect than the PVAR(12) coefficients, it is still somewhat difficult to interpret such a complex model by considering only coefficients. Tables in this section shed some additional light on the results. We will inspect both the short-run and long-run effects of structural shocks.

First, we will consider the own-shock impact.[18] We rearrange Equation (3) to compute the short-run effect. Our estimation sample comprises 48 states, and the effect for each state differs slightly based on the number of nearby neighbors. For reporting purposes, we compute the average of the own-shock short-run effect from the 48 states: a one standard deviation innovation in the HPA equation (1.08 percent) results in a 1.98 percent increase in house prices and a 13.1 percent decline in the foreclosure rate. A standard deviation (16.5 percent) to the log foreclosure start rate leads to a 1.62 percent decline in house prices and a 27.1 percent increase in the foreclosure rate.

There is no long-run own-shock impact to the foreclosure rate. The model is stationary. However, because we specified house prices in log differences, we can compute the cumulative long-run own-shock impact to the level of house prices. A one standard deviation shock to house prices leads to a cumulative increase in house prices of 2.6 percent, while a one standard deviation shock to the foreclosure rate leads to a 2 percent decline in house prices.

Using the estimated coefficients, we can also compute the impulse response to a structural innovation in house prices or foreclosure rates. Note that this is only a partial response, as we have not estimated the full dynamic relationship between our endogenous variables (HPA and FCL) and our predetermined variables. Because our interest is in foreclosure innovations and because our Forecast Error Variance Decompositions indicates that foreclosure innovations contribute only a small amount to variations in our predetermined variables (Employ, Income, and Permit), this partial impulse response captures most of the dynamics that a fully specified model is likely to generate.

Turning to the cross-impact,[19] we will first consider the cross-impact of a one standard deviation structural shock (FCL and HPA respectively) in one state on the HPAs of nearby states. For illustration purposes we choose Nevada and present the results for nearby states, Arizona, California, Idaho, Oregon, and Utah. To compare the own-shock impact against the cross-shock impact, we also report Nevada's responses to its shocks in Tables 4 to 7. Because of the spatial lag in our model, shocks to Nevada generated responses in its neighbors (the results extend to all states but die off quickly with distance).

[18] We use own-shock impact to denote a state's response to its own structural shock (not from nearby states).

[19] We use cross-shock impact to denote a state's response to its neighbor's structural shock (not from itself).

Table 4: Cumulative Real House Price Response to a Standardized Nevada Foreclosure Shock

Horizon	AZ	CA	ID	NV	OR	UT
4	-0.0075	-0.0109	-0.007	-0.0252	-0.0097	-0.0063
8	-0.0053	-0.0076	-0.0049	-0.0229	-0.0068	-0.0044
24	-0.0014	-0.0021	-0.0013	-0.0195	-0.0019	-0.0011

Table 4 shows the cumulative response of house prices 4, 8, and 24 quarters following a structural shock to Nevada FCL. After four quarters of a one standard deviation shock, the Nevada foreclosure equation results in a cumulative decline of 2.5 percent in Nevada house prices. Neighboring California also experiences a decline but of a more modest amount (1.1 percent). After 24 quarters, the cumulative decline is smaller in absolute value as prices recover. And in nearby states, the cumulative response is almost zero (0.21 percent for California).

Table 5: Cumulative Real House Price Response to a Standardized Nevada Real House Price Shock

Horizon	AZ	CA	ID	NV	OR	UT
4	0.0107	0.0156	0.0099	0.0321	0.0139	0.0089
8	0.0094	0.0137	0.0087	0.0307	0.0121	0.0078
24	0.0056	0.0085	0.0049	0.0265	0.0072	0.0045

We also compute the HPA response of each of the six states to a Nevada HPA shock (Table 5). Following a one standard deviation shock to Nevada HPA, house prices in Nevada are up 3.2 percent four quarters later and 2.65 percent 24 quarters later. Prices in neighboring California are up 1.6 percent four quarters later and 0.85 percent 24 quarters later.

We also consider the cross-impact of a one standard deviation structural shock (FCL and HPA respectively) in Nevada on the FCLs of its nearby states. We do not compute the cumulative response but rather the response in the log of foreclosure starts 4, 8, and 24 quarters following a shock.

Table 6: Log Foreclosure Response to a Standardized Nevada Foreclosure Shock

Horizon	AZ	CA	ID	NV	OR	UT
1	0.0198	0.0301	0.0175	0.2731	0.0256	0.016
4	0.0244	0.0339	0.0235	0.244	0.032	0.0205
8	-0.0012	-0.0037	-0.0005	0.1699	-0.0013	-0.0012
24	-0.0129	-0.0214	-0.0117	0.0561	-0.0167	-0.0115

Following a foreclosure shock, Nevada FCL rate is up 27 percent. The foreclosure rate in

California is up 3 percent as spatial spillovers are positive (recall that the system accounts for impact on both FCL and HPA). But after 24 quarters, Nevada foreclosure rates are still up 5.6 percent, while foreclosure rates in neighboring states have declined modestly (2.1 percent for California). This decline could be due to displaced demand. Households in Nevada who were foreclosed may move to nearby states, bolstering housing markets and leading to (very modest) declines in the FCL rate in those states.

Table 7: Log Foreclosure Response to a Standardized Nevada Real House Price Shock

Horizon	**AZ**	**CA**	**ID**	**NV**	**OR**	**UT**
1	-0.0275	-0.0422	-0.0242	-0.1329	-0.0356	-0.0223
4	-0.043	-0.062	-0.0403	-0.1409	-0.0559	-0.0361
8	-0.0177	-0.0256	-0.0164	-0.0918	-0.0228	-0.0148
24	0.0049	0.0077	0.0045	-0.0229	0.0064	0.0042

Our results show that the cumulative response of the level of real house prices to a one standard deviation shock to foreclosure rates (Table 4) is similar to the response in the log level of the foreclosure rate in response to a one standard deviation house price shock (Table 7). After six years, a one standard deviation shock to Nevada foreclosures lowers real house prices in the state by 1.95 percent. By contrast, six years after a one standard deviation shock to Nevada house prices, foreclosure rates decline by 2.29 percent. Thus, the cumulative response to a standardized shock is only 36 percent larger for house prices on foreclosure than for foreclosure on house prices. This result stands in contrast to CLM (Figure 3 in CLM's paper) who find that the standardized foreclosure response to prices is 79 percent larger than the standardized price response to foreclosures.

It is also useful to compare our results in terms of the magnitude of responses. MST find that a one standard deviation increase in foreclosures results in an 8 to 12 percent decline in house prices over nine quarters. In contrast, CLM find a shock that results in a two-year increase in the foreclosure start rate of 4.3 percentage points leads to a nine-quarter cumulative decline in house prices of 2.7 percent and 6.8 percent over the long run. Tables 4 through 7 show the response of a standardized shock and thus are not directly comparable to MST or CLM. However, we can compute the size of a standardized foreclosure shock that is sufficient to increase a state's foreclosure rate by one standard deviation (as measured in data). The standard deviation of the log foreclosure rate in our sample (Table 1) is 0.59 percent. A standardized shock to Nevada's foreclosure rate increases the state's foreclosure rate 0.1699 after eight quarters (Table 6). Thus, a shock of 3.47 standard deviations (0.59/0.1699) is needed to generate a one standard deviation increase in Nevada's foreclosure rate. Multiplying our result in Table 4 by 3.47 indicates that a one standard deviation shock (comparable to the one considered in MST and CLM) decreases real house prices 7.9 percent after eight quarters.

5.3 Policy Experiment

The effects we captured in the exercises above are somewhat conservative because shocks are constrained within a single state. While this conservatism helps us to make a direct comparison to MST and CLM, which do not allow for state spillovers, we may be understating the degree to which fluctuations in house prices and foreclosures spill over to other states. Our system assumes that innovations for states are uncorrelated. In other words, conditional on a one standard deviation shock to a single state, say Nevada, the expected shock for a neighboring state, say California, would remain zero. However, this is only true for a typical shock, and the most recent housing market bust and the policy response was anything but typical.

To illustrate, consider an experiment in which a hypothetical policy innovation directly lowers each state's foreclosure rate by 10 percent (0.1 log points). What impact would such a policy have on average state house prices and foreclosure rates, considering the dynamic interactions estimated by our model?

Figures 1 and 2 show the results. Note that because we applied the same shock to all states, the responses are the same for each state. While the hypothetical policy directly lowers the foreclosure rate in each state by 10 percent, the maximum impact is more than 30 percent after accounting for spillovers and the endogenous response of house prices and foreclosures (Figure 1). Over time, the effect wanes, and in the long run the effect on foreclosure rates is zero.

The effect on house prices is shown in Figure 2. Following the policy intervention, real house prices rise in response to lower foreclosure rates. The effect reaches its peak in four to five quarters when real house prices increase about 5.5 percent. As the foreclosure rate impact fades to zero, house prices give back some of their gain, until after 24 quarters the cumulative impact on the level of real house prices is about 2 percent. These results show that a national foreclosure mitigation program that lowers the foreclosure rate by a modest amount (less than a one standard deviation innovation) can have a significant impact on house prices over an extended period.

5.4 Alternative Weight Matrices

In this section we present results using alternative weight matrices. We consider two alternatives. In the first, we group states based on U.S. Census Bureau divisions. States within the same division are all neighbors, while states in other divisions are not. For example, Texas, Louisiana, Oklahoma, and Arkansas (members of the West South Central division) are all neighbors, but New Mexico is not a neighbor with Texas because New Mexico is in the Mountain division. We exclude Hawaii and Alaska from our analysis, so the Pacific division consists of only California, Oregon, and Washington.

In our second alternative weight matrix, we use state-to-state migration flows based on Internal Revenue Service (IRS) data. We consider the number of exemptions filed in a particular state where the return had been filed in a different state the previous year. We base our weight matrix on the number of in-migrants (not net flows) from one state to another. To smooth volatility, we compute the annual average number of in-migrants to each state from 1995 to2005. The weights are based on the share of all in-migrants during that period who came from a particular state. Because California has a large number of out-migrants, this weighting scheme effectively places more weight on California.

Flow data are compiled from administrative records from the IRS's Individual Master File, which includes a record for every individual income tax return filed. The data are developed by matching the records of individual income tax returns filed in the "base year," using the social security number (SSN) of the primary taxpayer with the tax return filed the following year.

When the SSN of the primary taxpayer on the return filed in the base year matches the SSN of the return filed the following year, the county residence is compared to determine if the taxpayer has relocated. If the county address matches, then the taxpayer is counted as a "non-migrant." If the county address does not match, then the taxpayer is considered an "out-migrant" relative to the county address on the return filed in the base year and an "in-migrant" relative to the county address on the return filed in the current year. Only returns for which the SSN reported on the return in the base year matches the SSN reported on the return the following year are included.

The consistent results from Tables 8 and 9 when compared with those from Table 3 suggest our main findings are quite robust and not sensitive to the specifications of alternative weight matrices. The magnitude and signs of our key variables and other control variables are fairly similar.

Table 8: DSSES Estimation - Division Weights

	Beta 3SLS	**Std Error**	**t-value**	**p-value**
HPA: FCL ($-\gamma_{12}$)	-0.037	0.005	-7.547	0
*HPA: W*HPA* (ψ_{11})	0.516	0.039	13.398	0
HPA: HPA_lag1 (ρ_{11})	0.206	0.05	4.165	0
HPA: FCL_lag1 (ρ_{12})	0.034	0.005	6.932	0
HPA: Pop ($\pi_{.1}$)	0.219	0.181	1.211	0.113
HPA: Employ ($\pi_{.1}$)	0.355	0.051	6.983	0
HPA: Income ($\pi_{.1}$)	-0.079	0.019	-4.196	0
HPA: Permit ($\pi_{.1}$)	-0.002	0.001	-1.539	0.062
FCL: HPA ($-\gamma_{21}$)	-5.422	0.842	-6.437	0
*FCL: W*FCL* (ψ_{22})	-0.025	0.035	-0.712	0.238
FCL: HPA_lag1 (ρ_{21})	0.72	0.863	0.834	0.202
FCL: FCL_lag1 (ρ_{22})	0.902	0.04	22.295	0
FCL: ARMreset ($\pi_{.2}$)	0.017	0.006	2.905	0.002
FCL: Employ ($\pi_{.2}$)	1.095	1.06	1.033	0.151
FCL: Income ($\pi_{.2}$)	-0.394	0.34	-1.16	0.123
FCL: Permit ($\pi_{.2}$)	-0.073	0.019	-3.763	0

HPA:	HPA equation
FCL:	FCL equation
*W*HPA:*	spatial lag in the HPA equation
*W*FCL:*	spatial lag in the FCL equation
HPA_lag1:	1 quarter time lag of HPA
FCL_lag1:	1 quarter time lag of FCL

Table 9: DSSES Estimation- IRS Migration Weights

	Beta 3SLS	**Std Error**	**t-value**	**p-value**
HPA: FCL ($-\gamma_{12}$)	-0.055	0.006	-8.823	0
*HPA: W*HPA* (ψ_{11})	0.245	0.028	8.676	0
HPA: HPA_lag1 (ρ_{11})	0.221	0.063	3.534	0
HPA: FCL_lag1 (ρ_{12})	0.05	0.006	8.167	0
HPA: Pop ($\pi_{.1}$)	0.754	0.237	3.184	0.001
HPA: Employ ($\pi_{.1}$)	0.527	0.065	8.099	0
HPA: Income ($\pi_{.1}$)	-0.134	0.023	-5.729	0
HPA: Permit ($\pi_{.1}$)	-0.003	0.002	-1.663	0.048
FCL: HPA ($-\gamma_{21}$)	-4.479	0.933	-4.799	0
*FCL: W*FCL* (ψ_{22})	0.007	0.016	0.439	0.33
FCL: HPA_lag1 (ρ_{21})	1.121	0.85	1.319	0.094
FCL: FCL_lag1 (ρ_{22})	0.862	0.031	28.033	0
FCL: ARMreset ($\pi_{.2}$)	0.03	0.006	5.079	0
FCL: Employ ($\pi_{.2}$)	-0.412	1.131	-0.364	0.358
FCL: Income ($\pi_{.2}$)	-0.271	0.359	-0.753	0.226
FCL: Permit ($\pi_{.2}$)	-0.06	0.02	-3.047	0.001

HPA:	HPA equation
FCL:	FCL equation
*W*HPA:*	spatial lag in the HPA equation
*W*FCL:*	spatial lag in the FCL equation
HPA_lag1:	1 quarter time lag of HPA
FCL_lag1:	1 quarter time lag of FCL

6 Conclusion

In this paper, we study the dynamic relationship of house prices and foreclosure rates across space and time using a panel data from 48 U.S. states. Our results show an economically significant impact of house prices on foreclosure rates and foreclosure rates on house prices. Moreover, even at the state level, neighborhood effects are important. Shocks to the foreclosure rate in one state not only affect house prices in that state but also the foreclosure rates and house prices in nearby states. When it comes to the housing market, what happens in Vegas doesn't always stay in Vegas. Our DSSES model estimation results show that a one standard deviation foreclosure shock leads to a short-run real house price decline of 1.6 percent and a 2 percent decline in real house prices over the long run. A one standard deviation shock to real house prices lowers the foreclosure rate 13 percent in the short run. We also find significant spatial spillovers in both house prices and foreclosure rates across states. For example, four quarters after a one standard deviation shock to Nevada's foreclosure rate, real house prices in California decline a cumulative 1 percent.

This paper also introduces a novel modeling strategy to account for the space and time dynamics in regional studies: the DSSES. We also contribute to the growing literature on the interactions of house prices and foreclosure rates by identifying two potentially useful instruments for state panel models. The ARM payment shock could be used to identify the effects of foreclosure rates, while the natural rate of population growth could serve as a useful instrument for housing demand shocks that are less likely to be correlated with economic factors other than pure population growth.

The fact that foreclosure rates have an economically meaningful impact on house prices at the state level could be useful information for policymakers evaluating the effectiveness of foreclosure mitigation programs. The literature has established that the spillover effects from the foreclosure of any individual property die off after a short distance. However, the aggregate effect of multiple foreclosures in an area can affect not only local housing markets but can lead to ripple effects across space and time, magnifying the foreclosure rate's aggregate impact. Studies that omit these important effects—contemporaneous causality and spatial lags—are likely to underestimate that impact of foreclosure rates on house prices and thus understate the potential benefits of foreclosure mitigation activities.

7 Bibliography

Agarwal, S., Ambrose, B. W., Chomsisengphet, S., Sanders, A. B., 2012. Thy neighbor's mortgage: Does living in a subprime neighborhood affect one's probability of default? Real Estate Economics 40 (1), 1–22.

Alvarez, J., Arellano, M., 2003. The time series and cross-section asymptotics of dynamic panel data estimators. Econometrica 71 (4), 1121–1159.

Anselin, L., Lozano-Gracia, N., 2009. Spatial hedonic models. In: Palgrave handbook of econometrics. Springer, pp. 1213–1250.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. The Review of Economic Studies 58 (2), 277–297.

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. Journal of Econometrics 68 (1), 29–51.

Bajari, P., Chu, C. S., Park, M., 2008. An empirical model of subprime mortgage default from 2000 to 2007. Tech. rep., National Bureau of Economic Research.

Basu, S., Thibodeau, T. G., 1998. Analysis of spatial autocorrelation in house prices. The Journal of Real Estate Finance and Economics 17 (1), 61–85.

Calomiris, C. W., Longhofer, S. D., Miles, W. R., 2013. The foreclosure–house price nexus: a panel var model for US states, 1981–2009. Real Estate Economics 41 (4), 709–746.

Campbell, J. Y., Giglio, S., Pathak, P., 2011. Forced sales and house prices. American Economic Review 101 (5), 2108–31.

Canova, F., Ciccarelli, M., 2013. Panel vector autoregressive models: A survey. In: VAR Models in Macroeconomics–New Developments and Applications: Essays in Honor of Christopher A. Sims. Emerald Group Publishing Limited, pp. 205–246.

Carroll, T., Clauretie, T., Neill, H., 1997. Effect of foreclosure status on residential selling price: comment. Journal of Real Estate Research 13 (1), 95–102.

Chomsisengphet, S., Kiefer, H., Liu, X., 2018. Spillover effects in home mortgage defaults: Identifying the power neighbor. Regional Science and Urban Economics 73, 68–82.

Clauretie, T. M., Daneshvary, N., 2009. Estimating the house foreclosure discount corrected for spatial price interdependence and endogeneity of marketing time. Real Estate Economics 37 (1), 43–67.

Cliff, A. D., Ord, J. K., 1973. Spatial autocorrelation, monographs in spatial environmental systems analysis. London: Pion Limited.

Elhorst, J. P., 2010. Dynamic panels with endogenous interaction effects when t is small. Regional Science and Urban Economics 40 (5), 272–282.

Fingleton, B., Le Gallo, J., 2008. Estimating spatial models with endogenous variables, a spatial lag and spatially dependent disturbances: finite sample properties. Papers in Regional Science 87 (3), 319–339.

Foote, C. L., Gerardi, K., Willen, P. S., 2008. Negative equity and foreclosure: Theory and evidence. Journal of Urban Economics 64 (2), 234–245.

Foster, C., Van Order, R., 1984. An option-based model of mortgage default. Housing Fin. Rev. 3, 351.

Gerardi, K., Rosenblatt, E., Willen, P. S., Yao, V., 2015. Foreclosure externalities: New evidence. Journal of Urban Economics 87, 42–56.

Goodstein, R., Hanouna, P., Ramirez, C. D., Stahel, C. W., 2011. Are foreclosures contagious? FDIC Center for Financial Research Working Paper 2011-4.

Guiso, L., Sapienza, P., Zingales, L., 2013. The determinants of attitudes toward strategic default on mortgages. The Journal of Finance 68 (4), 1473–1515.

Gupta, A., 2019. Foreclosure contagion and the neighborhood spillover effects of mortgage defaults. The Journal of Finance 74 (5).

Harding, J. P., Rosenblatt, E., Yao, V. W., 2009. The contagion effect of foreclosed properties. Journal of Urban Economics 66 (3), 164–178.

Hartley, D., 2014. The effect of foreclosures on nearby housing prices: Supply or dis-amenity? Regional Science and Urban Economics 49, 108–117.

Kelejian, H. H., Prucha, I. R., 2004. Estimation of simultaneous systems of spatially interrelated cross sectional equations. Journal of Econometrics 118 (1-2), 27–50.

Kiefer, H., 2011. The house price determination process: Rational expectations with a spatial context. Journal of Housing Economics 20 (4), 249–266.

Lee, L.-f., Yu, J., 2014. Efficient gmm estimation of spatial dynamic panel data models with fixed effects. Journal of Econometrics 180 (2), 174–197.

LeSage, J. P., Pace, R. K., 2004. Models for spatially dependent missing data. The Journal of Real Estate Finance and Economics 29 (2), 233–254.

Makridis, C., Ohlrogge, M., 2018. The local effects of foreclosures. Available at SSRN 2985827.

Mian, A., Sufi, A., Trebbi, F., 2015. Foreclosures, house prices, and the real economy. Journal of Finance 70 (6), 2587–2634.

Pace, R. K., Barry, R., Sirmans, C. F., 1998. Spatial statistics and real estate. Journal of Real Estate Finance and Economics 17 (1), 5–13.

Revelli, F., 2001. Spatial patterns in local taxation: tax mimicking or error mimicking? Applied Economics 33 (9), 1101–1107.

Se Can, A., Megbolugbe, I., 1997. Spatial dependence and house price index construction. Journal of Real Estate Finance and Economics 14 (1-2), 203–222.

Sigmund, M., Ferstl, R., 2019. Panel vector autoregression in r with the package panelvar. The Quarterly Review of Economics and Finance (In Press).

Towe, C., Lawley, C., 2013. The contagion effect of neighboring foreclosures. American Economic Journal: Economic Policy 5 (2), 313–35.

Yang, K., Lee, L.-f., 2018. Identification and estimation of spatial dynamic panel simultaneous equations models. Regional Science and Urban Economics 76, 32–46.

Zhu, S., Pace, R. K., 2014. Modeling spatially interdependent mortgage decisions. Journal of Real Estate Finance and Economics 49 (4), 598–620.

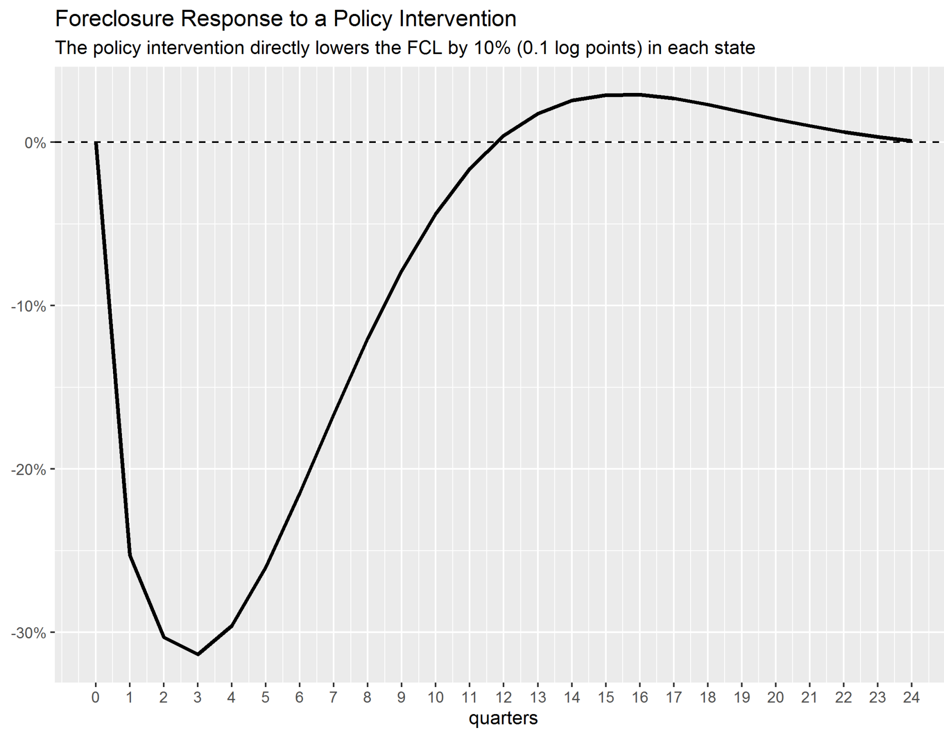

Figure 1: Foreclosure Response to a Policy Shock

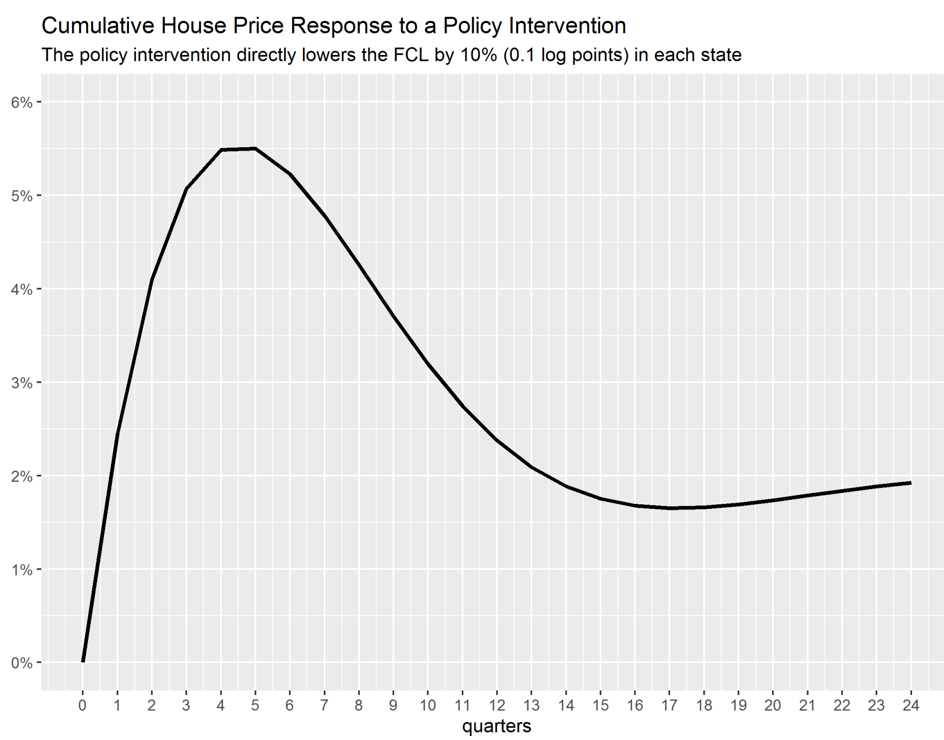

Figure 2: Cumulative House Price Response to a Policy Intervention

Appendix A FOD Transformation

Arellano and Bover, 1995 show the FOD transformation preserves the i.i.d. feature of the original error terms. We follow Lee and Yu, 2014's notation and express the FOD operator as, $F_{T-p,T-p-1}$, as a $(T-p) \times (T-p-1)$ matrix consisting of a subset of the eigenvectors of $J_{T-p} = (I_{T-p} - \frac{1}{T-p} l_{T-p} l'_{T-p})$ (where I_{T-p} is a $(T-p) \times (T-p)$ identity matrix and l_{T-p} is a $(T-p)$-dimensional vector of ones) - the eigenvectors corresponding to the unit eigenvalues, i.e., $J_{T-p}F_{T-p,T-p-1} = F_{T-p,T-p-1}$, $F_{T-p,T-p-1}F'_{T-p,T-p-1} = J_{T-p}$, and $F'_{T-p,T-p-1}F_{T-p,T-p-1} = I_{T-p-1}$. To illustrate the idea of FOD transformation, it is convenient to express the input variables of Equation (1a) in their vectorized forms. Let

$$\begin{aligned}
&\left[\mathrm{vec}(Y_{nm}(1)), \mathrm{vec}(Y_{nm}(2)), \cdots, \mathrm{vec}(Y_{nm}(T-p-1))\right] = \\
&\qquad \left[\mathrm{vec}(Y^*_{nm}(1)), \mathrm{vec}(Y^*_{nm}(2)), \cdots, \mathrm{vec}(Y^*_{nm}(T-p))\right] F_{T-p,T-p-1}, \\
&\left[\mathrm{vec}(Y_{nm}(0)), \mathrm{vec}(Y_{nm}(1)), \cdots, \mathrm{vec}(Y_{nm}(T-p-2))\right] = \\
&\qquad \left[\mathrm{vec}(Y^*_{nm}(0)), \mathrm{vec}(Y^*_{nm}(1)), \cdots, \mathrm{vec}(Y^*_{nm}(T-p-1))\right] F_{T-p,T-p-1},
\end{aligned}$$

and we can further show the FOD transformation at the individual observation level (e.g., for spatial unit i at time t in equation l) as

$$y_{l,i}(t) = \left(\frac{T-p-t}{T-p-t+1}\right)^{\frac{1}{2}} \left[y^*_{l,i}(t) - \frac{1}{T-p-t} \sum_{h=t+1}^{T-p} y^*_{l,i}(h)\right], \tag{6a}$$

$$y_{l,i}(t-1) = \left(\frac{T-p-t}{T-p-t+1}\right)^{\frac{1}{2}} \left[y^*_{l,i}(t-1) - \frac{1}{T-p-t} \sum_{h=t}^{T-p-1} y^*_{l,i}(h)\right]. \tag{6b}$$

Similar definitions apply to the disturbances, intercepts, and location fixed effects. Because $F'_{T-p,T-p-1}l_{T-p} = 0$, both the intercept and location fixed effects are eliminated from Equation (1). Also, the FOD-transformed residuals, $u_{l,i}(t)$s, are still i.i.d. across is and ts with

$$E(u_{m,i}(t)u_{l,j}(s)) = \{ \begin{array}{c} 0 \text{ if } m \neq l \text{ or } i \neq j \text{ or } t \neq s \\ \sigma_{ml} \text{ if } m = l \text{ and } i = j \text{ and } t = s \end{array},$$

because $F'_{T-p,T-p-1}F_{T-p,T-p-1} = I_{T-p-1}$.

The FOD-transformed lth equation ($\forall l = 1, 2, \cdots, m$) at time t can be specified as

$$y_{l,nm}(t) = \sum_{j=1}^{p} Y_{nm}(t-j)\rho_{j,\cdot l} + u_{l,nm}(t). \tag{7}$$

Stacking observations from all ts, the lth equation becomes

$$y_{l,nm,T-p-1} = \sum_{j=1}^{p} Y^{(-j)}_{nm,T-p-1}\rho_{j,\cdot l} + u_{l,nm,T-p-1}. \tag{8}$$

The superscript $(-j)$ of $Y^{(-j)}_{nm,T-p-1}$ indicates the time-lagged property of this variable. It is important to note that the total number of observations in the lth equation reduces from $n(T-p)$ to $n(T-p-1)$ after the FOD transformation. $y_{l,nm,T-p-1}$ and $u_{l,nm,T-p-1}$ are now $n(T-p-1)$ vectors. The dimensions of $Y^{(-j)}_{nm,T-p-1}$ is $n(T-p-1) \times m$.

From Equation (6b), it is obvious that after FOD transformation, $y_{l,i}(t-1)$, depends on observation not only at $t-1$ but also those in the future time periods (i.e., $t, t+1, \cdots, T-p-1$). Therefore, the transformed own time-lagged term, $y_{l,i}(t-1)$, is now correlated with the transformed error term, $u_{l,i}(t)$.

Appendix B FMIV and 3SLS

Valid IVs for the FOD-transformed own time lag, $y_{l,n2}(t-j)$, suggested in the dynamic panel literature include exogenous variables from all the time periods (i.e., $X_n(t)$ $\forall t = 1, 2, \cdots, \mathcal{T}$) and own untransformed terms from the current time period and all the previous time periods (i.e., $y^*_{l,i}(t-j)$, $y^*_{l,i}(t-j-1), \cdots$).[20] The number of feasible IVs is a function of t, and therefore the dimension of the corresponding IV matrix increases with t. A large number of IVs constructed from all available time lags is beneficial, in principle, in terms of improving the asymptotic efficiency of the IV estimator. However, when $\mathcal{T}$ gets large, the many IVs issue occurs: many IVs decrease the variance of the IV estimator but increase its bias.

Lee and Yu, 2014 first show that the 2SLS estimator based on FMIV approach is consistent and asymptotically normal in a single-equation spatial dynamic panel setting (though less efficient than the GMM estimator proposed in their paper).[21] The non-spatial simultaneous equations system literature suggests the use of exogenous variables excluded from the lth equation and the exogenous variables included in the lth equation as instruments to address the endogeneneity arising from the simultaneous movement of multiple equations. Meanwhile, common IVs suggested in the spatial literature for dealing with spatial lags call for first-order and higher-order spatially lagged exogenous variables. To adapt to the introduction of a simultaneous equations system to the single-equation spatial dynamic panel framework, Yang and Lee, 2018 extend Lee and Yu, 2014's FMIV specification and suggest a 3SLS estimator. Our IV matrix of Equation (4) strictly follows the IV strategy in Yang and Lee, 2018.

After stacking observations from all ts ($\forall t = 1, 2, \cdots, \mathcal{T}$), the IV can be written into a matrix

[20] Among others, see Arellano and Bond, 1991; Elhorst, 2010; Alvarez and Arellano, 2003; Kelejian and Prucha, 2004; Revelli, 2001 for examples.

[21] The set of IVs suggested by Lee and Yu, 2014 consists of both linear and quadratic moments. Owing to the complication in our main model specification-the DSSES is an equations system but not a single equation-the quadratic moments become less straightforward. We therefore adopt only the linear moments from Lee and Yu, 2014 instead of pursuing their best IV estimator.

as

$$\mathcal{G}_{n,\mathcal{T}} = \begin{bmatrix} Y^*_{n2}(1-p) & W_n Y^*_{n2}(1-p) & W_n^2 Y^*_{n2}(1-p) \\ \vdots & \vdots & \vdots \\ Y^*_{n2}(\mathcal{T}-p) & W_n Y^*_{n2}(\mathcal{T}-p) & W_n^2 Y^*_{n2}(\mathcal{T}-p) \end{bmatrix},$$
$$\begin{matrix} X_n(1) & W_n X_n(1) & W_n^2 X_n(1) \\ \vdots & \vdots & \vdots \\ X_n(\mathcal{T}) & W_n X_n(\mathcal{T}) & W_n^2 X_n(\mathcal{T}) \end{matrix}\Bigg]$$

with a dimension of $n\mathcal{T} \times (6+6k)$.

We stack observations from all ts ($\forall t = 1, \cdots, \mathcal{T}$) for the lth equation and let $\mathcal{W}_{n2,\mathcal{T}} = I_2 \otimes I_{\mathcal{T}} \otimes W_n$ for conciseness, thus Equation (3b) becomes

$$\begin{aligned} y_{l,n2,\mathcal{T}} &= -Y_{n2,\mathcal{T}}\gamma_{\cdot l} + \mathcal{W}_{n2,\mathcal{T}} Y_{n2,\mathcal{T}}\psi_{\cdot l} + X_{l,n,\mathcal{T}}\pi_{\cdot l} + \sum_{|=\infty}^{p} Y^{(-j)}_{n2,\mathcal{T}}\rho_{j,\cdot l} + u_{l,n2,\mathcal{T}}, \\ &\forall l = 1, 2, \end{aligned} \tag{9}$$

where $Y_{n2,\mathcal{T}}$, $\mathcal{W}_{n2,\mathcal{T}} Y_{n2,\mathcal{T}}$, and $Y^{(-j)}_{n2,\mathcal{T}}$ ($\forall j = 1, \cdots, p$) are all endogenous. Let

$$\begin{aligned} Z_{l,n,\mathcal{T}} &= \begin{bmatrix} Y_{n2,\mathcal{T}} & \mathcal{W}_{n2,\mathcal{T}} Y_{n2,\mathcal{T}} & X_{l,n,\mathcal{T}} & Y^{(-1)}_{n2,\mathcal{T}} & \cdots & Y^{(-p)}_{n2,\mathcal{T}} \end{bmatrix}, \text{and} \\ \theta_l &= \begin{bmatrix} -\gamma'_{\cdot l} & \psi'_{\cdot l} & \pi'_{\cdot l} & \rho'_{1,\cdot l} & \cdots & \rho'_{p,\cdot l} \end{bmatrix}', \end{aligned}$$

Equation (9) can be simplified to

$$\begin{aligned} y_{l,n2,\mathcal{T}} &= Z_{l,n,\mathcal{T}}\theta_l + u_{l,n2,\mathcal{T}}, \\ &\forall l = 1, 2. \end{aligned} \tag{10}$$

We first estimate Equation (10) separately for each equation. The 2SLS estimator of the lth equation has the form of

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

where $P^{\mathcal{G}} = \mathcal{G}_{n,\mathcal{T}}(\mathcal{G}'_{n,\mathcal{T}}\mathcal{G}_{n,\mathcal{T}})^{-1}\mathcal{G}'_{n,\mathcal{T}}$ is the projection matrix of the instrument matrix $\mathcal{G}_{n,\mathcal{T}}$. The 2SLS estimator's asymptotic distribution follows

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

with large n and $\mathcal{T}$.

To further extend the 2SLS estimator to a 3SLS estimator suggested by Yang and Lee, 2018 for an improved estimation efficiency, we stack both equations from Equation (9) and write the system into a vectorized form as

$$y_{n2,\mathcal{T}} = Z_{n,\mathcal{T}}\theta + u_{n2,\mathcal{T}}, \tag{11}$$

where $y_{n2,\mathcal{T}} = \begin{bmatrix} y'_{1,n2,\mathcal{T}} & y'_{2,n2,\mathcal{T}} \end{bmatrix}'$, $Z_{n,\mathcal{T}} = diag[\ Z_{1,n,\mathcal{T}},\ \ Z_{2,n,\mathcal{T}}\ ] = \begin{bmatrix} Z_{1,n,\mathcal{T}} & 0 \\ 0 & Z_{2,n,\mathcal{T}} \end{bmatrix}$, $\theta = \begin{bmatrix} \theta'_1 & \theta'_2 \end{bmatrix}'$, and $u_{n2,\mathcal{T}} = \begin{bmatrix} u'_{1,n2,\mathcal{T}} & u'_{2,n2,\mathcal{T}} \end{bmatrix}'$. The variance-covariance matrix of the residuals in Equation (11) is of the form, $\Sigma \otimes I_{n,\mathcal{T}}$, with $\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}$,[22] and $I_{n,\mathcal{T}}$ denoting an $n\mathcal{T} \times n\mathcal{T}$ identify matrix. The 3SLS estimator of the entire equation system is

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

with $\widehat{Z}_{n,\mathcal{T}} = diag[\ P^{\mathcal{G}}Z_{1,n,\mathcal{T}},\ \ P^{\mathcal{G}}Z_{2,n,\mathcal{T}}\ ] = \begin{bmatrix} P^{\mathcal{G}}Z_{1,n,\mathcal{T}} & 0 \\ 0 & P^{\mathcal{G}}Z_{2,n,\mathcal{T}} \end{bmatrix}$, and the variance-covariance components of $\widehat{\Sigma} = \begin{bmatrix} \widehat{\sigma}_{11} & \widehat{\sigma}_{12} \\ \widehat{\sigma}_{21} & \widehat{\sigma}_{22} \end{bmatrix}$ can be estimated using a first stage estimator, $\widehat{\theta}^{\mathcal{G}}_{l,2sls}$.[23] Yang and Lee, 2018 note the asymptotic distribution of this estimator is

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

with large n and $\mathcal{T}$.

Appendix C PVAR Estimate

We chose 12 lags to match CLM. The PVAR was estimated using the R package panelvar in Sigmund and Ferstl, 2019, which implements GMM estimator described in Section 3.1 and the references therein.

Table 10: Dynamic Panel VAR Estimation: One-Step GMM

	Employ	Income	Permit	HPA	FCL
Employ_lag1	0.3155***	0.3998**	2.0836	0.1371	0.6284
	-0.0428	-0.1297	-2.372	-0.0907	-1.4671
Income_lag1	0.0275***	-0.3072***	0.2179	-0.1690***	1.0253**
	-0.0078	-0.0487	-0.2796	-0.0152	-0.3306
Permit_lag1	0.0045***	-0.0044*	-0.4770***	0.0038**	-0.0685**

[22] The i.i.d. assumption of the disturbances suggests that $\sigma_{12} = \sigma_{21} = 0$ in our specification. Relaxing this i.i.d. assumption to allow for cross-equation correlations in the disturbances is easily applicable by estimating σ_{12} and σ_{21} using the 2SLS estimator. However, to simplify our shock analyses (i.e., independent structural shocks between house prices and foreclosures), we assume away such correlations.

[23] As suggested by Kelejian and Prucha, 2004, the first stage estimator, $\widehat{\theta}^{\mathcal{G}}_{l,2sls}$, can be used to calculate the residuals in $\widehat{u}_{l,n2,\mathcal{T}}$, which in turn are used to form estimates of the elements in Σ as $\widehat{\sigma}_{ml} = \frac{1}{n\mathcal{T}}\widehat{u}'_{m,n2,\mathcal{T}}\widehat{u}_{l,n2,\mathcal{T}} (\forall m, l = 1, 2)$.

	-0.0007	-0.0021	-0.0674	-0.0013	-0.0264
HPA_lag1	-0.0573***	0.1361***	0.1953	0.4055***	-0.7065*
	-0.0068	-0.0247	-0.3999	-0.0431	-0.3336
FCL_lag1	0	0.0025	-0.0414*	-0.0132***	0.6029***
	-0.0006	-0.0032	-0.0193	-0.0023	-0.0319
Employ_lag2	0.1493***	0.2063*	0.941	-0.3257**	-1.5619
	-0.0228	-0.0897	-1.0948	-0.1011	-1.1555
Income_lag2	0.0206**	0.0805**	0.6547**	0.1766***	-0.5055
	-0.0078	-0.0277	-0.2315	-0.0267	-0.3264
Permit_lag2	0.0054***	-0.0059*	-0.2683***	0.0120***	-0.1242***
	-0.0006	-0.0025	-0.0718	-0.0023	-0.0254
HPA_lag2	0.0438***	0.0463	3.0295***	-0.2524***	-0.9125*
	-0.0085	-0.031	-0.6421	-0.0283	-0.3579
FCL_lag2	0.0016***	0.0044	-0.0242	-0.0141***	0.1523***
	-0.0004	-0.0029	-0.0287	-0.002	-0.0336
Employ_lag3	0.0074	0.0646	-4.8265**	0.4806***	-0.385
	-0.0267	-0.094	-1.7279	-0.1101	-1.1723
Income_lag3	-0.0039	0.0001	-0.291	0.0880***	0.1601
	-0.0079	-0.0241	-0.3858	-0.0259	-0.3231
Permit_lag3	0.0071***	0.0007	-0.1013	0.0074***	-0.1401***
	-0.0006	-0.0037	-0.0726	-0.0017	-0.0281
HPA_lag3	0.0567***	-0.0358	1.6650***	0.0283	-0.9879*
	-0.0061	-0.0267	-0.4689	-0.03	-0.4023
FCL_lag3	-0.0005	-0.0027	0.0495	0.0009	0.0465
	-0.0006	-0.0017	-0.0307	-0.0017	-0.0323
Employ_lag4	-0.1659***	-0.6371***	-8.8992***	0.127	1.5232
	-0.0307	-0.0897	-1.6458	-0.0928	-0.8366
Income_lag4	0.0241*	-0.0861**	0.0912	-0.0369	0.8381*
	-0.0094	-0.0281	-0.6306	-0.0308	-0.4101
Permit_lag4	0.0080***	-0.0028	0.2958***	0.0002	-0.2056***
	-0.0008	-0.003	-0.039	-0.0017	-0.0403
HPA_lag4	0.0364***	0.0595	0.6623	-0.0741*	-1.1314**
	-0.011	-0.0323	-0.5466	-0.0291	-0.4088
FCL_lag4	-0.0002	-0.0036	-0.0136	0.0065**	0.1143***
	-0.0005	-0.002	-0.0257	-0.0021	-0.0274
Employ_lag5	-0.0425	0.0962	0.5879	-0.2367***	-1.1427
	-0.0266	-0.1338	-1.1512	-0.0634	-1.2265

Income_lag5	0.0053	-0.0572*	0.4997	0.0029	0.6269*
	-0.0078	-0.0274	-0.3056	-0.0207	-0.3024
Permit_lag5	0.0059***	-0.0002	0.1127	-0.0071**	-0.1334**
	-0.0008	-0.0027	-0.0672	-0.0026	-0.0417
HPA_lag5	0.0287***	0.0063	-0.9547***	0.0544*	-0.5745
	-0.0073	-0.0345	-0.2618	-0.0251	-0.3537
FCL_lag5	0.0007	0.0056**	0.0292	0.0081***	0.0129
	-0.0006	-0.0019	-0.0295	-0.0019	-0.0233
Employ_lag6	-0.0188	-0.1076	2.3433	0.0153	-0.7122
	-0.0306	-0.0928	-1.232	-0.0898	-1.0905
Income_lag6	0.0215**	-0.0841**	0.5249	0.0470*	-0.9804***
	-0.0083	-0.0274	-0.3642	-0.0209	-0.2613
Permit_lag6	0.0056***	0.003	0.0653	-0.0113***	-0.1385**
	-0.0007	-0.0026	-0.0429	-0.0034	-0.043
HPA_lag6	0.0375***	0.1509***	-2.5350***	0.0585*	-0.0126
	-0.0103	-0.0291	-0.2382	-0.0259	-0.4082
FCL_lag6	0.0002	0.0011	0.0038	-0.0090***	0.0254
	-0.0006	-0.0021	-0.0216	-0.0019	-0.025
Employ_lag7	-0.0727**	-0.3248**	0.7768	0.3918***	-0.0973
	-0.0261	-0.1087	-1.0915	-0.1023	-1.094
Income_lag7	-0.0133	-0.0981***	0.45	-0.0197	-0.3514
	-0.0095	-0.0256	-0.3698	-0.0231	-0.5115
Permit_lag7	0.0027**	-0.003	0.028	-0.0039	-0.1142**
	-0.0008	-0.0027	-0.0457	-0.003	-0.0412
HPA_lag7	-0.0525***	-0.0471*	-1.5671**	-0.0003	1.4592***
	-0.0074	-0.0232	-0.5933	-0.0234	-0.32
FCL_lag7	0.0008	0.002	0.0503*	-0.0002	-0.0627
	-0.0006	-0.0021	-0.0245	-0.0014	-0.0361
Employ_lag8	-0.1180***	0.1818*	-2.9672***	0.4247***	2.4385
	-0.0329	-0.0763	-0.874	-0.0634	-1.432
Income_lag8	0.0141	-0.0248	0.0254	-0.1410***	-0.6935*
	-0.0085	-0.0298	-0.3497	-0.0221	-0.2887
Permit_lag8	0.0046***	0.0142***	0.1649***	-0.0015	-0.1035**
	-0.0011	-0.0026	-0.0322	-0.0025	-0.0371
HPA_lag8	0.0115	0.048	-0.1634	0.0565**	1.0628***
	-0.0071	-0.0279	-0.3353	-0.0207	-0.2928
FCL_lag8	0.0005	0.0006	-0.0314	0.0057***	0.0337

	-0.0004	-0.0021	-0.0269	-0.0016	-0.0258
Employ_lag9	-0.0161	-0.1409	-0.7629	0.0627	1.7948
	-0.0247	-0.0798	-0.8083	-0.0601	-1.2654
Income_lag9	0.0059	0.0827**	0.1948	0.0285	0.5078
	-0.0093	-0.0254	-0.3749	-0.0201	-0.2724
Permit_lag9	0.0051***	0.0187***	0.1836***	-0.0056*	-0.0873**
	-0.0011	-0.0026	-0.0281	-0.0027	-0.0291
HPA_lag9	-0.0272***	0.1408***	-0.8998*	-0.0575**	-0.6910*
	-0.008	-0.0271	-0.3763	-0.0201	-0.3089
FCL_lag9	-0.0004	0.0059**	-0.0564	0.0050*	0.0419
	-0.0007	-0.002	-0.0584	-0.0021	-0.0265
Employ_lag10	0.0495	0.1143	1.2114	-0.1697**	-3.2371***
	-0.027	-0.151	-1.3497	-0.0638	-0.9408
Income_lag10	0.0223***	-0.025	1.1664***	-0.1032***	-0.2892
	-0.0064	-0.0205	-0.2927	-0.0208	-0.2092
Permit_lag10	0.0051***	0.0174***	0.0666*	-0.0088*	-0.0481
	-0.0008	-0.0027	-0.0311	-0.0045	-0.0294
HPA_lag10	0.0132	-0.0354	1.7553***	-0.0167	-0.6371
	-0.0076	-0.0213	-0.4866	-0.0259	-0.3593
FCL_lag10	0.0003	-0.0102***	0.0826**	-0.0029	0.0102
	-0.0007	-0.0018	-0.0311	-0.0021	-0.0257
Employ_lag11	-0.0448*	-0.3182**	-3.7948***	0.3718***	3.7532***
	-0.0222	-0.1032	-0.807	-0.054	-0.9046
Income_lag11	0.0012	-0.0724**	0.2399	0.0562**	-0.5252*
	-0.0066	-0.0259	-0.1889	-0.0191	-0.2459
Permit_lag11	0.0060***	0.0152***	0.0826**	-0.0103**	-0.038
	-0.0007	-0.0031	-0.0304	-0.0036	-0.0263
HPA_lag11	0.0192*	-0.1035***	0.7591	0.0182	0.9341**
	-0.0076	-0.0275	-0.4547	-0.0277	-0.3198
FCL_lag11	0.0001	0.0054*	0.0102	0.0044*	-0.0826***
	-0.0005	-0.0022	-0.0269	-0.0021	-0.0195
Employ_lag12	-0.1138***	-0.037	-3.3337*	-0.1767*	0.8647
	-0.0179	-0.0753	-1.3842	-0.088	-0.8378
Income_lag12	0.0051	-0.0594**	-0.0262	-0.0057	-0.8895**
	-0.008	-0.0196	-0.4236	-0.0179	-0.2929
Permit_lag12	0.0012*	0.0006	0.1154*	-0.0026	-0.0323
	-0.0005	-0.0018	-0.0544	-0.0019	-0.0263

HPA_lag12	0.0222***	0.0122	1.6581***	-0.1344***	0.7040*
	-0.0054	-0.0209	-0.4859	-0.0282	-0.2822
FCL_lag12	-0.0010*	-0.0091***	-0.0017	-0.0014	0.0823***
	-0.0005	-0.0017	-0.0213	-0.0014	-0.0232

Transformation: Forward orthogonal deviations

Group variable: fipn

Time variable: yq

Number of observations = 1920

Number of groups = 48

Obs per group: min = 40

Obs per group: avg = 40

Obs per group: max = 40

Number of instruments = 575

$p < 0.001$, $p < 0.01$, $p < 0.05$

Instruments for equation

Standard

GMM-type

Dependent vars: L(2,24))

Collapse = TRUE

Hansen test of overid. restrictions: chi2(275) = 8.22 Prob > chi2 = 1

(Robust, but weakened by many instruments.)