Institute for Economic Studies, Keio University

Keio-IES Discussion Paper Series

Credit expansion and boom-bust cycle of housing prices

Masaya Sakuragawa, Satoshi Tobe

2 June, 2025
DP2025-011
https://ies.keio.ac.jp/en/publications/26130/

Institute for Economic Studies, Keio University
2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan
ies-office@adst.keio.ac.jp
2 June, 2025

Credit expansion and boom-bust cycle of housing prices

Masaya Sakuragawa, Satoshi Tobe

Keio-IES DP2025-011
2 June, 2025
JEL Classification: G12, G21
Keywords: Credit, Housing Prices, Local Projections

Abstract

This paper empirically investigates if there is a causal relation from credit expansion to housing prices, using a data set of an unbalanced panel that covers 20 developed countries from 1980 to 2019, which includes many episodes of boom and bust of housing prices. The estimates based on the local projections with instrumental variables (LP-IV) show that an exogeneous increase in credit supply leads to a boom of housing prices at short horizons, and to a bust at longer horizons. The boom lasts for two and a quarter years, turns into a bust in three years after the initial shock, and then the bust lasts for three and a half years. Our results favor the Kindleberger–Minsky view that the combination of expectation errors and the credit-supply shock leads to financial crises. We also study the cumulative effects, differential effects of current account position, and effects of a longer credit expansion.

Masaya Sakuragawa
Faculty of Economics, Keio University
masaya@econ.keio.ac.jp

Satoshi Tobe
School of Policy Studies, Kwansei Gakuin University
stobe@kwansei.ac.jp

Acknowledgement: We are extremely thankful to Mototsugu Fukushige, Shin-ichi Kitasaka, Fumio Hayashi, Hibiki Ichiue, Yoshifumi Konishi, Ryo Nakajima, Yohei Yamamoto, and participants of seminars in Keio University, Kaetsu University, Waseda University, Kyusyu University, Sophia University, and the Australian meeting of the Econometric Society for valuable comments. This work was supported by JSPS KAKENHI Grant Number JP20K13532.

Credit expansion and boom-bust cycle of housing prices*

Masaya Sakuragawa[1]
Satoshi Tobe[2]

June 2, 2025

Abstract

This paper empirically investigates if there is a causal relation from credit expansion to housing prices, using a data set of an unbalanced panel that covers 20 developed countries from 1980 to 2019, which includes many episodes of boom and bust of housing prices. The estimates based on the local projections with instrumental variables (LP-IV) show that an exogeneous increase in credit supply leads to a boom of housing prices at short horizons, and to a bust at longer horizons. The boom lasts for two and a quarter years, turns into a bust in three years after the initial shock, and then the bust lasts for three and a half years. Our results favor the Kindleberger–Minsky view that the combination of expectation errors and the credit-supply shock leads to financial crises. We also study the cumulative effects, differential effects of current account position, and effects of a longer credit expansion.

Keywords: Credit, Housing Prices, Local Projections
JEL classification: G12, G21

---

* We are extremely thankful to Mototsugu Fukushige, Shin-ichi Kitasaka, Fumio Hayashi, Hibiki Ichiue, Yoshifumi Konishi, Ryo Nakajima, Yohei Yamamoto, and participants of seminars in Keio University, Kaetsu University, Waseda University, Kyusyu University, Sophia University, and the Australian meeting of the Econometric Society for valuable comments. This work was supported by JSPS KAKENHI Grant Number JP20K13532.
[1] Department of Economics, Keio University, 2-15-45, Mita, Minato-ku, Tokyo, 108-8345, Japan, masaya@econ.keio.ac.jp.
[2] School of Policy Studies, Kwansei Gakuin University, 2-1, Gakuen, Sanda, Hyogo 669-1337, Japan. E-mail address: stobe@kwansei.ac.jp

1. Introduction

As is well known, credit booms are very often accompanied by asset price booms. Booms and busts in real estate markets occurred for the past forty years around the world: in Nordic countries and Japan in the late 1980s and in the US and European countries in the early 2000s. Panel A of Figure 1 represents the relation between the ratio of credit to household sector to GDP and housing prices of the contemporaneous period in the growth term for 20 OECD countries for 1980–2019. The figure shows a positive correlation. The data on Japan in 1987 and the US in 2003 are located at the north-east of the graph, showing that the credit boom is accompanied by a housing market boom. However, asset price booms do not last long. Panel B represents the relation between the ratio of credit to household sector to GDP and that of housing prices for 5 years ahead. The figure shows a negative correlation, suggesting that the credit boom results in the bust of the housing market. The data for Japan in 1992 and the US in 2008 are located at the south-east of the figure. These two figures suggest that a credit boom leads to the cycle of boom and bust of housing prices.

[Insert Figure 1 here]

This financial cycle reminds us of the narrative of Kindleberger (1978) and Minsky (1986). In their language, credit expansion begins with an exogeneous shock that they call a "displacement" and is accompanied by an economic and asset price boom, but eventually results in the depreciation of asset prices, banking crises, and deep recessions. A growing body of literature has pointed out that credit expansion is the real cause of eventual crises and recessions. The literature includes Schularick and Taylor (2012), Mian, Sufi, and Verner (2017), Baron and Xiong (2017), López-Salido, Stein, and Zakrajšek (2017), Greenwood et al. (2022), and Müller and Verner (2023).

Economists and policymakers commonly understand that the rise and fall in asset prices is a central channel that links credit expansion eventually to financial crises, but at least to our small knowledge, no empirical studies have uncovered the causal effect from credit expansion and the rise and fall in asset prices. This paper focuses on the causal effects of credit expansion on house prices to complete the transmission mechanism from credit supply to financial crisis.

In this paper, we study if there is a causal relation from credit supply to housing prices in an unbalanced panel of 20 developed countries from 1980 to 2019, which includes many episodes of boom and bust of housing prices. The estimates based on the local projections with instrumental variables (LP-IV) show that an exogeneous increase in credit supply leads to a boom at short horizons, and to a bust of housing prices at longer horizons. Our result favors the Kindleberger-Minsky view that provides a foundation for the "credit-supply shock" as a starting point for the boom-bust cycle. The boom lasts for two and a quarter years, turns into a bust in three years after the initial shock, and then the bust lasts for three and a half years. The availability of quarterly data permits us to estimate a more accurate pattern of a boom-bust cycle. The local projections require an estimation of a series of regressions for each horizon and are well suited for estimating nonlinear dynamics such as a boom followed by a bust.[3]

We also estimate the cumulative effects of boom and bust. An exogenous increase in the annual growth rate of credit by 1 percent leads to a boom in the housing price growth by 0.935 percent, and later leads to a bust by 0.879 percent. At the end of the bust, most of the house prices that rose during the boom are lost.

The prediction of a boom followed by a bust is at odds with rational expectation models that predict monotonic convergence. It rather favors the Kindleberger-Minsky view that errors in expectations lead to excessive borrowing and investment during credit booms, and the revision to overly optimistic beliefs gives rise to busts and crises, as is formalized in recent theoretical models, that include Bordalo, Gennaioli, and Shleifer (2018), Gennaioli and Shleifer (2018), and Greenwood, Hanson, and Jin (2016).

In principle, it is not easy to identify the exact channel from credit supply to housing prices. Credit variables and macro aggregates are closely connected and involve multiple causal links. The credit and asset price booms may be a result of an economic boom. An omitted variable,

[3] Impulse response functions obtained from the local projections have several advantages, such as flexibility of specifications and robustness to nonlinearity. In contrast, the VAR approach estimates parameters of horizon 0 and using those parameters to iterate forward to construct impulse response functions, and may miss the estimation of busts (Jordà, 2005).

such as the GDP growth and consumption growth, may give rise to the correlation between credit and housing variables. In addition, a reverse causality may arise from housing prices to credit. The optimistic expectation on housing prices relaxes the constraint on collateral requirement, thereby shifting the demand for credit (e.g., Kiyotaki and Moore, 1997). The contemporaneous feedback between credit and housing prices leads to a serious endogeneity issue.

To test for the channel through which credit-supply expansion affects housing prices, an ideal natural experiment would entail an exogeneous shock to credit supply that could, in theory, boost asset prices. To do this, we use the Bartik-like instrument that combines a country-specific characteristic (exposure variable) with the time-varying global credit growth (shock variable).[4] What our IV is trying to capture is how sensitive a country's credit growth reacts when the time-varying global credit growth affects a country's credit condition.

The instrumental variable used here is based on the notion that the domestic credit market is integrated into global financial markets. This suggests that international capital flows have an impact on the pattern of the financial cycle (see for example CaIvo et al., 1996). It would be natural to expect that a country's current account balance influences the boom and bust of the domestic asset market.

To estimate the effects of current account balance on the pattern of cycle, we consider the heterogeneity in coefficients by grouping data of current account surpluses and deficits. The estimates show that surplus countries experience a boom but no bust, while deficit countries experience a cycle of a large boom and an even large bust. When countries run deficits, an exogeneous increase in the annual growth rate of credit by 1 percent leads to a boom in the housing price growth by 1.287 percent, and later leads to a bust by 1.765 percent.

Our results of one-year credit growth suggest the presence of people's irrational expectations. It will be interesting to see whether the error in forecasting for the credit shock will be corrected or amplified by extending the interval of credit growth. The literature typically

[4] Our strategy shares the idea of the Bartik instrument approach, in which the instrument is formed by interacting local employment share across industries and industry growth rates at the national level (see Borusyak, Hull, and Jaravel, 2022, and Goldsmith-Pinkham, Sorkin, and Swift, 2020).

uses the three-year interval as the length of "credit expansion" from the observation that credit expands rapidly over three to four years during credit booms (see Mian et al., 2017, and Müller and Verner, 2023). An exogeneous increase in the three-year growth rate of credit by 1 percent leads to a boom in the housing price growth by 3.063 percent, and later leads to a bust by 2.656 percent. As the interval of credit expansion gets longer, the bust is more serious. At the end of the bust, most of the house prices that rose during the boom are lost.

In addition, we show that the impulse responses of house prices and nonperforming loans are mirror images of each other. Those results jointly support the view that a prolonged credit expansion leads to a larger decline in asset prices, worsening banks' balance sheets and increasing the likelihood of a financial crisis.[5]

Our results show that the boom-bust cycle of housing prices is predictable, and that a prolonged credit expansion, such as the three-year credit growth, becomes a warning signal to predict a large depreciation of asset prices and the vulnerability of the banking system. Our estimates are roughly consistent with the finding of the financial crisis literature, such as Schularick and Taylor (2012) and Greenwood et al. (2022) that have found that credit growth predicts an increase in the probability of a financial crisis for 2 or 3 years ahead.

When our result favors the Kindleberger–Minsky view, the identified credit shock is expected to reflect the credit-supply shock. Indeed, our identified shock reflects the credit-supply shock rather than the demand shock. We investigate the impulse responses of interest rate variables. The credit shock leads to a rise in the short-term nominal rate and a fall in the maturity spread in the first several periods, suggesting the downward pressure on longer-term interest rates. This finding is consistent with the credit-supply shock model proposed by Justiniano, Primiceri, and Tambalotti (2019), who demonstrate that the relaxation of supply constraints, combined with collateral constraint, leads to a fall in the interest rate and a boom in the asset price. Our result is also consistent with anecdotal episodes that asset bubbles are caused by disturbances in financial markets, that include financial liberalization, financial innovation, and a surge in inflows of foreign capital.

[5] As the recent literature indicates, the credit growth of longer interval captures well negative features of "credit expansion," that includes the deterioration of banks' balance sheets.

This paper is related to works that investigate the channel through which credit supply affects housing prices. Mian and Sufi (2009) demonstrate that a rapid expansion in the supply of mortgages explains a large fraction of US house price appreciation and subsequent mortgage defaults. Favara and Imbs (2015) and Di Maggio and Kermani (2017) use measures of US banks' branching deregulation to establish that an exogeneous expansion in mortgage credit has significant effects on housing prices.[6] Jordà, Schularick, and Taylor (2015) identify the exogeneous variation of monetary policies, demonstrating that loose monetary conditions lead to booms in real estate lending and housing bubbles. Mian, Sufi, and Verner (2020) treat banking deregulation of the US in the 1980s as a natural experiment, demonstrating that credit-supply expansion can increase productive capacity and boost household demand. Mian and Sufi (2022) show that the surge in mortgage securitization in 2003 affects an expansion of credit supply and the boom-bust cycle of housing activities. Justiniano, Primiceri, and Tambalotti (2019) provide a theoretical foundation for how to separate a credit-supply shock from other shocks, demonstrating that the relaxation of credit-supply constraints, combined with collateral constraint, leads to a fall in the interest rate during a credit boom.

Our findings are related to the recent literature that shows that rapid increases in credit predict economic downturns. Schularick and Taylor (2012) show that the credit growth over the past five years predicts the financial crisis. Mian, Sufi, and Verner (2017) show that a rapid household credit growth forecasts low GDP growth over the medium run. López-Salido, Stein, and Zakrajšek (2017) show that low credit spreads, driven possibly by market overheating, predict both a rise in credit spreads and lower economic growth at a horizon of two years. Baron and Xiong (2017) show for a sample of 20 developed countries that bank credit expansion predicts increased bank equity crash risk in the subsequent one to three years. Greenwood et al. (2022) show that the combination of rapid credit and asset price growth over the previous three years is associated with a 40 percent probability of entering a financial crisis within the next three years.[7]

[6] See also Landvoigt, Piazzesi, and Schneider (2015).
[7] Gourinchas and Obstfeld (2012) show that domestic credit expansion has been one of the robust predictors of financial crises. Brunnermeier et al. (2021) find evidence of long-run negative response of output to credit growth.

A growing number of empirical studies use Bartik instruments and shift-share instruments that combine weighted averages of a common set of shocks with weights reflecting heterogeneous shock exposures. Since the seminal works of Bartik (1991) and Blanchard and Katz (1992), the recent literature includes Autor, Dorn, and Hanson (2013), Nunn and Qian (2014), and Blanchard et al. (2017). Autor, Dorn, and Hanson (2013) identify the China shock on US employment by combining industry-specific change in Chinese import competition with local exposure given by the lagged industrial composition of US regions. Nunn and Qian (2014) identify food aid supply shocks on civil conflicts by combining US food aid supply shocks with different exposure across countries. Blanchard et al. (2017) identify shocks of gross capital flows on economic growth by combining globally aggregated gross flows with country-specific exposure. To our knowledge, our paper is the first attempt that applies Bartik instruments to the empirical analysis of macroeconomics.

This paper is organized as follows. The next section reports the main empirical findings on credit boom and housing prices and discusses the underlining stories. Section 3 investigates what the identified shock implies, and Section 4 presents robustness checks. Section 5 concludes.

2. Household Credit and Housing Prices

2.1 Data

We construct a country-level unbalanced panel data set that includes macroeconomic variables on housing prices, credit, GDP, interest rates, the maturity spread, the consumer price index, and population. Housing prices and GDP are converted into the real term using the CPI-based inflation rate. The countries covered in the data are 20 developed countries, which are listed in Table 1. The data are quarterly and range from the first quarter of 1980 to the fourth quarter of 2019.[8] The availability of quarterly data permits us to study a more accurate pattern of a boom-bust cycle.

[8] Since around 1970s, the credit to the household sector has been channeled into housing markets, along with the development of housing markets, which created a close link between the credit supply and housing prices. Bank credit has dramatically risen relative to GDP. The ratio of bank credit to GDP roughly doubled between 1980 and 2010. We limit the data until 2019 because the COVID-19 started at the end of 2019.

[Insert Table 1 here]

Here we refer to the housing price of country i and period t as $HP_{i,t}$. Let $\Delta_k HP_{i,t}(= \ln HP_{i,t} - \ln HP_{i,t-k})$ denote the growth rate of the housing price from period $t-k$ to period t. As the data are quarterly, $\Delta_4 HP_{i,t}$ $(k = 4)$ means the one-year growth rate.

The housing price is defined by the residential property price provided by the Bank of International Settlements (BIS). The BIS data set provides housing price indices, based on a definition as comparable as possible across a broad sample of countries. The definition in terms of the growth rate is intended to eliminate problems about the definition and coverage of hosing prices that are heterogeneous across countries.

We refer to the credit to the household sector as a proportion of GDP that lags one period (one quarter) as $Credit_{i,t}$. Let $\Delta_k Credit_{i,t}(= \ln Credit_{i,t} - \ln Credit_{i,t-k})$ denote the growth rate of the credit variable from period $t-k$ to period t. $\Delta_4 Credit\ _{i,t}$ $(k = 4)$ means the one-year growth rate.

The credit variable is divided by the lagged GDP to exclude the effect of the innovation in GDP. This credit variable represents how fast the credit grows relative to GDP, and the so-called, "credit expansion," which is often intended to capture the faster and longer credit growth, accompanied simultaneously by the deterioration of credit quality. When the credit growth is fast, the rapid increase in the new lending may coincide with lower lending quality, followed by subsequent losses in the banking sector.

The numerator of the credit variable is defined by the total credit provided by "Long series on total credit and domestic bank credit to the private nonfinancial sector" in the BIS data set. Total credit comprises financing from all sources, including domestic, other domestic financial corporations, nonfinancial corporations, and nonresidents (including foreign banks). [9] Additionally, the financial instruments covered by the "credit" are loans and debt securities (bonds and short-term paper). Details of the variables are summarized in Table 2.

[9] Financing from all sources includes commercial banks, savings banks, credit unions, mortgage associations, and building societies.

[Insert Table 2 here]

[Insert Table 3 here]

Table 3 displays summary statistics. The average of housing price growth ($\Delta_4 HP$) is 1.77 percent; the average of credit growth ($\Delta_4 Credit$) is 2.09 percent; and the average of GDP growth ($\Delta_4 GDP$) is 2.38 percent. The housing price growth and credit growth are more volatile than the GDP growth. The standard deviation of housing price growth is almost twice as large as that of GDP growth.

[Insert Figure 2 here]

Figure 2 plots events of booms and busts of housing price growth for each country. The event of a boom is identified by a higher growth rate than the country-specific mean plus its one standard deviation. The dark blue indicates the boom events. Likewise, the bust event is identified by a lower growth rate than the country-specific mean minus its one standard deviation. The event lasting for only one quarter is excluded from the figure. There are many booms and busts, and several booms are followed by busts, while other booms are not. Typical boom-and-bust cycles are observed in three Nordic countries and Japan in the late 1980s, and globally in the first decade of the 2000s. In the latter, 14 out of 20 countries, except for Belgium, Germany, Italy, Japan, Korea, and Switzerland, experienced a heavy bust in the late 2000s. It is also noticeable that the boom-bust cycles in the late 1980s and the 2000s seem to comove across countries. Many countries have experienced cycles of boom and bust of housing prices at the same time, suggesting that common factors played an important role in explaining the cycle.

2.2 Instrument

The causal effect that we are focusing on is the one from credit supply to housing prices. However, the reverse causation or/and the omitted variable problem makes it difficult to estimate the magnitude of the channel through which credit-supply expansion affects housing prices.

Our instrument is constructed by combining the time-varying shock with the country-specific exposure, following the idea of the shift-share instrumental variable (Borusyak, Hull, and Jaravel, 2022) and Bartik-instrument variable (Goldsmith-Pinkham, Sorkin, and Swift, 2020). In recent years, there are increasing papers that employ this strategy.[10]

The shock variable is defined as the cross-country sample mean of the annual growth rate of the ratio of credit to the household sector to GDP, denoted by $\frac{1}{N-1}\sum_{j\neq i}\Delta_4 Credit_{j,t}$, where the variable of own country i is omitted. By the construction of the leave-one-out nature, the shock in the housing market of each specific country will have an impact on the credit growth of that country, but have no direct effect on the global credit variable. However, that shock might have an effect on the global credit variable if credit growth rates are correlated across countries. One effective way to avoid this channel is to control for time-fixed effects.

As an alternative global credit variable, one may think of the "real" global credit growth, $\sum_{j\neq i}\frac{\omega_{j,t}}{1-\omega_{i,t}}\Delta_4 Credit_{j,t}$, which is constructed based on the credit growth multiplied by the credit share $\omega_{j,t}$. We do not use this variable for the following reason. The normalization by the denominator $(1-\omega_{i,t})$ captures the effect of leave-one-out, which means that this variable potentially reflects the effect of the credit growth of own country i. This concern will be trivial if the share $\omega_{i,t}$ is small for all i's, but will not if the share is large for some country. Unfortunately, the credit share of the United States is very large, 43 percent on average. The error term affects the domestic credit growth through the reverse causation from the housing price to credit, which may in turn affect the credit share $\omega_{i,t}$, and thus has a direct effect on the global credit growth. Accordingly, this global credit growth variable violates the exclusion restriction of instrument. This channel is absent when using the sample mean.

The global credit growth and the credit growth of its individual country may be complements or substitutes. The global saving glut gives downward pressure on the global

[10] Autor, Dorn, and Hanson (2013) consider a shift-share instrument that combines industry-specific change in Chinese import competition (the shock) with local exposure given by the lagged industrial composition of US regions (the exposure share). Blanchard et al. (2017) uses a combination of globally aggregated gross flows and country-specific exposure to identify the shocks in gross capital flows on economic growth.

interest rate, thereby stimulating both the global credit growth and the country's credit growth. The boom in the global GDP stimulates the global credit growth, and at the same time, gives an upward pressure on the global interest rate. This in turn may repress the credit growth of a country that failed in riding on the global boom.

Figure 3 depicts the correlation between the global credit growth and the credit growth of each specific country. The estimation represented by the fitted line yields a coefficient of 0.774 (clustered standard error = 0.138), indicating that the credit growth of each specific country is positively related to the global credit growth. The global credit growth seems helpful to explain the exogenous variation of the domestic credit variable.

[Insert Figure 3 here]

We turn to the exposure variable, which will capture the cross-country difference in the sensitivity to the shock variable. It is defined by the log of the ratio of the total credit to GDP in 1980, denoted by $\ln Total\ Credit/GDP_{i,1980}$. As is well known, this variable is widely understood as one measure of financial depth that reflects a country's domestic financial development, but we expect this variable to link to the subsequent credit growth through the channel of financial liberalization when the sample is limited to 20 developed countries.

Historically, governments have imposed extensive regulations on the supply of credit to the household sector to direct credit more to the corporate sector. The situation changed around 1980. Cross-border financial markets emerged and there was a political swing in favor of new liberalism, and in response, a wave of banking deregulation started. We naturally expect that the low ratio of total credit to GDP of a country reflects severe regulations in 1980, and thus in response to deregulation, that country would have realized faster credit growth for housing purchases. In addition, we have investigated anecdotal observations on banking deregulation in the 1980s. The details are left to the section on robustness check.

[Insert Figure 4 here]

Figure 4 depicts the regression that shows how the initial ratio is related to the subsequent credit growth. The coefficients of the initial level are negative and significant for the intervals of 1990–1994, 1995–1999, and 2000–2004, while those are positive but insignificant for 1980–1984, 2010–2014, and 2015–2019. This result seems to support our regulation view, suggesting that countries with the low initial ratio realized faster credit growth at least during the period from 1990 to 2004. Indeed, among many countries, banking deregulation progressed on in the 1990s and the early 2000s.

2.3 Estimations

Given this preparation, our approach is to use local projections with instrumental variables (LP-IV). We estimate the first-stage regression:

$$\Delta_4 Credit_{i,t} = \alpha \ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1}\sum_{j\neq i} \Delta_4 Credit_{j,t} + \boldsymbol{\Pi X}_{i,t} + \boldsymbol{\Psi W}_{i,t-4} + \delta_i + \gamma_t + \varepsilon_{i,t}.$$

Here, i indexes country, t indexes time. The δ_i denotes the country-fixed effect that is meant to absorb the impact of any time-invariant country characteristics.[11] γ_t denotes the time-fixed effect, that is meant to absorb the impact of common shocks to all countries at any specific period, such as the global GDP boom and the global recession. $\varepsilon_{i,t}$ denotes the error term.

The dependent variable $\Delta_4 Credit_{i,t}$ represents the annual growth rate of the ratio of credit to the household sector to GDP. The interaction term $\ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1}\sum_{j\neq i} \Delta_4 Credit_{j,t}$ is our instrument. The coefficient is expected to be negative. As shown in Figure 3, the credit growth of each specific country tends to be positively related to the global credit growth, and as shown in Figure 4, a country with severely regulated banking in 1980 will be more exposed to the global credit conditions captured by the global credit growth, as banking deregulation progressed especially in the 1990s and early 2000s. The control $\boldsymbol{X}_{i,t}$ is the set of variables for the current period and $\boldsymbol{W}_{i,t-4}$ is the set of control variables for the four

[11] Examples are a country's regulation and business practices in the housing market, a country area, and the cross-country difference in the measurement of housing price index.

quarters (one year) lag. We select this lag length following the standard lag selection procedures of AIC and BIC.

Control variables are meant to focus on the direct effect of the change in credit on the housing price, but not to have an indirect effect through business cycle fluctuations or monetary policies. Those include the real annual GDP growth rate, the annual population growth rate, the nominal interest rate on the 3-month money market (a proxy to the short-term interest rate), the maturity spread defined by the return on a 10-year government bonds minus the short-term interest rate, and the CPI-based inflation rate. The real annual GDP growth rate is expected to control for the effect of business cycle fluctuations. The last three variables are expected to control for the effect of monetary policies. Additionally, those three are intended to separate components of the real long-term interest rate, which is expected to move along with the mortgage rate.

Using the instrumental variable, we estimate the second-stage regression:

$$\Delta_4 HP_{i,t+h} = \beta^h \Delta_4 \widehat{Credit}_{i,t} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-4} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h,$$

for $h = 0, 1, 2, \ldots, 40$, where $\Delta_4 \widehat{Credit}_{i,t}$ is the instrumented variable estimated by the first-stage regression. δ_i^h and γ_t^h are the country-fixed and time-fixed effects, and $\varepsilon_{i,t+h}^h$ is the error term. The dependent variable $\Delta_4 HP_{i,t+h}$ refers to the annual growth rate of housing prices at h periods ahead. The coefficient at h periods ahead, β^h $(h = 0, \ldots, 40)$, displays the impulse response of the housing price to the credit shock. For example, β^{20} $(h = 20)$ captures the effect of a current increase in the growth of the ratio of credit to GDP on the housing price growth five years ahead (20 periods ahead). For every estimation, standard errors are dually clustered on country and period.

The set of four-quarter lagged control variables $\boldsymbol{W}_{i,t-4}$ includes not only the control variables, but also the dependent variable (housing price growth variable), the explanatory variable (credit growth variable), and the instrumental variable to ensure that the possible mean reversion in the housing price growth is not responsible for the results. Notably, even if conditions for IV are satisfied, including the lagged IV, this could reduce the sample variance of the IV estimator by reducing the variance of the error term.[12]

Table 4 reports the estimates for every four periods ($h = 0, 4, 8, \ldots$). Panel A refers to the estimations that control for current and four-quarter (one-year) lagged control variables, and country and time-fixed effects.

In the first-stage regression, the coefficient at $h = 0$ is negative and significant at 1 percent significance level (column 1). The negative sign of the coefficients seems to support simultaneously the regulation view and the positive correlation of credit growth between a country and the global economy. The table reports F-statistics for checking weak instruments, that tests the null hypothesis that the instruments are excludable from the first-stage regression. Stock and Yogo (2002) recommend that F-statistics should take values above 10 lest the estimates indicate a potential problem with instrument relevance. Our instrument satisfies this recommendation. Additionally, our instrument satisfies this recommendation also when forecast horizons get longer (columns 2–11). Strictly, the estimates are not the same throughout the forecast horizon because the sample size becomes smaller as the forecast horizon gets longer. However, the coefficients are close to each other over the forecast horizon from $h = 0$ to $h = 40$. Thus, the concern about the sample size is not thought to be a serious issue.[13]

[Insert Table 4 here]

We turn to the second-stage regression. The coefficients at shorter horizons ($h = 0 \sim 5$) are positive and significant. The coefficient reaches 0.608 at peak ($h = 0$). An exogeneous increase in the credit growth by one percent leads to the increase in the housing price growth by 0.608 percent. This estimated value is larger than the recent research that uses measures of US

[12] Stock and Watson (2018) propose the inclusion of the lagged instrument as a control to improve efficiency.
[13] We conduct an estimation using the same credit shock over the forecast horizon. We set the observations to equal those of the estimate of the 40-period forecast (column 11 of Table 4). This setting ensures that the first-stage estimates are the same throughout the horizon from $h = 0$ to $h = 40$, and the second-stage estimates reflect the response of housing prices to exactly the same credit shock. One disadvantage of this setting is that all the available observations are not used, and this problem is not innocent especially in the shorter forecast horizons. For example, at $h = 0$, the estimation uses the observations from 1980 to 2009 but not from 1980 to 2019. Panel A of Figure A1 in the Appendix shows that the result for a boom-bust cycle is preserved over the forecast horizon from $h = 0$ to $h = 40$.

branching deregulation to estimate the effect of an exogeneous expansion in mortgage credit on housing prices. For example, the estimate of Favara and Imbs (2015) is 0.12 and the estimate of Di Maggio and Kermani (2017) is 0.33. The boom ends around $h = 8$, and later turns to a bust. The coefficients at longer horizons ($h = 17 \sim 27$) are negative and significant at the 5 percent significance level. The estimates reflect a dynamic pattern of a boom followed by a bust of housing price growth. The results are robust for controlling for current and lagged variables as well as time and country-fixed effects.

The impulse response for a boom followed by a bust contradicts rational expectation models, under which the impulse response function shows a monotone convergence to the initial zero growth. It rather favors the Kindleberger–Minsky view that behavioral biases such as expectation errors and sentiments lead to excessive lending and investment during credit booms, but the revision of overly optimistic beliefs gives rise to busts and crises. Recent theoretical models formalize this idea (e.g., Greenwood, Hanson, and Jin, 2016; Bordalo, Gennaioli, and Shleifer, 2018; Gennaioli and Shleifer, 2018; and others). In Gennaioli, Shleifer, and Vishny (2012), investors neglect tail risks, which leads to aggressive lending by the financial sector via debt contracts. In Greenwood, Hanson, and Jin (2016), credit-market sentiment boosts lending because lenders mistakenly extrapolate past low defaults when granting new loans. Bordalo, Gennaioli, and Shleifer (2018) provide a microfoundation for such mistakes by lenders, which they refer to as "diagnostic expectations."

The estimates of for the boom-bust cycle is roughly consistent with recent research showing that ex ante-signals of credit-market overheating, including rapid growth in outstanding credit, an erosion in borrower credit quality, or narrow credit spread, negatively forecast economic downturns at medium or longer horizons. Mian, Sufi, and Verner (2017) show that a rapid household credit growth forecasts low GDP growth over the medium run. López-Salido, Stein, and Zakrajšek (2017) show that periods of credit-market overheating predict a rise in credit spreads and lower real GDP growth at a horizon of two years. Baron and Xiong (2017) show that for a sample of 20 developed countries, bank credit expansion predicts increased bank equity crash risk in the subsequent one to three years.

We evaluate the robustness of estimates by picking up the issue of autocorrelation, endogeneity, and the contrast with the VAR. One might wonder if the autocorrelation in error terms is responsible for the significant part of the cyclical movement of housing prices. Panel B refers to the estimations that control only for control variables of the contemporaneous period. In the first-stage estimation, the F-statistics are larger and remain above 10. In the second-stage estimation, the coefficients are positive at shorter horizons and significant for the shorter interval ($h = 0 \sim 2$). The coefficient reaches a smaller value of 0.483 at peak ($h = 0$). The coefficients at longer horizons are negative and significant for the longer interval ($h = 13 \sim 27$) based on the 5 percent significance level. Relative to Panel A, the boom is shorter and smaller, while the bust is longer and deeper.

Panels A and B of Figure 5 report the impulse response functions of LP-IV with the 95 percent confidence interval, for the two estimations with/without lagged control variables. Both panels exhibit a similar dynamic pattern of boom and bust. The possible serial correlation may lead to some quantitative difference, but the estimates of Panel A are robust to the inclusion of lagged controls, which shows that the cycle of boom followed by bust is not driven by some spurious mean reversion in the housing price growth.[14]

Our interest is how the endogeneity between credit growth and housing prices influences the dynamic pattern. Panel C reports the impulse response functions of LP-OLS. The coefficients at shorter horizons are positive and significant ($h = 0 \sim 6$). The coefficient reaches 0.422 at peak ($h = 0$), which is smaller than the coefficient at peak of the IV estimation (0.608). The estimates suggest that the endogeneity is responsible for the weaker boom. Once the impulse response turns to the bust, the coefficients are negative and significant ($h = 18 \sim 27$). The coefficients of bust are almost similar to the coefficients in the IV estimates.[15] The effect of endogeneity appears at short horizons, but seems to disappear at longer horizons.

[Insert Figure 5 here]

[14] As a first step, we estimated the simple regression that controls only for country and time fixed effects. The estimates are similar to the ones in Panel B in Figure 5 (see Panel B of Figure A1 in the Appendix).

[15] In the bust, the coefficients of the IV estimation are a little larger, but the difference is not statistically significant.

Finally, we compare our LP-IV estimates with the recursive VAR. We estimate the recursive VAR for the set of seven variables: the population growth, the real GDP growth, the inflation rate, the short-term nominal interest rate, the maturity spread, the growth of the ratio of credit to the household sector to GDP, and the housing price growth.

The shocks are identified by Cholesky ordering that sets the housing price last, followed by the credit variable and the other controls described above.[16] This restriction excludes the contemporaneous channel that may arise from housing price to credit, the collateral channel emphasized by Kiyotaki and Moore (1997). The VAR includes four-quarter (one-year) lags to align with the setting of the LP-IV. Panel D exhibits the impulse response functions of VAR, where the shaded area shows the 95 percent confidence interval.

There are two distinguishable features. The coefficients at shorter horizons are positive and significant. The point estimate is around 0.6 at peak and comparable with our LP-IV analysis. The effects of the credit shock are, however, quite different at longer horizons. In the VAR, the effect of the credit shock diminishes monotonically over time, and the coefficients become insignificant as the horizons become longer. This is a natural result of the VAR approach that estimates parameters of horizon 0 and using them to iterate forward to construct impulse response functions.

In particular, if the bust is an endogenous response to the overheated boom, the VAR model can explain the boom at most. Specifically, when the true model is subject to dynamic nonlinearity, the VAR model may not be able to capture the bust. Taken together, we may conclude that the LP-IV can well estimate the cycle of boom and bust rather than the LP-OLS and the VAR.

2.4 Cumulative Effects of Boom and Bust

We next estimate the cumulative effects of boom and bust. To do that, we use the advantage of the local projections that are flexible to the choice of variables. Specifically, let $\Delta_k HP_{i,t+h}$(=

[16] The VAR needs identifying restrictions, such as Cholesky ordering, the long-run restriction, the sign restriction, etc.

$\ln HP_{i,t+h} - \ln HP_{i,t+h-k}$) denote the growth rate of the housing price from period $t+h-k$ to period $t+h$. Extending the interval of period k enables us to estimate the cumulative effect of the credit shock, which is reflected by its coefficient, denoted $\beta^{k,h}$. In estimating the cumulative effect of a boom, our strategy is to choose the combination (k, h) that maximizes the coefficient $\beta^{k,h}$.

We have to be careful with regard to the choice of the period when a boom starts. One might wonder if the boom starts at period t, but this guess will be generally incorrect. At the estimation, the housing price growth is highest at the contemporaneous period of the credit shock $(t = 0)$, which suggests that the boom may have started at four periods before at maximum because our estimation uses four-quarter (one-year) growth.

Table 5 summarizes the cumulative effects. As shown in columns 1–3 of Panel A, we find that the combination of $k = 9$ and $h = 5$ maximizes the coefficient of the credit growth, which means that the duration of the boom is nine periods from period $t-4$ to period $t+4$. An exogeneous increase in the credit growth by 1 percent leads to the boom in the housing price growth by 0.935 percent.

[Insert Table 5 here]

We turn to the bust. One difficulty is to find the period when the bust starts. The bust may start gradually, and it will be difficult to specify the starting period. We guess the starting period of bust from the estimates in the following way. The LP-IV estimates in Panel A of Figure 5 show that the coefficient of the credit growth is insignificant before the period $h = 16$, but begins to be negative and statistically significant from period $h = 17$ on, suggesting that the bust started between periods $t + 13$ and $t + 16$.

We find that the combination of $k = 14$ and $h = 27$ minimizes the coefficient of the credit growth, which means that the duration of the bust is 14 periods from period $t + 13$ to period $t + 27$. An exogeneous increase in the credit growth by 1 percent leads to the bust in the housing price growth by 0.879 percent.

Taken together, a boom lasts for two years and a quarter (9 quarters), turns into a bust three years after the shock, and then the bust lasts for three years and a half (14 quarters). At the end of the bust, most of the house prices that rose during the boom are lost.

2.5 Current Account Surpluses and Deficits

We have established the finding that the exogenous credit shock drives the boom followed by a bust of the housing price growth. The instrumental variable used here is based on the notion that the domestic credit market is integrated into global financial markets. Calvo Leiderman, and Reinhart (1996) and Benigno, Converse, and Fornaro (2015) document that international capital flows have an impact on the pattern of domestic financial cycles. It would be natural to expect that a country's current account balance influences the boom and bust of domestic asset markets.

The summary statistics in Table 3 show that deficits of the current account exhibit a higher mean growth of credit, but a lower mean growth of housing prices than surpluses. This seemingly counterintuitive observation may be interpreted to indicate that a country of current account deficits tends to experience a sharper boom-bust cycle of housing prices. In support of this suggestion, deficits exhibit a higher standard deviation of housing price growth.

We estimate the effects of current account balance on the pattern of cycle by considering the heterogeneity in coefficients by grouping data of surplus and deficit countries. Specifically, we construct dummy variables capturing either the current account surplus or deficit for each country and for each quarter.[17] The surplus dummy ($D_{i,t}^{surplus}$) takes a value of 1 if a country i in period t records a surplus, and zero otherwise. Likewise, the deficit dummy ($D_{i,t}^{deficit}$) takes a value of 1 if a country in period t records a deficit, and zero otherwise. The first-stage specification is written as

[17] When quarterly frequency current account balance series is not available in the IFS database, we use annual frequency data provided by WEO to increase data availability.

$$\Delta_4 Credit_{i,t} \times D_{i,t}^{m}$$
$$= \alpha_1^m \left(\ln \frac{Total\ Credit}{GDP}_{i,1980} \times \frac{1}{N-1} \sum\nolimits_{j \neq i} \Delta_4 Credit_{j,t} \right) \times D_{i,t}^{surplus}$$
$$+ \alpha_2^m \left(\ln \frac{Total\ Credit}{GDP}_{i,1980} \times \frac{1}{N-1} \sum\nolimits_{j \neq i} \Delta_4 Credit_{j,t} \right) \times D_{i,t}^{deficit}$$
$$+\boldsymbol{\Gamma}^m \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^m \boldsymbol{W}_{i,t-4} + \delta_i^m + \gamma_t^m + \varepsilon_{i,t}^m$$

for $m = surplus$ or $deficit$. The coefficients of our interest are $\alpha_1^{surplus}$ and $\alpha_2^{deficit}$. Accordingly, the second-stage specification is written as

$$\Delta_4 HP_{i,t+h} = \beta_1^h \widehat{\Delta_4 Credit_{i,t} \times D_{i,t}^{surplus}} + \beta_2^h \widehat{\Delta_4 Credit_{i,t} \times D_{i,t}^{deficit}} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-4} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h,$$

where $\widehat{\Delta_4 Credit_{i,t} \times D_{i,t}^{surplus}}$ and $\widehat{\Delta_4 Credit_{i,t} \times D_{i,t}^{deficit}}$ are the predictions of each instrumental variable.

[Insert Table 6 here]

Table 6 reports the estimation results. In the first-stage regression, the coefficients of surpluses $\alpha_1^{surplus}$ and deficits $\alpha_2^{deficit}$ are both negative and significant. The F-statistics over 10 show that there is little concern on estimation bias caused by weak instrument, which shows that the estimation for the heterogeneity in coefficients is robust to the grouping between surplus and deficit countries. The coefficients of surpluses are larger than those of deficits, which is seemingly counterintuitive, because the domestic credit market of a deficit country is subject to the conditions of the global credit market more sensitive than the one of a surplus country.

Panels A and B of Figure 6 depict the correlation between the global credit growth and the individual country's credit growth for observations with current account surpluses and deficits, respectively. As expected, the coefficient of the fitted line of current account deficits is 0.856 (standard error = 0.156), larger than the coefficient of the fitted line of surpluses, 0.695

(standard error = 0.152). Indeed, the figures of the scatters point out that the credit growth of deficits is more sensitive to the global credit growth than the one of surpluses. Another component of the instrument, the ratio of the total credit to GDP in 1980 in surpluses, exhibits a higher value than that of deficits. This is the reason why the implications on coefficients are counterintuitive.

[Insert Figure 6 here]

[Insert Figure 7 here]

Let us turn to the second-stage regression. Looking at the coefficients of short horizons, the coefficients of deficits are positive and higher than those of surpluses. The coefficient of deficits reaches 0.845 at peak ($h = 1$), which is almost as twice the coefficient of surpluses. This finding suggests that deficit countries tend to rely more on foreign capital in booms, and experience larger appreciations in housing prices than surplus countries. At longer horizons, coefficients of deficits are negative and significant for many of the 4–7 years ahead, while coefficients of surpluses are also negative but small in absolute values and insignificant. Deficit countries suffer larger depreciations in housing prices than surpluses countries, suggesting that deficit countries experience the cutback of foreign capital during the bust, while surplus countries do not experience the outflow of domestic capital. Figure 7 reports the impulse response functions of deficits (red line) and surpluses (blue line). The impulse response function of deficits shows a larger cycle of boom and bust than the one of surplus countries.

We turn to the cumulative magnitude of boom and bust. Panel D of Table 5 shows that in deficit countries, an exogeneous increase in the annual growth rate of credit by 1 percent leads to a boom in the housing price growth by 1.287 percent, and later leads to a bust by 1.765 percent. Deficit countries experience a cycle of a large boom and an even large bust. The measure of the shape of cycle goes up to 1.371 (column 7): at the end of the bust, all the house prices that rose during the boom are lost. In contrast, the magnitude of boom is small in surplus countries. Panel C of Table 5 shows that an exogeneous increase in the annual growth rate of credit by 1 percent leads to a boom in the housing price growth by 0.414 percent. Diebold and Richter (2023) state that the credit boom financed with foreign capital inflows are likely to be followed by GDP growth slowdown. Our findings are along the line with their results.

2.6 Credit Expansion

The results of one-year credit growth suggest the presence of people's irrational expectations, and it will be interesting to see whether the error in forecasting for the credit shock will be corrected or amplified by extending the interval of credit growth. It also examines how prolonged credit growth, often referred to as "credit expansion", affects the boom-and-bust cycle.

The recent literature indicates that the credit growth over longer periods captures features of the adverse consequences of effects through the worsening of bank balance sheets such as leverages and liabilities. Schularick and Taylor (2012) and Greenwood et al. (2022) find that the credit growth predicts an increase in the probability of financial crisis for 2 or 3 years ahead. Baron and Xiong (2017) find that the credit growth predicts an increased bank equity crash risk with lags of 2 or 3 years. A longer credit expansion could predict a deeper bust.

The literature typically uses the three-year interval as the length of credit expansion from the observation that credit expands rapidly over three to four years during credit booms (see Mian, Sufi, and Verner, 2017; Müller and Verner, 2023). We use two-year and three-year credit growth variables as explanatory variables instead of the annual credit growth. The summary statistics in Table 3 show that the means of the one-year, two-year, and three-year credit growth are very close, suggesting that if we find a different boom-bust pattern, the difference arises from the difference in the interval of credit growth.[18]

For example, the first-stage and second-stage regressions in the two-year growth specification are written as

[18] The standard deviations become slightly smaller for credit growth of longer intervals.

$$\Delta_8 Credit_{i,t} = \alpha \ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1}\sum\nolimits_{j\neq i} \Delta_8 Credit_{j,t} + \boldsymbol{\Pi X}_{i,t} + \boldsymbol{\Psi W}_{i,t-8} + \delta_i + \gamma_t + \varepsilon_{i,t}$$

and

$$\Delta_8 HP_{i,t+h} = \beta^h \Delta_8 \widehat{Credit}_{i,t} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-8} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h,$$

for $h = 0, 1, 2, \dots, 40$.

The two-year credit growth at period t, $\Delta_8 Credit_{i,t}$, is defined by the change in the variables from period $t-4$ (four quarters ago) to period $t+4$ (four quarters ahead): $\Delta_8 Credit_{i,t} = (\ln Credit_{i,t+4} - \ln Credit_{i,t-4})/2$. The housing price growth variable at period t has the same interval: $\Delta_8 HP_{i,t} = (\ln HP_{i,t+4} - \ln HP_{i,t-4})/2$. The control $\boldsymbol{X}_{i,t}$ is the set of variables for the current period, and includes the GDP growth rate, the CPI-based inflation rate, and the population growth rate from period $t-4$ to period $t+4$. It also includes short-term interest rate and maturity spreads at period $t+4$. The control $\boldsymbol{W}_{i,t-8}$ is the set of variables for the eight quarters (two year) lag, and includes the growth rates from period $t-12$ to period $t-4$ and the interest rates at period $t-4$. It includes housing price growth and credit growth variables, and the instrumental variable from period $t-12$ to period $t-4$. We also include housing price growth and credit growth variables of the additional lag, those for the sixteen quarters (four year) lag, from period $t-20$ to period $t-12$ to reduce the concern on serial correlation.[19]

Table 7 reports the estimation results. The coefficients at short horizons are positive and significant for all the three estimates. As the interval of credit growth becomes longer, the coefficients are a little larger. For example, the coefficient at peak is 0.608 ($h = 0$) in the one-year credit growth case (Panel A), while it is almost twice, 1.021 ($h = 0$), in the three-year credit growth case (Panel C). The turning point into bust is almost similar across the three between $h = 17$ and $h = 20$.

The difference in the estimates is stark at longer horizons. In all three, as the interval of credit growth becomes longer, the bust becomes deeper and more persistent. The coefficient at

[19] We confirm that the result holds when we exclude the additional lags. However, the confidence intervals become narrower, indicating a typical sign of serial correlation.

trough is -0.292 ($h = 19$) in the one-year credit growth case (Panel A), while it is -0.548 ($h = 26$), in the three-year credit growth case (Panel C). In the one-year credit growth case, the bust lasts almost three years from $h = 17$ to $h = 27$ at the significant level of 5 percent, while in the three-year credit growth case, the bust lasts almost four years from $h = 20$ to $h = 36$,

[Insert Table 7 here]

[Insert Figure 8 here]

Figure 8 compares the impulse response functions among the credit growth of different intervals. For example, Panel B shows that the bust of the three-year credit growth case (red line) becomes deeper and more persistent than the bust of the one-year credit growth (blue line). The longer is the interval of credit growth, the larger and longer is the boom-bust cycle. In the three-year credit growth case, one cycle from boom to bust ends with almost nine years (37 quarters).

In the above specification, following the change in the interval of credit growth, the intervals of other variables also change. To see if the interval of credit growth is the primary determinant to affect the pattern of the cycle, particularly the length of bust, we attempt the regressions that keep variables other than the credit growth variables as close as possible to the baseline one-year analysis. The first-stage and second-stage regressions using the two-year credit growth are written as

$$\Delta_8 Credit_{i,t} = \alpha \ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1}\sum_{j \neq i} \Delta_8 Credit_{j,t} + \boldsymbol{\Pi X}_{i,t} + \boldsymbol{\Psi W}_{i,t-4} + \delta_i + \gamma_t + \varepsilon_{i,t}$$

and

$$\Delta_4 HP_{i,t+h} = \beta^h \Delta_8 \widehat{Credit}_{i,t} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-4} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h,$$

for $h = 4, 5, 6, \dots, 40$. In both regressions, all the variables have the one-year interval except for the current and lagged credit growth variables and the lagged instrumental variable used as control.[20] We limit the estimation for longer horizons, $h \geq 4$, because regressions for short horizons, $h < 4$, would imply that the error term should include unrealized future information. For example, at the horizon $h = 0$, the error term at period t, $\varepsilon_{i,t}^{0}$, may include unrealized future information from period t to $t + 4$, leading to a correlation between the error term and the instrument. Due to this limitation, we focus on the analysis of bust, not of boom.

We observe a similar pattern. Panels C and D in Figure A1 show that the credit growth of longer intervals leads to more persistent bust. In the three-year credit growth case, the bust lasts almost four years from $h = 19$ to $h = 35$ (Panel D). The figure of four years is the same as the above estimate.

Greenwood et al. (2022) show the combination of rapid credit and asset price growth over the past three years is associated with a high probability of entering a financial crisis within the next three years, especially in the third year. The third year in theirs corresponds to $h = 24$ in our model, at when the housing price is falling at least for more than one year.

We estimate the cumulative magnitude of boom and bust when the interval of credit growth is longer. As shown in Panel B of Table 5, an exogeneous increase in the two-year growth rate of credit by 1 percent leads to a boom in the housing price growth by 1.973 percent, and later leads to a bust by 2.035 percent. Both boom and bust become stronger as the credit growth become longer from one to two years.

We turn to the three-year growth. As shown in Panel C of Table 5, an exogeneous increase in the three-year growth rate of credit by 1 percent leads to a boom in the housing price growth by 3.063 percent, and later leads to a bust by 2.656 percent. As the credit expands longer, the boom is stronger, and the bust is even stronger.

The estimates show that the three-year credit growth explains well the sharp rise and fall in housing prices. This result is consistent with other literature that has used the three-year credit growth to predict the financial crises, recessions, and the market downturns (e.g., Schularick and Taylor, 2012; Greenwood et al., 2022).

The next question is whether a larger decline in housing prices is associated with the

[20] The lagged instrumental variable is constructed by the two-year credit growth from period $t - 12$ to period $t - 4$.

worsening of banks' balance sheets and the increase in the likelihood of a financial crisis.

[Insert Figure 9 here]

We use the data on the banks' nonperforming loans to reveal the possible causal channel from credit expansion to the eventual deterioration of banks' balance sheets. Figure 9 shows the impulse response of the ratio of bank nonperforming loans to gross loans to the credit shock. A loan is defined as nonperforming when the principal or interest is 90 days or more past due, or when it is expected that future payments will not be received in full.[21] Data on nonperforming loans are provided at an annual frequency and cover the period from 1998 to 2019. To align the data frequency, all other variables, such as credit and GDP growth, are annualized by taking the Q4 values of each year. Due to the data availability, the estimates may capture the boom-bust cycles in the 2000s.

The figure also plots the impulse response of housing prices in Panel A of Figure 5, which is estimated by quarterly data covering the period from 1980 to 2019. In Panel A of Figure 9, we find an increase in the nonperforming loans at four and five years after the shock. It is noteworthy that the periods of increasing nonperforming loans roughly coincide with the periods of the fall in housing prices. This suggests that the fall in housing prices increases nonperforming loans, which in turn worsens balance sheets of banks.

This pattern becomes clearer when we use the three-year growth specification instead of the one-year growth specification. Panel B shows that a credit shock leads to a larger and longer increase in the nonperforming loans after four years from the shock. The impulse responses of house prices and nonperforming loans are mirror images of each other. This result is roughly consistent with the view that a prolonged credit expansion leads to a larger decline in housing prices, larger nonperforming loans, and the greater deterioration of balance sheets. This finding is consistent with Greenwood and Hanson (2013) who show that the credit quality of corporate

[21] To be careful, the data of the nonperforming loans cover only banks' nonperforming loans, while our main measure of credit is the total credit to the household sector by various types of financial institutions other than commercial banks. Our approach would be justified when they are similar. We obtain a correlation coefficient of 0.606.

debt issuers deteriorates during credit booms.

This additional analysis helps to unveil the implication of boom-bust cycles of housing prices on the eventual financial crises. A prolonged credit expansion will lead to a larger decline in asset prices, worsening banks' balance sheets, and increasing the likelihood of a financial crisis.

Our results show that the boom-bust cycle of housing prices is predictable, and that a prolonged credit expansion, such as the three-year credit growth, becomes a warning signal to predict the large swing of asset prices and the vulnerability of the economic system.

3. Supply Shock or Demand Shock?

If our result favors the Kindleberger–Minsky view, the identified credit shock has to reflect credit-supply shocks. The next question is how do we understand credit growth: in other words, does our credit variable used as an IV capture the demand shock or the supply shock? Basically, our specification is expected to explain the effect of the supply shock rather than the demand shock. Our credit variable is normalized by GDP, and if the coefficient of this credit variable is positive, it would imply that the fast credit growth reflects any shocks other than the demand shock captured by the GDP growth.

We first examine each of the two variables that construct our IV. As for the exposure variable, the negative correlation between the initial level of the total credit relative to GDP and the subsequent credit growth will support the supply shock view. The negative correlation is consistent with the story that a country of more severely regulated banking tends to realize faster credit growth to the housing sector in a wave of banking deregulation. One may wonder about a possible demand-side channel. Many growth regressions indicate that the initial ratio of the total credit to GDP leads to subsequent economic growth (see King and Levine, 1993, for example). Through its channel, the expected economic growth may stimulate the current credit growth. However, if this channel is present, the correlation should be positive. Nonetheless, our exposure variable seems to reflect the supply shock rather than the demand shock.

We turn to the shock variable. The global credit growth is, in principle, driven by both demand and supply factors in the global credit market, such as global growth and recessions (demand factors), and the global trend on financial liberalization and financial innovation, and the massive flow of funds from emerging countries, called the global savings glut (supply factors). To shed light on this issue, we exclude the demand factor from the global credit variable. We regress the global credit growth on the global GDP growth, and use the residuals of the estimation as the shock variable. Given this preparation, we construct the new IV and estimate impulse response functions. As shown in the next section, the cycle of boom and bust is preserved (Panel B of Figure 11). This suggests that the shock variable will capture well the supply factors. Taken together, we can safely judge that our IV reflects the supply shocks rather than the demand shocks.

An alternative approach is to check the implications of competing models to distinguish between models in which either credit-demand shocks or credit-supply shocks play the larger role. One natural story will be that credit growth is driven by higher demand for credit in response to expected income growth. Then, the credit-demand shock should be associated with higher interest rates. An alternative interpretation will be that it is driven by the credit-supply shock. Justiniano, Primiceri, and Tambalotti (2019) demonstrate that the relaxation of credit-supply constraints, combined with the collateral constraint, leads to a fall in the interest rate during the housing price boom. The credit-supply shock would reflect the relaxation of credit constraints for various reasons, such as increased international capital inflows, a new lending technology (e.g., securitization), and banking deregulation. In credit-supply shock models, periods of expanding credit should be associated with lower interest rates.[22]

Figure 10 shows the LP-IV impulse response functions of the decompositions of the long-term real interest rate: the nominal short-term interest rate, the maturity spread, and the CPI-based inflation rate.

[Insert Figure 10 here]

[22] Similarly, Schmitt-Grohé and Uribe (2016) model a small open economy where the interest rate faced by the economy suddenly declines, households boost their consumption, and external debt rises.

Panel A reports the estimates of the short-term interest rate. The short-term interest rate reacts positively, which seems to capture the fact that the central bank reacts to the credit shock by raising the policy rate. Panel B reports the estimates of the maturity spread. The maturity spread reacts negatively, suggestive of the presence of some force that drives the long-term interest rate to fall faster than the short-term rate. The mitigation of the credit-supply constraints enables banks to become willing to lend more. Given the demand for credit, this lending will push down interest rates on mortgages and hence the interest rate on government bonds of longer maturity through arbitrage. Conversely, if the identified shock represents the demand shock, an increase in the credit demand has to raise the interest rate.

One may wonder whether the real rates move along with the nominal rates. If the inflation rate reacts negatively to the credit shock, the response could lead to a rise in the real interest rate and might support the demand shock view. Panel C reports the estimates of the inflation rate. The inflation rate reacts positively for almost all periods. As a whole, the long-run real interest rate does not seem to rise.

We next estimate the response of the long-term real interest rate. We conduct this estimate by controlling for the long-term real interest rate as the control variable instead of the maturity spread. Panel D reports the estimates. The long-term interest rate reacts negatively to the credit shock, which is again supportive of the credit-supply view. Taken together, the responses of nominal and real movements seem to support the view that the IV captures supply shocks rather than demand shocks.

We may be able to detect the timing of the reversal of sentiments if the lending is excessive. The bust starts about four years after the shock, around when the maturity spread turns to rise. A rise in the longer-term interest rate relative to the short-term rate may be a trigger for the reversal of investors' sentiments.[23]

4. Robustness Check

This section checks some robustness of our estimations. In the early 1980s, several

[23] Mian, Sufi, and Verner (2017) define the interest spread as the difference between the interest rate on mortgage loans and the 10-year government bond, and report that the low interest rate is associated with an increase in the ratio of credit to GDP for a panel of annual data that cover 30 countries from 1960 to 2012.

countries implemented deregulation and experienced credit growth. The first reservation is whether the effects of the wave of deregulation on credit growth were predicted as of 1980. If so, even if the credit growth was not observed in 1980, expectations for future deregulation might have affected the housing market. In other words, the exposure variable, i.e., $\ln Total\ Credit/GDP_{i,1980}$, might violate the exclusion restriction.

We review observations of six countries that experienced banking deregulation in the 1980s. The US experienced a period of banking deregulation in the late 1970s and 1980s, differing across states.[24] All states removed interstate branching restrictions to allow banks to expand their branch network across states since 1982, while many states removed intrastate branching restrictions from the 1980s. The starting year of the positive credit growth is 1983Q1. The literature treats banking deregulation in the 1980s as an exogeneous event (e.g., Kroszner and Strahan, 1999; Mian, Sufi, and Verner, 2020). In addition, the banking reform in the 1980s was together with a package of economic reforms, called “Reaganomics,” that started after Ronald Reagan took office as the President in 1981. We could not find any news that he had released plans for economic reforms before he took office.

In Japan, banking deregulation started as a response to the trade frictions with the United States in the early 1980s. To lessen the trade imbalance, the United States requested a stronger Japanese yen and liberalizing financial markets. Interest rates for certificated deposits of large scale were liberalized in 1985, which was a first step for banking deregulation (Takeda and Turner, 1992). The starting year of the positive credit growth is 1986Q1.

Nordic countries experience bank deregulation in the 1980s, as a reaction to the emergence of unregulated Euro markets (Drees and Pazarbasioglu, 1998). The Norwegian government mitigated restrictions on loan rates in 1980 by switching to interest rate declaration that provided some flexibility in the structure of interest rates, but its effectiveness was limited. Major reforms began in 1985 when interest rate declaration was removed. The starting year of the positive credit growth is 1982Q2.

In Sweden, deregulation started in 1978. Ceilings on deposit rates were formally abolished

[24] Mian, Sufi, and Verner (2020) reports the starting year of interstate and intrastate deregulation across states.

by interbank agreement, linking deposit rates to the government discount rate, which continued for some years. Major reforms began from 1983 when the requirement on liquidity ratios for banks was abolished. The ceilings and restrictions on average loan rates were lifted in 1985. The starting year of the positive credit growth is 1986Q2.

In Finland, deregulation started in 1983, and in 1986, the restrictions on average loan rates were abolished. The credit growth rates were positive over the 1980s, but relatively low in 1984Q2 and Q3, at 1.3 percent annually. Across those five countries, it will not be reasonably conceived that the effects of the wave of deregulation on credit growth were predicted as of 1980.

In the UK, building societies (mortgage lending unions) had a dominant share in the mortgage market. Deregulation started in mid-1980, and then banks were permitted to re-entry into the mortgage market. The deregulation was accompanied by credit growth. The credit growth rates were positive over the 1980s, and accelerated from 1981Q1 to 1983Q1. The deregulation led to unanticipated consequences. The large-scale entry of banks in 1981–82 put pressure on building societies. Building societies shifted policies toward using variations in interest rates rather than rationing to meet mortgage demand, and finally regained market share. The direction of increased competition and liberalization was followed by the expansion of mortgage lending of building societies rather than banks. In the United Kingdom, deregulation led to credit growth, but did in some unanticipated manner. It will be questionable if the effects of deregulation on credit growth were predicted accurately as of 1980.

Anecdotal observations in six countries make endogeneity unlikely at least for the UK. We next present the empirical evidence to check the exogeneity of the initial ratio of the total credit to GDP in 1980. The first-stage regressions in Table 4 suggest that the exposure variable, i.e., $\ln Total\ Credit/GDP_{i,1980}$, is correlated with the subsequent credit growth. The exogeneity of the initial ratio of the total credit to GDP requires this correlation to have been unanticipated as of 1980.

We conduct a placebo sample test to check the exogeneity by regressing the credit growth during the 1970s on the ratio of the total credit to GDP in 1980. The credit data in the 1970s are not available for most countries in the BIS data, and we use the annual frequency panel data of Jordà, Shularick, and Taylar (2016) and Müller and Verner (2023).[25] Table 8 reports the result. We find no correlation between the credit growth in the 1970s and the ratio of the total credit to GDP in 1980 with/without controls, supporting that there is little concern on the effects of future expected deregulation on the housing prices at the time of 1980.[26]

[Insert Table 8 here]

Despite there not being a pre-event trend result, we might not be able to exclude the possibility that the causal relation from deregulation to credit growth was anticipated at the time of 1980. Figure 4 shows that there was a positive relationship between the ratio of the total credit to GDP and the credit growth during the period 1980–1984 (although not statistically significant), indicating that deregulation tended to have occurred in countries that had already high ratios of the total credit to GDP. However, it would be perceived that the endogeneity, if at all, is unlikely to have had an impact on the estimation results. This is because the estimates show a negative relationship as a whole between the ratio of the total credit to GDP and the credit growth. If this view is correct, then when the pre-1984 data are excluded from the sample, the estimate should be almost unchanged. Panel A of Figure 11 shows that our main results are preserved.

[Insert Figure 11 here]

We next check the exclusion restrictions of the shock variable. By construction, the global

[25] As is similar to the BIS data, Müller and Verner (2023) cover the total credit to the household sector, while Jordà, Shularick, and Taylar (2016) cover only bank credit to the household sector. We check the correlation between the credit growth of the two data sets, with a correlation coefficient of 0.733, and confirm that the difference in this coverage does not cause a serious problem.

[26] We also conduct an additional test. We run regression to see if the ratio of the total credit to GDP in 1970 is correlated with the subsequent credit growth following the same procedure of Figure 4 (see Figure A2 in the Appendix). The coefficients of the credit growth during 1990–1999 are negatively significant. However, the ratio in 1970 fails to predict the credit growth during 2000–2004. The result suggests that the initial value in 1970 has less predictive power in expecting the subsequent credit growth, unlike the ratio in 1980.

credit growth is exogeneous to demand and supply shocks of the housing market of each specific country. One might guess that if demand shocks are correlated across countries, the change in the global GDP growth will influence the sample mean of the credit growth, which may violate the orthogonal condition of the instrument. In principle, this concern will be avoided by controlling for the time-fixed effects. As a further check, we regress the global credit growth on the global GDP growth and use the residuals of the estimation as the shock variable. Panel B of Figure 11 shows that our main results are preserved.

Our framework assumes that each country is “small” relative to the global credit markets. The United States, a large country, may create a cluster in our data set, and may violate the orthogonality condition of the instrument. For example, monetary policies of the United States can potentially have spillover effects in other countries, influencing the global interest rates and the global credit growth. This concern will be avoided by controlling for country-fixed effects as well as time-fixed effects. Just in case, we perform a conservative estimation that excludes the United States from the sample. Panel C of Figure 11 shows that our main results are preserved.

Finally, one might wonder if the experience of global financial crisis is responsible for the cycle of boom and bust. Panel D examines if the cycle of boom and bust is preserved when the sample is limited to 2007, the year just before the global financial crisis. The bust is a bit shorter, but the basic pattern of boom and bust is preserved. The impulse response shows that the general pattern of boom and bust does not rely crucially on the experience of the global financial crisis.

6. Conclusion

This paper empirically investigates if there is a causal relationship from credit expansion to housing prices, using a data set of an unbalanced panel that covers 20 developed countries from 1980 to 2019. The estimates based on the local projections with instrumental variables show that an exogeneous increase in credit supply leads to a boom at short horizons, and to a bust of housing prices at longer horizons.

Our result favors the Kindleberger–Minsky view that provides a foundation for a “credit-supply shock” as a starting point for a boom-bust cycle. The impulse response for a boom followed by a bust supports the behavioral bias view that the “excessive” credit supply typically due to overextrapolation leads to the overheating of housing markets, and results in a bust when these optimistic beliefs are revised.

Our finding for the causal effects of credit expansion on housing prices unravels the important channel of the propagation from credit cycles to crises. Our results show that the boom-bust cycle of housing prices is predictable, and that a prolonged credit expansion such as a three-year credit growth becomes a warning signal to predict the large swing of asset prices and the vulnerability of the economic system.

References

Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review, 103(6), 2121–68.*

Baron, M. & Xiong, W. (2017). Credit expansion and neglected crash risk. *The Quarterly Journal of Economics, 132(2), 713–764.*

Bartik, T. J. (1991). Who benefits from state and local economic development policies? *Kalamazoo, MI: WE Upjohn Institute for Employment Research.*

Benigno, G., Converse, N. and Fornaro, L. (2015), "Large Capital Inflows, Sectoral Allocation, and Economic Performance", *Journal of International Money and Finance,* 55, 60–87.

Blanchard, O. J., & Katz, L. F. (1992). Regional Evolutions. *Brookings Papers on Economic Activity, 1992(1), 1–75.*

Blanchard, O. J, Ostry, J. D., Ghosh, A. R., & Chamon, M. (2017). Are capital inflows expansionary or contractionary? Theory, policy implications, and some evidence. *IMF Economic Review, 65(3), 563-585.*

Bordalo, P., Gennaioli, N., & Shleifer, A. (2018). Diagnostic expectations and credit cycles. *Journal of Finance, 73(1), 199–227.*

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies, 89(1), 181–213.*

Brunnermeier, M., Palia, D., Sastry, K. A., & Sims, C. A. (2021). Feedbacks: financial markets and economic activity. *American Economic Review, 111(6), 1845–79.*

Calvo, G. A., Leiderman, L., & Reinhart, C. M. (1996). Inflows of Capital to Developing Countries in the 1990s. *Journal of economic perspectives*, *10(2), 123-139*.

Diebold, L., & Richter, B. (2023). When two become one: foreign capital and household credit expansion. *Available at SSRN 3817595*.

Di Maggio, M., & Kermani, A. (2017). Credit-induced boom and bust. *The Review of Financial Studies, 30(11), 3711-3758.*

Drees, M. B., & Pazarbasioglu, C. (1998). The Nordic Banking Crisis: Pitfalls in Financial Liberalization: Pitfalls in Financial Liberalization. International monetary fund.

Favara, G. & Imbs J. (2015). Credit supply and the price of housing. *American Economic Review, 105(3), 958–92.*

Gennaioli, N., & Shleifer, A. (2018). *A Crisis of Beliefs, Investor Psychology and Financial Fragility,* Princeton University Press, NY.

Gennaioli, N., Shleifer, A., & Vishny, R. (2012). Neglected risks, financial innovation, and financial fragility. *Journal of Financial Economics, 104, 452–468.*

Gourinchas, P. O. & Obstfeld, M. (2012). Stories of the twentieth century for the twenty-first. *American Economic Journal: Macroeconomics, 4(1), 226–265.*

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review, 110(8), 2586-2624.*

Greenwood, R., & Hanson, S. G. "Issuer Quality and Corporate Bond Returns," *Review of Financial Studies,* 26 (2013), *1483–1525*.

Greenwood, R., Hanson, S. G., & Jin, L. J. (2016). A model of credit market sentiment. *Harvard Business School Working Paper, No. 17-015.*

Greenwood, R., Hanson, S. G., Shleifer, A., & Sørensen, J. A. (2022). Predictable financial crises. *The Journal of Finance*, 77(2), *863-921*.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review, 95(1), 161–182.*

Jordà, Ò., Schularick, M., & Taylor, A. M. (2015). Betting the house. *Journal of International Economics, 96, S2–S18.*

Jordà, Ò., Schularick, M., & Taylor, A. M. (2016). Macrofinancial history and the new business cycle facts. *NBER Macroeconomics Annual 2016, v.31.*

Justiniano, A., Primiceri, G. E., & Tambalotti, A. (2019). Credit supply and the housing boom. *Journal of Political Economy Volume 127(3), 1317–1350*.

Kindleberger, C. P. (1978). Manias, panics and crashes: A history of financial crises. *Palgrave Macmillan.*

King, R. G. and R. Levine, (1993), Finance and Growth: Schumpeter Might Be Right, *Quarterly Journal of Economics,* 108, *717-738*.

Kiyotaki. N., and J. Moore, (1997), Credit Cycles, *Journal of Political Economy,* 105, 211-48.

Kroszner, R. S., & Strahan, P. E. (1999). What drives deregulation? Economics and politics of the relaxation of bank branching restrictions. *The Quarterly Journal of Economics, 114(4), 1437-1467.*

Landvoigt, T., M. Piazzesi, and M. Schneider. 2015. The housing market (s) of San Diego. *The American Economic Review 105:1371–407.*

López-Salido, David., Jeremy C. Stein, Egon Zakrajšek, (2017), Credit-Market Sentiment and the Business Cycle, *The Quarterly Journal of Economics, Volume 132(3), 1373–1426.*

Mian, A. & Sufi, A. (2009). The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis. *The Quarterly Journal of Economics, 124(4), 1449–1496.*

Mian, A. & Sufi, A. (2022). Credit Supply and Housing Speculation, *The Review of Financial Studies 35, 680–719*.

Mian, A., Sufi, A., & Verner, E. (2017). Household debt and business cycles worldwide. *The Quarterly Journal of Economics, 132(4), 1755—1817.*

Mian, A., Sufi, A., & Verner, E. (2020), How Does Credit Supply Expansion Affect the Real Economy? The Productive Capacity and Household Demand Channels, *The Journal of Finance, Volume 75(2), 949-994*

Minsky, H. P. (1986). Stabilizing an unstable economy. *A Twentieth Century Fund Report. Yale University Press.*

Müller, K., & Verner, E. (2023). Credit allocation and macroeconomic fluctuations. *The Review of Economic Studies, 1-32.*

Nunn, N., & Qian, N. (2014). US food aid and civil conflict. *American Economic Review, 104(6), 1630—66.*

Schmitt-Grohé, S., & Uribe, M. (2016). Downward nominal rigidity, currency pegs, and involuntary unemployment. *Journal of Political Economy, 124(5), 1466–1514*

Schularick, M., & Taylor, A. M. (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870–2008. *American Economic Review, 102(2), 1029–1061.*

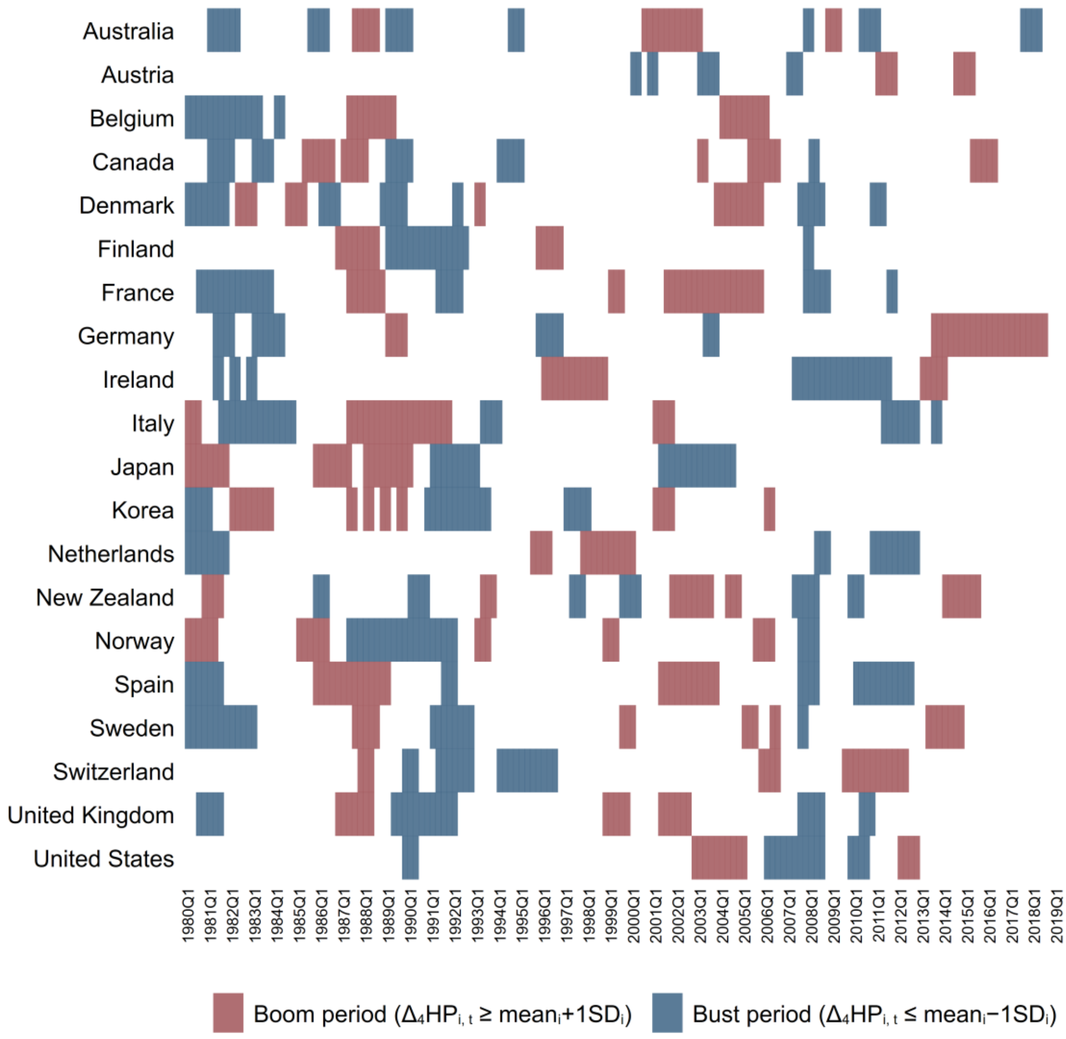
Stock, J. H., & Watson, M. W. (2018). Identification and estimation of dynamic causal effects

in macroeconomics using external instruments. *The Economic Journal, 128(610), 917-948.*
Stock, J. H., & Yogo, M. (2002). Testing for weak instruments in linear IV regression. NBER Technical Working Paper 284.
Takeda, M., & Turner, P. (1992). The liberalisation of Japan's financial markets: some major themes, *BIS Economic Papers 34*.

Figure 1. Boom-and-bust cycles of housing price

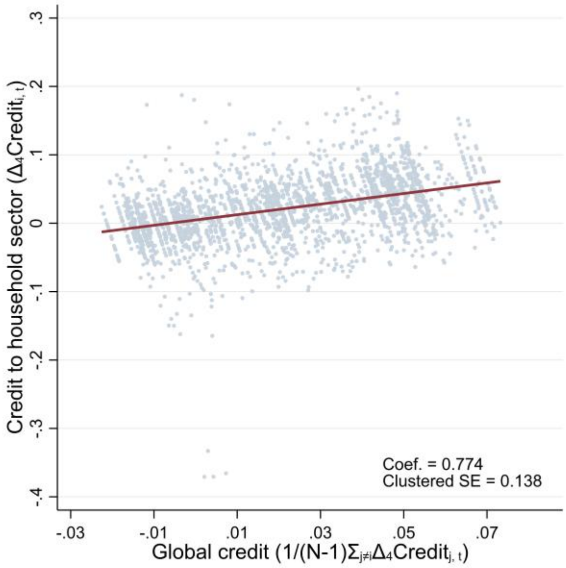
Note: This figure plots the correlation between the annual growth rate of housing price and the ratio of credit to household sector to GDP with a fitted line (solid line). Panel A shows the contemporaneous relationship between house price and credit growth. Panel B shows the intertemporal relationship between current credit growth and house prices five years ahead.

Figure 2. Events of boom and bust of housing price



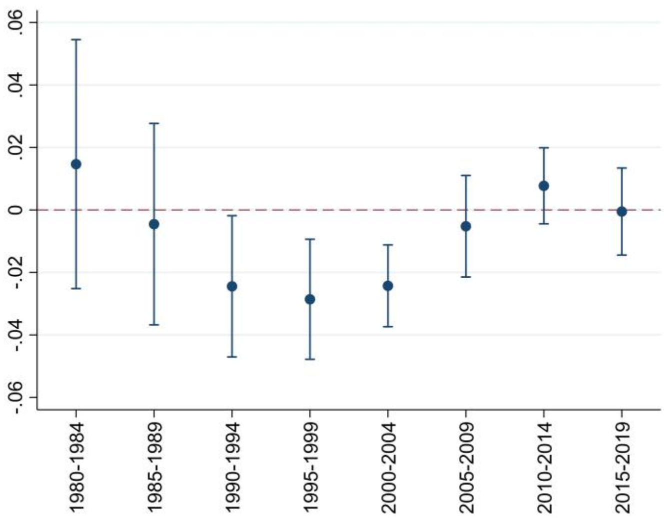
Note: This figure plots events of booms and busts of housing prices. The events are identified using the definition that housing price growth becomes higher/lower than the country-specific mean of housing price plus/minus its one standard deviation. The events lasting for only one quarter are excluded from the figure. The dark blue and light blue periods indicate events of booms and busts of housing price, respectively.

Figure 3. Global and individual country's credit growth



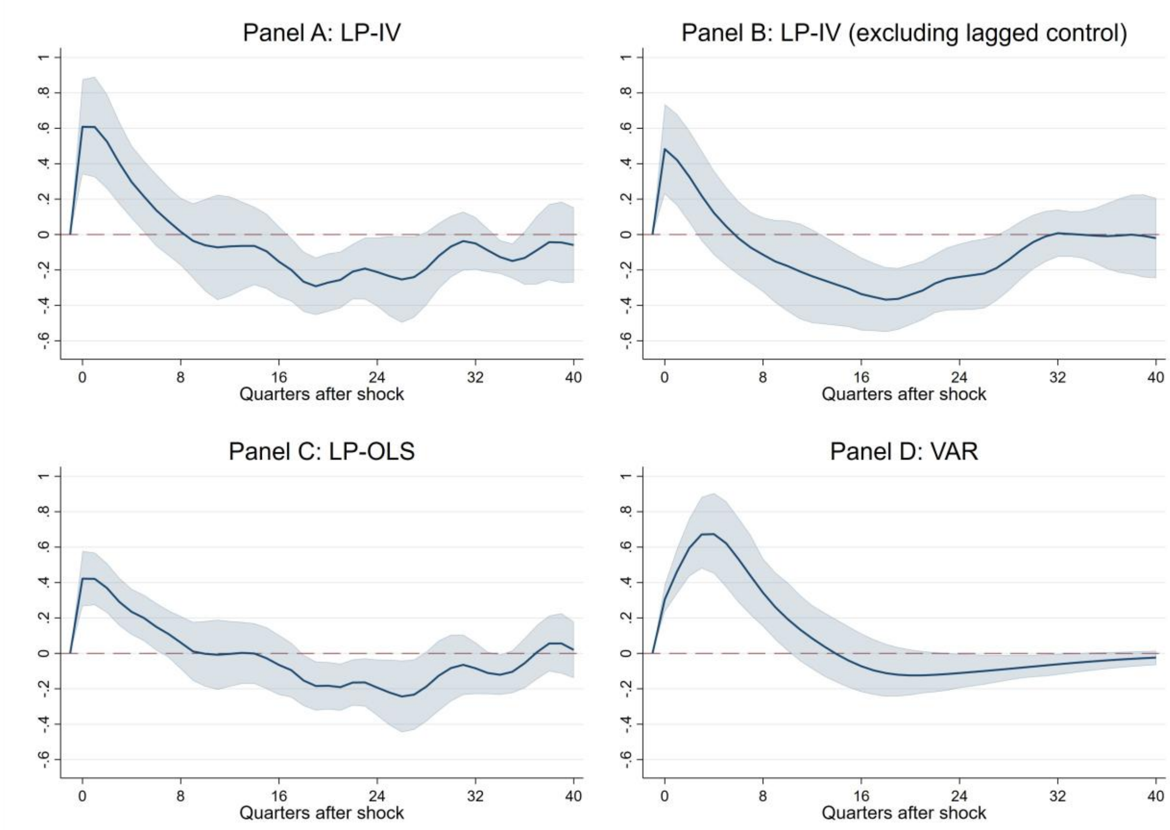
Note: This figure plots the correlation between global credit growth and individual country's credit growth with a fitted line (solid line).

Figure 4. Predictive power of total credit to GDP ratio in 1980



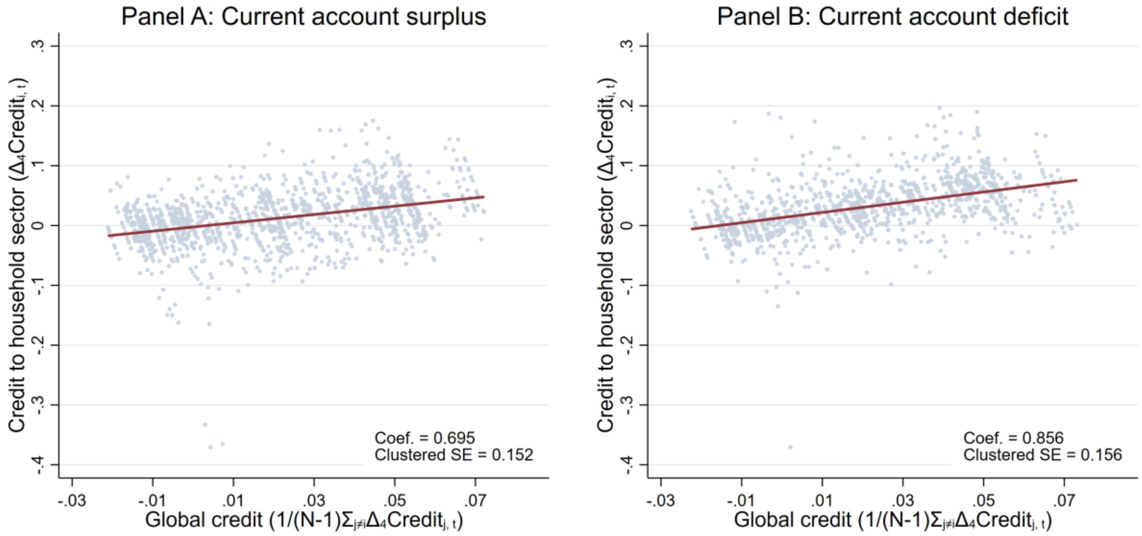
Note: This figure reports the coefficients of total credit to GDP ratio in 1980Q1 on subsequent growth of the ratio of credit to household sector to GDP with a 95 percent confidence interval. The coefficients are estimated based on the following model: $\Delta_4 Credit_{i,t} = \sum_k \beta_k \, ln \, Total \; Credit/GDP_{i,1980} \times D_k + \boldsymbol{\Gamma X_{i,t}} + \boldsymbol{\Phi W_{i,t-4}} + \gamma_t + \varepsilon_{i,t}$. The subscript k represents five-year intervals from 1980 to 2019, such as the period from 1980Q1 to 1984Q4. D_k is the dummy variable that takes the value one if observations belong to each five-year interval, otherwise zero. 95 percent confidence intervals are computed using standard errors dually clustered on country and quarter.

Figure 5. Impulse responses of housing prices



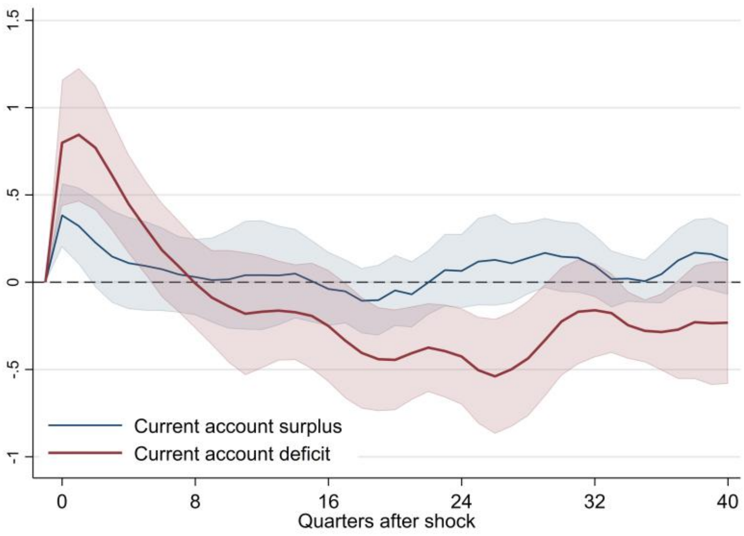
Note: This figure reports impulse responses estimated by LP-IV, LP-OLS, and VAR. Each panel shows the housing price response to an increase in credit to the household sector. The model in Panel A is $\Delta_4 HP_{i,t+h} = \beta^h \Delta_4 \widehat{Credit}_{i,t} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-4} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h$, for $h = 0, \dots, 40$. $\Delta_4 \widehat{Credit}_{i,t}$ is the prediction associated with the instrumental variable: $\ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1} \sum_{j \neq i} \Delta_4 Credit_{j,t}$ in the first-stage regression. Panel B excludes lagged control variables (i.e., $\boldsymbol{W}_{i,t-4}$) from the model. Panel C reports impulse responses estimated by LP-OLS. Panel D reports impulse responses estimated by a recursive panel VAR including the same set of the variables used in LP-IV. The model includes four lags. The shocks are identified using a Cholesky ordering that sets housing price as the last variable. The order is as follows: population growth, real GDP growth, inflation rate, short-term nominal interest rate, maturity spread, growth of the ratio of credit to the household sector to GDP, and housing price growth. Solid line represents impulse responses, and the shaded area represents the 95 percent confidence interval computed by standard errors dually clustered on country and quarter (Panels A–C) or Monte-Carlo (Panel D). The horizontal axis represents the time period (quarterly frequency).

Figure 6. Global and individual country's credit growth of current account surpluses and deficits



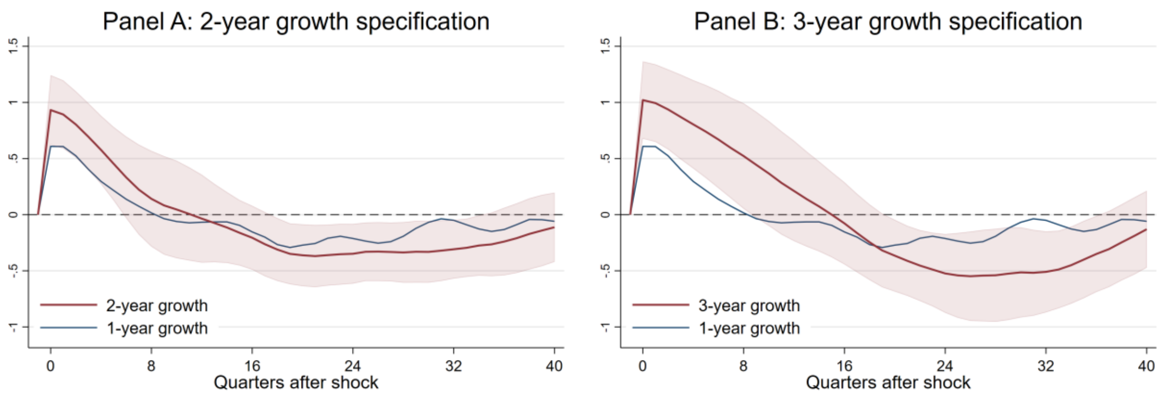
Note: This figure plots the correlation between global credit growth and individual country's credit growth with a fitted line (solid line). Panel A depicts the scatter plot using observations of current account surpluses, and Panel B depicts the ones of deficits.

Figure 7. Impulse responses for current account surplus and deficit country



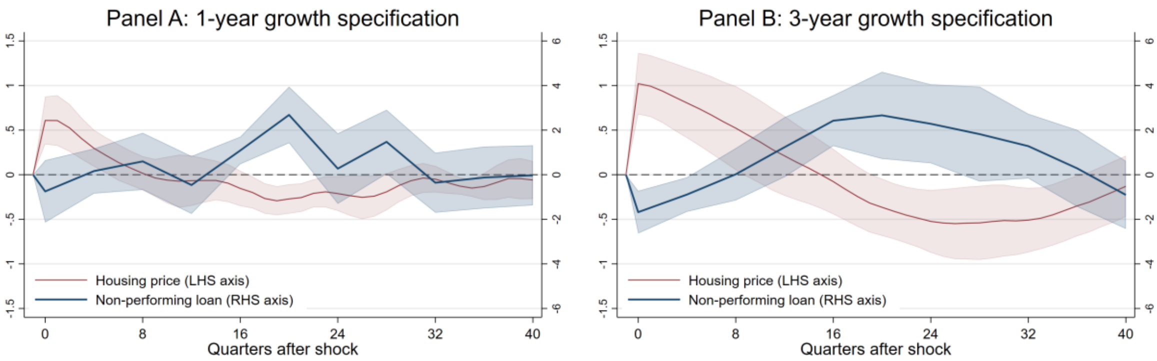
Note: This figure reports impulse responses estimated by LP-IV, showing the housing price response to an increase in credit to the household sector. The model is $\Delta_4 HP_{i,t+h} = \beta_1^h \widehat{\Delta_4 Credit_{i,t} \times D_{i,t}^{surplus}} + \beta_2^h \widehat{\Delta_4 Credit_{i,t} \times D_{i,t}^{deficit}} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-4} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h$, for $h = 0, \dots, 40$. $\widehat{\Delta_4 Credit_{i,t} \times D_{i,t}^{surplus}}$ and $\widehat{\Delta_4 Credit_{i,t} \times D_{i,t}^{deficit}}$ are the predictions associated with the instrumental variable: $\ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1} \sum_{j \neq i} \Delta_4 Credit_{j,t} \times D_{i,t}^{surplus}$ and $\ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1} \sum_{j \neq i} \Delta_4 Credit_{j,t} \times D_{i,t}^{deficit}$ in the first-stage regression. Solid red and blue lines represent impulse responses, and shaded area represents the 95 percent confidence interval computed using standard errors dually clustered on country and quarter. The horizontal axis represents the time period (quarterly frequency).

Figure 8. Impulse responses of housing prices to 2-year and 3-year credit growth



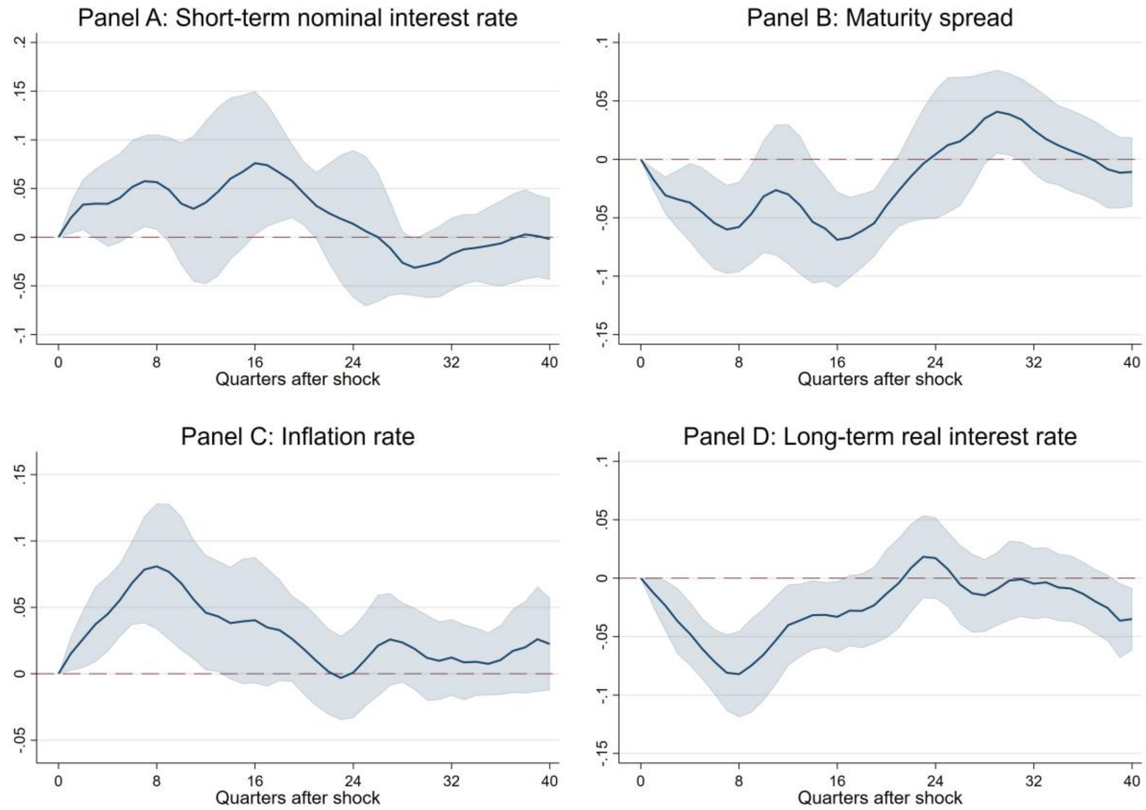
Note: This figure reports impulse responses estimated by LP-IV. Each panel shows the housing price response to an increase in credit to the household sector. The model of Panel A is $\Delta_8 HP_{i,t+h} = \beta^h \Delta_8 \widehat{Credit}_{i,t} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-8} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h$, for $h = 0, \ldots, 40$. $\Delta_8 \widehat{Credit}_{i,t}$ is the prediction associated with the instrumental variable: $\ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1} \sum_{j \neq i} \Delta_8 Credit_{j,t}$ in the first-stage regression. Panel B uses 3-year growth rate of the variables (e.g., $\Delta_{12} HP_{i,t}$ *and* $\Delta_{12} Credit_{i,t}$). These credit measures are instrumented with the instrumental variables constructed by the corresponding interval of credit growth. Red solid lines represent impulse responses, and shaded area represents the 95 percent confidence interval computed using standard errors dually clustered on country and quarter. Blue line represents the baseline impulse responses using one-year credit growth. The horizontal axis represents the time period (quarterly frequency).

Figure 9. Responses of bank nonperforming loans



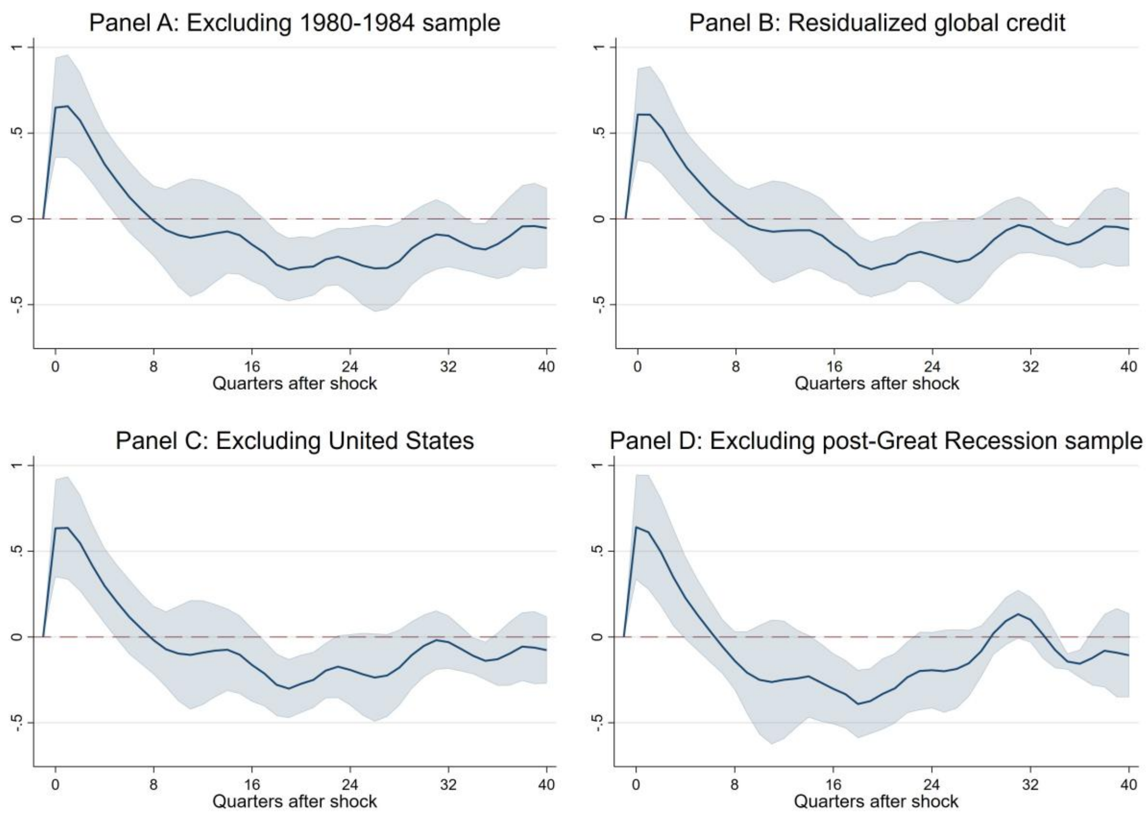
Note: This figure reports impulse responses estimated by LP-IV. Each panel shows the response of the ratio of bank nonperforming loans to gross loans to an increase in credit to the household sector using annualized data covering from 1998 to 2019. The model of Panel A is $\Delta_4 NPL_{i,t+h} = \beta^h \Delta_4 \widehat{Credit}_{i,t} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-4} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h$, for $h = 0, \ldots, 40$. $\Delta_4 \widehat{Credit}_{i,t}$ is the prediction associated with the instrumental variable: $\ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1} \sum_{j \neq i} \Delta_4 Credit_{j,t}$ in the first-stage regression. Panel B uses 3-year growth rate of the variables (e.g., $\Delta_{12} HP_{i,t}$ *and* $\Delta_{12} Credit_{i,t}$). These credit measures are instrumented with the instrumental variables constructed by the corresponding interval of credit growth. Blue lines represent impulse responses, and shaded area represents the 95 percent confidence interval computed using standard errors dually clustered on country and year. Red lines represent the impulse responses of housing price estimated by quarterly data covering the period from 1980 to 2019. The horizontal axis represents the time period (quarterly frequency).

Figure 10. Responses of short-term interest rate, maturity spread, and inflation rate



Note: This figure reports impulse responses estimated by LP-IV. Each panel shows the response to an increase in credit to the household sector. The basic model is $Y_{i,t+h} = \beta^h \Delta_4 \widehat{Credit}_{i,t} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-4} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h$, for $h = 1, \ldots, 40$. $\Delta_4 \widehat{Credit}_{i,t}$ is the prediction associated with the instrumental variable: $\ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1} \sum_{j \neq i} \Delta_4 Credit_{j,t}$ in the first-stage regression. Outcome variables (i.e., $Y_{i,t+h}$) in Panels A, B, C, and D are short-term nominal interest rate, maturity spread, inflation rate, and long-term real interest rate, respectively. Solid lines represent impulse responses, and shaded area represents the 95 percent confidence interval computed using standard errors dually clustered on country and quarter. The horizontal axis represents the time period (quarterly frequency).

Figure 11. Robustness



Note: This figure reports impulse responses estimated by LP-IV. Each panel shows the housing price response to an increase in credit to the household sector. The basic model is $\Delta_4 HP_{i,t+h} = \beta^h \Delta_4 \widehat{Credit}_{i,t} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-4} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h$, for $h = 0, \dots, 40$. $\Delta_4 \widehat{Credit}_{i,t}$ is the prediction associated with the instrumental variable: $\ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1} \sum_{j \neq i} \Delta_4 Credit_{j,t}$ in the first-stage regression. Panel A uses the sample from 1985 to 2019. Panel B uses the interaction term of the residualized global credit and the initial value as an IV. Panel C uses the sample excluding the US. Panel D uses the sample covering from 1980 to 2007. Solid lines represent impulse responses, and shaded area represents the 95 percent confidence interval computed using standard errors dually clustered on country and quarter. The horizontal axis represents the time period (quarterly frequency).

Table 1. List of countries

Australia	Austria	Belgium	Canada	Denmark
Finland	France	Germany	Ireland	Italy
Japan	Korea	Netherlands	New Zealand	Norway
Spain	Switzerland	Sweden	United Kingdom	United States

Table 2. Notations and data sources

Notation	Description	Source
Δ_4HP	Residential property price deflated by consumer price index, 1-year (4-quarter) growth from t-4 to t	BIS
Δ_8HP	Residential property price deflated by consumer price index, 2-year (8-quarter) growth from t-4 to t+4.	BIS
Δ_{12}HP	Residential property price deflated by consumer price index, 3-year (12-quarter) growth from t-4 to t+8.	BIS
Δ_4Credit	Total credit to household sector divided by 1-quarter lagged GDP, 1-year (4-quarter) growth from t-4 to t.	BIS
Δ_8Credit	Total credit to household sector divided by 1-quarter lagged GDP, 2-year (8-quarter) annualized growth from t-4 to t+4.	BIS
Δ_{12}Credit	Total credit to household sector divided by 1-quarter lagged GDP, 3-year (12-quarter) annualized growth from t-4 to t+8.	BIS
Δ_4GDP	GDP deflated by consumer price index, local currency, 1-year (4-quarter) growth from t-4 to t. Where data for Japan is not available, we have supplemented the data provided by the Cabinet Office and the Ministry of Finance of Japan.	IFS (IMF)
Short_rate	Interest rate based on 3-month money market rates.Where data for Japan is not available, we have supplemented the data provided by the Cabinet Office and the Ministry of Finance of Japan.	OECD
Spread	Interest rate on a 10-year government bond minus interest rate based on 3-month money market rates	OECD
Δ_4CPI	Consumer price index, 1-year (4-quarter) growth from t-4 to t.	IFS (IMF)
Δ_4Population	Population, 1-year (4-quarter) growth from t-4 to t.	WEO (IMF)
$1/(N-1)\Sigma_{j\neq i}\Delta_4$Credit	Cross-sectional sample mean of 1-year (4-quarter) growth of the household credit to GDP ratio excluding country i	BIS (authors' calculation)
$1/(N-1)\Sigma_{j\neq i}\Delta_8$Credit	Cross-sectional sample mean of 2-year (8-quarter) annualized growth of the household credit to GDP ratio excluding country i	BIS (authors' calculation)
$1/(N-1)\Sigma_{j\neq i}\Delta_{12}$Credit	Cross-sectional sample mean of 3-year (12-quarter) annualized growth of the household credit to GDP ratio excluding country i	BIS (authors' calculation)
ln.Total Credit/GDP$_{i,\ 1980}$	Total credit to nonfinancial private sector to GDP ratio in 1980 (log)	BIS
CA	Current account, millions of USD, if IFS quarterly series is not available, we use WEO annual series.	IFS and WEO (IMF)
Δ_4NPL	Bank non-performing loans to gross loans, 1-year growth, annual frequency data	World Bank

Table 3. Summary statistics

	Obs.	Mean	Std. dev.	Min	Max	Std. dev. /Std. dev. (Δ_4GDP)
Δ_4HP	3040	0.0177	0.0678	-0.2477	0.2910	1.9819
Δ_4HP (CA surpluses)	1646	0.0185	0.0592	-0.2477	0.2819	1.7321
Δ_4HP (CA deficits)	1394	0.0167	0.0766	-0.2403	0.2910	2.2415
Δ_8HP	2960	0.0183	0.0592	-0.2307	0.2378	1.7312
Δ_{12}HP	2880	0.0191	0.0531	-0.1953	0.2058	1.5525
Δ_4Credit	2395	0.0209	0.0480	-0.3708	0.1963	1.4032
Δ_4Credit (CA surpluses)	1296	0.0118	0.0475	-0.3706	0.1753	1.3907
Δ_4Credit (CA deficits)	1099	0.0316	0.0462	-0.3708	0.1963	1.3525
Δ_8Credit	2315	0.0212	0.0428	-0.2652	0.1798	1.2527
Δ_{12}Credit	2235	0.0215	0.0399	-0.2077	0.1611	1.1681
Δ_4GDP	2535	0.0238	0.0342	-0.1150	0.3197	1.0000
Short_rate	3006	0.0517	0.0476	-0.0090	0.2578	1.3916
Spread	2876	0.0085	0.0155	-0.1383	0.0921	0.4532
Δ_4CPI	3120	0.0294	0.0287	-0.0632	0.2236	0.8409
Δ_4Population	3120	0.0062	0.0049	-0.0062	0.0284	0.1444
$1/(N-1)\Sigma_{j\neq i}\Delta_4$Credit	2395	0.0209	0.0245	-0.0226	0.0732	0.7169
$1/(N-1)\Sigma_{j\neq i}\Delta_8$Credit	2315	0.0212	0.0222	-0.0176	0.0657	0.6506
$1/(N-1)\Sigma_{j\neq i}\Delta_{12}$Credit	2235	0.0215	0.0210	-0.0137	0.0640	0.6156
Δ_4NPL	405	-0.0295	0.3348	-2.0794	1.6405	9.7935
ln.Total Credit/GDP$_{i,\ 1980}$	20	4.5030	0.3130	3.8959	5.0093	-

Table 4. Responses of housing prices to credit to the household sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	h = 0	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*	*h = 28*	*h = 32*	*h = 36*	*h = 40*
	(year 0)	*(year +1)*	*(year +2)*	*(year +3)*	*(year +4)*	*(year +5)*	*(year +6)*	*(year +7)*	*(year +8)*	*(year +9)*	*(year +10)*
Panel A: Current and lagged control											
Second-stage											
Δ_4Credit$_{i,t}$	0.608***	0.297***	0.0160	-0.0668	-0.154	-0.271***	-0.212**	-0.192*	-0.0499	-0.132*	-0.0590
	(0.137)	(0.105)	(0.0971)	(0.144)	(0.101)	(0.0837)	(0.0987)	(0.105)	(0.0754)	(0.0767)	(0.108)
First-stage											
1/(N-1)$\Sigma_{j\neq i}\Delta_4$Credit$_{i,t}$×ln.Total Credit/GDP$_{i,1980}$	-1.865***	-1.853***	-1.854***	-1.852***	-1.776***	-1.738***	-1.749***	-1.750***	-1.750***	-1.802***	-1.919***
	(0.225)	(0.224)	(0.223)	(0.218)	(0.180)	(0.166)	(0.168)	(0.170)	(0.173)	(0.178)	(0.182)
Kleibergen-Paap rk Wald F statistic	68.98	68.36	68.91	71.86	96.87	109.0	108.0	105.8	102.9	102.4	111.2
Country-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Current control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lagged control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Number of Country	20	20	20	20	20	20	20	20	20	20	20
Observation	2186	2106	2026	1946	1866	1786	1706	1626	1546	1466	1386
Panel B: Current control											
Second-stage											
Δ_4Credit$_{i,t}$	0.483***	0.123	-0.114	-0.236*	-0.336***	-0.340***	-0.239**	-0.143	0.00746	-0.00902	-0.0204
	(0.129)	(0.121)	(0.107)	(0.134)	(0.105)	(0.0866)	(0.0952)	(0.0893)	(0.0678)	(0.0945)	(0.115)
First-stage											
1/(N-1)$\Sigma_{j\neq i}\Delta_4$Credit$_{i,t}$×ln.Total Credit/GDP$_{i,1980}$	-1.930***	-1.924***	-1.933***	-1.939***	-1.894***	-1.878***	-1.899***	-1.908***	-1.922***	-1.982***	-2.019***
	(0.187)	(0.185)	(0.183)	(0.181)	(0.159)	(0.151)	(0.153)	(0.155)	(0.159)	(0.164)	(0.166)
Kleibergen-Paap rk Wald F statistic	106.9	108.1	112.2	114.2	142.0	154.3	155.0	151.4	146.8	146.4	147.2
Country-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Current control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lagged control											
Number of Country	20	20	20	20	20	20	20	20	20	20	20
Observation	2266	2190	2114	2038	1962	1883	1803	1723	1643	1563	1483

Note: This table reports impulse responses estimated by LP-IV. Each panel shows the housing price response to an increase in credit to the household sector. The basic model is $\Delta_4 HP_{i,t+h} = \beta^h \Delta_4 \widehat{Credit}_{i,t} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-4} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h$, for $h = 0, \ldots, 40$. $\Delta_4 \widehat{Credit}_{i,t}$ is the prediction associated with the instrumental variable: $\ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1}\sum_{j\neq i} \Delta_4 Credit_{j,t}$ in the first-stage regression. Standard errors in parentheses are dually clustered on country and quarter. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 5. Cumulative effects of credit growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Boom period			Bust period			
	From	*Duration (quarter, k)*	*Coef.*	*From*	*Duration (quarter, k)*	*Coef.*	*Bust/boom (column (6)/(3))*
Panel A: 1-year growth							
Δ_4Credit$_{i,t}$	t-4	9	0.935***	t+13	14	-0.879***	0.940
			(0.227)			(0.275)	
Panel B: 2-year growth							
Δ_8Credit$_{i,t}$	t-4	9	1.973***	t+14	20	-2.035***	1.051
			(0.338)			(0.516)	
Panel C: 3-year growth							
Δ_{12}Credit$_{i,t}$	t-4	12	3.063***	t+16	20	-2.656***	0.867
			(0.527)			(0.732)	
Panel D: Current account surplus							
Δ_4Credit$_{i,t}$×D^{surplus}	t-4	5	0.414***	-	-	-	-
			(0.122)				
Panel E: Current account deficit							
Δ_4Credit$_{i,t}$×D^{deficit}	t-4	9	1.287***	t+13	16	-1.765***	1.371
			(0.295)			(0.530)	

Note: This table reports cumulative effects of credit growth. The model of Panel A is $\Delta_k HP_{i,t+h} = \beta^{k,h}\Delta_4\widehat{Credit}_{i,t} + \boldsymbol{\Gamma X}_{i,t} + \boldsymbol{\Phi W}_{i,t-4} + \delta_i + \gamma_i + \varepsilon_{i,t+h}$. $\Delta_4\widehat{Credit}_{i,t}$ is the prediction associated with the instrumental variable: ln $Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1}\sum_{j\neq i}\Delta_4 Credit_{i,j}$ in the first-stage regression. Panels B and C use 2-year or 3-year growth (e.g., $\Delta_8 HP_{i,t}$ and $\Delta_{12}Credit_{i,t}$) instead of 1-year growth. These credit measures are instrumented with the instrumental variables constructed by the corresponding interval of credit growth. Likewise, Panels D and E uses the interaction terms of credit growth and the current account surplus/deficit dummies (i.e., $\Delta_4 Credit_{i,t} \times D_{i,t}^{surplus}$ and $\Delta_4 Credit_{i,t} \times D_{i,t}^{deficit}$). The instrumental variable is also interacted with the dummies. Standard errors in parentheses are dually clustered on country and quarter. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 6. Responses of housing prices for current account surplus and deficit country

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	h = 0	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*	*h = 28*	*h = 32*	*h = 36*	*h = 40*
	(year 0)	*(year +1)*	*(year +2)*	*(year +3)*	*(year +4)*	*(year +5)*	*(year +6)*	*(year +7)*	*(year +8)*	*(year +9)*	*(year +10)*
Second-stage											
$\Delta_4 Credit_{i,t} \times D^{surplus}$	0.383***	0.109	0.0299	0.0408	-0.0387	-0.0470	0.0647	0.139	0.0937	0.0463	0.127
	(0.0932)	(0.134)	(0.111)	(0.160)	(0.108)	(0.104)	(0.108)	(0.105)	(0.0908)	(0.0851)	(0.101)
$\Delta_4 Credit_{i,t} \times D^{deficit}$	0.799***	0.447***	-0.00651	-0.169	-0.251	-0.445***	-0.426***	-0.436***	-0.161	-0.285**	-0.232
	(0.184)	(0.144)	(0.131)	(0.165)	(0.163)	(0.147)	(0.141)	(0.168)	(0.137)	(0.112)	(0.179)
First-stage											
$1/(N-1)\Sigma_{j\neq i}\Delta_4 Credit_{i,t} \times \ln.Total\ Credit/GDP_{i,1980} \times D^{surplus}$	-1.059***	-1.049***	-1.048***	-1.035***	-0.943***	-0.932***	-0.942***	-0.939***	-0.937***	-0.971***	-1.044***
	(0.214)	(0.214)	(0.214)	(0.208)	(0.188)	(0.193)	(0.200)	(0.200)	(0.203)	(0.210)	(0.231)
$1/(N-1)\Sigma_{j\neq i}\Delta_4 Credit_{i,t} \times \ln.Total\ Credit/GDP_{i,1980} \times D^{deficit}$	-0.709***	-0.709***	-0.707***	-0.715***	-0.733***	-0.693***	-0.689***	-0.690***	-0.692***	-0.700***	-0.733***
	(0.155)	(0.155)	(0.155)	(0.156)	(0.170)	(0.165)	(0.165)	(0.165)	(0.168)	(0.174)	(0.180)
Kleibergen-Paap rk Wald F statistic	54.19	55.38	54.84	55.49	55.80	54.88	54.08	53.22	52.80	56.38	51.06
Country-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Control (current and lagged)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Number of Country	20	20	20	20	20	20	20	20	20	20	20
Observation	2186	2106	2026	1946	1866	1786	1706	1626	1546	1466	1386

Note: This table reports impulse responses estimated by LP-IV. Each panel shows the housing price response to an increase in credit to the household sector. The model is $\Delta_4 HP_{i,t+h} = \beta_1^h \widehat{\Delta_4 Credit_{i,t} \times D_{i,t}^{surplus}} + \beta_2^h \widehat{\Delta_4 Credit_{i,t} \times D_{i,t}^{deficit}} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-4} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h$, for $h = 0, \dots, 40$. $\widehat{\Delta_4 Credit_{i,t} \times D_{i,t}^{surplus}}$ and $\widehat{\Delta_4 Credit_{i,t} \times D_{i,t}^{deficit}}$ are the predictions of the instrumental variables: $\ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1}\sum_{j\neq i} \Delta_4 Credit_{j,t} \times D_{i,t}^{surplus}$ and $\ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1}\sum_{j\neq i} \Delta_4 Credit_{j,t} \times D_{i,t}^{deficit}$, respectively, in the first-stage regression. Standard errors in parentheses are dually clustered on country and quarter. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 7. Responses of housing prices to 1-year, 2-year, or 3-year credit growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	h = 0	*h = 4*	*h = 8*	*h = 12*	*h = 16*	*h = 20*	*h = 24*	*h = 28*	*h = 32*	*h = 36*	*h = 40*
	(year 0)	*(year +1)*	*(year +2)*	*(year +3)*	*(year +4)*	*(year +5)*	*(year +6)*	*(year +7)*	*(year +8)*	*(year +9)*	*(year +10)*
Panel A: 1-year growth											
Δ_4Credit$_{i,t}$	0.608***	0.297***	0.0160	-0.0668	-0.154	-0.271***	-0.212**	-0.192*	-0.0499	-0.132*	-0.0590
	(0.137)	(0.105)	(0.0971)	(0.144)	(0.101)	(0.0837)	(0.0987)	(0.105)	(0.0754)	(0.0767)	(0.108)
Kleibergen-Paap rk Wald F statistic	68.98	68.36	68.91	71.86	96.87	109.0	108.0	105.8	102.9	102.4	111.2
Observation	2186	2106	2026	1946	1866	1786	1706	1626	1546	1466	1386
Panel B: 2-year growth											
Δ_8Credit$_{i,t}$	0.932***	0.577***	0.141	-0.0352	-0.205	-0.362**	-0.348**	-0.336**	-0.308**	-0.239	-0.112
	(0.158)	(0.156)	(0.218)	(0.200)	(0.145)	(0.140)	(0.136)	(0.138)	(0.133)	(0.153)	(0.157)
Kleibergen-Paap rk Wald F statistic	98.74	100.9	99.78	102.8	104.8	102.8	97.85	84.74	73.93	74.58	72.02
Observation	1902	1822	1742	1662	1582	1502	1422	1342	1262	1182	1102
Panel C: 3-year growth											
Δ_{12}Credit$_{i,t}$	1.021***	0.805***	0.522**	0.212	-0.0769	-0.365**	-0.523***	-0.540**	-0.509***	-0.350**	-0.129
	(0.176)	(0.201)	(0.240)	(0.228)	(0.187)	(0.163)	(0.179)	(0.211)	(0.184)	(0.173)	(0.175)
Kleibergen-Paap rk Wald F statistic	136.7	143.7	137.9	139.6	141.2	137.5	110.7	88.25	95.82	78.40	71.67
Observation	1680	1600	1520	1440	1360	1280	1200	1120	1040	960	884
Country-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time-FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Control (current and lagged)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Number of Country	20	20	20	20	20	20	20	20	20	20	20

Note: This table reports impulse responses estimated by LP-IV. Each panel shows the housing price response to an increase in credit to the household sector. The model of Panel A is $\Delta_4 HP_{i,t+h} = \beta^h \Delta_4 \widehat{Credit}_{i,t} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-4} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h$, for $h = 0, \dots, 40$. $\Delta_4 \widehat{Credit}_{i,t}$ is the prediction associated with the instrumental variable: $\ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1} \sum_{j \neq i} \Delta_4 Credit_{i,j}$ in the first-stage regression. Panels B and C use 2-year or 3-year growth of the variables (e.g., $\Delta_8 HP_{i,t}$ and $\Delta_{12} Credit_{i,t}$) instead of 1-year growth. These credit measures are instrumented with the instrumental variables constructed by the corresponding interval of credit growth. Standard errors in parentheses are dually clustered on country and quarter. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

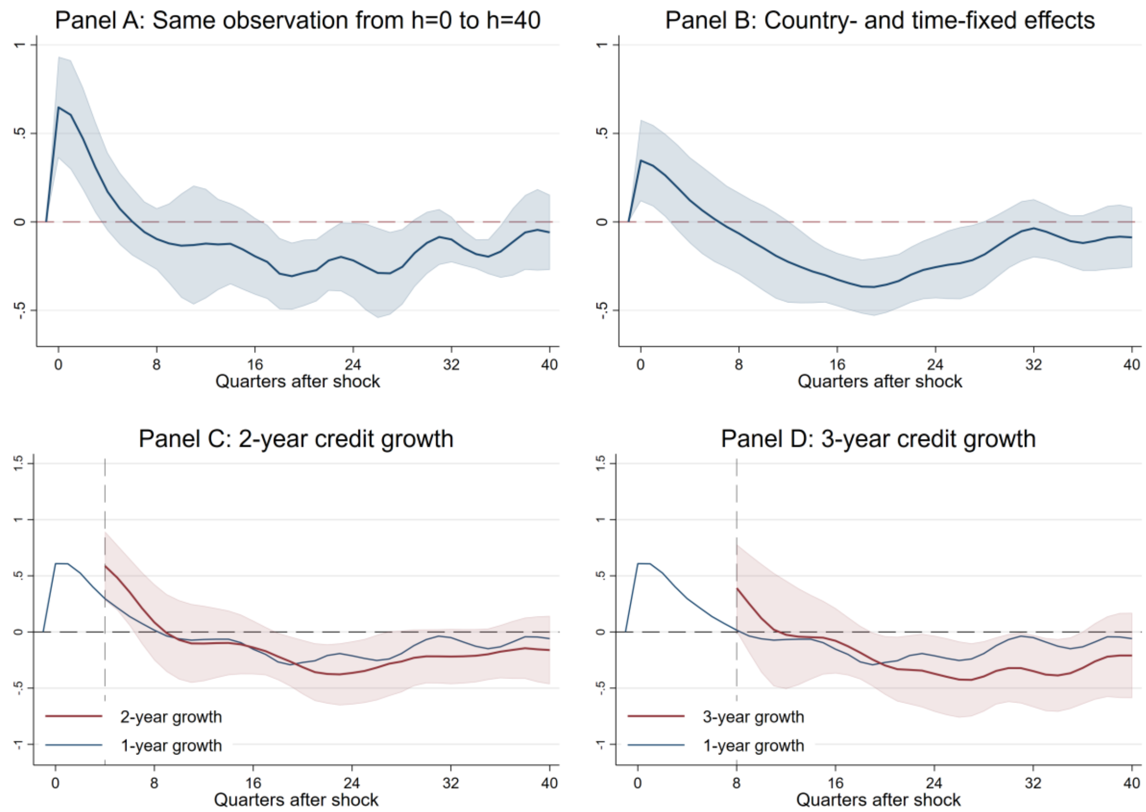
Table 8. Placebo sample test

	(1)	(2)	(3)	(4)
	Δ_4Credit$_{i,t}$ (placebo sample period from 1970 to 1979)			
	Jordà, Schularick, and Taylor (2016)		Müller and Verner (2023)	
ln.Total Credit/GDP$_{i,1980}$	0.0343	0.0333	0.0108	0.0144
	(0.0255)	(0.0307)	(0.0134)	(0.0260)
Time-FE	✓	✓	✓	✓
Control (current and lagged)		✓		✓
Number of Country	16	15	17	15
Observation	145	126	153	126

Note: This table reports a placebo sample test regressing 1-year credit growth during the 1970s on total credit to GDP ratio in 1980. We use the annual frequency panel data of Jordà, Shularick, and Taylar (2016) and Müller and Verner (2023). The model is $\Delta_4 Credit_{i,t} = \beta\, ln\, Total\ Credit/GDP_{i,1980} + \boldsymbol{\Gamma X}_{i,t} + \boldsymbol{\Phi W}_{i,t-1} + \gamma_t + \varepsilon_{i,t}$. Standard errors in parentheses are dually clustered on country and year. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

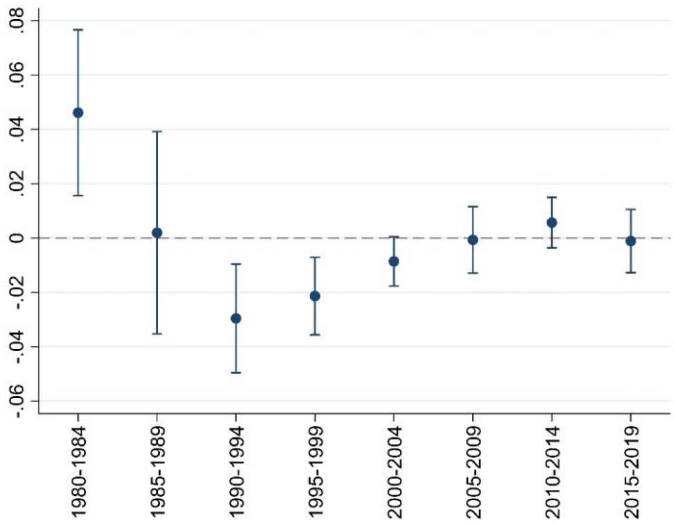
Appendix

Figure A1. Impulse response of housing price based on alternative settings



Note: This figure reports impulse responses estimated by LP-IV. Each panel shows the housing price response to an increase in credit to the household sector. The basic model is $\Delta_4 HP_{i,t+h} = \beta^h \Delta_4 \widehat{Credit}_{i,t} + \boldsymbol{\Gamma}^h \boldsymbol{X}_{i,t} + \boldsymbol{\Phi}^h \boldsymbol{W}_{i,t-4} + \delta_i^h + \gamma_t^h + \varepsilon_{i,t+h}^h$, for $h = 0, \dots, 40$. $\Delta_4 \widehat{Credit}_{i,t}$ is the prediction associated with the instrumental variable: $\ln Total\ Credit/GDP_{i,1980} \times \frac{1}{N-1}\sum_{j\neq i} \Delta_4 Credit_{j,t}$ in the first-stage regression. Panel A uses the same observation throughout the forecast horizon from $h = 0$ to $h = 40$. Panel B only controls country- and time-fixed effects. Panels C and D conduct estimations of 2-year and 3-year credit growth (i.e., $\Delta_8 Credit_{i,t}$ and $\Delta_{12} Credit_{i,t}$), by keeping the setting of controls unchanged as the baseline specification. Solid line represents impulse responses, and shaded area represents the 95 percent confidence interval computed by standard errors dually clustered on country and quarter. The horizontal axis represents the time period (quarterly frequency).

Figure A2 Predictive power of total credit to GDP ratio in 1970



Note: This figure reports the coefficients of total credit to GDP ratio in 1970Q1 on subsequent growth of the ratio of credit to household sector to GDP with a 95 percent confidence interval. The coefficients are estimated based on the following model: $\Delta_4 Credit_{i,t} = \sum_k \beta_k \, ln \, Total \; Credit/GDP_{i,1970} \times D_k + \boldsymbol{\Gamma X}_{i,t} + \boldsymbol{\Phi W}_{i,t-4} + \gamma_t + \varepsilon_{i,t}$. The subscript k represents five-year intervals from 1980 to 2019, such as the period from 1980Q1 to 1984Q4. D_k is dummy variable that takes value one if observations belong to each five-year interval, otherwise zero. The 95 percent confidence intervals are computed using standard errors dually clustered on country and quarter.