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## Income inequality and house prices in the United States: A panel VAR analysis

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## Abstract

This paper examines empirically the dynamic relationship between upper-end measures of income inequality, such as top 1% income share, and house price-to-income ratio (HPIR) by employing panel VAR technique over the period from 1975 to 2015 using a panel of annual U.S. state-level data. Impulse response analysis provides that inequality positively affects HPIR. This finding is robust to changes in the measures of inequality used, as well as to VAR order. In contrast, there exist no significant impacts of HPIR shocks on inequality in the baseline model. The PVAR in the reverse order shows that HPIR has a positive contemporaneous effect on inequality but the effect dies out within two years. This finding implies that the positive correlation between inequality and house prices is mainly driven by the positive effect of inequality on house prices.

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# 1. Introduction

In recent decades, many countries have experienced the concurrent rise in both income inequality and house prices. For example, Zhang (2016) states that house price inflation is positively correlated with the growth in top 5 percent income share across states in the United States as well as across countries. Accordingly, researchers have paid more attention to the relationship between inequality and house prices nowadays. So far, the main concern of this area has been the impact of inequality on house prices.

According to Goda et al. (2019), house prices theoretically can be influenced by inequality via two demand paths. On the consumption side, rising inequality may increase the number of households who are willing to pay higher prices for their houses. On the asset side, inequality is expected to raise total savings and so increase the demand for houses because houses are an investment good for high-income households. Gyourko et al. (2013) assume that there exist some preferred locations with inelastic house supply and excess demand. As the number of high-income households grows, more people would like to live in and pay for the preferred houses. As a result, the average house price appreciation may be driven by the upsurge of house price in the preferred residential areas. Määttänena and Terviö (2014) present an assignment model that differentiates between high- and low-quality houses. With rising inequality, low-income households bid less for low-quality houses while high-income households bid more for high-quality houses. Therefore, their model predicts that the effect of increasing inequality on house prices depends on these two pressures on the housing market. Nakajima (2005) suggests a life-cycle general equilibrium model in which agents decide how to allocate their savings between a financial asset and a housing asset. A rise in income inequality (or higher earnings volatility) induces workers to increase their precautionary savings. Consequently, house prices increase due to the increased demand for houses. Zhang (2016) presents an incomplete market model with heterogeneous households that can choose to save in either bonds or housing. Because housing assets can be adjusted with substantial transaction costs, households who purchase housing assets should consider an illiquidity premium. Top-income households are less constrained by the adjustment costs and can increase investment in housing assets in accordance with the increase in their incomes. Low-income households, on the other hand, are reluctant to buy housing assets due to the illiquidity premium. Therefore, a shift of resources from the poor to the rich shrinks the illiquidity premium and drives up house prices.

There have been several empirical studies related to the current issue. Matlack and Vigdor (2008) focus on the relationship between income inequality and housing affordability. In particular, they take note of the possibility that income increases at the top end of the distribution worsen housing market outcomes for those at the bottom of the distribution. They find that rising inequality is closely linked to adverse changes in housing outcomes (higher rents and greater crowding) among households headed by a high school dropout in markets with low-vacancy rates using U.S. metropolitan areas housing market data between 1970 and 2000. Dewilde and Lancee (2013) analyze the relationship between income inequality and access to housing for low-income households using data from the EU-Statistics on Income and Living Conditions. They show that higher inequality magnifies the likelihood of housing affordability problems for poor households. They also find that house prices have risen more sharply in countries with a higher increase in income inequality between 2003 and 2008. Goda et al. (2019) argue that inequality has pushed up house prices through the increase in total demand for houses. They find that income inequality and house prices were positively correlated during 1975-2010 in most OECD countries and for most countries inequality Granger-caused house price inflation. Zhang et al. (2016) find that the Gini coefficient is positively associated with the house price-to-income ratio as well as the house vacancy rate using China's Urban Household Survey data. According to their estimates, increasing inequality can account for roughly 6% of the increase in the price-to-income ratio and 10% of the rise in the vacancy rate during 2002 and 2009.

Meanwhile, some literature suggests the channels that housing market fluctuations to income inequality. Charles et al. (2018) find that the U.S. housing boom during 2000-2006 significantly increased employment, mainly among non-college educated men and women in construction and finance, insurance and real estate sectors. However, there exist no persistent employment effects of housing booms. A possible reason is that housing booms were followed by the bursting of the housing bubble. Bostic et al. (2009) find that the effect of housing wealth on consumption is considerably large compared with other financial assets. Mian and Sufi (2014) show that counties with a larger decline in housing net value also experience a larger drop in non-tradable employment between 2007 and 2009. These studies imply that housing boom might temporarily improve income distribution through labor market outcomes or housing wealth effects.

In this paper, I estimate panel vector autoregression (hereafter, PVAR) to investigate the dynamic relation between income inequality and house price-to-income ratio (hereafter, HPIR) using a panel of annual U.S. state-level data. One advantage of this approach is that the state-level data help reduce the measurement error problem associated with capturing structural differences in cross-country data, as previously emphasized by Frank (2009).[1] Furthermore, PVAR allows us to examine both the effect of inequality on HPIR, as well as the reverse effect of HPIR on inequality. Surely, a bivariate VAR model might omit relevant information. I believe, however, this empirical approach allows for a parsimonious framework for understanding the relationship between inequality and house prices.

The results from PVAR estimation show that an increase in income inequality, measured by the income share of top earners or Theil Entropy Index, does have a positive impact on HPIR. On the other hand, HPIR does not have a significant effect on income inequality in the baseline model. Even if there exists a positive effect in the alternative specifications, the positive response shifts to the negative direction in the following year and becomes insignificant soon. This implies the channels that house market cycle to inequality are unclear or may be valid temporarily.

The rest of the paper is organized as follows: Section 2 provides the overview of the data. Section 3 presents the empirical specification and methodology. Section 4 provides the estimation results of PVAR model and Section 5 concludes.

[1] In particular, many researchers are concerned about the quality and comparability of the income inequality data in cross-country studies. See Atems and Jones (2015) for details.

# 2. Data

The current dataset consists of annual data on various income inequality measures and several variables related to house prices for the 50 states of the U.S. and DC from 1975 to 2015. From Professor Mark Frank's website I obtain data on income inequality. In this paper, I focus on upper-end measures of income inequality such as top 1, 5 and 10 % income shares. This is because IRS income data omit lots of low-end income earners and so a broad-based income inequality measures, notably the Gini coefficients, may be misleading (Frank, 2009; Atems and Jones, 2015). The data on house price index were collected from the Federal Housing Finance Agency (FHFA). The baseline state-level median home values are obtained from the 2000 census. The panel on house prices was constructed using a method suggested by Case and Shiller (2003):

$$V_{it} = V_{i2000} \cdot HP_{it} \tag{1}$$

where

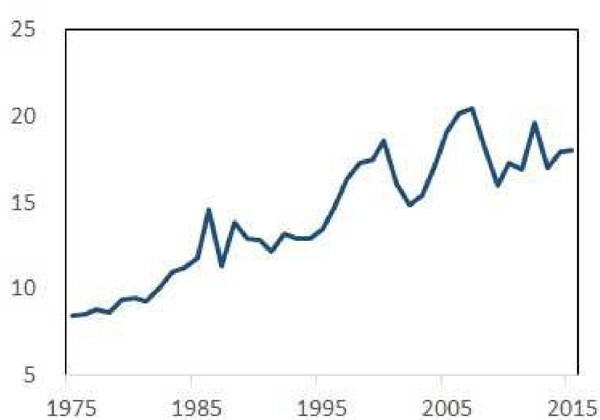
$$\begin{aligned} V_{it} &= \text{adjusted median home value in state } i \text{ at year } t \\ V_{i2000} &= \text{median value of owner-occupied homes in state } i \text{ in 2000} \\ HP_{it} &= \text{house pirce index for state } i \text{ at year } t \end{aligned}$$

Dividing the adjusted median home value by the annual disposable income per capita for each state, I calculate the figures for HPIR. The data on nominal disposable income per capita were collected from the US Bureau of Economic Analysis (BEA).

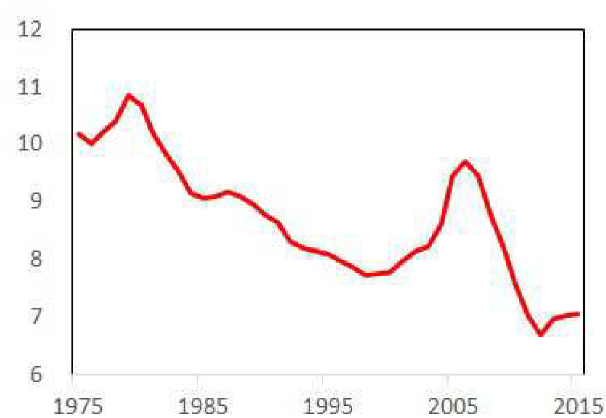
Figure 1 shows state-averaged top 1% income share, and the corresponding HPIR from 1975 to 2015. Figure 1(a) displays that income inequality in the U.S. has steadily increased since the early 1980s. Figure 1(b) shows HPIR movements over time. It is difficult to recognize the cyclical fluctuations in HPIR, but the figure characterizes at least two apparent peaks in housing price cycles: 1979 and 2006. HPIR has been on the increase from 2013 onwards, showing a gradual recovery since the sub-prime mortgage crisis.

Figure 1 State-averaged top 1% income share and HPIR: 1975-2015

(a) Top 1% income share




(b) HPIR



To begin with, I conduct a series of unit root tests to check the stationarity of the concerned variables. Various procedures exist for testing for the existence of a unit root in panel data, notably the Levin-Lin-Chu (LLC) test, the Harris-Tzavalis (HT) test, the Im-Pesaran-Shin (IPS) test, the Fisher-type augmented Dickey-Fuller (ADF) test, and the Hadri test. The first four tests test the null-hypothesis that panels contain unit roots. Therefore, a rejection of the null hypothesis of these tests does not necessarily imply that all the panels are stationary. On the other hand, the null-hypothesis of the Hadri test is that all panels are stationary. All the tests are implemented on demeaned data in order to mitigate the effects of cross-sectional correlation as proposed by Levin et al. (2002). Table 1 presents the p-values of panel unit root test results. Although most of the test results suggest the possibility of stationarity of both variables, the Hadri test indicates that at least one of panels might contain a unit root. Therefore, I log-difference each series to achieve stationarity.

Table 1 Panel Unit Root Test Results (p-values)

| Test | Level | | Growth Rate | |
|---|---|---|---|---|
| | Intercept | Intercept and Trend | Intercept | Intercept and Trend |
| Top 1% share of income | | | | |
| LLC | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| HT | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| IPS | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| ADF | 0.0594 | 0.0000 | 0.0000 | 0.0000 |
| Hadri | 0.0000 | 0.0000 | 0.9679 | 0.0012 |
| house price-to-income ratio | | | | |
| LLC | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| HT | 0.0058 | 0.9962 | 0.0000 | 0.0000 |
| IPS | 0.0166 | 0.0274 | 0.0000 | 0.0000 |
| ADF | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Hadri | 0.0000 | 0.0010 | 0.9995 | 0.6338 |

# 3. Empirical Methodology

To analyze the dynamic relationship between income inequality and HPIR, I compute the impulse response functions from an estimated PVAR. PVAR technique combines the traditional VAR model with the panel-data approach, which takes into account unobserved individual heterogeneity. The baseline specification is a bivariate PVAR model of the growth rate of the income inequality measure and the growth rate of HPIR. Denote the growth rate in the top 1% income share of state $i$ in year $t$ by $\Delta x_{it}$, and the growth rate of the HPIR of state $i$ in year $t$ by $\Delta p_{it}$. The growth rates are measured in log-differences. Then, a reduced-form panel VAR model can be written as:

$$y_{it} = A(L)y_{it-1} + \mu_i + \varphi_t + \epsilon_{it} \tag{2}$$

where $y_{it} = (\Delta x_{it}, \Delta p_{it})'$, $L$ is the lag operator, $A(\cdot)$ is a polynomial matrix in $L$, $\mu_i$ denotes $2 \times 1$ state-specific fixed effects, and $\epsilon_{it}$ is a $2 \times 1$ error term. The state fixed effects account for unobserved time-invariant heterogeneity across states. Time fixed effects $\varphi_t$ $(2 \times 1)$ are introduced to capture aggregate macro shocks that may affect all states at the same time. The VAR includes only one lag, which is selected using the Bayesian information criterion.

The PVAR approach requires that the underlying structure is identical for each state. One popular way to overcome this restriction is to introduce unobserved fixed effects, denoted by $\mu_i$ in the model. However, the fixed effects are intrinsically correlated with the regressors due to the autoregressive nature of the PVAR. Hence, we cannot obtain unbiased coefficients from the usual mean-differencing procedure used to eliminate fixed effects.[2] I use forward mean-differencing developed by Arellano and Bover (1995), also known as the 'Helmert procedure' to avoid this problem. This procedure removes only the mean of all the future variables in the VAR model. The transformed variables are orthogonal to the lagged regressors, so we can estimate the coefficients by system GMM using lagged regressors as instruments.[3] I also subtract cross-sectional averages from all series to control for time effects prior to the Helmert transformation.[4]

To identify the shocks, we need to determine the order of the variables. The typical assumption is that a variable that comes earlier in the ordering have a contemporaneous impact on the following variable while a variable that appears later affects the preceding variable with a lag. I assume that changes in income inequality may affect HPIR contemporaneously, while the reverse effect can only occur after a lag. I believe this assumption is acceptable because income is used in the calculation of HPIR, so changes in income will have contemporaneous effects on HPIR. In contrast, house prices may affect income inequality with a lag via consumption and employment shocks. As a robustness check, I also consider the VAR in the reverse recursive order.

# 4. Estimation and Results

Figure 2 displays the impulse-response functions derived from the estimated PVAR, together with their corresponding 90% confidence intervals.[5] The confidence intervals were generated by Monte Carlo simulation methods based on 1,000 draws. Consider first the diagonal panels (top-left and bottom-right). It appears that the responses of both the top 1% income share and HPIR to their own shocks are transitory. The off-diagonal panels show the response of the top 1% income share to shocks in HPIR (top-right) and the response of HPIR to shocks in the top 1% income share (bottom-left), which are central to this paper. The top-right impulse response shows that HPIR has no significant effect on the top 1% income share. By contrast, the bottom-left impulse response shows that an increase in the top 1% income share has a significant positive effect on HPIR and the effect lasts for about four years.

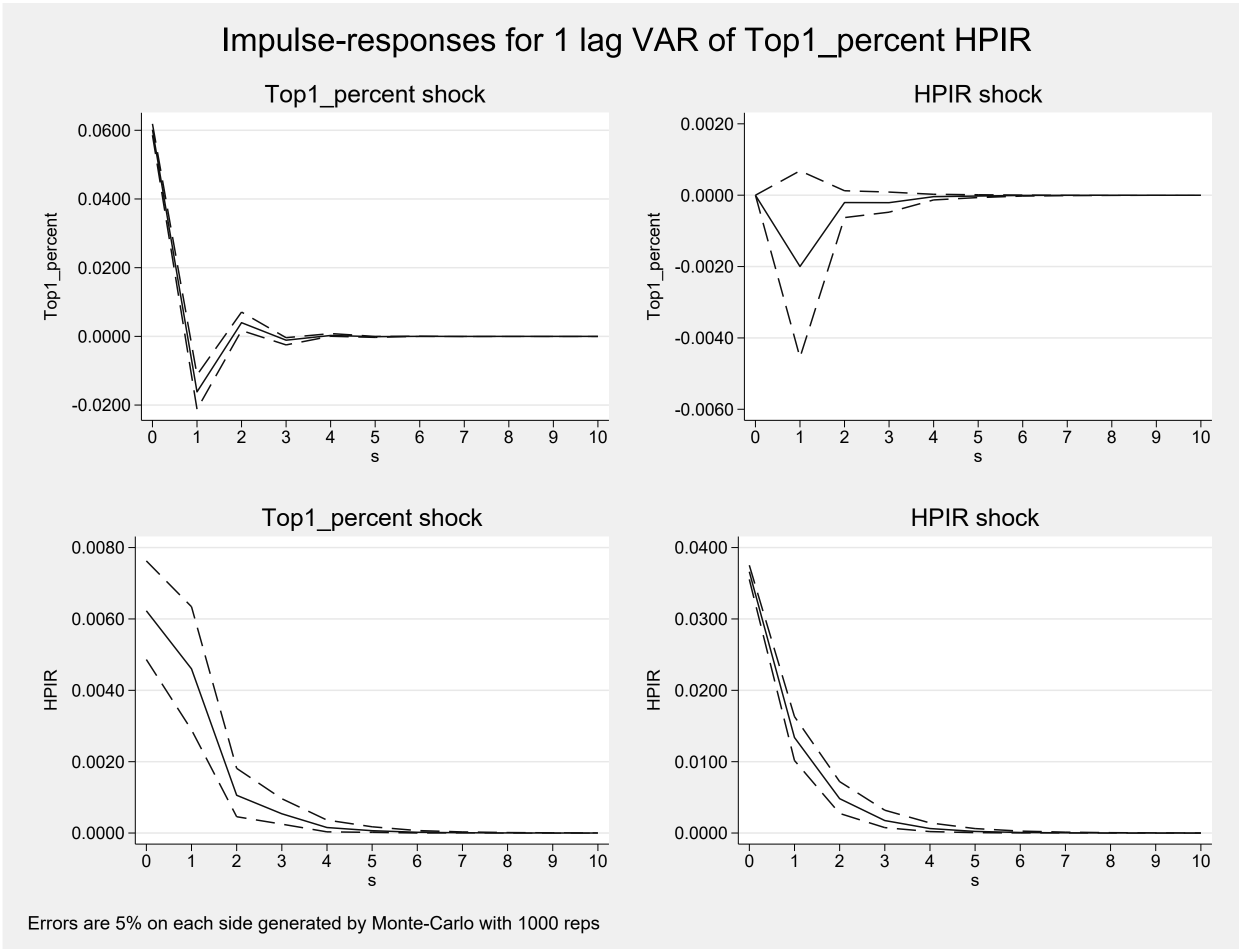
[2] See Nickel (1981) for details.

[3] I use the pvar2 program in Stata that was originally developed by Inessa Love and modified by Ryan Decker.

[4] See Abrigo and Love (2016) for details.

[5] The impulse response functions (IRFs) shown in this paper are not the cumulative IRFs, and so they must be interpreted as the effect of each shock on the growth rates and not the levels of the dependent variables.

Figure 2 Response of Top 1 percent share and HPIR

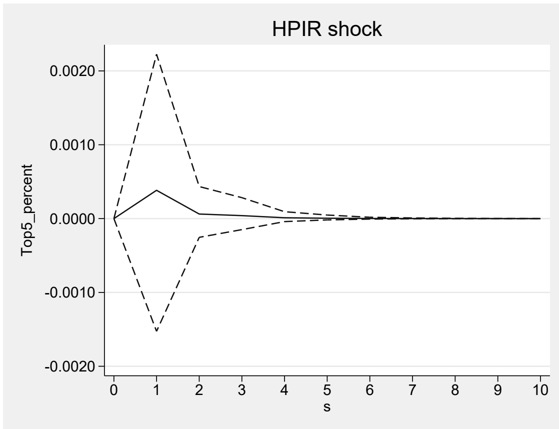



In Figure 3, I consider two alternative measures of income inequality, namely top 5% and 10% income shares to examine how robust the results are to different inequality measures. Compared to Figure 2, I display only the off-diagonal panels, showing the response of inequality to shocks in HPIR (top) and the response of HPIR to shocks in inequality (bottom). Figure 3 shows that the results seem highly similar to those depicted in Figure 2. I find that an increase in income inequality raises HPIR, making it permanently higher than it otherwise would have been. However, HPIR does not have a significant effect on inequality.

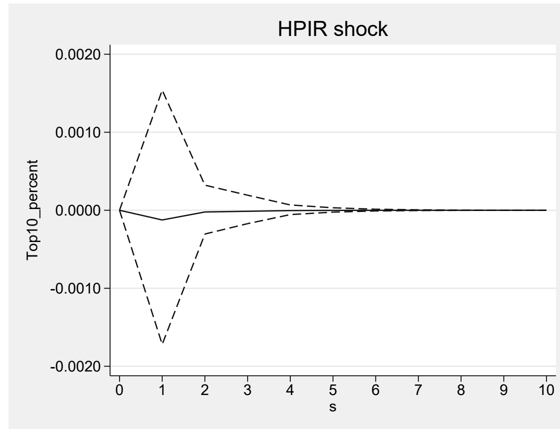
Next, I reverse the ordering of the benchmark model to check robustness. Figure 4 reproduces the off-diagonal panels of Figure 2 in the reverse order. The left panel shows that an unexpected increase in HPIR leads to an increase in the top 1% income share instantly. The effect, however, turns negative in the following year and wears off in significance from the second year onwards. On the other hand, I still find a positive effect of the top 1% income share on HPIR.

Figure 3 Response of Top 5 & 10 percent shares and HPIR

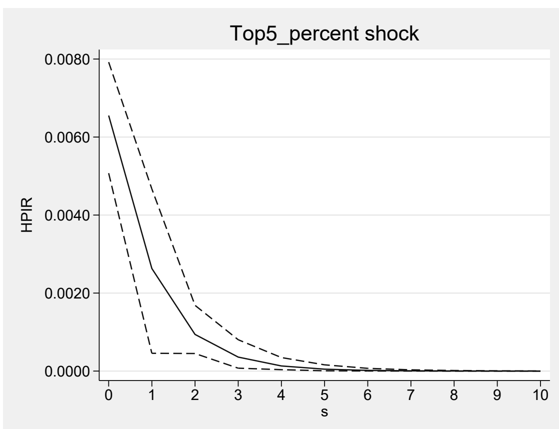
(a)




(b)




(c)




(d)

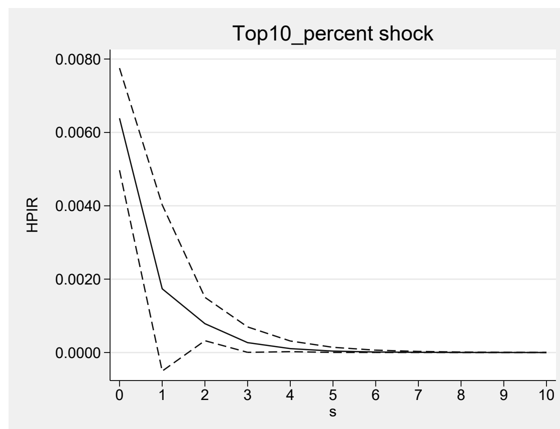
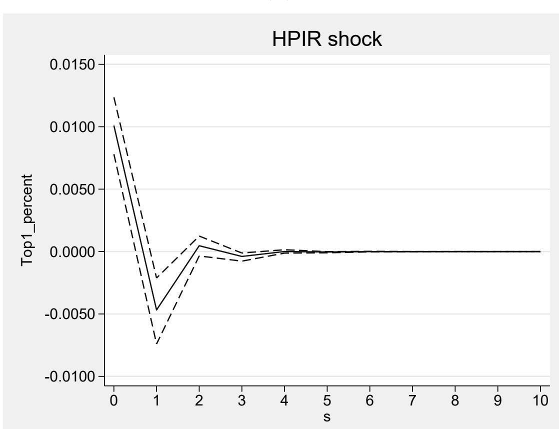



Figure 4 Response of Top 1 percent share and HPIR (recursive order reversed)

(a)




(b)

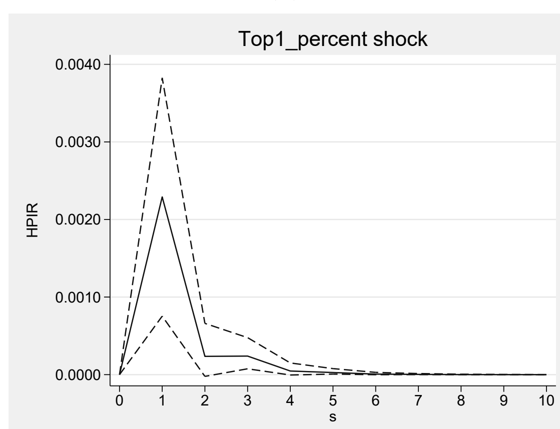
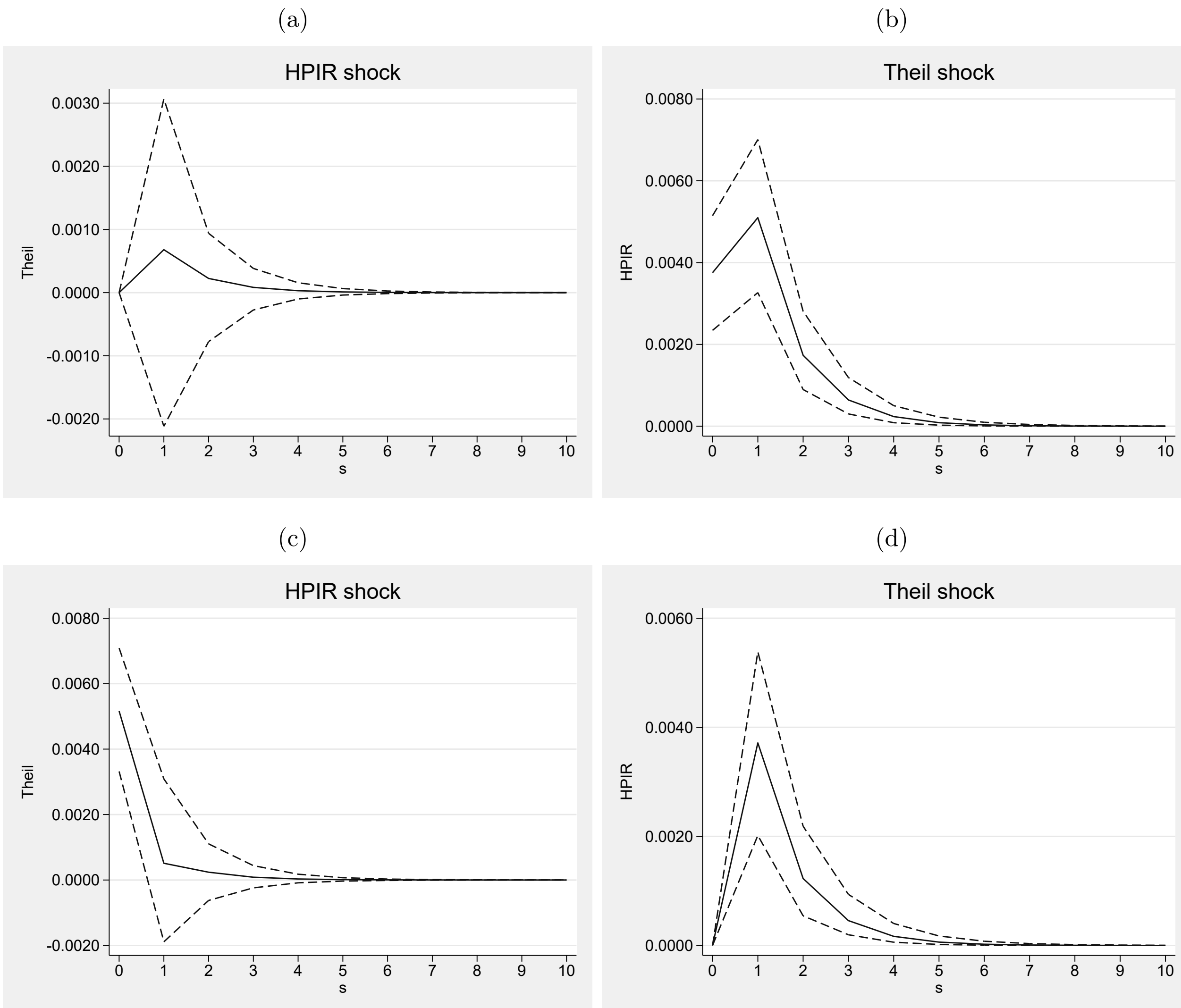


Figure 5 Response of Theil Index and HPIR




Finally, I consider another alternative measure of income inequality, that is the Theil Entropy Index.[6] This index is known to be most sensitive to inequality in the top range in the distribution unlike the Gini index (Kovacevic, 2010). In Figure 5, the top panels reproduce the off-diagonal panels of Figure 2 by replacing the top 1% income share with the Theil Entropy index. The bottom panels reproduce the responses in the reverse order like Figure 4. Figure 5 shows that the response of HPIR to a shock in the Theil Entropy Index is very similar to those presented in Figure 2 and 4.

[6]Refer to Frank (2009) for the method used for construction of this index.

# 5. Conclusion

This paper examines the dynamic relationship between income inequality and house price-to-income ratio (HPIR) using a panel of annual U.S. state-level income inequality data for the period 1975-2015. The baseline bivariate PVAR model indicates that a shock to the top 1% income share leads to an increase in HPIR. This result is robust to other upper-end measures of income inequality and to the alternative ordering. However, I find no significant impact or a temporary positive impact of HPIR shocks on income inequality. This paper provides a further support to the "income inequality and house prices" literature. According to the current empirical results, the positive correlation between inequality and house prices is mainly driven by the positive effect of inequality on house prices.

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