The Impact of Macro-Prudential Policies on Chinese Housing Markets: A Panel VAR-X Approach

Job Market Paper

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Abstract

This paper studies the impact of macro-prudential policy on regional Chinese housing markets. A structural panel VAR-X with time-varying parameters (TVPs) and stochastic volatilities (SVs) is estimated on real GDP, real loans, and real house prices across seven economic regions of mainland China from February 2005 to March 2013. The predetermined variable is one of two measures of Chinese macro-prudential policies. Canova and Ciccarelli (2007, "Estimating multicountry VAR models," International Economic Review, 50, 929-959) are the source of the Metropolis-within-Gibbs sampler used to estimate the panel VAR-X. My results show the dynamics of regional house price growth respond more to the housing demand shocks of other regions than to own regional shocks. The time-varying responses of regional house prices to regional housing demand shocks are lower in longer horizons during the 2007-2009 financial crisis compared with the rest of the sample. Unanticipated changes to macro-prudential policies have a larger impact on house prices than on real GDP and loans. Macro-prudential policies also appear to be less effective during the 2007-2009 financial crisis and 2011-2013.

JEL codes: E21, E27, E51, G18, R31

Key words: Housing, China, Bayesian panel VAR, Macro-prudential

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1 Introduction

Stabilizing the housing markets in China has been a critical issue for Chinese policy makers during the last 20 years, especially after the 2007-2009 financial crisis. For example, house prices in China grew at an annual rate of 25% in early 2010. Although the pace of house price growth has slowed recently, Chinese house prices were still increasing by more than 9% in September 2019.[1] As a result, Chinese regulators remain concerned that a correction in house prices could lead to a crash in the financial markets and a severe recession. Causation running from housing markets to the real economy comes from a commonly held view of economists and policy makers that shocks to house prices can be transmitted to the rest of the economy; see, for example, Liu, Wang, and Zha (2013).

Chinese policy makers have responded to the growth of house prices with an array of macro-prudential policies. Macro-prudential policy making is vested in the People's Bank of China, the State Council of China, and the Banking Regulatory Commission of China. Chinese policy makers use macro-prudential tools to solve several problems, but the main goal of macro-prudential policy in China is to mitigate systemic risk in financial markets. This often entails using macro-prudential policies to smooth shocks to financial markets. Chinese regulators smooth these shocks using macro-prudential policies to reduce the procyclical response of asset prices and credit to real and financial shocks; see the People's Bank of China (2017). The macro-prudential policies available to policy makers in China include reserve requirements (RR), liquidity requirements (LIQ), limits on credit growth (CRE) on commercial banks, maximum debt-service-to-income ratio (DSTI) and housing-related taxes (TAX) on borrowers, maximum loan-to-value ratio (LTV) on mortgages, and loan prohibition (PROH) on buyers of second or third houses, foreigners, or nonresidents.[2] The RR, LTV, and PROH are the most frequently

[1]Chinese house price data are compiled by CEIC Data and available at `https://www.ceicdata.com/en/indicator/china/house-prices-growth`.

[2]The macro-prudential tools evaluated in this paper differ from policies used by Chinese regulators and measured by Shim et al. (2013). The reason is the ways in which commercial banks comply with the policies this paper analyzes influence their quarterly Macro-Prudential Assessment (MPA) conducted by the People's Bank of China. The review is grounded in indicators tied to the capital, leverage, liquidity,

used macro-prudential policy tools by Chinese policy makers.

This paper studies the responses of Chinese regional real GDP growth, real loan growth, and real house price growth to identified regional supply, credit, and housing shocks. I also present evidence on the impact of macro-prudential policy on regional Chinese housing markets. The estimates rest on a Bayesian panel VAR with time-varying parameters (TVPs) and stochastic volatilities (SVs). The panel VAR is estimated on real GDP growth, real loan growth, and real house price growth across seven regions in China. Macro-prudential policy is introduced as an exogenous policy intervention, which leads to a Bayesian panel VAR-X. I identify output, loan, and housing market shocks using a recursive ordering of real GDP growth, real loan growth, and real house price growth region by region in China. The panel VAR-X yields evidence about the static and dynamic interactions and dynamic responses to the identified shocks within and across the regions in China. Conditional on estimates of these dynamic interactions and responses, I report evidence on the effectiveness of macro-prudential policies to alter the paths of real activity, loan markets, and house prices in China. To the best of my knowledge, this paper is the first to use a panel VAR-X with TVPs and SVs to study regional supply, credit supply, and housing demand shocks along with surprises to macro-prudential policy.

The panel VAR-X is highly parameterized. This is a challenging estimation problem. Canova and Ciccarelli (2009) solve the problem by mapping a panel VAR into a dynamic factor model. The dynamic factor allows for static and dynamic interdependencies, cross-sectional heterogeneities, and dynamic heterogeneities. When shocks in two regions are correlated, these regions have static interdependencies. Dynamic interdependencies exist when one region's lagged variables affect (i.e., Granger-cause) another region's variables. Cross-section heterogeneity occurs when the parameters across the regional VARs differ. Dynamic heterogeneity occurs when regional VARs have TVPs and the structural shocks are affected by the SVs. In this way, TVPs and SVs produce evidence about the way

pricing of liabilities, asset quality, foreign debt risk, and compliance with credit regulations of commercial banks. The MPA assigns commercial banks grades of A, B, or C. Conditional on its grade, a commercial bank has to comply with a menu of regulatory policies in the next quarter to lessen its riskiness.

in which regional responses to own shocks and other regions' shocks are time varying, movements in the volatility of the identified shocks change over time, and the time-varying impact of macro-prudential policies on real activity, loan markets, and house prices.

I employ Bayesian methods to estimate the panel VAR-X. Since a panel VAR-X can be mapped into a dynamic factor model, Canova and Ciccarelli (2009) exploit its state-space representation for estimation. They develop a Metropolis within Gibbs Markov chain Monte Carlo (MCMC) sampler to compute the posterior distribution of the panel VAR-X. I also use sparse matrix methods to estimate the posterior of the panel VAR-X. Dieppe, Legrand, and van Roye (2016) apply sparse matrix methods to ease computational demands compared with using the Kalman filter to estimate the panel VAR-X.

I estimate the panel VAR-X on monthly Chinese regional real GDP growth, real loan growth, and real house price growth. The predetermined macro-prudential policy variable is common to all the regions. The sample period is 2005m02 to 2013m03.

The panel data consists of seven economic regions in China. However, the layout of the economic regions starts with the eight regions proposed by Li and Hou (2003).[3] I combine two of the eight regions because they are close both geographically and economically. The data for the seven regions are constructed by aggregating data at the provincial and city-tier levels.

The monthly regional GDP data are built on quarterly provincial GDP that is provided by the National Bureau of Statistics of China (NBSC). I aggregate the provincial GDP data to regional GDP data. I deflate the nominal regional GDP series using aggregate CPI for China to produce regional real GDP. The quarterly regional real GDP data are interpolated from quarterly to monthly data using linear regression methods.

The source of monthly regional loans is the monthly provincial loan data provided by CEIC Data. Monthly city-level house prices are obtained from Fang et al. (2016). I aggregate city-level house prices into regional house prices by taking weighted averages.

[3]Chinese policy makers often depend on the eight economic regions defined by Li and Hou (2003). The National Bureau of Statistics of China (NBSC) has also come to rely on their division of the regions of China when reporting economic statistics.

The weights of the house prices come from the floor space of residential buildings sold. I deflate the regional nominal loan and house price data by the Chinese CPI to produce regional real loan and real house price data.

The effects of macro-prudential policy interventions are represented using either of two exogenous variables. The first is a dummy-type national-level macro-prudential policy index constructed by Shim et al. (2013). I use the maximum LTV on mortgages, which is taken from Alam et al. (2019), as an alternative macro-prudential policy tool.[4] Exogeneity requires the macro-prudential policy (MPP) index and change in the LTV on mortgages ΔLTV to be uncorrelated with the history of the structural shocks of the panel VAR.

There is a large literature stream estimating spillovers in intercity, interprovincial, and interregional house prices. The spillovers extend to the responses of house prices to macro-prudential policies in China. Shih, Li, and Qin (2014) have estimates of house price spillovers at the province level, especially for the regions covering Beijing and Shanghai. Chow, Fung, and Cheng (2016) report that city-level house prices converge, but spatial spillovers exist. Funke, Leiva-Leon, and Tsang (2017) find that house price synchronization increased until 2015. After 2015, regional house prices decoupled because macro-prudential policies differed across regions. Unlike this literature, I focus on a different division of the economic regions of China. This paper also expands research on the impact of the macro-prudential policies common to all of China on regional economic activity, loan markets, and house prices.

In another contribution to the literature, I investigate the linkages between regional real activity, loan markets, and house prices in China. Bian and Gete (2015) investigate the drivers of China's housing prices. Their results indicate that output, credit, and tax policy are the main causes of changes in house prices in China. In contrast, Ding et al. (2017) find that different cities in China respond differently to changes in the minimum LTV ratio set by regulators. Goodhart and Hofmann (2008) claim to obtain estimates

[4] Section 3 and appendix B discuss the regional Chinese data and macro-prudential policy variables in greater detail.

that indicate there are multi-directional responses in similar data for the UK. They also contend that the response of house prices to loan market shocks is state dependent. Richter, Schularick, and Shim (2018) quantify the impact of the maximum LTV ratio on the macroeconomy. Their results suggest that changes in the maximum LTV ratio have substantial effects on output, loan, and house prices.

Estimates of the panel VAR-X yield five main results. First, coastal regions' housing demand shocks generate larger responses of other regions' house price growth than the shocks from interior. Second, housing demand shocks generate negative impulse response functions (IRFs) of output and loans. Third, interregional house price IRFs with respect to housing demand shocks are smaller in the middle of the financial crisis compared with other periods in the sample. The IRFs of interior house prices are more state dependent compared with the coastal regions. Fourth, unanticipated changes to macro-prudential policies have a larger impact on house prices than on output and loans. Fifth, macro-prudential policy interventions appear to be less effective during the 2007-2009 financial crisis than in constraining booms in financial and housing markets.

The remainder of the paper is organized as follows. Section 2 presents the panel VAR-X estimator used in this paper. The data are described in section 3. Results are discussed in section 4 and 5. Section 6 concludes.

2 The Panel VAR-X Estimator

This section introduces the panel VAR-X. Section 2.1 describes a panel TVP-VAR-X with SV. Canova and Ciccarelli (2009) reduce the computational difficulty of estimating the panel VAR-X by factorizing the TVPs and SVs into a dynamic factor model that has a state-space representation. Posterior distributions of the TVPs and SVs are built by running the Metropolis within Gibbs MCMC sampler developed by Canova and Ciccarelli (2009). This paper also follows the sparse matrix approach proposed by Chan and Jeliazkov (2009) and applied by Dieppe, Legrand, and van Roye (2016) to estimate the TVPs and SVs. More details are found in appendixes D and E.

Table 1: China's Seven Economic Regions

Regions		Provinces
Coastal Regions		
SC		Fujian, Guangdong, Hainan
EC		Shanghai, Jiangsu, Zhejiang
NC		Beijing, Tianjin, Hebei, Shandong
Interior Regions		
NE		Heilongjiang, Jilin, Liaoning
YEL		Shaanxi, Shanxi, Henan, Inner Mongolia
YNG		Hubei, Hunan, Jiangxi, Anhui
WST	**Southwest**	Yunnan, Sichuan, Chongqing, Guizhou, Guangxi
	Northwest	Gansu, Xinjiang, Qinghai, Ningxia, Tibet

* This table lists provinces in each of the seven economic regions in mainland China.

The panel VAR-X is estimated on monthly regional real GDP growth ($\Delta lnGDP$), real loan growth ($\Delta lnLoan$), real house price growth ($\Delta lnHP$), and MPP, or ΔLTV. The division of economic regions starts with Li and Hou (2003). They divide mainland China into eight economic regions, which are the south coast (SC), east coast (EC), north coast (NC), northeast (NE), middle reaches of the Yellow River (YEL), middle reaches of the Yangtze River (YNG), southwest, and northwest. Since the southwest and northwest regions are the least developed, these regions are combined into the west region (WST). The result is the seven economic regions of China. I also refer to the SC, EC, and NC regions as coastal and the NE, YEL, YNG, and WST regions are called interior. Table 1 lists the provinces in each region. [5] The regional data consisting of seven economic regions in China begins in 2005m02 and ends with 2013m03.[6]

In the baseline panel VAR-X, M1, the variables on which I estimate the panel VAR-X are collected in $Y_t = (y_{1t}', ..., y_{7t}')'$, where $y_{it} = (\Delta lnGDP_{it}, \Delta lnLoan_{it}, \Delta lnHP_{it})$ is a vector of variables in region $i = 1, ..., 7$ from 2005m02 to 2013m03 ($t = 1, ..., 97$), and $D_t = \Delta LTV_t$ or MPP_t is a predetermined variable common to all regions. The regions are ordered as [SC, EC, NC, NE, YEL, YNG, WST].

[5] Figure 14 in appendix A is a map of China with the economic regions. Tables 9 and 14 in appendix A provides more information about the seven regions.

[6] Section 3 discusses data.

2.1 Panel VAR-X with TVPs and SVs

The panel VAR-X is

$$Y_t = A_{0,t} + A_t Y_{t-1} + C_t D_{t-1} + e_t, \tag{2.1}$$

where Y_t is a vector of variables as defined earlier in section 2, $e_t \sim N(0_{21\times1}, \Sigma_{t(21\times21)})$ is a 21×21 disturbance matrix, and $\Sigma_t \equiv exp(\zeta_t)\tilde{\Sigma}$ is the time-varying covariance matrix. ζ_t is heteroskedasticity part of the variance, and $\tilde{\Sigma}$ is the homoskedasticity part. The time-varying covariance matrix allows for heteroskedasticity. The matrices A_t and C_t contain time-varying lag and intervention response parameters of the reduced-form panel VAR. The intercept $A_{0,t}$ is also time-varying.

Canova and Ciccarelli (2009) propose a dynamic factor structure of the coefficients to reduce the dimensionality by transforming the panel VAR in a state-space model.[7] The observation equation of the state-space model becomes

$$Y_t = \chi_t \theta_t + e_t, \tag{2.2}$$

where χ_t is a matrix that reloads $I_{21} \otimes X_t^{'}$, with $X_t = (Y_{t-1}^{'}, I^{'}, D_{t-1}^{'})^{'}$. The factor loadings are a vector $\theta_t \equiv (\theta_{1t}^{'}, \theta_{2t}^{'}, \theta_{3t}^{'}, \theta_{4t}^{'})^{'}$. Factor θ_{1t} is the component common to all variables in all regions, factors $\theta_{2t} = (\theta_{21t}, \theta_{22t}, ..., \theta_{27t})^{'}$ are components common to the corresponding regions, $\theta_{3t} = (\theta_{31t}, \theta_{32t}, \theta_{33t})^{'}$ are components common to the corresponding endogenous variables, and $\theta_{4t} = (\theta_{41t}, \theta_{42t})^{'}$ is common component comes from the intercept and the exogenous variable D_t to all other variables. These factors capture the coefficient variations that are common to the corresponding groups. They can also be seen as the weights of each components. Thus, each variable is a weighted average of all other variables.

The law of motion of the factors is assumed to follow

$$\theta_t = (1-\rho)\bar{\theta} + \rho\theta_{t-1} + \eta_t, \tag{2.3}$$

[7] See appendix D.2.

where the error term $\eta_t \sim N(0, B)$, and B is a block diagonal matrix of variance of the factors b_i, $i = 1, ..., 4$. The long-run average of the factor, $\bar{\theta}$, is obtained from OLS estimation of the observation equation (2.2). The parameter $0 \leq \rho \leq 1$ decides the persistence of the factors over time.

The law of motion of the heteroskedastic part of the covariance matrix is defined as

$$\zeta_t = \gamma \zeta_{t-1} + \nu_t, \tag{2.4}$$

where the error term $\nu_t \sim N(0, \varphi)$, with φ a time-invariant variance, and γ determines the persistence of the heteroskedasticity of this model.

2.2 Estimation

The Bayesian algorithm used in estimating the state-space form dynamic structural factor model mapped from the panel VAR-X is M-G. The parameters of interest are factors $\theta = \{\theta_t\}_{t=1}^{T=97}$, heteroskedastic component in variance, $\zeta = \{\zeta_t\}_{t=1}^{T=97}$, residual variance, φ, factor variance, $b = \{b_i\}_{i=1}^{4}$, and homoskedasitic component in variance, $\tilde{\Sigma}_{21\times 21}$. This subsection shows the estimation of these parameters. Appendix E provides more details for this subsection.

2.2.1 Sparse Matrix Approach of θ and ζ

I followed the sparse matrix approach developed by Dieppe, Legrand, and van Roye (2016) in estimating the dynamic factors θ and the heteroskedastic component in variance, ζ. The approach is first proposed by Chan and Jeliazkov (2009) in estimating a state-space model. The approach is more efficient in computing and replaces the Kalman filter used by Canova and Ciccarelli (2009). The sparse matrix approach is described below.

The equation (2.3) defines the law of motion of the dynamic factors θ. The sparse matrix approach starts by stacking the factors over time into a compact matrix, $\Theta =$

$(\theta_1, \theta_2, ..., \theta_T)^{'}$. Then map the law of motions over time into simultaneous equation form,

$$H\Theta = \tilde{\Theta} + \eta, \tag{2.5}$$

where the transition matrix across time H is a $T \times T$ diagonal matrix that is composed of I_d on the main diagonal and $-\rho I_d$ on the subdiagonal, where ρ is defined in equation (2.3), and $d = 13$ is the number of factors. The compact matrix $\tilde{\Theta} = ((1-\rho)\bar{\theta} + \rho\theta_0, (1-\rho)\bar{\theta}, ..., (1-\rho)\bar{\theta})^{'}_{1\times T}$, where θ_0 is the initial value, and $\bar{\theta}$ is the mean.

The law of motion of the dynamic coefficient ζ is similarly mapped into a simultaneous equation form. Define the stacked dynamic coefficient $Z = (\zeta_1, \zeta_2, ..., \zeta_T)^{'}$ to construct

$$KZ = v, \tag{2.6}$$

where the transition matrix across time K is a $T \times T$ diagonal matrix that is composed of 1 on the main diagonal and $-\gamma$ on the subdiagonal, where γ is the persistence of ζ_t, as defined in equation (2.4). The vector $v = (\nu_1, \nu_2, ..., \nu_T)$ stacks the errors of the heteroskedastic component over time, as defined in equation (2.4).

2.2.2 Metropolis within Gibbs Algorithm

The Bayesian MCMC algorithm used in this paper is M-G for estimating the parameters of interest. This subsection briefly introduces the M-G algorithm.

Table 2 reports the priors. Posterior distributions are obtained given the priors and likelihood of the data from the observation equation (2.2). The posterior distributions are listed in table 3.

The draws of the parameters $\tilde{\Sigma}$, φ, b_i, Σ, and θ are obtained by Gibbs sampler, while a Metropolis step is used to estimate ζ. The M-G algorithm is summarized.

1. Set the starting values for the parameters. The starting value of factors θ_t is obtained from OLS estimation of the observation equation (2.2). The variance of factors $b_i^{(0)} = 10^5$. The homoskedasticity component $\tilde{\Sigma}^{(0)} = \frac{1}{T}\sum_{i=1}^{T} e_t e_t^{'}$. The

Table 2: Priors for Parameters and Hyperparameters

Parameter	Interpretation	Prior Distribution
Θ	factors θ_t	$N(\Theta_0, B_0)$
Z	heteroskedasticity component ζ_t	$N(0, \Phi\{(K^{'}K))\}^{-1}$
φ	residual variance	$IG(\frac{\alpha_0}{2}, \frac{\delta_0}{2})$
b_i	factor variance	$IG(\frac{a_0}{2}, \frac{c_0}{2})$ for $i = 1, ..., 4$
$\tilde{\Sigma}$	homoskedasticity component	$\lvert\tilde{\Sigma}\rvert^{(21+1)/2}$
Hyperparameter	**Interpretation**	**Prior**
ρ	autoregressive coefficient in factors	0.6
γ	autoregressive coefficient in residual variance	0.75
a_0	inverse gamma shape in factor variance	10000
c_0	inverse gamma scale in factor variance	1
α_0	inverse gamma shape in residual variance	10000
δ_0	inverse gamma scale in residual variance	1

* This table summarizes the priors for parameters and hyperparameters needed in estimating the state-space model. Details are described in appendix E.2.

Table 3: Posterior Distributions of Parameters of Interest

Parameter	Interpretation	Posterior Distribution
Θ	factors θ_t	$N(\bar{\Theta}, \bar{B_0})$, where $\bar{B} = (\xi^{'}(\Sigma)^{-1}\xi + B_0^{-1})^{-1}$, and $\bar{\Theta} = \bar{B}(\xi^{'}(\Sigma)^{-1}y + B_0^{-1}\Theta_0)$
ζ	heteroskedasticity component	$N(\bar{\zeta}, \bar{\varphi})$, where $\bar{\zeta} = \bar{\varphi}\frac{\gamma(\zeta_{t-1}+\zeta_{t+1})}{\varphi}$, and $\bar{\varphi} = \frac{\varphi}{1+\gamma^2}$
φ	residual variance	$IG(\frac{97+\alpha_0}{2}, \frac{Z^{'}G^{'}GZ+\delta_0}{2})$
b_i	factor variance	$IG(\frac{97d_i+a_0}{2}, \frac{\sum t{=}1^{97}(\theta_{i,t}-\theta_{i,t-1})^{'}(\theta_{i,t}-\theta_{i,t-1})+c_0}{2})$
$\tilde{\Sigma}$	homoskedasticity component	$IW(\bar{S}^{(n)}, T)$, where $\bar{S}^{(n)} = \sum_{t=1}^{T}(e_t^{(n-1)})exp(-\zeta_t^{(n-1)})(\sum_{t=1}^{T}(e_t^{(n-1)})^{'}$

* This table summarizes the posterior distributions of the parameters. Details are described in appendix E.3.

** The Metropolis algorithm is applied in updating candidates of ζ_t.

heteroskedasticity component $\zeta_t^{(0)} = 0$. The variance of the dynamic coefficient $\varphi^{(0)} = 0.001$.

2. Draw the parameters $\tilde{\Sigma}$, ζ, φ, b_i, Σ, and θ consequently from the posterior distribution.

   (a) The draws of $\tilde{\Sigma}$, φ, b_i, Σ, and θ are obtained from the Gibbs sampler. The priors of the sparse matrices Θ and Z defined in section 2.2.1 are used for drawing θ and φ.

   (b) The heteroskedasticity component ζ is obtained from a Metropolis step. First, draw the candidate of ζ from the transition kernel $\zeta^{(n)} = \zeta^{(n-1)} + \omega$ in each iteration, where $\omega \sim N(0, \phi I_T)$ and $\phi = 10^5$ is chosen to balance the variance and acceptance rate. Next, update the draws using the acceptance rule.

3. Repeat step 2 until the total number of iterations is reached.

I make 80,000 draws from the posterior and drop the first 20,000 draws. I thin one from every 12 in the last 60,000 draws.[8]

2.3 Identification

Identification of the structural shocks depends on theoretical linkages between the real economy and financial sectors. The ordering of the regional data block y_{it} places the supply shock structurally causal prior to the credit supply and housing demand shocks. The regional supply shock is ordered first because the productivity shock in DSGE models often occurs before any other disturbances. An implication is the financial sector has repercussions for the real economy through the credit channel, but only with a lag. Examples of this financial transmission mechanism are the borrower balance sheet channel in Bernanke, Gertler, and Gilchrist (1999) and Kiyotaki and Moore (1997) and the bank balance sheet channel of Bernanke and Blinder (1988) and Gilchrist and Zakrajšek

[8]The Matlab program used in estimation is the Bayesian Estimation, Analysis, and Regression (BEAR) toolbox (version 4.0) developed by the external developments division of the European Central Bank.

(2012). These channels also predict supply and credit supply shocks drive asset prices at impact, which motivates placing the housing demand shock last. Finally, I order the coastal region first and then interior regions by assuming the coastal regions, which are more economically developed than the interior regions, and more sensitive to the identified shocks.

3 The Data

This section describes the data used in the panel VAR-X. Table 10 in appendix B lists the raw data used in constructing $\Delta lnGDP$, $\Delta lnLoan$, $\Delta lnHP$, MPP, and ΔLTV. Appendix B has more information about the regional Chinese data. For example, table 11 reports the unconditional summary statistics of the data.

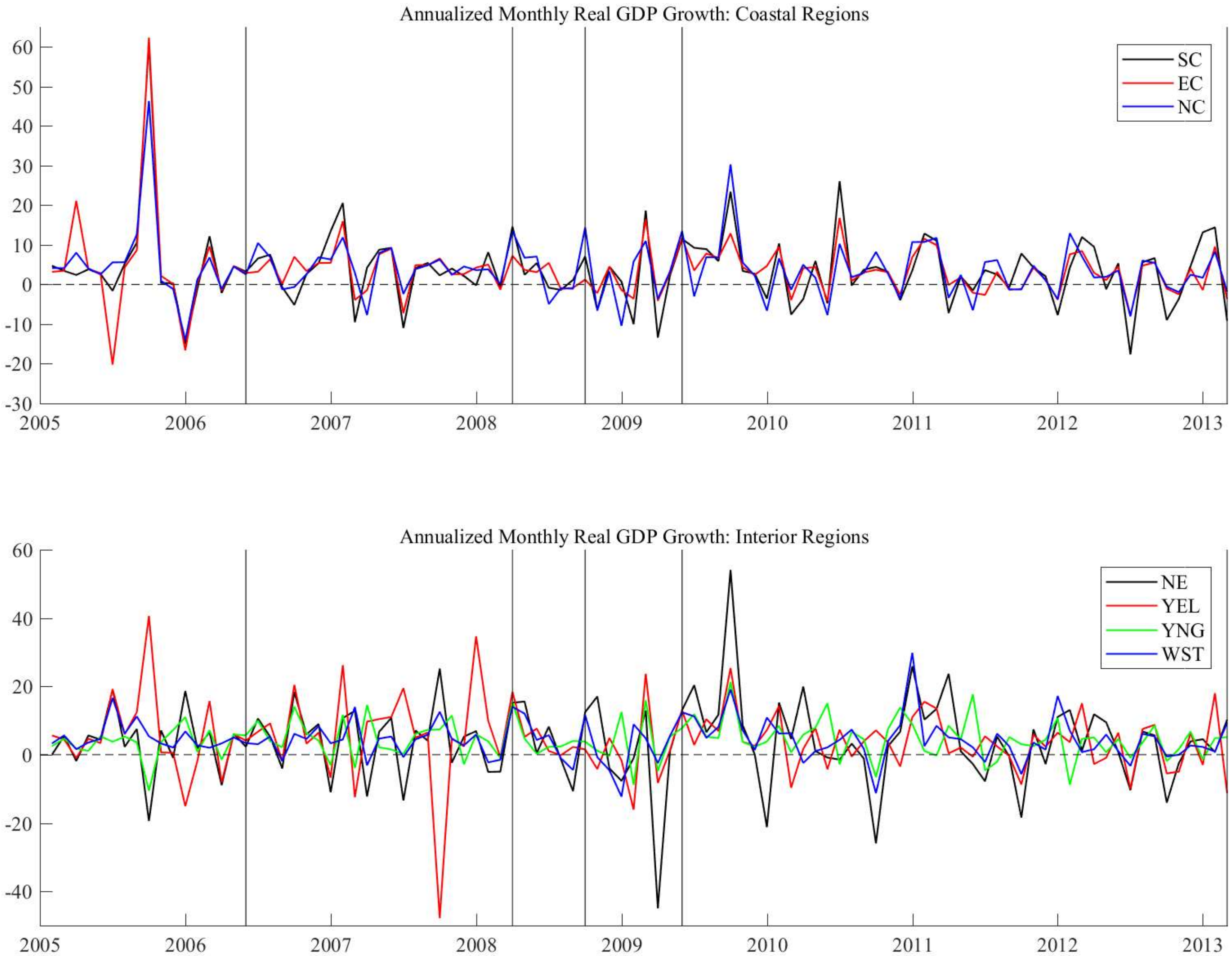
3.1 Real GDP Growth ($\Delta lnGDP$)

Figure 1 plots the real regional GDP growth rates from 2005m02 to 2013m03. Monthly GDP is temporally disaggregated from the quarterly frequency to the monthly using linear regression methods.The interpolation procedure creates monthly real regional GDP growth rates that are more volatile before 2011 than after for the coastal and interior regions. Coastal real GDP growth displays greater comovement than the interior regions during the entire sample. However, the interior regions exhibit more comovement after 2011. Moreover, the YEL, YNG, and WST regions have greater real GDP growth rates than in the other regions, but the former three regions have lower levels of real GDP compared with the four other regions in China as suggested by table 9 in appendix A.

3.2 Total Real Loan Growth ($\Delta lnLoan$)

Figure 2 plots the annualized monthly real regional loan growth from 2005m02 to 2013m03. Total loans include short-, medium-, and long-term loans, designated loans, bill financing, and other loans of all financial institutions in China in current currency units. After deflating by the national CPI, the WST region has the highest average

Figure 1: Annualized Monthly Real Regional GDP Growth Rate



Note: This figure plots the regional $\Delta lnGDP$ that constructed in this paper. The top panel plots the regional $\Delta lnGDP$ in the coastal regions, and the bottom panel plots the regional $\Delta lnGDP$ in the interior regions. The sample period is 2005m02 to 2013m03.

monthly growth rate of real loans.[9] The NE region had the lowest average and greatest variance, which coincides with the fact that the NE experienced an economic recession and disinvestment after 2005 along with a continued loss of population. Moreover, across the regions, real loan growth rates have volatilities that change over the sample. Before 2009, real loan growth in every region of China is volatile. The volatilities peak around 2009.[10] There is a decline in the volatilities after 2010 compared with earlier years in the sample.

3.3 Real House Price Growth ($\Delta lnHP$)

The raw data used in constructing the regional house price index growth rate ($\Delta lnHP$) come from the 120 city-level nominal house price indexes provided by Fang et al. (2016). They compute nominal house price indexes for 120 cities from 2003m01 to 2013m03 based on the sales of newly built houses of the 120 cities, I use 98 cities that have a complete sequence of observations on the sample.[11] Regional house price indexes are calculated as weighted averages instead of arithmetic averages.[12] The weights are computed based on the yearly city-level and provincial floor space of residential buildings sold. These data are provided by NBSC. Next, I deseasonalize the monthly regional house price indexes to obtain monthly regional real house price indexes.[13]

Figures 3 displays regional house price growth rates. Across the regions, house price growth is similar. There appear to be breaks and changes in the volatility of house price growth over the sample. For example, regional house prices were rising in China pre-2008. A trough occurs in house price growth across the regions from 2008 to 2010. House price growth recovers to pre-financial crisis highs in 2011 as these rates converge by the end of the sample.

[9] The Great Western Development Strategy contributed to the high growth rate of real loans in the WST region. The goal was to attract investments to western China starting in 2000, especially investments in infrastructure.

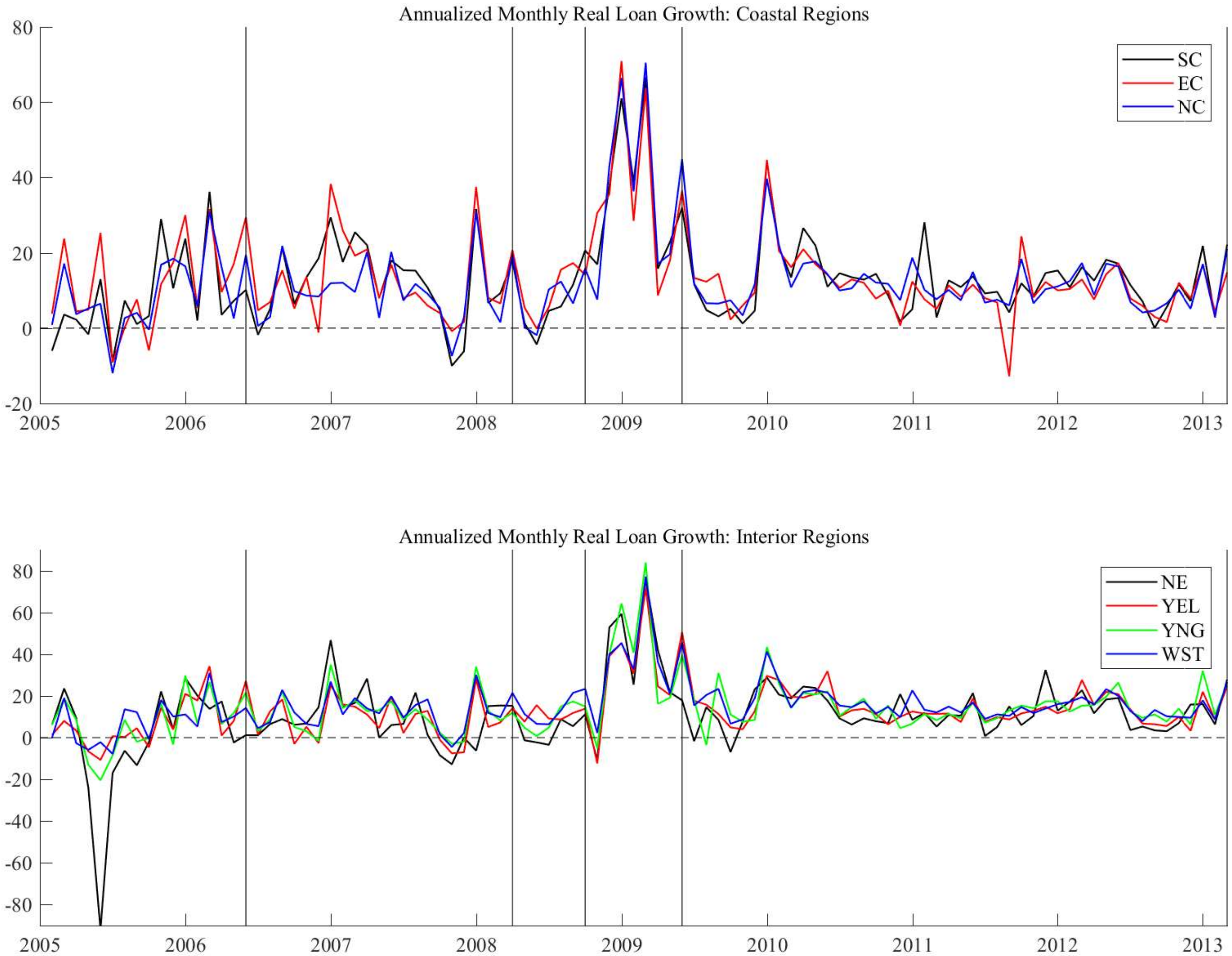
[10] The Chinese Economic Stimulus Plan of four trillion yuan in November 2008 increased the growth rate of real loan.

[11] Table 14 in appendix B.3 lists the cities.

[12] Only selected cities are covered in Fang et al. (2016). As a result, using arithmetic averages of city-level house price indexes in constructing regional-level indexes may cause larger bias.

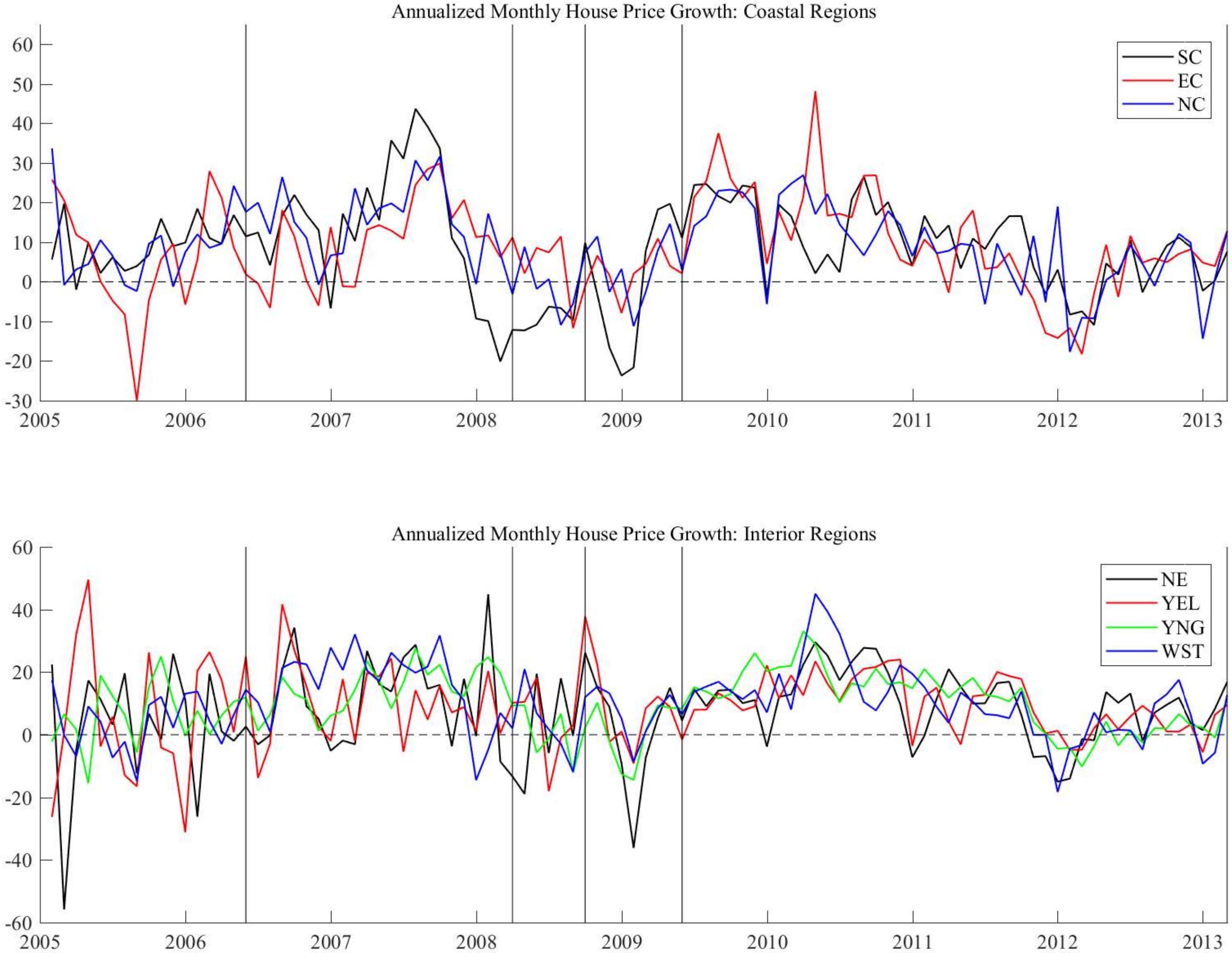
[13] Appendix B.3 provides more details about constructing $\Delta lnHP$.

Figure 2: Annualized Monthly Real Regional Loan Growth Rate



Note: This figure plots the regional $\Delta lnLoan$ that constructed in this paper. The top panel plots the regional $\Delta lnLoan$ in the coastal regions, and the bottom panel plots the regional $\Delta lnLoan$ in the interior regions. The sample period is 2005m02 to 2013m03.

Figure 3: Annualized Monthly Regional House Price Growth Rate



Note: This figure plots the regional $\Delta lnHP$ that constructed in this paper. The top panel plots the regional $\Delta lnHP$ in the coastal regions, and the bottom panel plots the regional $\Delta lnHP$ in the interior regions. The sample period is 2005m02 to 2013m03.

3.4 Macro-Prudential Policy Index (MPP)

The Chinese macro-prudential policy index is taken from the policy action data set of 60 economies used in Kuttner and Shim (2016) and Shim et al. (2013). The dummy-type indexes are discrete count numbers of macro-prudential policy newly imposed every month. A contractionary policy, such as a decrease in the maximum LTV ratio or an increase in housing-related tax, is recorded as negative one. An expansionary policy, such as a lower reserve ratio requirement or liquidity requirement, is recorded as one. If no macro-prudential instrument is used in a month, or the number of newly imposed contractionary policies is the same as the number of new expansionary policies, the index is zero for the month.

The macro-prudential instruments covered in their data include reserve requirements (RR), liquidity requirements (LIQ), limits on credit growth (CRE), maximum loan-to-value ratio (LTV), loan prohibition (PROH), maximum debt-service-to-income ratio (DSTI), and housing-related taxes (TAX). The data in Shim et al. (2013) starts in 1990m01 and ends on 2012m06. I extend the Chinese data to 2013m03 by collecting macro-prudential policy information from the People's Bank of China (PBC). A 12-month moving average is applied to the extended series as in Alam et al. (2019). The MPP index is contractionary before 2009, turns expansionary during 2008m09, reverts to being contractionary in 2009m09, and is expansionary after 2011m09. The MPP is plotted in the top panel in figure 4.

3.5 Maximum Loan-to-Value Ratio Change (ΔLTV)

I also use the change of the maximum loan-to-value ratio (ΔLTV) in the panel VAR-X as a predetermined policy intervention. The LTV ratio is the mortgage to appraised property value. The People's Bank of China and the China Banking Regulatory Commission regulate the LTV ratios by setting their maximum amount. Alam et al. (2019) is the source of the Chinese maximum LTV ratio. The LTV ratio is an unweighted moving average of all existing regulations of the LTV ratios in use by Chinese regulators. I take the moving average of the most recent 12 months of changes of the LTV ratio. The LTV

Figure 4: 12-Month Average Macro-Prudential Policy Index and Maximum Loan-to-Value Ratio Change

Note: This figure plots the 12-month moving averages of MPP in the top panel, and the 12-month moving averages of LTV in the bottom panel. The data are described in section 3.4. The sample period is 2005m02 to 2013m03.

declines from 2005 to 2008 followed by increases in 2008 before falling in 2009 to the end of the sample. The ΔLTV is plotted in the bottom panel in figure 4.

4 Empirical Results

This section presents results of estimating the real GDP growth, real loan growth, and real house price growth from February 2005 to March 2013 by the panel VAR-X with TVPs and SVs. The results include cumulative IRFs of house prices with respect to supply, credit supply, and housing demand shocks. I also report the multiplier effects of a macro-prudential policy intervention ΔLTV on regional growth rates of real GDP, real loans, and real house prices.[14]

4.1 House Price Spillovers

The cumulative IRFs of $\Delta lnHP$ with respect to the regional housing demand shocks across the seven regions show there are statistically and economically important house price spillovers across the regions of China.[15] The spillovers suggest a transmission mechanism that runs from the housing market in the coastal regions of China to its interior. Regional supply and credit supply shocks also generate movements in $\Delta lnHP$ while they are less economically important than house price spillovers.

There are interregionally spillovers created by the regional housing demand shocks onto the real economy and financial markets. However, there is little evidence of positive spillover effects from the regional housing markets to the real economy and financial markets in China.

4.1.1 House Price Spillovers Across Regional Housing Markets

Figures 5 to 8 display the IRFs of regional $lnHP$ to housing demand shocks within and across the coastal and interior sub-national regions. All seven regions have IRFs that

[14] Structural shocks are reported in appendix F.1.
[15] See figure 5 to 8.

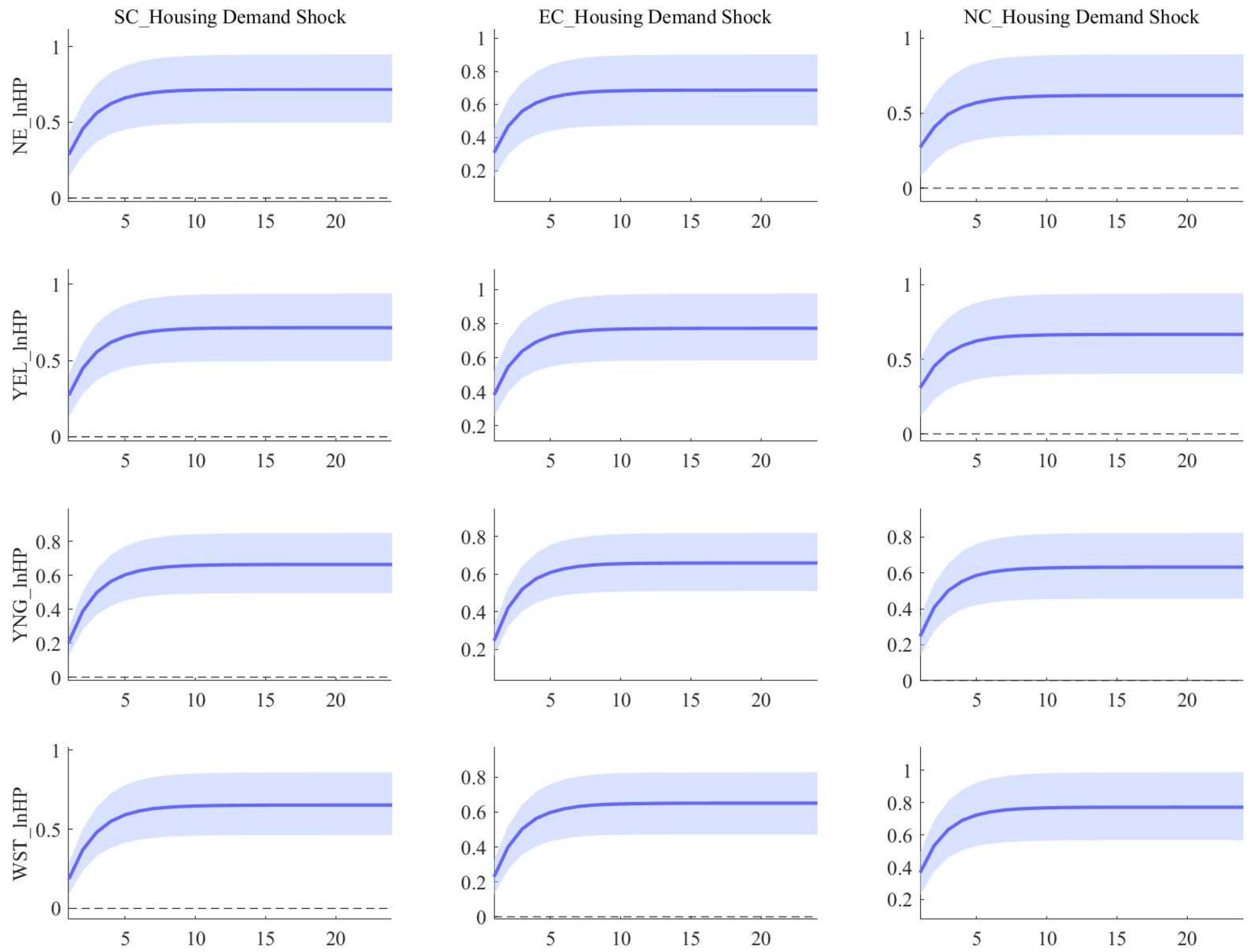
rise in response to their own regions' and the other regions' housing demand shocks. This is evidence of spillovers in house prices across the regions of China.

Housing demand shocks in the coastal regions are responsible for large responses in the $lnHP$ of the interior regions displayed in figure 5. These IRFs rise from impact to the six month horizon before leveling off. However, the 68% uncertainty bands surrounding the IRFs run from about 0.4 to near one at the two year horizon. Although figure 6 shows coastal $lnHP$ have similarly shaped IRFs to interior housing demand shocks, the height of these IRFs is lower from the six to 24 month horizons. Another contrast with figure 5, figure 6 reports narrower 68% uncertainty bands. The upshot is coastal region housing demand shocks have a greater impact on the dynamic responses on interior region $lnHP$ than the converse responses show.

Figures 7 and 8 display the IRFs of regional $lnHP$ to own sub-regional housing demand shocks. These IRFs are remarkably similar in shape to the IRFs in figures 5 and 6. The own housing demand shocks of the coastal and interior regions produce larger responses in the $lnHP$, which are on the diagonals of figure 7 and 8, compared with the off-diagonal IRFs. The off-diagonal IRFs in figure 8, although rising from impact to a plateau at the six month horizon, these plateaus are lower than the maximum height observed for the diagonal IRFs. As a result, figure 7 and 8 give additional evidence about the spillovers on $lnHP$ produced by housing demand shocks across the regions of China.

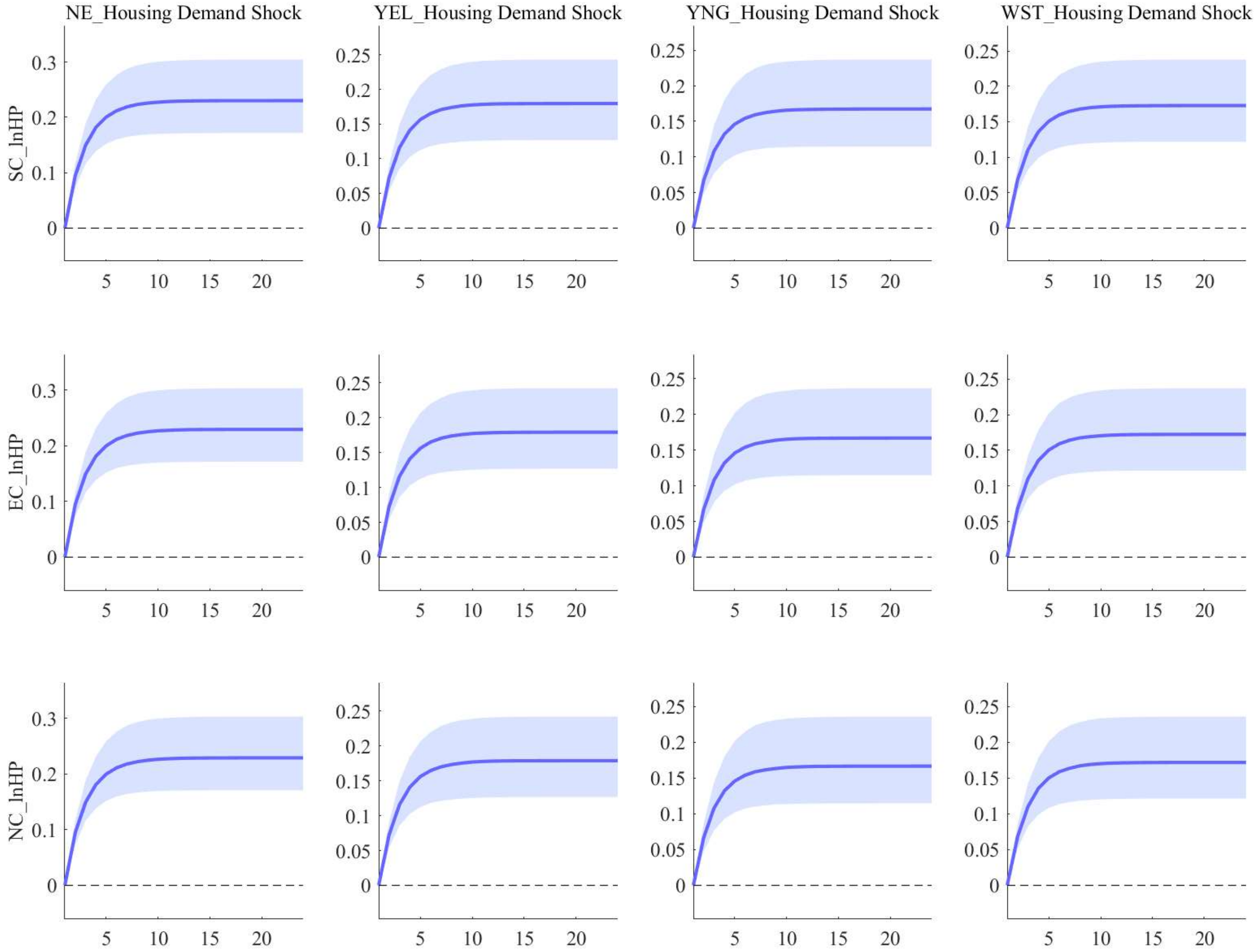
House price spillovers can be explained by the following two factors. First, housing decisions to move across the regions (Lin et al. (2018) and Rogoff and Yang (2020)) are a source of house price spillovers. A related factor is the mismatch of population and land supply. The mismatch is caused by interregional migration flows to economically developed regions as argued by Lu and Xia (2016) and Wang, Hui, and Sun (2017). Moreover, changes to land-use quotas helped to generate migration across China, according to Han and Lu (2017). The coastal regions have received the largest inflows of migration. There has also been migration to the interior regions of YEL, YNG, and

Figure 5: IRFs of $lnHP$ in the Interior Regions to Coastal Regions' Housing Demand Shocks



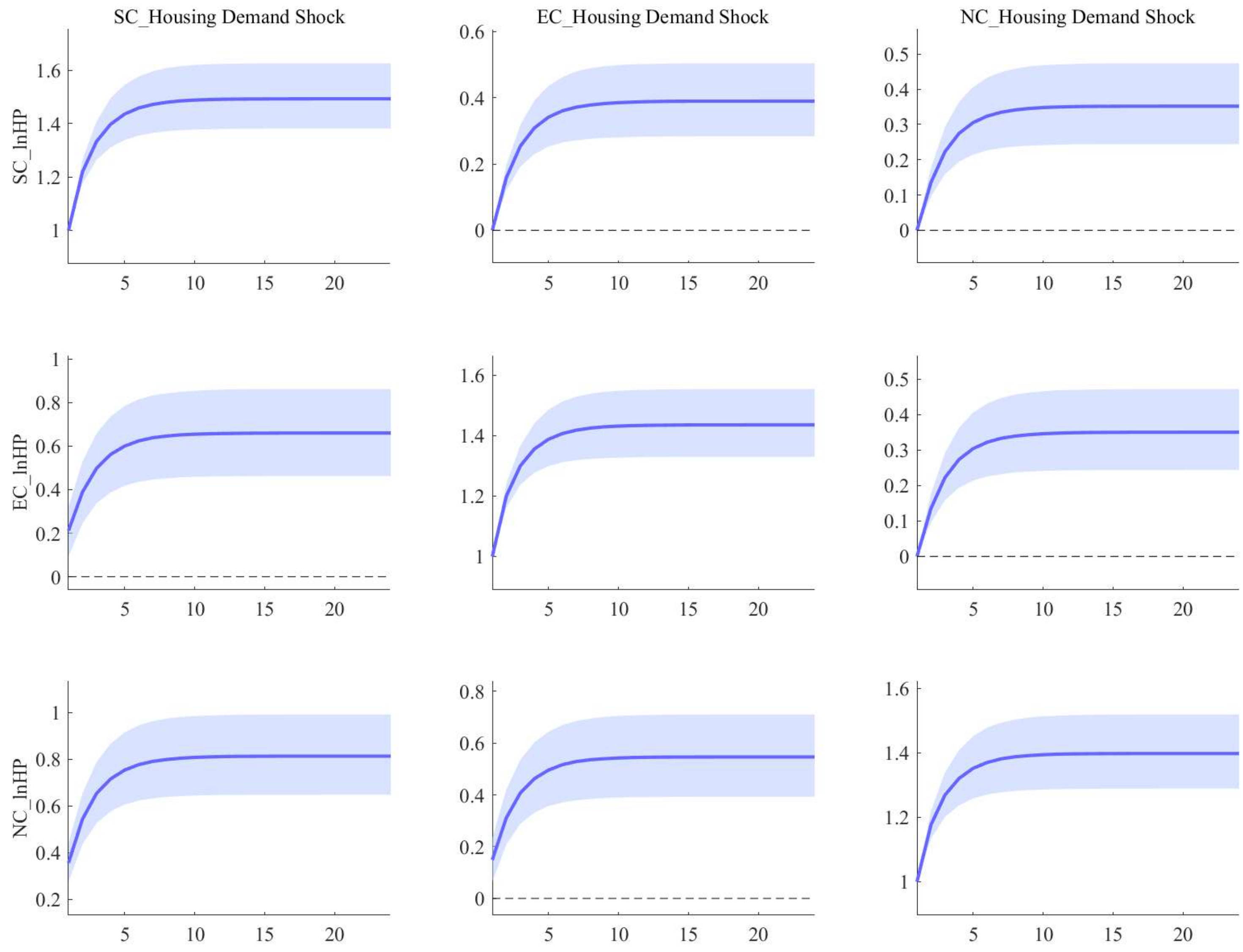
Note: This figure displays the medians of IRFs of $lnHP$ in the interior regions to housing demand shocks of the coastal regions from impact to the 24 month in dark blue. The light blue shadings are 68% uncertainty bands. The coastal regions are SC, EC, and NC, and the interior regions are NE, YEL, YNG, and WST.

Figure 6: IRFs of $lnHP$ in the Coastal Regions to Interior Regions' Housing Demand Shocks



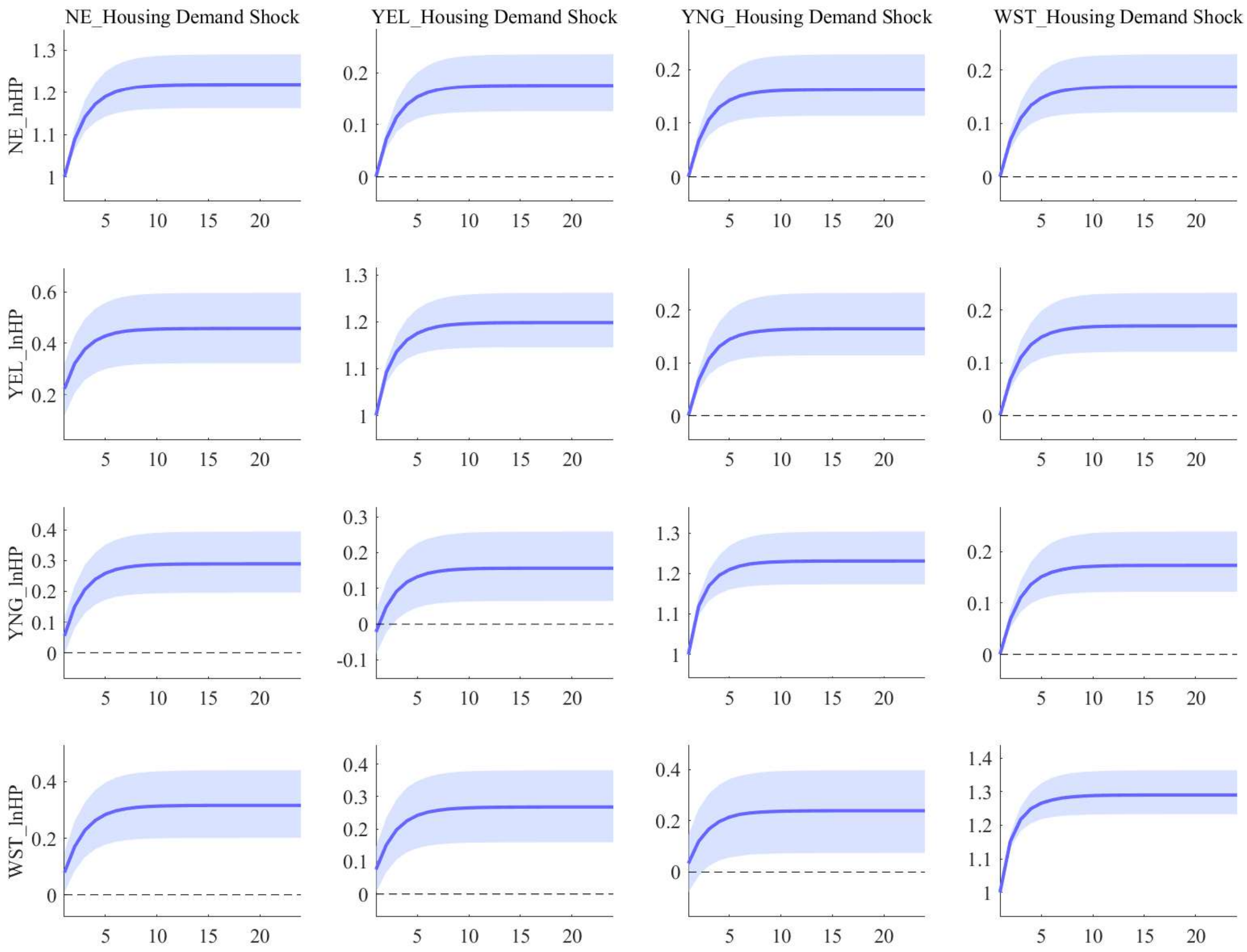
Note: This figure displays the medians of IRFs of $lnHP$ in the coastal regions to housing demand shocks of the interior regions from impact to the 24 month in dark blue. The light blue shadings are 68% uncertainty bands. The coastal regions are SC, EC, and NC, and the interior regions are NE, YEL, YNG, and WST.

Figure 7: IRFs of $lnHP$ in the Coastal Regions to Coastal Regions' Housing Demand Shocks



Note: This figure displays the medians of IRFs of $lnHP$ in the coastal regions to housing demand shocks of the coastal regions from impact to the 24 month in dark blue. The light blue shadings are 68% uncertainty bands. The coastal regions are SC, EC, and NC, and the interior regions are NE, YEL, YNG, and WST.

Figure 8: IRFs of $lnHP$ in the Interior Regions to Interior Regions' Housing Demand Shocks



Note: This figure displays the medians of IRFs of $lnHP$ in the interior regions to housing demand shocks of the interior regions from impact to the 24 months in dark blue. The light blue shadings are 68% uncertainty bands. The coastal regions are SC, EC, and NC, and the interior regions are NE, YEL, YNG, and WST.

WST while NE has experienced the greatest outflow.[16] The migration patterns across the coastal and interior regions, which are driven in part by housing decisions, can go some way to explain the evidence on regional house price spillovers in China reported here.

4.1.2 Supply and Credit Spillovers onto Regional House Prices

This subsection compares the spillovers running from regional supply and credit shocks to Chinese housing markets with the spillovers created by regional housing demand shocks. The supply and credit spillovers are not as economically important as the house price spillovers presented in section 4.1.1. Tables 4 and 5 and section 4.1.1 give evidence that house price spillovers appear to dominate the within-region supply and credit spillovers onto regional house prices.

Table 4: IRFs of $lnHP$ with Respect to Regional Supply Shocks at a Two-Year Horizon

Response \ Shock	**SC**	**EC**	**NC**	**NE**	**YEL**	**YNG**	**WST**
SC	*0.0339* ** (−0.2033 0.2699)	0.2226 (0.0432 0.4132)	−0.2032 (−0.3842 −0.0271)	−0.0916 (−0.1467 −0.0406)	−0.0683 (−0.1142 −0.0244)	*-0.0222* (−0.0859 0.0445)	*-0.0397* (−0.0842 0.0076)
EC	*0.0801* (−0.1433 0.3116)	*0.3714* (−0.0018 0.7720)	−0.2012 (−0.3814 −0.0262)	−0.0907 (−0.1458 −0.0397)	−0.0677 (−0.1135 −0.0244)	*-0.0219* (−0.0856 0.0448)	*-0.0393* (−0.0837 0.0076)
NC	*-0.0129* (−0.2234 0.2030)	0.5117 (0.1848 0.8387)	*-0.1051* ** (−0.4592 0.2370)	−0.0903 (−0.1450 −0.0394)	−0.0675 (−0.1137 −0.0243)	*-0.0219* (−0.0849 0.0446)	*-0.0393* (−0.0838 0.0079)
NE	*-0.0026* (−0.2749 0.2646)	*0.1783* ** (−0.3045 0.6536)	−0.8311 (−1.3237 −0.3472)	−0.2081 (−0.3713 −0.0380)	−0.0636 (−0.1083 −0.0221)	*-0.0183* (−0.0809 0.0449)	*-0.0371* (−0.0800 0.0074)
YEL	0.3631 (0.1040 0.6204)	0.6959 (0.2698 1.1545)	*-0.2225* (−0.7024 0.2552)	−0.3021 (−0.4537 −0.1504)	*0.0441* (−0.0940 0.1779)	*-0.0202* (−0.0831 0.0452)	*-0.0380* (−0.0819 0.0074)
YNG	*0.0450* (−0.0521 0.1434)	0.4103 (0.0715 0.7478)	*-0.2778* (−0.6134 0.0599)	−0.1462 (−0.2509 0.0446)	0.0999 (0.0168 0.1812)	*0.0011* ** (−0.2711 0.2651)	*-0.0400* (−0.0846 0.0077)
WST	*0.0647* (−0.0512 0.1753)	0.4169 (0.0465 0.8030)	−0.4261 (−0.8098 −0.0128)	*-0.0607* ** (−0.1839 0.0583)	−0.3755 (−0.5035 −0.2462)	*0.1031* (−0.1418 0.3464)	*0.0886* ** (−0.1993 0.3687)

* This table summarizes the maximum (or minimum if the response is negative) median IRFs of $lnHP$ with respect to regional supply shocks, and their 68% credible intervals.
** The response has a different sign at impact.
*** Italicized numbers are that the 68% credible intervals cover zero.

I report the maximum (or minimum) median IRFs of $lnHP$ with respect to supply and credit supply shocks at the two year horizon in tables 4 and 5. Of the responses of $lnHP$ to supply shocks, table 4 shows more than half of the 68% credible sets cover zero. The 21 entries that do not reveal there is a mix of negative and positive spillovers at the two year horizon. The second column of responses show the supply shock in

[16] See Wu (2002), Ma, Qiu, and Zhou (2020), and the 2015 One Percent National Sample Census in China. Table 18 in appendix F.2 gives more information on migration.

the EC produces positive and economically important spillovers for the SC, NC, YEL, YNG, and WST. However, the NC produces negative spillovers for the SC, EC, NE, and WST. The SC only has a positive spillover with a 68% credible set lacking zero that is responded by the YEL region.

Regional supply shocks in the interior regions almost always generate negative spillovers to house prices at the two year horizon. However, only the shocks in the NE and YEL regions yield 68% credible sets off zero. Notably, the NE and YEL regions contribute negative supply spillovers to other regions.

Table 5: IRFs of $lnHP$ with Respect to Regional Credit Supply Shocks at the Two-Year Horizon

Shock / Response	**SC**	**EC**	**NC**	**NE**	**YEL**	**YNG**	**WST**
SC	-0.6075 $(-0.8048\ -0.4035)$	-0.2539 $(-0.3827\ -0.1339)$	-0.4323 $(-0.5780\ -0.2910)$	-0.1305 $(-0.1798\ -0.0798)$	-0.1250 $-0.1888\ -0.0554$	-0.1552 $(-0.2112\ -0.1035)$	-0.0580 $(-0.1016\ -0.0092)$
EC	-0.4964 $(-0.6858\ -0.3067)$	*-0.2690* $(-0.5203\ -0.0053)$	-0.4331 $(-0.5779\ -0.2933)$	-0.1310 $(-0.1801\ -0.0803)$	-0.1257 $(-0.1894\ -0.0565)$	-0.1555 $(-0.2110\ -0.1037)$	-0.0581 $(-0.1017\ -0.0104)$
NC	-0.5540 $(-0.7362\ -0.3686)$	-0.2955 $(-0.5150\ -0.0752)$	-0.9446 $(-1.1976\ -0.6989)$	-0.1312 $(-0.1802\ -0.0807)$	-0.1260 $(-0.1896\ -0.0570)$	-0.1556 $(-0.2111\ -0.1040)$	-0.0583 $(-0.1018\ -0.0104)$
NE	-0.4884 $(-0.7060\ -0.2701)$	-0.7535 $(-1.0529\ -0.4441)$	-0.5055 $(-0.8759\ -0.1325)$	-0.3833 $(-0.5073\ -0.2578)$	-0.1323 $(-0.1933\ -0.0660)$	-0.1571 $(-0.2107\ -0.1085)$	-0.0615 $(-0.1026\ -0.0166)$
YEL	-0.5166 $(-0.7267\ -0.3018)$	-0.3531 $(-0.6514\ -0.0602)$	*-0.2964* $(-0.6584\ 0.0659)$	-0.1951 $(-0.3214\ -0.0697)$	*-0.1726* $(-0.4146\ 0.0653)$	-0.1565 $(-0.2110\ -0.1066)$	-0.0598 $(-0.1021\ -0.0136)$
YNG	-0.3160 ** $(-0.4973\ -0.1365)$	-0.3659 $(-0.5905\ -0.1438)$	-0.7399 $(-0.9910\ -0.4852)$	-0.1484 $(-0.2343\ -0.0631)$	*-0.1114* $(-0.2675\ 0.0460)$	-0.2396 $(-0.4142\ -0.0651)$	-0.0573 $(-0.1016\ -0.0083)$
WST	-0.3084 ** $(-0.4966\ -0.1011)$	-0.3706 $(-0.6285\ -0.1274)$	-0.7992 $(-1.0992\ -0.4983)$	0.1093 $(0.0473\ 0.1738)$	*-0.0937* $(-0.2829\ 0.0941)$	-0.5238 $(-0.7207\ -0.3282)$	*-0.0260* $(-0.2120\ 0.2799)$

* This table summarizes the maximum (or minimum if the response is negative) median IRFs of $lnHP$ with respect to regional credit supply shocks and their 68% credible intervals.
** The response has a different sign at impact.
*** Italicized numbers are that the 68% credible intervals cover zero.

Table 5 shows only five of the credit spillovers to the regional house prices have the 68% credible sets contain zero, three of which are from the YEL region. The other entries show only negative spillovers at the two year horizon. The spillovers in the first three columns that from the coastal regions are always larger in absolute value than those from the interior regions. Two exceptions are the credit spillover within the NE, and the spillover from the YNG to the WST.

The elements on the diagonals of tables 4 and 5 are the within-region supply and credit spillovers to house prices. They are either negative spillovers or the credible sets cover zero. They give evidence along with the house price spillovers in section 4.1.1 that the regional house prices take more economically important spillovers from other regions' housing demand shocks than from their own supply and credit supply shocks.

4.1.3 Housing Demand Spillovers onto Regional Output and Loans

Tables 6 and 7 are similar in that the coastal regions are responding to the interior regions because credible sets often exclude zero. Differences are that table 7 shows the interior regions often responding to the interior while table 6 has fewer of these responses. Another is the SC region is generating negative spillovers to other regions in table 7 while it is not true in table 6. For table 6, the EC and NC regions' housing demand shocks spillover more to other regions than the housing demand shocks in other regions.

Table 6: IRFs of $lnGDP$ with Respect to Regional Housing Demand Shocks at the Two-Year Horizon

Response \ Shock	SC	EC	NC	NE	YEL	YNG	WST
SC	*-0.0083* ** (−0.0381 0.0213)	−0.0677 (−0.0917 −0.0427)	−0.0685 (−0.0938 −0.0426)	−0.0319 (−0.0446 −0.0176)	−0.0267 (−0.0377 −0.0138)	−0.0337 (−0.0460 −0.0190)	−0.0327 (−0.0436 −0.0177)
EC	*-0.0061* ** (−0.0615 0.0505)	*-0.0201* (−0.0487 0.0083)	−0.0690 (−0.0945 −0.0437)	−0.0325 (−0.0449 −0.0185)	−0.0271 (−0.0379 −0.0146)	−0.0341 (−0.0462 −0.0194)	−0.0331 (−0.0437 −0.0185)
NC	*-0.0309* ** (−0.0874 0.0254)	−0.1279 (−0.1808 −0.0741)	*-0.0222* (−0.0524 0.0073)	−0.0327 (−0.0452 −0.0188)	−0.0272 (−0.0379 −0.0147)	−0.0343 (−0.0465 −0.0198)	−0.0333 (−0.0438 −0.0189)
NE	*-0.0408* ** (−0.1717 0.0943)	−0.1771 (−0.3106 −0.0410)	0.3502 (0.1674 0.5233)	−0.0431 (−0.0593 −0.0260)	−0.0303 (−0.0401 −0.0198)	−0.0380 (−0.0489 −0.0259)	−0.0366 (−0.0458 −0.0257)
YEL	*-0.0767* (−0.1831 0.0268)	−0.2256 (−0.3304 −0.1195)	*-0.1558* (−0.3039 −0.0087)	*0.0502* (−0.0271 0.1306)	*-0.0075* (−0.0240 0.0107)	−0.0361 (−0.0476 −0.0228)	−0.0349 (−0.0446 −0.0226)
YNG	*0.0493* ** (−0.0135 0.1118)	*-0.0619* (−0.1316 0.0082)	0.1786 (0.0921 0.2672)	*-0.0323* (−0.0759 0.0121)	*-0.0145* (−0.0583 0.0283)	0.0317 (0.0124 0.0532)	−0.0323 (−0.0434 −0.0171)
WST	*-0.0609* (−0.1416 0.0200)	−0.1724 (−0.2472 −0.0943)	*0.0827* (−0.0043 0.1660)	−0.1353 (−0.1816 −0.0895)	*0.0230* (−0.0184 0.0633)	0.1031 (0.0354 0.1712)	0.0850 (0.0613 0.1127)

* This table summarizes the maximum (or minimum if the response is negative) median IRFs of $lnGDP$ with respect to regional housing demand shocks and their 68% credible intervals.
** The response has a different sign at impact.
*** Italicized numbers are that the 68% credible intervals cover zero.

The panel VAR-X is silent on the underlying reasons for the negative housing demand spillovers onto regional output and loans. Possible explanations for the negative spillovers in tables 6 and 7 are that the negative income effects for renters in a region dominate positive wealth effects for home owners, and the investment crowding-out effects from the housing sector to other sectors outweigh the collateral effects (Wu, Gyourko, and Deng (2013) and Chen and Zha (2018)).

The spillovers on the off-diagonals of tables 4 to 7 shows the spillovers across housing markets and the real economy or the financial markets also exist interregionally. The transparent information in regional output, loans, and house prices and its timely dissemination across the country (Zhang, Hui, and Wen (2017)) can be a reason for the existence of the interregional spillovers.

Table 7: IRFs of *lnLoan* with Respect to Regional Housing Demand Shocks at the Two-Year Horizon

Response \ Shock	SC	EC	NC	NE	YEL	YNG	WST
SC	−0.1189 (−0.2051 −0.0318)	*-0.0537* (−0.1322 0.0295)	−0.1205 (−0.2099 −0.0247)	−0.0912 (−0.1265 −0.0512)	−0.0788 (−0.1083 −0.0453)	−0.0493 (−0.0796 −0.0130)	−0.0563 (−0.0827 −0.0220)
EC	−0.3076 (−0.4374 −0.1769)	*-0.0052* ** (−0.0854 0.0791)	−0.1209 (−0.2106 −0.0259)	−0.0918 (−0.1268 −0.0517)	−0.0791 (−0.1086 −0.0461)	−0.0497 (−0.0797 −0.0136)	−0.0568 (−0.0827 −0.0225)
NC	−0.1622 (−0.2901 −0.0375)	*0.0060* (−0.1125 0.1276)	*-0.0738* (−0.1633 0.0200)	−0.0918 (−0.1270 −0.0521)	−0.0792 (−0.1087 −0.0466)	−0.0499 (−0.0799 −0.0139)	−0.0568 (−0.0831 −0.0231)
NE	*-0.1485* ** (−0.3667 0.0644)	*0.1723* (0.0108 0.3365)	*-0.0873* ** (−0.3700 0.1923)	−0.1022 (−0.1384 −0.0626)	−0.0820 (−0.1104 −0.0521)	−0.0535 (−0.0823 −0.0206)	−0.0600 (−0.0850 −0.0304)
YEL	−0.1921 (−0.3457 −0.0432)	*-0.0281* ** (−0.1752 0.1242)	*-0.0321* ** (−0.2099 0.1419)	−0.1243 (−0.2023 −0.0442)	−0.0595 (−0.0914 −0.0243)	−0.0516 (−0.0810 −0.0173)	−0.0584 (−0.0842 −0.0266)
YNG	−0.2033 (−0.3655 −0.0461)	0.1221 (0.0077 0.2379)	*-0.0313* ** (−0.2269 0.1630)	−0.1287 (−0.2105 −0.0436)	−0.1095 (−0.1792 −0.0379)	0.0348 (0.0165 0.0532)	−0.0560 (−0.0824 −0.0212)
WST	−0.1680 (−0.3168 −0.0193	*0.0512* (−0.0501 0.1583)	*-0.1048* (−0.2760 0.0687)	*-0.0743* ** (−0.1526 0.0060)	−0.1265 (−0.1880 −0.0600)	*0.0769* (−0.0021 0.1519)	0.0756 (0.0497 0.1041)

[*] This table summarizes the maximum (or minimum if the response is negative) median IRFs of *lnLoan* with respect to regional housing demand shocks and their 68% credible intervals.

[**] The response has a different sign at impact.

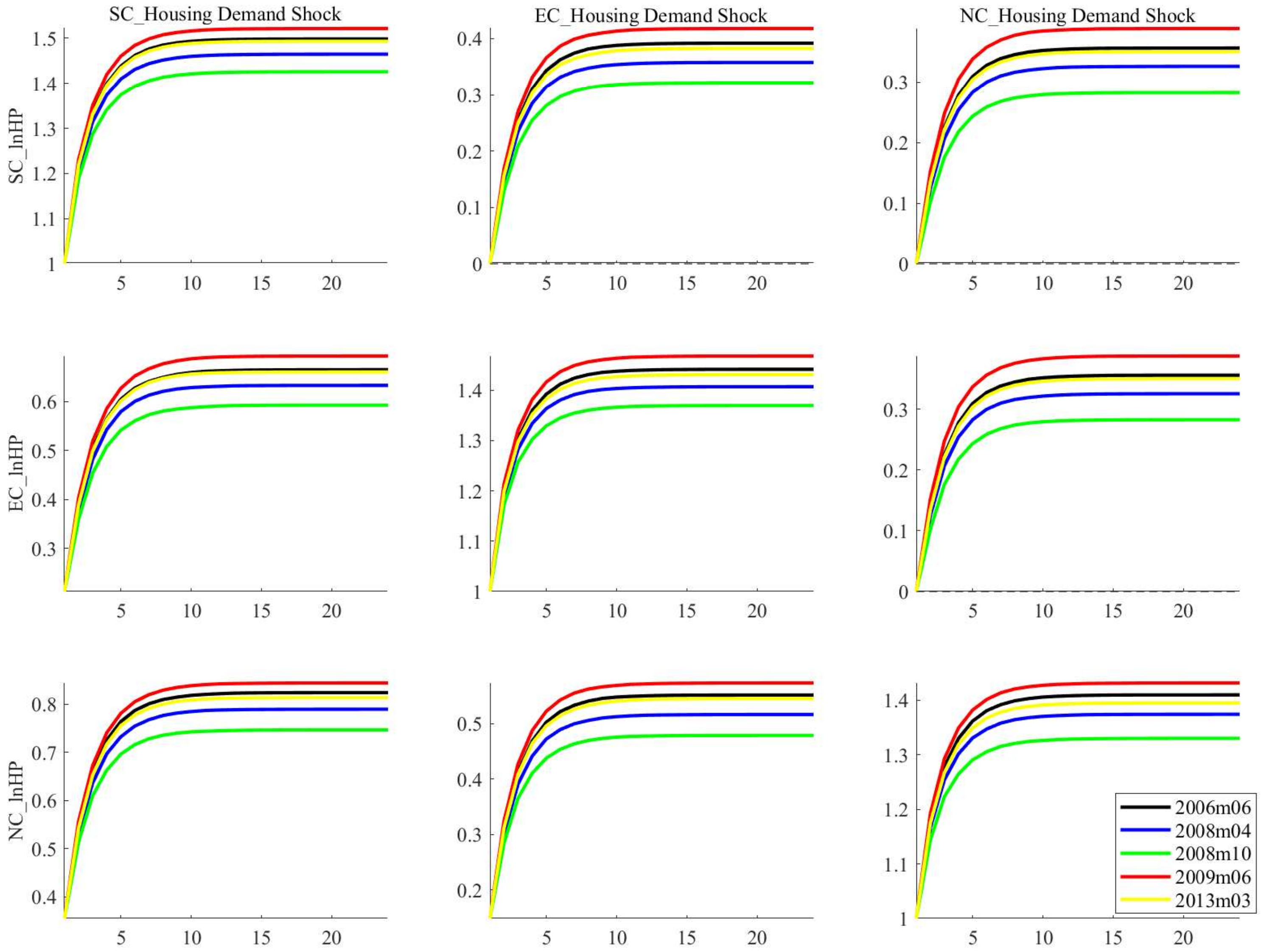
[***] Italicized numbers are that the 68% credible intervals cover zero.

4.2 House Price Spillovers During the Financial Crisis

The TVP panel VAR-X renders IRFs of house prices to housing demand shocks that change over time. This subsection studies the impact of the 2007-2009 financial crisis on house price spillovers by comparing the cumulative IRFs at different months in the sample. The focus is on five months from the sample, which are 2006m06, 2008m04, 2008m10, 2009m06, and 2013m03. I chose these moments in the sample because 2006m06 is in the beginning of the sample and avoids holiday seasons, 2008m04 is the month after the collapse of Bear Stearns, 2008m10 is the month after the bankruptcy of Lehman Brothers, 2009m06 is the beginning of the last NBER dated expansion, and 2013m03 is the end of the sample.

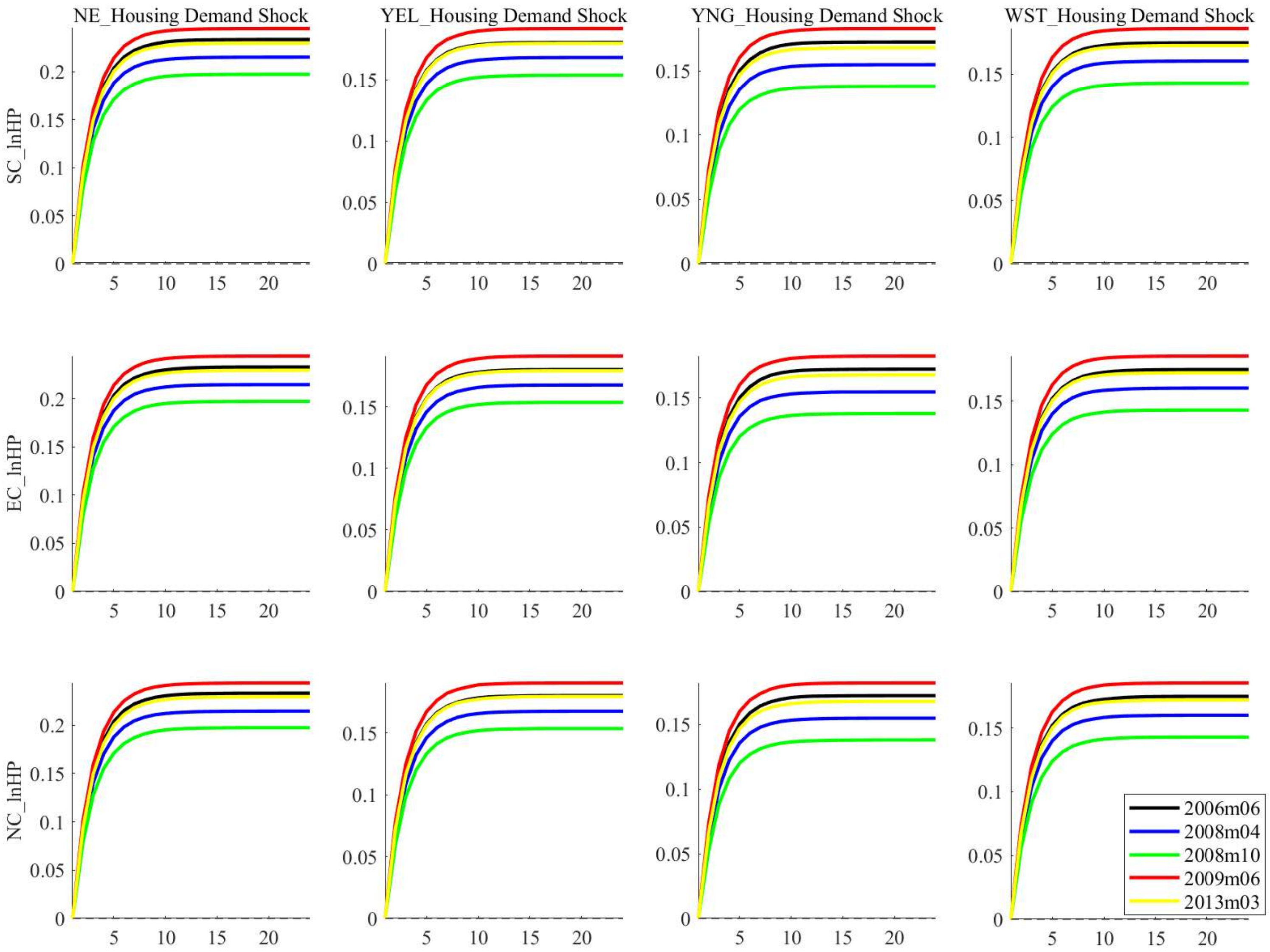
Figures 9 to 12 plot cumulative IRFs of regional house prices to housing demand shocks across the regions at each of the five months. A regional housing demand shock spills over to the other regions in different ways at different moments in time. The collapse of Bear Stearns and Lehman Brothers resulted in the smallest house price spillovers. It is the beginning of the last expansion that produces the largest house price spillovers. The house price spillovers from the interior regions exhibit less time-dependence than the IRFs of the coastal regions. These results suggest state dependence in house price spillovers that are economically meaningful for regional fluctuations in China.

Figure 9: IRFs of Coastal House Prices to Coastal Housing Demand Shocks



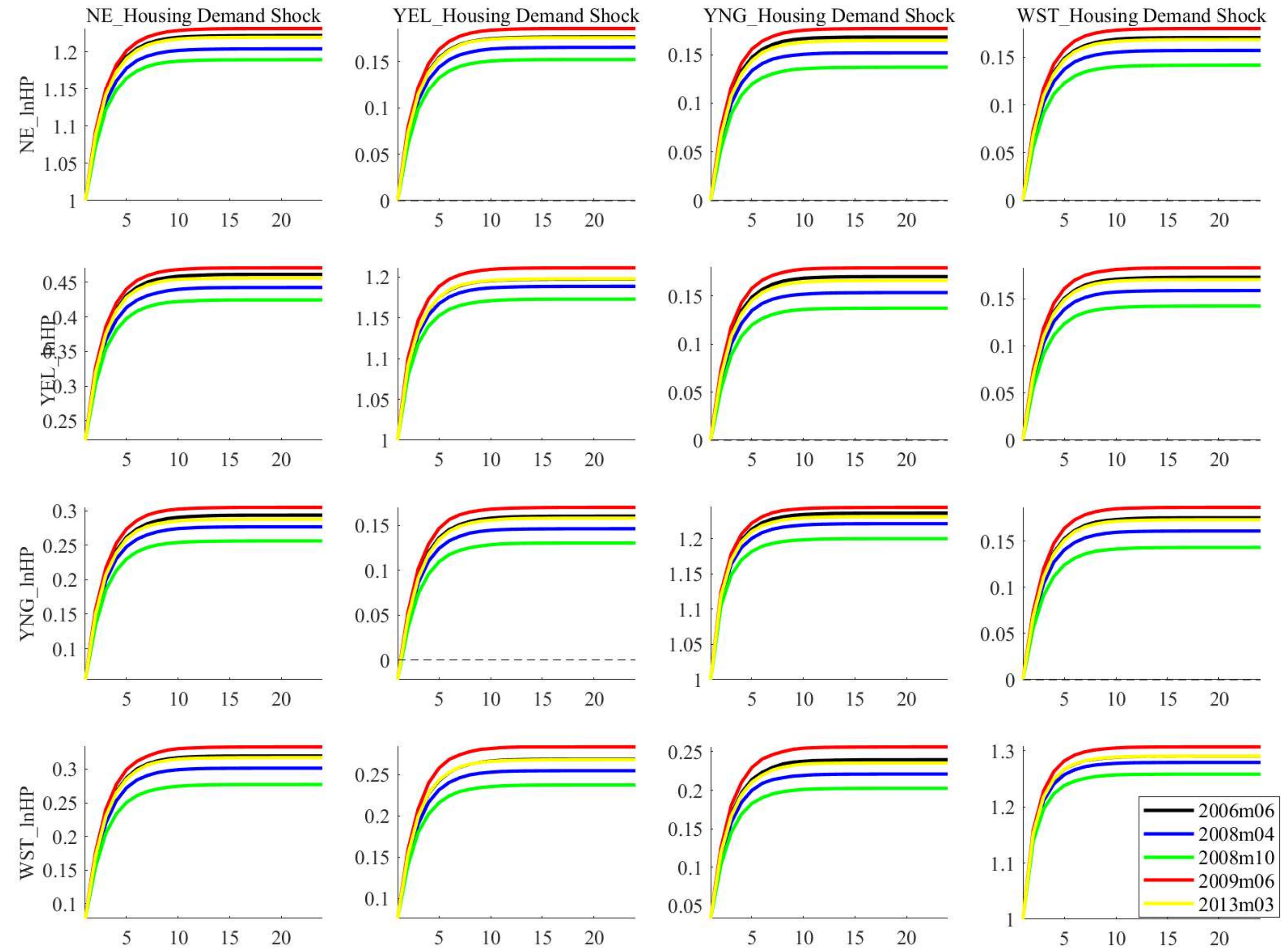
Note: The plots are IRFs of coastal region $lnHP$ to coastal region housing demand shocks at 2006m06, 2008m04, 2008m10, 2009m06, and 2013m03 from impact to a 24 month horizon.

Figure 10: IRFs of Coastal House Prices to Interior Housing Demand Shocks



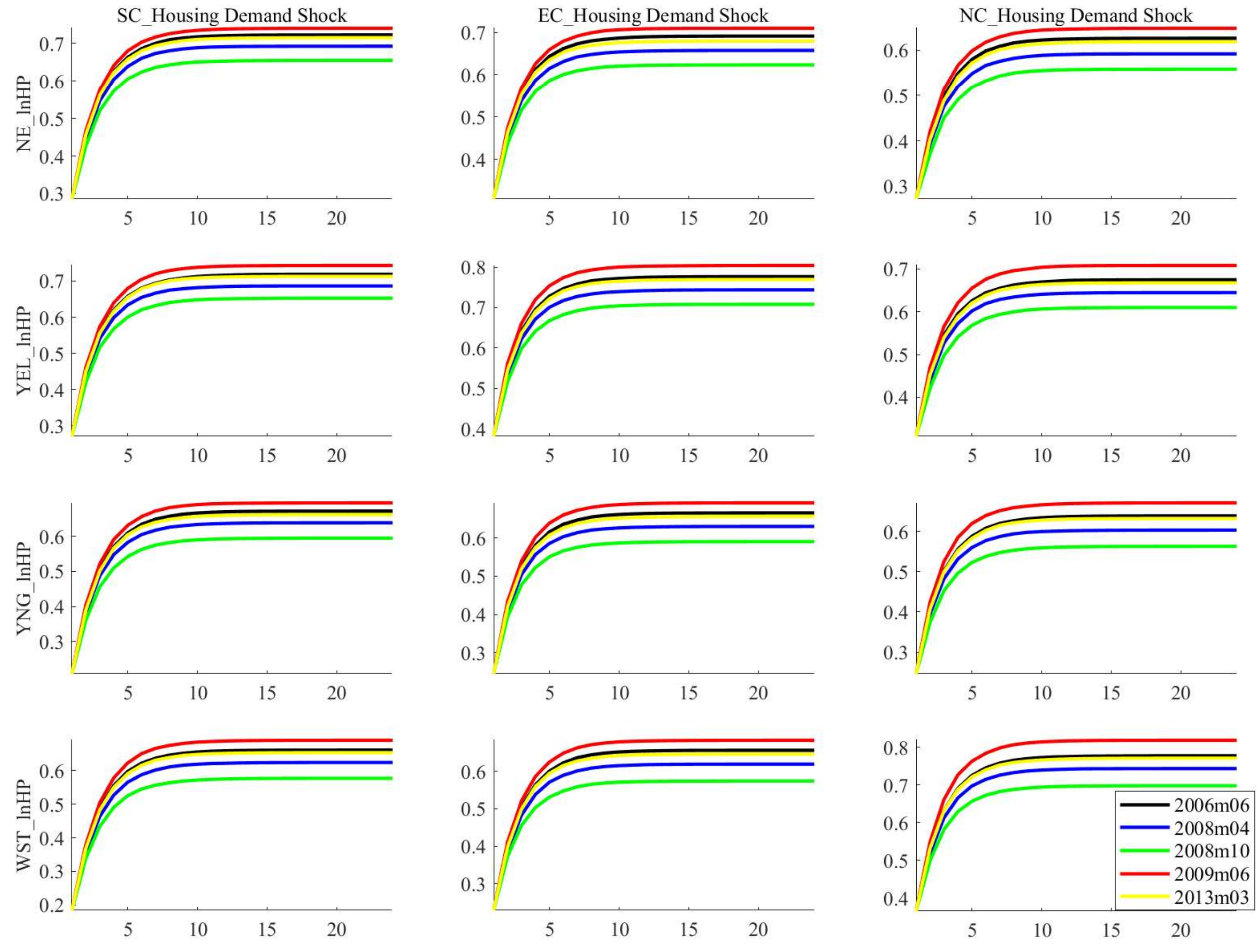
Note: The plots are IRFs of coastal region $lnHP$ to interior region housing demand shocks at 2006m06, 2008m04, 2008m10, 2009m06, and 2013m03 from impact to a 24 month horizon.

Figure 11: IRFs of Interior House Prices to Interior Housing Demand Shocks



Note: The plots are IRFs of coastal region $lnHP$ to coastal region housing demand shocks at 2006m06, 2008m04, 2008m10, 2009m06, and 2013m03 from impact to a 24 month horizon.

Figure 12: IRFs of Interior House Prices to Coastal Housing Demand Shocks



Note: The plots are IRFs of coastal region $lnHP$ to coastal region housing demand shocks at 2006m06, 2008m04, 2008m10, 2009m06, and 2013m03 from impact to a 24 month horizon.

5 The Effects of Macro-Prudential Policies

The results produced by the panel VAR-X with MPP as the predetermined policy intervention show it has minimal effects on regional outputs, loans and house prices in China. These results suggest estimating the panel VAR-X with ΔLTV. The results show that macro-prudential policies were less effective during the 2007-2009 financial crisis and the period of slow growth in the Chinese housing market, in terms of house price growth and house construction, from 2011 to 2013.

I conduct a multiplier analysis to study the impact of changes in a macro-prudential policy on real GDP, real loan, and real house price growth. Multiplier analysis is used to analyze the treatment effect of or intervention by a predetermined variable. Following Lűtkepohl (2005, section 10.6), the multiplier of the exogenous variable is computed from the infinite-order vector moving average of the panel VAR-X,

$$Y_t = (I - A_t(L))^{-1} C_t D_{t-1} + e_t. \tag{5.1}$$

The operator $(I - A_t(L))^{-1} C_t$ is the total multiplier of the predetermined macro-prudential policy intervention. Since the panel VAR has one lag, the first period multiplier is the total multiplier.

Table 8 reports summary statistics of the total multipliers of ΔLTV to the elements of Y_t. The result shows that if the macro-prudential policy authorities expand macro-prudential policy, such as increasing the ΔLTV during the previous 12 months, house price growth increases between two to three percent, loan growth increases by 2 to 2.7 percent, and real GDP growth increases by 0.6 to 1.4 percent across the seven regions. These findings are consistent with the existing literature qualitatively; see Alam et al. (2019).

The differences across the responses of the seven Chinese regions are significant. The coastal regions have very similar multipliers. However, these responses are not as large as in the YNG and WST. The coastal regions have deeper and wider mortgage markets. The complexity in the coastal regions makes the regions less responsive to a

Table 8: Multipliers in Response to the ΔLTV Intervention

	$\Delta lnGDP$			$\Delta lnLoan$			$\Delta lnHP$		
Region	**Lower**	**Median**	**Upper**	**Lower**	**Median**	**Upper**	**Lower**	**Median**	**Upper**
SC	0.7894	1.0147	1.3213	1.7897	2.3758	3.2530	1.8667	2.5362	3.5521
EC	0.7551	0.9752	1.2806	1.7716	2.3484	3.1714	1.8338	2.5118	3.5375
NC	0.7543	0.9769	1.2615	1.7750	2.3430	3.1561	1.8495	2.5080	3.4912
NE	0.5044	0.6960	0.9387	1.5287	2.0550	2.8269	1.5990	2.2145	3.1508
YEL	0.6234	0.8285	1.0901	1.6398	2.2069	3.0003	1.7124	2.3623	3.3354
YNG	0.8099	1.0411	1.3576	1.8398	2.4177	3.2565	1.8962	2.5695	3.5995
WST	1.0139	1.3127	1.6989	2.0273	2.6832	3.6417	2.0999	2.8444	3.9459

* This table summarizes medians of the multipliers of real GDP, real loan, and real house price growth with respect to the ΔLTV policy intervention across the seven regions and their median 68% credible sets. "Lower" stands for lower bound, and "Upper" stands for upper bound.

policy intervention than the YNG and WST, as suggested by Kim and Mehrotra (2019). For example, the stronger foreign demand outside China for houses in the coastal regions does not depend on borrowing from China, and it dampens the transmission channel of macro-prudential policies, as suggested by IMF (2014).

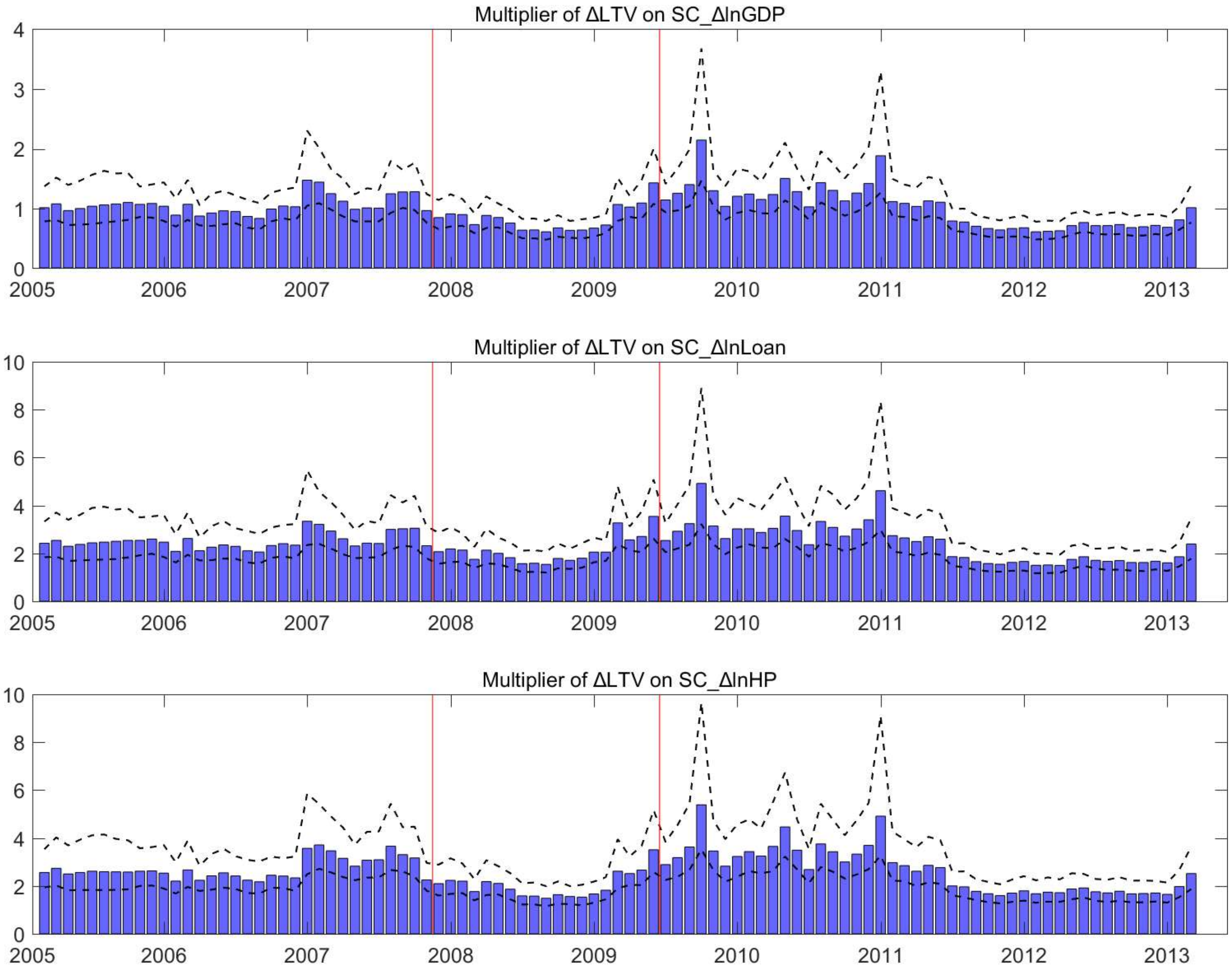
Figure 13 plots the multipliers of ΔLTV to the output, loan, and house price growth in the SC region from 2005m02 to 2013m03. The labeled interval is the 2007-2009 financial crisis. The multipliers are positive over the sample. The multipliers are smaller during the financial crisis and the housing market slow growth period in 2011-2013.

During the small effect periods which are 2007-2009 and 2011-2013, macro-prudential policies were expansionary. The multipliers indicate macro-prudential policies are more effective at constraining a boom than stimulating the economy. The estimates also suggest macro-prudential policy interventions have asymmetric effects in China from 2005m02 to 2013m03. Cerutti, Claessens, and Laeven (2017) report similar results for macro-prudential policy in a study on 119 countries.

6 Conclusion

This paper estimates a panel VAR-X with time-varying parameters and stochastic volatilities for real GDP, real loan, and real house price growth across seven economic regions

Figure 13: ΔLTV Multipliers of the SC Region, 2005m02-2003m03



Note: The plots are the medians of ΔLTV multipliers of the output, loan, and house price growth in SC region over the sample with their 68% credible sets. The labeled interval is the 2007-2009 financial crisis.

in China. The panel VAR-X is employed to study the regional real GDP, real loan, and real house prices to identified own and other regional supply, credit supply, and housing demand shocks. A contribution of the paper is a new monthly data set of Chinese regional real GDP growth, real loan growth, and real house price growth from 2005m02 to 2013m03 on which the panel VAR-X is estimated. I also report estimates of the impact of a predetermined macro-prudential policy intervention, which is the X in the panel VAR.

The posterior of the panel VAR-X contains several useful results. First, the IRFs of house prices in all regions show a larger response to shocks that originate in the coastal regions compared with the interior regions of China. Further, regional house prices respond more to the housing demand shocks of other regions than to own supply and credit shocks. This is evidence of economically important house price spillovers across the regions of China. Second, there are negative spillovers from regional housing markets to the real economy and financial markets. Third, house prices exhibit smaller responses to housing demand shocks from other regions in the middle of the 2007-2009 financial crisis compared with the rest of the sample. This phenomenon is more significant for the interior regions of China. Fourth, macro-prudential policy interventions have a larger impact on house prices than real GDP and real loans. Fifth, macro-prudential policy interventions are more effective at constraining a boom compared with spurring activity in regional financial and housing markets in China during a financial crisis.

My research suggests several directions for future research. First, the analysis of this paper ignores monetary policy. It will be interesting to examine the impact of monetary policies on regional housing markets in China. Another potentially interesting avenue of research is to study the impact on Chinese regional housing markets of movements in mortgage spreads. This suggests introducing short-term and long-term interest rates to the model. I hope this paper stimulates this research.

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