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RESEARCH ARTICLE

Inequality, Household Credit Shocks, and House Price Dynamics

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Abstract
We empirically examine whether income inequality amplifies the effect of household credit shocks on real house prices using a two-stage analysis. In the first stage, we estimate how house prices dynamically respond to household credit shocks in each country using country-specific structural vector autoregression (VAR) models for a sample of 42 advanced and emerging market economies. In the second stage, we conduct a cross-country analysis to investigate the role of income inequality in amplifying the estimated response of household credit shocks on house prices. Our results suggest that higher levels of income inequality increase the sensitivity of house prices to household credit shocks, even after controlling for other factors. This pattern holds even when using wealth inequality, and alternative specifications including dynamic panel VAR and single-equation estimation. Our study has important policy implications. Policies aimed at improving income and wealth distribution may help mitigate housing market fluctuations, a factor that contributed significantly to the Global Financial Crisis.

JEL Classification E21 · E32 · E44 · E51 · R21

1 Introduction

Income distribution varies widely across countries. As of 2022, the top 1 percent of income earners in the USA received 20.7 percent of the pre-tax national income, compared to just 10.6 percent in Finland. Emerging market economies also show significant disparities: in Turkey, the income share of the top 1 percent of the income

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earners was 22.39 percent, while in Argentina, this share was only 12.36 percent (Source: World Inequality Database).

Does income distribution matter for the stability of the housing market? This paper addresses this question by studying the role of income inequality in determining the effects of household credit shocks on real house prices. Income inequality is particularly relevant to house price fluctuations due to its influence on credit constraints across income groups. Borrowing limits are largely determined by income, a key factor in assessing repayment capacity (Dell'Ariccia et al. 2012; Greenwald 2018). As income inequality increases, the declining income shares of low- and middle-income households restrict their access to credit, leaving a larger portion of the population subject to binding credit constraints.

Theoretically, we expect that inequality strengthens the relationship between household credit and house prices by increasing the proportion of credit-constrained households. In more unequal countries, an exogenous positive credit shock relaxes the credit constraints of this larger pool of households, who typically exhibit a higher marginal propensity to consume (MPC). As a result, such countries are likely to experience more pronounced house price responses to household credit shocks. If inequality measures effectively capture the tendency of greater income dispersion to shift more households closer to borrowing constraints, then we expect to find a stronger response of house prices to household credit shocks. In sum, our prior view is that income inequality increases the sensitivity of house prices to household credit shocks, by disproportionately affecting a larger share of credit-constrained, high-MPC households.

To empirically examine this relationship, we adopt a two-stage methodology following the approach of Cecchetti (2001), Lastrapes and Douglas McMillin (2004), Aizenman et al. (2019), Herrera and Rangaraju (2019), Bahadir et al. (2020), among many others. In the first stage, we estimate vector autoregressions (VAR) for each country to estimate the effects of household credit shocks on real house prices. The identification of household credit shock is achieved using the standard Cholesky decomposition. Subsequently, we conduct cross-country regressions to examine the effect of income inequality on the strength of the relationship between household credit shocks and real house prices obtained in the first stage of the empirical analysis. We measure income inequality for the sample of countries as the Gini coefficient of the after-tax national income.

Our findings from the first stage indicate that, in the majority of instances, household credit shocks yield immediate positive effects on real house prices. The magnitudes of these responses vary significantly across countries. For some countries, we observe a pattern of boom-bust cycles in house prices. Household credit shocks initially have a positive impact on house prices; however, this effect weakens over time and becomes negative. The transition to negative effects may be associated with factors such as overvaluation, economic downturns, or deleveraging in the face of mounting debt, resulting in a correction in house prices. Conversely, in certain countries, we observe an initial decline in house prices, followed by subsequent increases. The diverse outcomes across different countries underscore the heterogeneity in housing market dynamics. Our second-stage analysis aims to identify income inequality as one of the potential factors contributing to this heterogeneity.

The results from the second stage confirm that countries characterized by higher income inequality experience a more substantial boom in house prices in the short run. Factors such as financial development levels, age distribution, current account deficits, and overall economic conditions may also contribute to variations in the relationship between household credit shocks and house prices. Our main result on the importance of income inequality in amplifying house price booms following household credit shocks remains robust to the inclusion of these additional control variables.

We expand our empirical analysis in three key ways to test the robustness of our results and gain additional insights. First, we include real GDP in the first stage of our analysis and re-estimate the second-stage regressions using the responses from this larger VAR specification. Even with the inclusion of real GDP, our results remain statistically significant and economically meaningful. Second, we examine the role of wealth inequality, as household wealth, much like income, can significantly influence access to credit. Incorporating wealth inequality as an alternative measure does not alter our main findings; the results remain consistent and robust. Finally, we explore alternative empirical specifications, conducting both panel VAR and single-equation estimations. Across both types of analyses, we find that higher income inequality consistently increases the sensitivity of house prices to household credit shocks, further confirming our main results.

Our paper is related to three strands of literature. The first line of research, which expanded significantly since the onset of the 2007-2009 Financial Crisis, considers household credit expansions as a key factor influencing house prices and business cycles. On the theoretical side, several studies show that a relaxation of financing constraints leads to an increase in borrowing, house prices, and an overall surge in demand (Bahadir and Gumus 2016; Favilukis et al. 2017; Justiniano et al. 2019). On the empirical side, the effect of exogenous credit supply shocks on house prices has been extensively studied. Notable contributions include Favara and Imbs (2015), Di Maggio and Kermani (2017), and Mian and Sufi (2022). Furthermore, several studies focus on the two-way interaction between house prices and household debt (Gerlach and Peng 2005; Anundsen and Jansen 2013; Oikarinen 2009; Fitzpatrick and McQuinn 2007; Basten and Koch 2015). While the literature has already established a strong link between credit shocks and house prices, the determinants of the strength of this relationship remain less understood. Our paper aims to address this gap by identifying the role of inequality in strengthening the link between household credit shocks and house price dynamics.

The second related line of research examines inequality as a factor in shaping the response of macroeconomic variables to economic shocks and stabilization policies. In their study on fiscal multipliers, Brinca et al. (2016) argue that wealth inequality leads to higher marginal propensity to consume (MPC) and amplifies the fiscal policy multiplier. Matusche and Wacks (2023) study the implications of wealth inequality for the transmission of monetary policy and show that higher inequality is associated with stronger real effects of monetary policy. Krueger et al. (2016) investigate how households in different segments of the wealth distribution are affected by income changes and find that wealth inequality can significantly amplify the impact of an aggregate shock. We complement this literature by emphasizing the role of inequality and credit constraints in understanding the effect of household credit shocks on house prices.

The third strand of literature examines the interaction between household debt, business cycles, and inequality. Kumhof et al. (2015) theoretically analyze the relationship between leverage, crises, and the growing share of high-income households, while Iacoviello (2008) investigates the trends and cyclical behavior of household debt, linking its rise to the concurrent increase in income inequality. However, neither paper examines the effect of inequality on the link between household credit shocks and business cycles. A closely related paper is Bahadir et al. (2020), which examines how income distribution influences the relationship between household credit and consumption. Our research builds on and extends their work by analyzing the link between house prices and household credit shocks, with a specific focus on how inequality amplifies the risks tied to the distribution of household debt in the housing market. This focus is particularly important given the significant role house prices played in the Global Financial Crisis of 2007–2009. By emphasizing the impact of inequality on the housing market's vulnerability to credit shocks, our study provides new insights into the broader macroeconomic implications of distributional factors.

The interaction between income distribution, credit dynamics, and housing market behavior underscores the intricate relationship between economic disparities and the volatility of house prices. Our results suggest that policymakers should take these interconnections into account when formulating measures to address inequality and promote stability in the housing market. Policies aimed at improving distributional factors within an economy may also prove beneficial in mitigating fluctuations in the housing market, a factor that played a substantial role in the Global Financial Crisis.

2 Data and Empirical Framework

The objective of our study is to understand the role of income and wealth inequality in explaining cross-country variation in house price responses to household credit shocks. We conduct our empirical analysis in two stages following earlier works of Cecchetti (2001), Lastrapes and Douglas McMillin (2004), Aizenman et al. (2019), Herrera and Rangaraju (2019), Bahadir et al. (2020), among many others. In the first stage of our empirical exercise, we estimate country-specific dynamic responses of house prices to household credit shocks for a sample of 42 advanced and emerging market economies. We do so by estimating a structural VAR model using a recursive identification similar to the one in Hofmann (2004) to obtain impulse responses. In the second stage, we attempt to investigate the estimated cross-country variation in house prices in response to the household credit shocks (obtained from the first stage) by specifically focusing on the role played by income and wealth inequality.

2.1 Data

For our first-stage VAR analysis, we select a sample of 42 advanced and emerging market countries, for which quarterly time series data on real house price, interest rate, firm debt, and household debt are available. Our study period is 1990:Q1-2018:Q4. The availability of quarterly time series data, particularly for real house prices, varies across countries. While most countries have data starting from 1995, for some, the series begins later.

For each of the 42 countries, we measure the level of real house price as the real house price index, the interest rate as the three-month interbank rate, the household and non-financial firm debt as household debt-to-GDP ratio and non-financial firm debt-to-GDP ratio, respectively. We utilize quarterly time series data on real house price index, household debt-to-GDP ratio, and non-financial firm debt-to-GDP ratio from the Bank for International Settlements (BIS) database. Since mortgage interest rate for most countries is not available, we use the three-month interbank rate from the Federal Reserve Economic Data (FRED) as our prime measure of the interest rate. Additionally, as part of our robustness exercise, we include the log of each country's real GDP from FRED in the VAR to control for aggregate demand fluctuations.[1]

We normalize the debt by the size of the economy, as in principle, it is the growth of debt relative to the size of the economy that matters (Mian et al. 2017). The house price index is log transformed prior to use. Table 1 reports the list of countries, and the time averages of their log real house price index, household debt to GDP and firm debt to GDP, as well as the summary cross-sectional mean and standard deviation.

For our second-stage cross-sectional analysis, we use three Gini measures to capture inequality. The first two are net income inequality (after-tax inequality) measures from two different sources. The first is the Standardized World Income Inequality Database (SWIID), which provides harmonized and comprehensive income inequality data across a broad range of countries. We collect this data from Solt (2020); $Gini_{income_{Solt}}$. The second source is the World Inequality Database (WID), which also reports an after-tax Gini coefficient for a broad sample of countries; $Gini_{income_{WID}}$. For our third measure, we use the wealth inequality Gini from the WID; $Gini_{wealth_{WID}}$.[2] For all three measures of Gini indices, we compute time averages over 1995–2018.

In our second-stage analysis, we include fundamental national-level controls: the financial development index, real GDP per capita, the current account-to-GDP ratio, and the age composition of each country. Data for the financial development index

[1] The only country for which quarterly real GDP data is not available is Malaysia. Consequently, we have to drop Malaysia from our sample in this robustness exercise.

[2] Another resource for income inequality data is the Luxembourg Income Study (LIS), which primarily focuses on advanced economies. Additionally, Credit Suisse Global Data provides wealth inequality measures, including the Gini coefficient, but this dataset starts only in 2010. Given these limitations, we rely on SWIID and WID for the Gini measures in our analysis.

Table 1 Summary statistics

No.	Country	$ln(hpi)$	$\frac{hhdebt}{gdp}$	$\frac{firmdebt}{gdp}$
1	Argentina	7.60	0.17	0.05
2	Australia	4.30	0.69	0.88
3	Austria	4.64	0.85	0.49
4	Belgium	4.42	1.23	0.48
5	Brazil	4.35	0.39	0.18
6	Canada	4.37	0.88	0.76
7	Chile	4.70	0.81	0.34
8	China	4.58	1.29	0.31
9	Colombia	4.55	0.33	0.17
10	Czech Republic	4.62	0.58	0.20
11	Denmark	4.49	0.99	1.07
12	Finland	4.37	1.00	0.47
13	France	4.32	1.13	0.43
14	Germany	4.73	0.65	0.61
15	Greece	4.43	0.63	0.59
16	Hongkong	4.48	1.48	0.55
17	Hungary	4.63	0.65	0.20
18	India	4.91	0.68	0.35
19	Indonesia	4.71	0.20	0.13
20	Ireland	4.65	1.73	0.80
21	Israel	4.60	0.72	0.37
22	Italy	4.46	0.68	0.33
23	Japan	4.77	1.10	0.64
24	Korea	4.61	0.90	0.63
25	Luxembourg	4.68	2.09	0.49
26	Malaysia	4.78	0.93	0.62
27	Mexico	4.64	0.20	0.12
28	Netherlands	4.46	1.39	1.01
29	New Zealand	4.40	0.89	0.70
30	Norway	4.28	1.19	0.71
31	Poland	4.51	0.36	0.22
32	Portugal	4.54	1.03	0.70
33	Russia	4.19	0.50	0.09
34	Singapore	4.46	1.09	0.47
35	South Africa	4.61	0.36	0.39
36	Spain	4.33	0.97	0.62
37	Sweden	4.28	1.20	0.62
38	Switzerland	4.59	0.99	1.11
39	Thailand	4.67	0.98	0.62
40	Turkey	4.70	0.33	0.08
41	UK	4.34	0.70	0.76
42	USA	4.64	0.65	0.78
	mean	4.60	0.85	0.50

Table 1 (continued)

No.	Country	$ln(hpi)$	$\frac{hhdebt}{gdp}$	$\frac{firmdebt}{gdp}$
	std. dev.	0.50	0.41	0.27

The table reports the time averages of log of real house price index, $ln(hpi)$; firm debt-to-GDP ratio, $\frac{firmdebt}{gdp}$; and household debt-to-GDP ratio, $\frac{hhdebt}{gdp}$ for the selected sample of countries over the available sample period. All data are taken from the Bank for International Settlements (BIS) database. The last row reports the cross-sectional mean and std. deviation of the variables

are sourced from Svirydzenka (2016), while data on GDP per capita, the current account, and the proportion of the working-age population (15–64) are obtained from the World Bank's World Development Indicators database. Table 2 presents the time averages for each country's inequality measure along with the other national-level variables used in the second-stage regressions. Although inequality is our primary focus, these additional variables are included as controls.

2.2 Empirical Framework

2.2.1 Estimating the Impulse Response of House Price to Household Credit Shocks

We first conduct a country-by-country vector autoregression analysis over sample period 1990Q1-2018Q4. We estimate separate structural vector autoregression (VAR) models for each country and obtain their dynamic house price response to the household credit shock. For each country, consider the specification for a vector of endogenous variables, Z_t, in the following order as in Eq. 1. In an alternate model specification, we also include the log of real GDP in the VAR in Eq. 1, ordering it before log real house price index, to account for aggregate demand changes.

$$Z_t = \begin{bmatrix} ln(hpi) \\ inr \\ \frac{firmdebt}{gdp} \\ \frac{hhdebt}{gdp} \end{bmatrix} \quad (1)$$

where $ln(hpi)$ is log real house price index, inr is the interest rate, $\frac{firmdebt}{gdp}$ is the non-financial firm debt-to-GDP ratio, and $\frac{hhdebt}{gdp}$ is the household debt-to-GDP ratio. The reduced form of the model is given by:

$$Z_t = B(L)Z_{t-1} + \epsilon_t \quad (2)$$

where Z_t is a $m \times 1$ vector that follows the following linear dynamic process:

$$Z_t = B_1 Z_{t-1} + \cdots B_p Z_{t-p} + \epsilon_t, \quad (3)$$

Table 2 Summary Statistics

No.	Country	$Gini_{income_{Solt}}$	$Gini_{income_{WID}}$	$Gini_{wealth_{WID}}$	fdi	$ln(gdp_{pc})$	ca	age_{15-64}
1	Argentina	0.42	0.55	0.77	0.31	9.39	− 0.64	0.63
2	Australia	0.32	0.36	0.72	0.89	10.83	− 4.37	0.67
3	Austria	0.27	0.32	0.79	0.61	10.63	2.37	0.67
4	Belgium	0.26	0.29	0.67	0.63	10.54	1.19	0.66
5	Brazil	0.50	0.65	0.87	0.52	8.95	− 2.33	0.67
6	Canada	0.31	0.38	0.73	0.81	10.60	− 0.81	0.68
7	Chile	0.48	0.67	0.91	0.46	9.28	− 1.47	0.67
8	China	0.41	0.51	0.68	0.48	8.44	3.23	0.71
9	Colombia	0.50	0.66	0.83	0.30	8.51	− 2.87	0.65
10	Czech Republic	0.25	0.28	0.72	0.41	9.62	− 2.47	0.69
11	Denmark	0.24	0.17	0.71	0.67	10.83	4.10	0.66
12	Finland	0.25	0.25	0.74	0.57	10.62	2.72	0.66
13	France	0.30	0.28	0.71	0.73	10.46	0.24	0.64
14	Germany	0.28	0.33	0.74	0.72	10.52	4.00	0.67
15	Greece	0.33	0.39	0.75	0.53	9.88	− 5.98	0.67
16	Hong Kong	0.40	0.55	0.70	0.73	10.44	6.78	0.73
17	Hungary	0.28	0.31	0.75	0.45	9.29	− 3.46	0.68
18	India	0.44	0.56	0.71	0.44	7.00	− 1.35	0.63
19	Indonesia	0.44	0.53	0.76	0.32	7.83	0.33	0.65
20	Ireland	0.31	0.30	0.88	0.72	10.77	− 0.76	0.67
21	Israel	0.36	0.49	0.78	0.53	10.36	1.15	0.62
22	Italy	0.33	0.36	0.71	0.72	10.36	0.25	0.66
23	Japan	0.31	0.43	0.74	0.77	10.40	2.76	0.65
24	Korea	0.33	0.39	0.74	0.77	10.01	2.62	0.72
25	Luxembourg	0.27	0.33	0.76	0.73	11.50	6.38	0.68
26	Malaysia	0.41	0.52	0.78	0.61	8.96	7.49	0.65
27	Mexico	0.47	0.70	0.88	0.34	9.16	− 1.43	0.63
28	Netherlands	0.26	0.27	0.68	0.79	10.65	6.11	0.67
29	New Zealand	0.33	0.35	0.72	0.56	10.45	− 3.74	0.66
30	Norway	0.25	0.24	0.73	0.64	11.17	10.20	0.65
31	Poland	0.30	0.35	0.85	0.40	9.16	− 3.62	0.69
32	Portugal	0.33	0.35	0.75	0.68	9.85	− 5.58	0.66
33	Russia	0.36	0.48	0.77	0.48	8.92	5.76	0.70
34	Singapore	0.39	0.48	0.74	0.74	10.69	18.56	0.76
35	South Africa	0.63	0.60	0.95	0.47	8.61	− 2.41	0.64
36	Spain	0.33	0.33	0.69	0.81	10.12	− 2.43	0.68
37	Sweden	0.26	0.21	0.74	0.73	10.72	4.76	0.64
38	Switzerland	0.29	0.27	0.74	0.94	11.26	8.16	0.68
39	Thailand	0.42	0.61	0.87	0.57	8.44	3.06	0.71
40	Turkey	0.41	0.54	0.83	0.42	9.02	− 3.02	0.66
41	UK	0.33	0.30	0.72	0.85	10.63	− 2.70	0.65
42	USA	0.38	0.47	0.82	0.89	10.85	− 3.19	0.66

Table 2 (continued)

No.	Country	$Gini_{income_{Solt}}$	$Gini_{income_{WID}}$	$Gini_{wealth_{WID}}$	fdi	$ln(gdp_{pc})$	ca	age_{15-64}
	Mean	0.35	0.41	0.77	0.61	9.90	1.13	0.67
	Std. dev.	0.08	0.14	0.07	0.17	1.00	4.81	0.03

Source: Data on income inequality $Gini_{income_{Solt}}$ are taken from Solt (2020). Data on income inequality $Gini_{income_{WID}}$ and wealth inequality $Gini_{wealth_{WID}}$ are taken from World Inequality Database (WID). Data on the financial development index *fdi* are obtained from Svirydzenka (2016) and serve as the fundamental control variable in our second-stage regression. Data on GDP per capita, $ln(gdp_{pc})$; current account, *ca*; and fraction of working-age population, age_{15-64}, are obtained from World Bank database and serve as additional control variables in our second stage regression. Values are time averages from 1995–2018. The last row reports the cross-sectional mean and std. deviation of the variables

$B(L)$ is a lag polynomial defined in terms of the $m \times m$ coefficient matrices B_i and ϵ_t is the one-step ahead prediction error with variance–covariance matrix Σ. The system in Eq. (3) is the reduced form, obtained from a dynamic structural model. Our objective is identifying the structural household credit shock. The structural representation of Eq. (3) in moving average form is given by:

$$Z_t = (I - B(L)L)^{-1} D_z u_t \tag{4}$$

$$Z_t = (D_0 + D_1 L + D_2 L^2 + \cdots) u_t, \tag{5}$$

where u_t is a vector of aggregate structural shocks and $E\left(u_t u_t'\right)$ is normalized to be the identity matrix. The mapping from the reduced form to the structural form imposes restrictions on the covariance structure:

$$\Sigma = E\left(\epsilon_t \epsilon_t'\right) = D_z E\left(u_t u_t'\right) D_z' = D_z D_z' \tag{6}$$

Once we identify the $m \times m$ lower triangular matrix D_z from this mapping, we can derive the dynamic multipliers of interest from Eq. (3) using (4) and (5). Note that we need not fully identify D_z because we are solely interested in recovering the impulse responses to the household credit shock. We therefore impose only three identification restrictions that are sufficient to just identify the structural shocks of interest: we assume that the real house price index, the interest rate, and the firm debt-to-GDP ratio do not respond contemporaneously to the household credit shock. These restrictions are established in the literature; see, for example, Mian et al. (2017), and can be implemented using the standard Cholesky decomposition of the D_z matrix in Eq. (6), given the ordering noted in Eq. 1 (identification using a recursive ordering). In our study, we are primarily interested in the response of the first variable, $ln(hpi)$ to the last structural shock, $\frac{hhdebt}{gdp}$, i.e., the household credit shock.[3]

[3] We check the robustness of our findings by changing the ordering of the variables in the Cholesky decomposition. Our results are robust to the change in the order of the variables. For brevity, we don't report these results in the main paper. But they can be made available upon request.

The transparent, simple, and least restrictive Cholesky decomposition particularly appeals in our study because it is based on a minimalist set of identification restrictions which makes it both a) consistent with a wide range of theoretical models and b) feasible to implement for a wide range of countries without any data challenges.[4]

We estimate VAR models for each country in two lags of the levels of the variables and add a constant.[5] We compute impulse responses for each country over horizon h to both a) a unit household credit shock to compare responses across countries to a shock of a common magnitude and b) a standard deviation household credit shock to allow for potential differences in the scale of the shock across countries.[6]

A natural question is whether the structural household credit shock, identified in Eq. 6, is demand or supply driven? Although we do not attempt at this stage to distinguish between a credit demand and a credit supply shock, the response of the interest rate to the household credit shock can provide supporting evidence for the type of shock per se (Mian et al. 2017). Mian et al. (2017) argue that an exogenous increase in the supply of household credit will be associated with *a decline* in the interest rate as opposed to an increase. This implies that if the credit shock is a supply-driven shock, then the interest rate response to the credit shock should be *negative*.

We therefore ask the following question. For the sample of 42 countries, on average, what is the impact of the household credit shock on the interest rate over the study period? We are particularly interested in the direction of the interest rate response. To do so, we first estimate the country-by-country VAR using OLS and obtain the impulse response functions of the interest rate variable to the household credit shock by employing the Cholesky decomposition of the covariance matrix of the structural VAR residual. We then average out the cross-country interest rate response to the household credit shock at each forecast horizon.[7] We find that the interest rate response for the countries, on average, is largely negative over the first 18 quarters (see Appendix Figure A1). We thus find supporting evidence that the household credit shock in our sample period is largely a credit supply shock.

2.2.2 Cross-Country Variation in the House Price Response and the Role of Inequality

What role does income inequality play in explaining the estimated house price responses to household credit shocks (obtained from the VAR in the previous

[4] We also check the robustness of our findings by computing impulse responses using the Jorda LP direct inference approach in Appendix. Our results remain robust to using the Jorda LP method.

[5] Following Mian et al. (2017) and Bahadir et al. (2020), we have chosen to maintain our specification in levels (and not in first differences) because this is least restrictive and more meaningful, especially when we attempt to explain cross-country variation in the next stage. Also, we use 2 lags to account for the relatively short time period of data for some countries in our sample.

[6] We estimate impulse responses for each country with a one-standard deviation confidence error band, computed using standard Monte Carlo integration methods. However, so as not to clutter the graphs, the confidence error bands are not shown in the baseline results but can be made available upon request.

[7] In essence, this is tantamount to estimating a heterogeneous dynamic panel VAR using the mean group estimate of Pesaran and Smith (1995), Pesaran et al. (1996)

subsection)? In this subsection, we attempt to explain the cross-country variation in house price response to a household credit shock, by focusing on inequality. We do so by estimating a stage II cross-sectional regression equation of the following form:

$$y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \epsilon_i \tag{7}$$

for countries $i = 1, \dots, 31$, where the dependent variable y_i is a summary measure of each country's dynamic house price response to household credit shocks estimated above in the first-stage VAR. Because we are interested in how inequality impacts the sensitivity of the real house price response to household credit shocks, we focus on three summary measures of the estimated real house price response, i.e, the dependent variable in our regression Eq. 7. We run cross-country regressions separately for the following three measures of the dependent variable, y_i: a) the maximum response of real house price index over the first 18 quarters, hpi_{max}, b) the average response of real house price over the first 18 quarters, $\bar{hpi}_{q1}^{q18}$ and c) the cumulative response of real house price over the first 18 quarters, $\sum_{q1}^{q18} hpi$.

The explanatory variable z_{i1} is a measure of the country $i's$ average financial development index over 1995-2018 and serves as the fundamental control variable, while z_{i2} is the country $i's$ average inequality index over 1995-2018. As explained in Sect. 2.1, we alternate between three Gini measures to capture the country's inequality index a) income inequality $Gini_{income_{Solt}}$ taken from (Solt 2020) income inequality $Gini_{income_{WID}}$ taken from World Inequality Database (WID), and c) wealth inequality $Gini_{wealth_{WID}}$ taken from World Inequality Database (WID). In Eq. 7, β_1 and β_2 measure the marginal effects of financial development and inequality index on the estimated dynamic house price response to the household credit shock; our primary focus is β_2.[8] We further test the robustness of our findings using the following additional national-level controls in Eq. 7: GDP per capita, current account, and age composition.

[8] The primary advantage of using a two-step approach to understanding cross-sectional variation in the dynamic house price response is appealing in our study as it does not require us to impose the very restrictive constraint that parameters are identical across countries, as in conventional panel data methods (Lastrapes and Douglas McMillin 2004; Bahadir et al. 2020). Note that, although in a two-step approach the impulse responses for the dependent variable (log real house price index) are generated from the first-stage VAR regression, any measurement and specification error in the first stage will be captured by the cross-sectional regression error term in the second-stage and will lead to biased estimates only to the extent that measurement error is correlated with the primary explanatory variables. We do not foresee any obvious reason for such a correlation to exist. In addition, we also control for any heteroskedasticity in the regression error term stemming from the estimated dependent variable, by using heteroskedastic-robust standard errors.

3 Empirical Results

3.1 Country-by-Country Analysis

3.1.1 First-Stage Results

We present the impulse response functions derived from our baseline VAR model for each country in Figs. 1, 2. While Fig. 1 reports the response of log real house price to a unit household credit shock, Fig. 2 reports the same to a std. deviation household credit shock, over an 18-quarter horizon. It is important to note in Fig. 1 that, by construction, the initial effect of a one-unit household credit shock will increase the household credit ratio by one percentage point on impact for each country (red curve). However, the estimated dynamics of the response over the remaining horizons are determined by the data.

Figure 1 shows that in many countries the household credit ratio consistently rises in the short to medium term following the shock, although the level of persistence differs significantly among nations. Countries such as Canada, Germany, and Denmark observe household credit as a proportion of GDP well above its initial steady state for up to 15 quarters after the shock. Conversely, in countries such as the Czech Republic, Turkey, and Poland, the household credit ratio initially increases but then converges to its initial steady-state level soon after the shock.

Figure 1 reveals significant heterogeneity in the responses of real house price to a household credit shock across the sample of countries. An evident pattern, however, is that an increase in the household credit to GDP in high-inequality countries leads to a relatively larger house price response in the short run. For instance, countries with relatively higher income inequality such as the USA, UK, Australia, and Spain demonstrate significant increases in the real house price index following a unit household credit shock. Specifically, the responses range from 1.45 percent in Australia, 1 percent in Spain, to 2.22, and 2 percent in the USA and UK, respectively. In contrast, in countries with low levels of income inequality such as Japan and Denmark, the response of house prices to a positive household credit shock is notably lower, around 0.44 and 0.20, respectively. While we do not attempt to investigate all possible sources of the cross-country heterogeneity in the house price response, we do observe certain patterns in the VARs that point to income inequality as a potential factor in influencing the response of real house price to a household credit shock.

Another potential explanation for the cross-country differences in real house price responses lies in the substantial variation in levels of financial development across countries. Some countries exhibit notably high household debt-to-GDP ratios, which are indicative of the development level of the financial institutions. Financial development levels may affect the relationship between household credit shocks and house prices in two different ways. On the one hand, higher levels of financial development reduce the number of credit-constrained households, potentially mitigating the impact of a household credit shock. When households

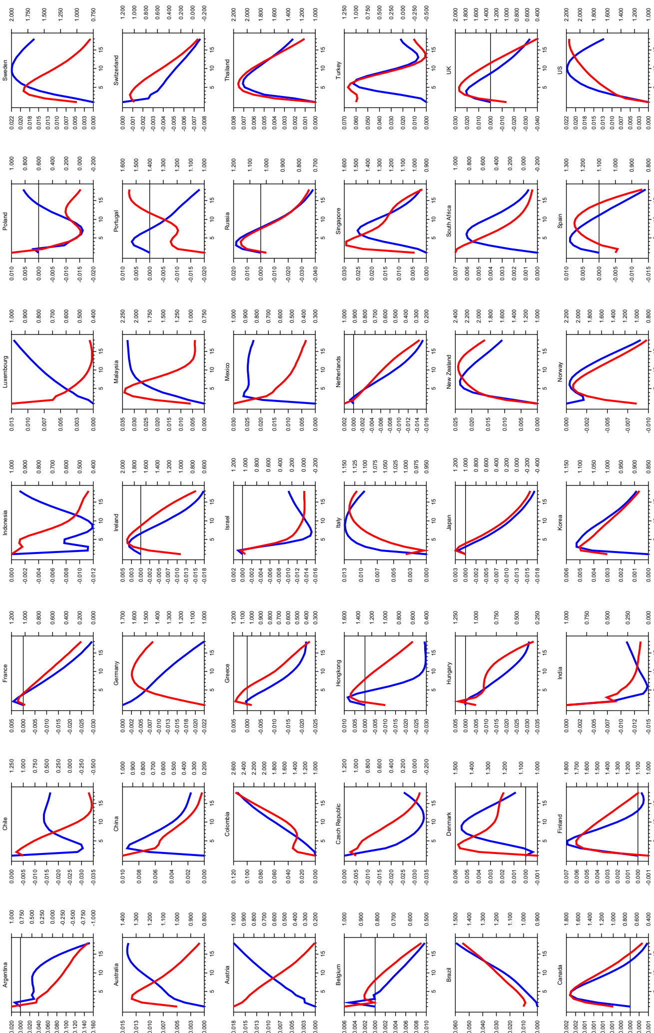

Fig. 1 Impulse responses for real house price to a unit household credit shock from baseline VAR. *Note:* Log real house price response, blue, left scale; unit household credit shock, red, right scale. Forecast horizons on horizontal axis range from 0 to 18. (Color figure online)

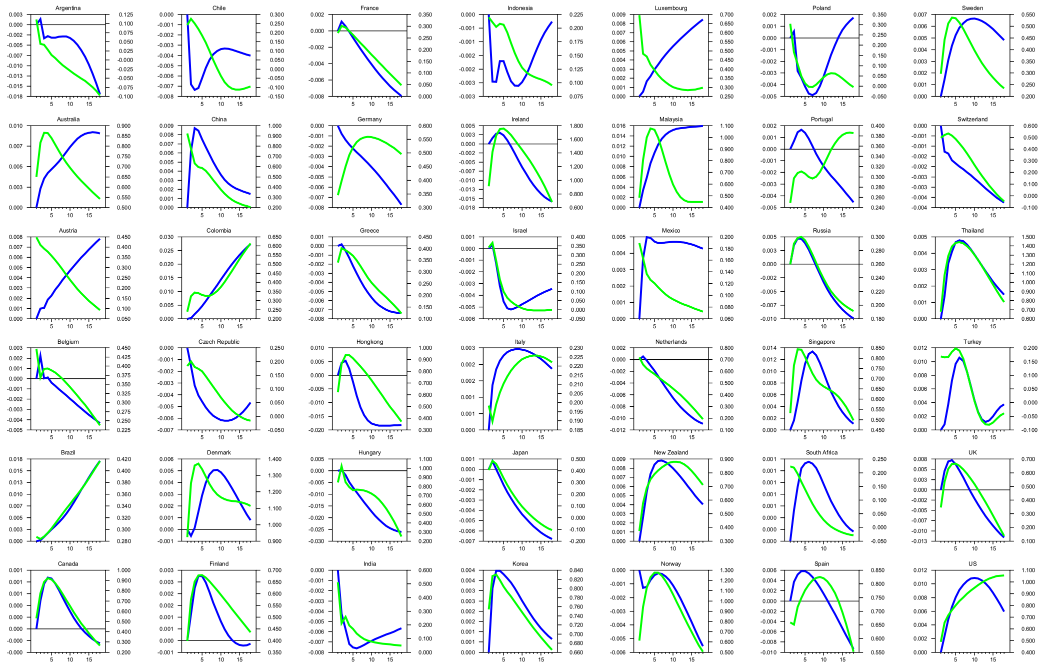

Fig. 2 Impulse responses for real house price to a std. deviation household credit shock from baseline VAR. *Note* Log real house price response, blue, left scale; one std. deviation household credit shock, green, right scale. Forecast horizons on horizontal axis range from 0 to 18. (Color figure online)

are not credit constrained, household credit shocks do not have large effects on their consumption and housing decisions. On the other hand, in countries where access to credit is more accessible, an increase in household credit may affect a larger portion of the population. The net effect depends on the relative strength of these two opposing effects.

We focus on a unit household credit shock in our primary first-stage outcome because it allows for a more straightforward comparison between countries with varying levels of household debt. The response of house price may differ if the size of the shocks vary across countries. For example, in the USA, the household debt-to-GDP ratio stands at 77 percent, and a one-unit shock implies an increase in the ratio to 78 percent. While this increment might not be significant for the USA, a one-unit increase in Mexico, for instance, where the household debt-to-GDP ratio is much lower at 12 percent, can be substantial. Examining the impact of a one-standard deviation shock does not change the direction of the response but only the magnitudes.

We use the estimated real house price response obtained from our first-stage VAR as the dependent variable in our second-stage cross-sectional regression and analyze the role played by income inequality in explaining the sensitivity of the house price response to the household credit shock. We do so for the estimated real house price response to both a) a unit and b) a standard deviation household credit shock. We also test the robustness of our findings by analyzing the role of wealth inequality in explaining the strength of the relationship between household debt and house prices. We first present our second stage analysis below for income inequality, followed by wealth inequality.

3.1.2 Second-Stage Results

Income Inequality

In the second stage, we regress the estimated real house price response to the household credit shock obtained from the first-stage VAR analysis on our income inequality measure after controlling for the degree of financial development. Tables 3 and 4 show the key findings from our second-stage analysis. In both tables, our primary emphasis is β_2, which represents the marginal effect of income inequality on the estimated real house price response. We find compelling evidence that in countries with higher levels of income inequality, both unit and one-standard deviation shocks to household credit are linked to more pronounced peak responses in the real house price index over an 18-quarter period. This suggests that income inequality amplifies the impact of household credit shocks on house prices, leading to more significant fluctuations in the real estate market. Also note that the financial development index is insignificant in the majority of the regressions.

Furthermore, we find that average house price responses and cumulative house price responses over 18 quarters are notably higher in countries characterized by greater income inequality. These measures provide a more comprehensive understanding of house price dynamics, encompassing both short-term fluctuations and longer-term trends influenced by household credit shocks. Overall, these findings underscore the role of income inequality in shaping the sensitivity of house prices to

Table 3 Cross-sectional regression: baseline results using average income inequality index from Solt (2020)

y	β_0		β_1		β_2		R^2	
	Unit	SD	Unit	SD	Unit	SD	Unit	SD
$y_i = hpi_{max}$	−0.010	−0.007	−0.012	0.004	0.091*	0.027*	0.18	0.13
	(0.583)	(0.207)	(0.503)	(0.378)	(0.082)	(0.069)		
$y_i = \bar{hpi}_{q1}^{q18}$	−0.036	−0.012	0.019	0.007	0.071**	0.024*	0.10	0.10
	(0.027)	(0.061)	(0.286)	(0.213)	(0.030)	(0.051)		
$y_i = \sum_{q1}^{q18} hpi$	−0.659	−0.227	0.351	0.127	1.288**	0.433*	0.10	0.10
	(0.027)	(0.061)	(0.286)	(0.213)	(0.030)	(0.051)		

Notes: Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \epsilon_i$, where y_i is a summary measure of each country's dynamic response of real house price index to a household credit shock in country i estimated from our baseline recursive VAR model; z_{i1} is the average financial development index (*fdi*), and z_{i2} is the average income inequality index ($Gini_{income_{Solt}}$) from Solt (2020). hpi_{max} indicates the peak response of real house price index over 18 quarters. $\bar{hpi}_{q1}^{q18}$ and $\sum_{q1}^{q18} hpi$ indicate, respectively, the average house price response and the cumulative house price response over 18 quarters. Columns indicate unit shock or standard deviation shock. p-values based on robust standard errors in parentheses

Table 4 Cross-sectional regression: results using average income inequality index from WID

y	β_0		β_1		β_2		R^2	
	Unit	SD	Unit	SD	Unit	SD	Unit	SD
$y_i = hpi_{max}$	−0.004	−0.006	−0.009	0.005	0.058**	0.018***	0.19	0.14
	(0.716)	(0.127)	(0.618)	(0.263)	(0.018)	(0.009)		
$y_i = \bar{hpi}_{q1}^{q18}$	−0.028	−0.010	0.020	0.007	0.041*	0.013	0.08	0.08
	(0.074)	(0.133)	(0.287)	(0.255)	(0.060)	(0.103)		
$y_i = \sum_{q1}^{q18} hpi$	−0.518	−0.181	0.360	0.131	0.737*	0.249	0.08	0.08
	(0.074)	(0.133)	(0.287)	(0.255)	(0.060)	(0.103)		

Notes: Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \epsilon_i$, where y_i is a summary measure of each country's dynamic response of real house price index to a household credit shock in country i estimated from our baseline recursive VAR model; z_{i1} is the average financial development index (*fdi*); and z_{i2} is the average income inequality index ($Gini_{income_{WID}}$) from WID. hpi_{max} indicates the peak response of real house price index over 18 quarters. $\bar{hpi}_{q1}^{q18}$ and $\sum_{q1}^{q18} hpi$ indicate, respectively, the average house price response and the cumulative house price response over 18 quarters. Columns indicate unit shock or standard deviation shock. p-values based on robust standard errors in parentheses

household credit shocks, highlighting the importance of considering distributional factors in analyzing real estate market dynamics.

The findings presented in Table 3 demonstrate both statistical significance and economic relevance. According to our estimates, a one-standard deviation increase in income Gini, i.e., $Gini_{income_{Solt}}$ (i.e., an increase by 0.08 percentage points), corresponds to a 0.73 percentage point increase (.08 × .091) in the response of real house price to a positive household credit shock (unit shock) at its peak. To contextualize, if the income Gini in the USA according to Solt (2020) were to rise from 0.38 to 0.46, the peak response of real house price would be expected to reach to 2.96 percent from 2.23 percent. Examining the average response of real house price to a household credit shock over 18 quarters, our estimates indicate that a one-standard deviation increase in income inequality would lead to a 0.57 percentage point increase in the house price response, which would elevate real house price to 2.2 percent from 1.63 percent.

Table 5 Cross-sectional regression: results using initial value of income inequality from Solt (2020)

y	β_0		β_1		β_2		R^2	
	Unit	SD	Unit	SD	Unit	SD	Unit	SD
$y_i = hpi_{max}$	− 0.013	− 0.007	− 0.009	0.004	0.094**	0.026**	0.21	0.13
	(0.421)	(0.142)	(0.607)	(0.331)	(0.031)	(0.032)		
$y_i = \bar{hpi}_{q1}^{q18}$	− 0.034	− 0.011	0.019	0.006	0.065**	0.021**	0.10	0.10
	(0.021)	(0.060)	(0.271)	(0.221)	(0.025)	(0.043)		
$y_i = \sum_{q1}^{q18} hpi$	− 0.621	− 0.207	0.355	0.125	1.183**	0.384**	0.10	0.09
	(0.021)	(0.060)	(0.271)	(0.221)	(0.025)	(0.043)		

Notes: Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \epsilon_i$, where y_i is a summary measure of each country's dynamic response of real house price index to a household credit shock in country i estimated from our baseline recursive VAR model; z_{i1} is the average financial development index (*fdi*); and z_{i2} is the initial value of income inequality measure ($Gini_{income_{Solt}}$) from Solt (2020). hpi_{max} indicates the peak response of real house price index over 18 quarters. $\bar{hpi}_{q1}^{q18}$ and $\sum_{q1}^{q18} hpi$ indicate, respectively, the average house price response and the cumulative house price response over 18 quarters. Columns indicate unit shock or standard deviation shock. *p*-values based on robust standard errors in parentheses

Table 6 Cross-sectional regression: results using initial value of income inequality from WID

y	β_0		β_1		β_2		R^2	
	Unit	SD	Unit	SD	Unit	SD	Unit	SD
$y_i = hpi_{max}$	− 0.007	− 0.006	− 0.006	0.006	0.061**	0.018***	0.22	0.16
	(0.537)	(0.085)	(0.704)	(0.186)	(0.017)	(0.009)		
$y_i = \bar{hpi}_{q1}^{q18}$	− 0.027	− 0.010	0.019	0.008	0.038*	0.015*	0.08	0.11
	(0.045)	(0.077)	(0.241)	(0.176)	(0.075)	(0.059)		
$y_i = \sum_{q1}^{q18} hpi$	− 0.488	− 0.196	0.357	0.147	0.686*	0.270*	0.08	0.11
	(0.045)	(0.077)	(0.241)	(0.176)	(0.075)	(0.059)		

Notes: Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \epsilon_i$, where y_i is a summary measure of each country's dynamic response of real house price index to a household credit shock in country i estimated from our baseline recursive VAR model; z_{i1} is the average financial development index (*fdi*); and z_{i2} is the initial value of income inequality index ($Gini_{income_{WID}}$) from WID. hpi_{max} indicates the peak response of real house price index over 18 quarters. $\bar{hpi}_{q1}^{q18}$ and $\sum_{q1}^{q18} hpi$ indicate, respectively, the average house price response and the cumulative house price response over 18 quarters. Columns indicate unit shock or standard deviation shock. *p*-values based on robust standard errors in parentheses

Table 7 Cross-sectional regression: robustness to other control variables using Solt (2020) Inequality data

$z_{i2} = Gini_{income_{Solt}}$	$y_i = hpi_{max}$		$y_i = \bar{hpi}_{q1}^{q18}$		$y_i = \sum_{q1}^{q18} hpi$	
	β_2	R^2	β_2	R^2	β_2	R^2
A. Unit Shock						
z_{i3}= $ln(gdp_{pc})$	0.125*	0.21	0.083*	0.10	1.504*	0.10
	(0.079)		(0.075)		(0.075)	
z_{i3}= curr. acct.	0.092*	0.18	0.072**	0.10	1.296**	0.08
	(0.081)		(0.029)		(0.029)	
z_{i3}= age (15–64)	0.092*	0.18	0.071**	0.10	1.287**	0.09
	(0.081)		(0.030)		(0.030)	
B. Standard Deviation Shock						
z_{i3}= $ln(gdp_{pc})$	0.034*	0.15	0.030*	0.11	0.555*	0.14
	(0.085)		(0.058)		(0.058)	
z_{i3}= curr. acct.	0.028*	0.14	0.024**	0.10	0.441**	0.11
	(0.060)		(0.048)		(0.048)	
z_{i3}= age (15–64)	0.027*	0.16	0.024*	0.10	0.433*	0.10
	(0.057)		(0.052)		(0.052)	

Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \beta_3 z_{i3} + \epsilon_i$, where y_i is a summary measure of each country's dynamic response of real house price index to a household credit shock in country i estimated from a recursive VAR, z_{i1} is the average financial development index (fdi), z_{i2} is the average income inequality index ($Gini_{income_{Solt}}$) from Solt (2020), and z_{i3} is the control variable. p-values based on robust standard errors in parenthesis

The "std. dev." column in Table 3 presents the second-stage cross-sectional regression results, using the estimated real house price response to a one-standard deviation household credit shock from the VAR in the first stage.[9] Our primary focus is β_2, the marginal effect of income inequality on the real house price response, which is also both statistically significant and economically meaningful. For instance, in the USA the peak response of real house price to a one-standard deviation household credit shock is 1.09 percent. Hence, if income inequality were to jump up by one standard deviation (i.e, by 0.08 percentage points), then the peak response of real house price would increase by .22 percentage points ($.08 \times .027$). This translates to an increase in the peak real house price response to 1.31 percent from 1.09 percent.

When using the Gini coefficient from the WID, i.e., $Gini_{income_{WID}}$, we get qualitatively similar results. Table 4 shows that a one-standard deviation increase in $Gini_{income_{WID}}$ (i.e., 0.14 percentage points) leads to a 0.81 percentage point increase in the response of the peak real house price to a one-unit household credit shock and a 0.25 percentage point increase in the response of the peak real house price to a one-standard deviation household credit shock.

[9] The coefficient magnitudes differ from the "unit" column, as the magnitude of the household credit shock varies across countries.

Table 8 Cross-sectional regression: robustness to other control variables using WID inequality data

$z_{i2} = Gini_{income_{WID}}$	$y_i = hpi_{max}$		$y_i = \bar{hpi}_{q1}^{q18}$		$y_i = \sum_{q1}^{q18} hpi$	
	β_2	R^2	β_2	R^2	β_2	R^2
A. Unit Shock						
z_{i3}= $ln(gdp_{pc})$	0.075**	0.21	0.044	0.08	0.802	0.08
	(0.021)		(0.129)		(0.129)	
z_{i3}= curr. acct.	0.059**	0.18	0.040*	0.08	0.737*	0.08
	(0.019)		(0.060)		(0.060)	
z_{i3}= age (15–64)	0.059**	0.18	0.042**	0.08	0.755**	0.08
	(0.017)		(0.048)		(0.048)	
B. Standard Deviation Shock						
z_{i3}= $ln(gdp_{pc})$	0.021**	0.16	0.016	0.09	0.298	0.09
	(0.016)		(0.125)		(0.125)	
z_{i3}= curr. acct.	0.018**	0.15	0.013	0.09	0.248	0.09
	(0.010)		(0.102)		(0.102)	
z_{i3}= age (15–64)	0.017**	0.16	0.014*	0.09	0.255*	0.09
	(0.015)		(0.084)		(0.084)	

Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \beta_3 z_{i3} + \epsilon_i$, where y_i is a summary measure of each country's dynamic response of real house price index to a household credit shock in country i estimated from a recursive VAR, z_{i1} is the average financial development index (*fdi*), z_{i2} is the average income inequality index ($Gini_{income_{WID}}$) from WID, and z_{i3} is the control variable. p-values based on robust standard errors in parenthesis

Table 9 Cross-sectional regression: baseline results using average income inequality index from Solt (2020) and including real GDP in first-stage VAR

y	β_0		β_1		β_2		R^2	
	Unit	SD	Unit	SD	Unit	SD	Unit	SD
$y_i = hpi_{max}$	− 0.003	− 0.004	− 0.004	0.006	0.051**	0.015*	0.13	0.10
	(0.791)	(0.225)	(0.700)	(0.090)	(0.043)	(0.057)		
$y_i = \bar{hpi}_{q1}^{q18}$	− 0.049	− 0.014	0.041	0.012	0.065***	0.021***	0.11	0.21
	(0.014)	(0.003)	(0.112)	(0.008)	(0.005)	(0.008)		
$y_i = \sum_{q1}^{q18} hpi$	− 0.895	− 0.266	0.755	0.214	1.168***	0.391***	0.11	0.20
	(0.014)	(0.003)	(0.112)	(0.008)	(0.005)	(0.008)		

Notes: Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \epsilon_i$, where y_i is a summary measure of each country's dynamic response of real house price index to a household credit shock in country i estimated from a recursive VAR model including real GDP; z_{i1} is the average financial development index (*fdi*), z_{i2} is the average income inequality index ($Gini_{income_{Solt}}$) from Solt (2020). hpi_{max} indicates the peak response of real house price index over 18 quarters. $\bar{hpi}_{q1}^{q18}$ and $\sum_{q1}^{q18} hpi$ indicate, respectively, the average house price response and the cumulative house price response over 18 quarters. Columns indicate unit shock or standard deviation shock. p-values based on robust standard errors in parentheses

Table 10 Cross-sectional regression: results using average income inequality index from WID, and including real GDP in first-stage VAR

y	β_0		β_1		β_2		R^2	
	Unit	SD	Unit	SD	Unit	SD	Unit	SD
$y_i = hpi_{max}$	0.000	− 0.004	− 0.003	0.006	0.032***	0.009***	0.13	0.11
	(0.983)	(0.196)	(0.785)	(0.063)	(0.009)	(0.014)		
$y_i = \bar{hpi}_{q1}^{q18}$	− 0.042	− 0.012	0.042	0.012	0.036**	0.013***	0.10	0.19
	(0.029)	(0.004)	(0.106)	(0.007)	(0.018)	(0.010)		
$y_i = \sum_{q1}^{q18} hpi$	− 0.760	− 0.233	0.759	0.223	0.658**	0.239***	0.09	0.19
	(0.029)	(0.004)	(0.106)	(0.007)	(0.018)	(0.010)		

Notes: Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \epsilon_i$, where y_i is a summary measure of each country's dynamic response of real house price index to a household credit shock in country i estimated from a recursive VAR model including real GDP, z_{i1} is the average financial development index (*fdi*), and z_{i2} is the average income inequality index ($Gini_{income_{WID}}$) from WID. hpi_{max} indicates the peak response of real house price index over 18 quarters. $\bar{hpi}_{q1}^{q18}$ and $\sum_{q1}^{q18} hpi$ indicate, respectively, the average house price response and the cumulative house price response over 18 quarters. Columns indicate unit shock or standard deviation shock. p-values based on robust standard errors in parentheses

Table 11 Cross-sectional regression: results using average wealth inequality index from WID

y	β_0		β_1		β_2		R^2	
	Unit	SD	Unit	SD	Unit	SD	Unit	SD
$y_i = hpi_{max}$	− 0.027	− 0.008	− 0.023	0.000	0.073	0.017	0.12	0.04
	(0.493)	(0.467)	(0.339)	(0.937)	(0.138)	(0.215)		
$y_i = \bar{hpi}_{q1}^{q18}$	− 0.072	− 0.021	0.015	0.004	0.083**	0.024*	0.08	0.06
	(0.050)	(0.106)	(0.472)	(0.395)	(0.038)	(0.098)		
$y_i = \sum_{q1}^{q18} hpi$	− 1.309	− 0.381	0.272	0.089	1.502**	0.430*	0.08	0.06
	(0.050)	(0.106)	(0.472)	(0.395)	(0.038)	(0.098)		

Notes: Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \epsilon_i$, where y_i is a summary measure of each country's dynamic response of real house price index to a household credit shock in country i estimated from our baseline recursive VAR model, z_{i1} is the average financial development index (*fdi*), and z_{i2} is the average wealth inequality index ($Gini_{wealth_{WID}}$) from WID. hpi_{max} indicates the peak response of real house price index over 18 quarters. $\bar{hpi}_{q1}^{q18}$ and $\sum_{q1}^{q18} hpi$ indicate, respectively, the average house price response and the cumulative house price response over 18 quarters. Columns indicate unit shock or standard deviation shock. p-values based on robust standard errors in parentheses

Our findings suggest that income inequality amplifies the sensitivity of the real house price response to household credit shocks. A limitation of our approach, however, is that we treat inequality as exogenous, assuming that household credit shocks do not affect income or wealth distribution. While some interaction between distributional variables and credit is possible, we argue that inequality is relatively persistent and does not change substantially over short periods.

To address this potential endogeneity concern, we also estimate our regressions using the initial value of income inequality instead of the average value. By using the initial level of inequality from the start of the sample period, we reduce the risk of reverse causality and simultaneity bias. This method ensures that the observed relationship between house prices and inequality is not impacted by changes in inequality due to credit expansions over the sample period, thereby providing a more robust estimation. Tables 5 and 6 demonstrate that our results remain consistent when using initial values of income inequality for both inequality measures, i.e., $Gini_{income_{Solt}}$ and $Gini_{income_{WID}}$; in fact, the coefficients are slightly larger.

To evaluate the robustness of our results concerning any potential omitted variable bias, we also control for GDP per capita, current account balance-to-GDP ratio, and age distribution in the second stage regressions. We include these variables in our second stage analysis as they may be potential factors influencing the response of house prices to household credit shocks. We note in Tables 7 and 8 that our main findings remain robust even after accounting for other potential factors that could influence real house prices. β_2 which captures the impact of income inequality on real house prices is positive and statistically significant. Even after controlling for GDP per capita, current account balance-to-GDP ratio, and age distribution, income inequality appears to play a significant role in amplifying the response of real house price to household credit shocks. The magnitude of the effects also remains consistent with the baseline specification.

Finally, we present the results in Tables 9 and 10, where real GDP is included in the first-stage VAR to account for additional sources that could influence household debt levels. For example, a positive news shock about future productivity or a shock

Table 12 Cross-sectional regression: results using initial value of wealth inequality from WID

y	β_0		β_1		β_2		R^2	
	Unit	SD	Unit	SD	Unit	SD	Unit	SD
$y_i = hpi_{max}$	− 0.018	− 0.004	− 0.024	− 0.000	0.062*	0.012	0.13	0.04
	(0.474)	(0.589)	(0.271)	(0.998)	(0.098)	(0.243)		
$y_i = \bar{hpi}_{q1}^{q18}$	− 0.059	− 0.018	0.013	0.004	0.068**	0.021*	0.10	0.09
	(0.038)	(0.107)	(0.496)	(0.394)	(0.033)	(0.097)		
$y_i = \sum_{q1}^{q18} hpi$	− 1.063	− 0.338	0.243	0.086	1.226**	0.383*	0.10	0.09
	(0.038)	(0.107)	(0.496)	(0.394)	(0.033)	(0.097)		

Notes: Estimates from $y_i = \beta_0 + \beta_1 z_{i1} + \beta_2 z_{i2} + \epsilon_i$, where y_i is a summary measure of each country's dynamic response of real house price index to a household credit shock in country i estimated from our baseline recursive VAR model, z_{i1} is the average financial development index (*fdi*), and z_{i2} is the initial value of wealth inequality index ($Gini_{wealth_{WID}}$) from WID. hpi_{max} indicates the peak response of real house price index over 18 quarters. $\bar{hpi}_{q1}^{q18}$ and $\sum_{q1}^{q18} hpi$ indicate, respectively, the average house price response and the cumulative house price response over 18 quarters. Columns indicate unit shock or standard deviation shock. p-values based on robust standard errors in parentheses

Table 13 Single-equation regression: results from a panel fixed effects regression

	(1) $\Delta_3 HP_{it}$	(2) $\Delta_3 HP_{it}$	(3) $\Delta_3 HP_{it}$	(4) $\Delta_3 HP_{it}$	(5) $\Delta_3 HP_{it}$	(6) $\Delta_3 HP_{it}$
$\Delta_3 HH_{it-1}$	0.004**	− 0.020**	− 0.008	0.003	− 0.021**	− 0.008
	(0.002)	(0.010)	(0.005)	(0.002)	(0.009)	(0.005)
$\Delta_3 HH_{it-1}$*$Gini_{income_{Solt}}$		0.075**			0.075**	
		(0.000)			(0.000)	
$\Delta_3 HH_{it-1}$*$Gini_{income_{WID}}$			0.033**			0.033**
			(0.014)			(0.015)
Constant	0.221**	0.202**	0.204**	0.281***	0.256***	0.262***
	(0.085)	(0.086)	(0.086)	(0.091)	(0.091)	(0.092)
N	696	696	696	688	688	688
Adjusted R-squared	0.335	0.350	0.348	0.349	0.362	0.360

Notes: Estimates from $\Delta_3 HP_{it} = \alpha_i + \beta_H \Delta_3 HH_{it-1} + \beta_F \Delta_3 FC_{it-1} + \beta_D \Delta_3 HH_{it-1} * D_{it-1} + X_{i,t-1} + \epsilon_{it}$, where $\Delta_3 HP_{it}$ is the change in log of real house price index from $t-3$ to t and $\Delta_3 HH_{it-1}$ and $\Delta_3 FC_{it-1}$ are the percentage change in household and firm debt-to-GDP ratios from $t-4$ to $t-1$, respectively. Control variables include 3-month interest rates and household credit levels in Columns (1) to (3). In Columns (4) to (6), we additionally control for the percentage change in firm debt relative to GDP and the level of firm debt to GDP. All regressions include time and country fixed effects. *p*-values based on dually clustered robust standard errors in parentheses

to anticipated income may lead to increased borrowing and house prices, representing an endogenous demand-driven credit shock, rather than the one originating purely from an exogenous increase in credit supply. Including real GDP in the first-stage VAR accounts for aggregate demand-driven shocks and allows us to isolate the effects of the exogenous household credit supply shock, which is our primary focus. Our findings remain robust even with the inclusion of real GDP, and this adjustment enhances the precision of our estimates.

Wealth Inequality

We examine the role of wealth inequality in Tables 11 and 12, and these results align closely with those observed for income inequality. Specifically, we find that higher levels of wealth inequality amplify the sensitivity of house prices to household credit shocks, similar to the amplification observed as a result of income inequality. This consistency underscores the broader influence of inequality—whether in income or wealth—on economic dynamics, particularly in the housing market. Wealth inequality, like income inequality, appears to exacerbate the transmission of credit shocks to house prices, suggesting that both forms of inequality may contribute to an environment where credit expansions have a more pronounced impact on housing markets.

3.2 Alternative Specifications

3.2.1 Single Equation Estimation

To further investigate the role of income inequality in the relationship between house prices and household credit, we estimate the following model using annual data:

$$\Delta_3 HP_{it} = \alpha_i + \beta_1 \Delta_3 HH_{it-1} + \beta_2 \Delta_3 FC_{it-1} + \beta_3 \Delta_3 HH_{it-1} * Gini_{it-4} + X_{i,t-1} L + \epsilon_{it} \tag{8}$$

where $\Delta_3 HP_{it}$ is the change in log of real house price index from $t-3$ to t and $\Delta_3 HH_{it-1}$ and $\Delta_3 FC_{it-1}$ are the percentage change in household and firm debt-to-GDP ratios from $t-4$ to $t-1$, respectively. The chosen lag structure follows Mian et al. (2017) and aims to capture the short-run impact of house credit expansions on house prices.

We are interested in β_3, which is the coefficient of the interaction term between the percentage change in household credit to GDP ratio and the inequality measures. The vector $X_{i,t-1}$ includes additional control variables such as the interest rate using the same lag structure as credit variables and the level of household and firm credit at time $t-1$. We include interest rates and the debt-to-GDP ratio to maintain consistency with our country-by-country analysis. The debt-to-GDP ratio is particularly relevant as it reflects both the degree of financial development and the level of indebtedness within the economy. All specifications control for year and country fixed effects. We dually cluster standard errors on country and year to account for within-country correlation and contemporaneous cross-country correlation in the error term. In particular, this accounts for the within-country correlation induced by overlapping observations.

Column (1) in Table 13 is our baseline specification that excludes the change in firm credit to GDP ratio and includes only the interest rate and the level of household credit GDP ratio as control variables. Our regression results confirm the positive association between household credit and house prices.

In Columns (2) and (3), we include an interaction term using both the inequality measures, i.e., $Gini_{income_{Solt}}$ and $Gini_{income_{WID}}$. To align with our country-by-country analysis, we use the sample averages for $Gini_{income_{Solt}}$ and $Gini_{income_{WID}}$, when interacting them with changes in credit. Our main coefficient of interest, β_3, is expected to be positive, indicating that the correlation between house prices and household credit expansions strengthens in higher-inequality countries. Our estimates confirm this hypothesis, as the interaction term is positive and significant at the 5 percent level for both $Gini_{income_{Solt}}$ and $Gini_{income_{WID}}$.

The main effect in Column (2) is negative and significant, but it remains nonnegative across the range of inequality. With the Gini coefficient ranging from 0.24 to 0.63, a household credit expansion has an insignificant impact on house prices at very low levels of inequality. As inequality rises, however, the effect shifts to positive and becomes statistically significant, consistent with our country-by-country findings. This pattern confirms that higher inequality amplifies the effect of household credit on house prices, while low inequality weakens it without inverting the

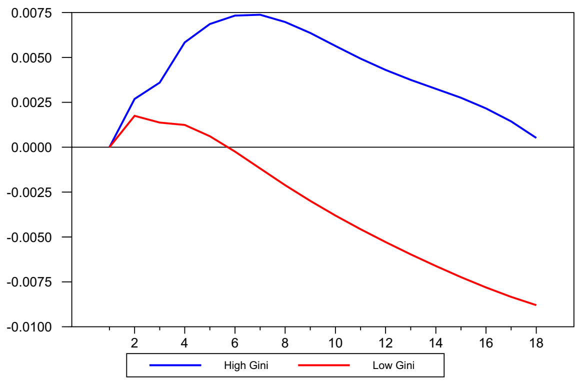

Fig. 3 Impulse response of real house price to a unit household credit shock from a panel VAR using mean group estimate. *Note* Log real house price response of high Gini pool, blue; log real house price response of low Gini pool, red. Forecast horizons on horizontal axis range from 0 to 18. (Color figure online)

effect. In Columns (4) to (6), we re-estimate the regressions, incorporating controls for both the change in firm credit and the level of firm credit. The results are consistent with our earlier findings.

In summary, the results in Table 13 align closely with our findings from the VAR analysis. They reveal that higher income inequality amplifies the impact of household credit shocks on house prices. This underscores the critical role of income inequality in shaping the transmission mechanism and affecting the housing market's sensitivity to credit fluctuations.

3.2.2 Panel VAR

In this section, we exploit another alternative specification of our baseline model. While in our baseline analysis we estimate a country-by-country VAR, here we estimate a dynamic heterogeneous panel vector autoregression model (Pesaran and Smith 1995; Pesaran et al. 1996). This approach enhances the generalizability of our findings across the sample and provides a clearer overall picture by pooling the data, while still accounting for cross-country heterogeneity.

We use the median value of income inequality in our sample of countries from Solt (2020), i.e., $Gini_{income_{Solt}}$ to group countries into a) the high Gini pool and b) the low Gini pool. All countries with income inequality higher than the median value comprise the high Gini pool, and those lower than the median value comprise the low Gini pool. Doing so, our sample includes 21 countries in the high Gini pool and 21 countries in the low Gini pool. We investigate the impact of a one-unit household credit shock as well as a one-standard deviation household credit shock on real house prices of these two pools, respectively, exploiting a heterogeneous dynamic panel VAR.

To avoid imposing restrictions on the slope coefficients of house prices across various countries in each group, we estimate the model for each group using the

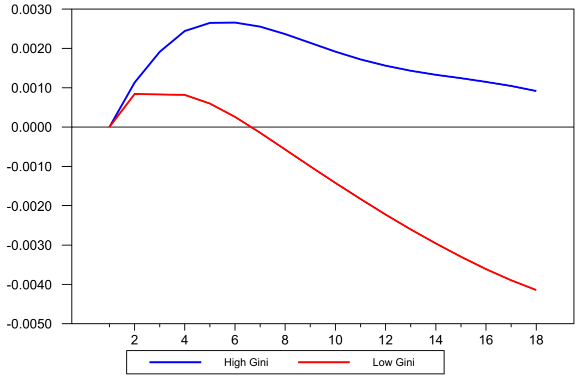

Fig. 4 Impulse response of real house price to a std. deviation household credit shock from a panel VAR using mean group estimate. *Note* Log real house price response of high Gini pool, blue; log real house price response of low Gini pool, red. Forecast horizons on horizontal axis range from 0 to 18. (Color figure online)

mean group estimator of Pesaran and Smith (1995) and Pesaran et al. (1996).[10] In essence, this is a dynamic panel estimation approach that allows for full country heterogeneity, as also used by Banti and Phylaktis (2019), Cesa-Bianchi et al. (2018). We first estimate a VAR for each country individually via OLS and estimate the impulse response functions (IRFs) by employing the Cholesky decomposition of the covariance matrix of the structural VAR residual. We then measure the average effect of the shock, across countries, in each group by averaging the cross-country responses at each forecast horizon, i.e., the mean group estimate (Pesaran and Smith 1995; Banti and Phylaktis 2019; Cesa-Bianchi et al. 2018). We explain the algorithm in detail below.

Specifically, for each country in the high Gini pool, consider the following reduced form model:

$$Z_t = B(L)Z_{t-1} + \epsilon_t \tag{9}$$

where Z_t is a $m \times 1$ vector that follows the following linear dynamic process:

$$Z_t = B_1 Z_{t-1} + \cdots B_p Z_{t-p} + \epsilon_t, \tag{10}$$

$B(L)$ is a lag polynomial defined in terms of the $m \times m$ coefficient matrices B_i and ϵ_t is the one-step ahead prediction error with variance-covariance matrix Σ. The structural representation of Eq. (10) in moving average form is given by:

$$Z_t = (I - B(L)L)^{-1} D_z u_t \tag{11}$$

$$Z_t = (D_0 + D_1 L + D_2 L^2 + \cdots)u_t \tag{12}$$

$$\Sigma = E\left(\epsilon_t \epsilon_t^{'}\right) = D_z E\left(u_t u_t^{'}\right) D_z^{'} = D_z D_z^{'} \tag{13}$$

[10] Pooled estimators are not consistent in dynamic heterogeneous panel data model with slope coefficients varying across countries (Pesaran and Smith 1995; Pesaran et al. 1996).

where u_t is a vector of aggregate structural shocks, and $E\left(u_t u_t'\right)$ is normalized to be the identity matrix. Our primary focus is the response of the real house price index to the structural household credit shock. Given the model specification and ordering noted in Eq. 1, we identify the household credit shock using the standard Cholesky decomposition of the D_z matrix in Eq. (13). We estimate VAR models for each country in two lags of the levels of the variables (i.e., $p = 2$) and add a constant. Next, for each country, we compute the impulse response of the house price to the structural household credit shock over horizon h following Eqs. 11-13.[11]

Finally, we compute the *mean* impulse response function of the real house price index to the household credit shock across countries in the high Gini pool at each forecast horizon, h (i.e., the mean group estimate). To this end, consider the following *IRF* for each country j in the high Gini pool:

$$IRF_j(h) = f\left(\left\{\hat{B}_i\right\}_{i=1}^{p}, h\right) \tag{14}$$

where the functional form in 14 follows from Eqs. 11-13. We compute the averages of the *IRF* across countries, N, at each forecast horizon, h to obtain the overall IRF for the high Gini pool.

$$IRF(h) = \frac{1}{N}\sum_{j=1}^{N} IRF_j(h) \tag{15}$$

We conduct a similar analysis for the low Gini pool of countries as well. Following the steps discussed above, we compute the mean impulse response function of the real house price index to the structural household credit shock across countries in the low Gini pool at each forecast horizon, h. This yields the overall impulse response function for the low Gini pool.

Figures 3 and 4 compare the mean impulse responses of the real house price index of the high Gini and low Gini pool to a unit household credit shock and a std deviation household credit shock, respectively, over the first 18 quarters. In response to a unit household credit shock, real house price of the high Gini pool of countries goes up by .74 percent at its peak, as opposed to only .17 percent in case of the low Gini pool. We see a similar picture in case of a std deviation shock as well. The peak house price response of the high Gini pool to a std deviation household credit shock is .27 percent, which is more than three times as much as that of the low Gini pool (.08 percent). Figures 3 and 4 provide compelling evidence that the high Gini pool of countries, on average, witness a larger house price response to household credit shocks.

3.3 Discussion of the Mechanism

In this section, we discuss a potential mechanism behind our primary finding, i.e., why inequality amplifies the response of house prices to a household credit shock. The mechanism we propose builds on the models outlined in Bahadir et al. (2020)

[11] We do so for both a) a unit household credit shock and b) a standard deviation household credit shock.

and Kaplan and Violante (2014) and focuses on binding credit constraints and differences in MPC driven by high inequality.

The role of inequality in understanding the share of credit-constrained households has been first studied in Bahadir et al. (2020), who provide a partial equilibrium model to examine the effect of household credit shocks on consumption for different income distributions. In their model, middle-income households play an important role due to their particular position within the income distribution: unlike low-income earners, who consistently face binding constraints due to limited resources, and high-income earners, who generally avoid credit constraints due to sufficient income, middle-income households have incomes that frequently hover around lending thresholds. The key idea in their model is that rising income inequality reduces the income share of middle-income households to a level that falls below the threshold set by banks loan approval. When their relative income decreases, their credit constraints begin to bind, resulting in a higher MPC.

Relying on the theoretical underpinnings of Bahadir et al. (2020), in our study too middle-income households' response can be particularly important for house price dynamics, given their higher potential for housing demand compared to low-income households. This effect can be even more pronounced when many middle-income households hold illiquid assets but lack substantial liquid wealth-often described as "wealthy hand-to-mouth" households (Kaplan and Violante 2014). Household credit expansions, often spurred by positive credit supply shocks and low interest rates, enable these constrained middle-income households to increase leverage, thereby amplifying housing demand and driving up house prices.

In conclusion, our proposed mechanism suggests that inequality amplifies the response of house prices to household credit shocks by increasing the credit constraints faced by middle-income households. As income inequality rises, the relative income of these households declines, pushing many closer to lending thresholds and raising their marginal propensity to consume. This effect is especially pronounced among "wealthy hand-to-mouth" households, who, despite owning illiquid assets, have limited access to liquid wealth. If our inequality measures effectively capture these dynamics-specifically, the shift of more household balance sheets closer to borrowing constraints—then the observed amplification is precisely what we would expect. Our empirical results align with this mechanism, showing that credit expansions in high-inequality environments lead to stronger housing demand and larger house price booms.

4 Conclusion

By analyzing cross-country data, we study how income distribution contributes to the strength of the relationship between household credit shocks and real house prices. Our findings reveal that income inequality increases the sensitivity of real house prices to household credit shocks. These outcomes remain robust to alternative empirical specifications as well as controlling for additional factors.

Our paper is a first pass at studying the role of income distribution for the link between household debt and house prices. It is important to note, however, that our empirical analysis is a reduced form approach and lacks the ability to uncover all causal mechanisms at play. A theoretical model that captures the general equilibrium effects of income distribution is needed to understand the exact mechanisms that generate the link between income inequality, household debt, and house prices.

Our findings have far-reaching implications for policy. Given the strong impact of inequality on the response of real house prices, policy makers should be careful in using policies that boost household credit and housing demand. Such policies may yield effects larger than anticipated in economies characterized by significant income inequality. The key takeaway is that evaluating the effects of macroeconomic policies requires accounting for the distribution of income, rather than solely focusing on the average income or wealth of borrowers.

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Data availability The data are available upon request.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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