Credit Composition and Housing Price Dynamics: A Disaggregation Approach

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Abstract

While credit plays an instrumental role in housing price dynamics, existing work has produced conflicting evidence of its real impact. This paper reconciles various inconclusive findings via a disaggregation strategy to decompose aggregate credit into *credit-to-the-real economy* (*cr*) and *credit-to-the-asset markets* (*cf*). We argue that these two credit components exert theoretically expected and distinct impacts on housing prices, identified separately through a housing demand and a housing supply credit-circulation channel. Using an international panel dataset and treating for periodic cycles, our panel VAR estimations show that *cr* and housing prices depict a mutually reinforcing positive relationship. However, *cf* exerts a negative but negligible impact on housing prices in the short-run; it has a strong and positive effect in the long-run. Further, controlling for effects of economic policy uncertainty strengthens the interactions between housing prices and the two credit components. Our results are robust and suggest that close monitoring of credit allocation to housing demand and supply sides, as well as the extent of pump-priming resource allocation to the real economy, should be of interest to policymakers.

Key Words: Credit disaggregation strategy; International housing price dynamics; Economic policy uncertainty; Panel VAR; Business cycles

JEL Classifications: E30, E51, R30

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1 Introduction

Lately, with a proliferation of economic policy uncertainties among nations and an objective to minimize repetition of yet another housing market crisis, increasing emphasis from both academics and policy practitioners is veering towards an understanding of the exact role of credit[1] in both the asset markets (such as housing market) and the real economy. Going by the findings in the extant empirical research, credit in aggregate form has delivered conflicting evidence of its real effects (i.e., positive, negative and insignificant effects) on housing prices (see for instance, Favara and Imbs, 2015; Gimeno and Martinez-Carrascal, 2010; Ling et al., 2016; Maas et al., 2018; Oikarinen, 2009).

A helicopter tour of the literature reveals that such conclusions arise mainly due to two reasons.[2] First, a majority of research papers use credit in its *aggregate* form in both theory and empirical constructs, disregarding perhaps the crucial links that run from distinct components of credit to the housing market. Second, the literature has mostly concentrated on the housing demand-side story of the credit-housing price relationship, neglecting the equally important supply-side dynamics. Hence, there is an observed over-emphasis of the demand-side dynamics of credit in determining housing price movements and an under-representation of the important role of the supply side. Indeed, credit - conceptualized in *aggregate* form - could mask the micro dynamic effects of its *components* and thus is likely to bias its real effects on housing prices. Our paper aims to fill this gap by uncovering the real effects of credit on housing prices through a classification of credit into *credit to the real economy (cr)* and *credit to the asset market (cf)*, for which we provide an intuitive explanation.

The conceptual foundation of the credit disaggregation strategy can be traced back to Keynes (1930).[3] To explain the economic prosperity in the 1920s, Keynes suggests that the aggregate deposit-money flow should be split into the different circulation channels, viz. the 'industrial' circulation and the 'financial' circulation. Recently, Werner (1997) provides important directions towards the coverage of *cr* and *cf*: the former is used for GDP transactions, where the latter is for non-GDP transactions. However, these definitions may not adequately proxy credit flow to the demand and supply circulation channels of a housing market, respectively.[4] We argue that the conventional definition of *cr* is too broad and encompasses some elements that are irrelevant to the demand side dynamics of a housing market.

Thus, we further refine the definition of *cr* and demonstrate how our modified cr robustly represents credit lending to the housing demand side. At the same time, we also refine the definition of *cf* to provide a better representation of credit lending to the housing supply side. Using this credit disaggregation strategy, we argue that the existing conflicting evidence regarding the exact impact of credit can be reconciled by separately mapping their distinct impacts on the housing demand and supply credit circulations. Moreover, this strategy also enables us to investigate potentially distinct impact patterns of the credit components (cr and cf) on economic growth.

Using a quarterly dataset of nine industrialized countries over more than two decades and a panel vector autoregressive (PVAR) method, we apply a disaggregation strategy to the interpretation of differential impacts of credit components flowing to housing demand and supply sides on housing price dynamics. Moreover, the latter can also be affected by a period of persistent uncertainty, during which credit is measurably rationed to the economy including housing markets (Baker et al., 2016). Our empirical analysis therefore considers levels of (economic policy) uncertainty to examine how this governs the interdependence between credit, the housing market and the real economy. In addition, a common but often neglected problem in an empirical analysis is the treatment of transient and periodic disturbances in short and/or medium terms, i.e. the business cycle. Thus, by employing a recently developed filtering method from Hamilton (2018) for business cycle removal, we uncover the real impacts of credit shocks on target economic factors.

We contribute to the extant literature broadly in two ways. First, we apply a disaggregation strategy in the housing market to separately identify credit to the demand and supply sides of housing using *credit to the real economy* and *credit to the asset markets*. Through this, distinct effects of the credit components via the demand and supply circulations on housing prices are uncovered, respectively. This strategy also helps separately capture the effects of credit components on the real economy and the asset markets. Second, we examine the potential bi-directional interaction between credit and housing prices by employing a panel vector autoregressive (PVAR) method including various parameter identification strategies, while controlling for the potential heterogeneity in the estimation.

Consistent with theoretical expectations, several unique results emerge from our empirical investigation: (i) *credit to the real economy* and housing prices clearly depict a mutually positive reinforcing relationship. However, the impact of *credit to the asset markets* on housing prices appears complex, i.e. insignificant and negative in the short-run but significant and positive in the long-run. (ii) *credit to the real economy* significantly and positively affects economic growth (i.e. nominal GDP), in contrast to an insignificant effect from *credit to the asset markets*. (iii) Controlling for persistent economic policy uncertainty deepens the interactions between housing prices and both types of disaggregated credit. (iv) Finally, we find significant negative effects of the level of uncertainty on our target economic variables, including housing prices and nominal GDP. Our results are robust to controls, sample stratification, credit shock restrictions and correcting for interdependence and heteroskedasticity, and support the effectiveness of monetary policy, when monitoring the credit allocation among housing market participants and the allocation between the real economy and the asset markets.

The rest of this paper is structured as follows. Section 2 presents a conceptual framework through a credit disaggregation strategy to explain the nexus between credit and housing prices. Section 3 discusses methodology and estimation mechanism. Section 4 presents data and some preliminary results. Section 5 provides detailed empirical analyses including robustness exercises. Finally, Section 6 concludes with a discussion of the policy implications of our main findings.

2 Credit - Housing Price Interaction: A Review

What drives the interdependence between credit and a housing market across countries? It is known that a rise (decrease) in housing prices is an indication of economic prosperity (recession) reflected by strong (poor) macroeconomic fundamentals that further expand (shrink) bank credit (Kuang, 2014; Ling et al., 2016). In turn, a change in bank lending volumes can also impact housing price movements by shifting demand and supply curves of housing through mediating effects of macroeconomic fundamentals (Duan et al., 2018, 2019; Goodhart and Hofmann, 2008). However, existing literature lays excessive emphasis either on credit in aggregate form or on *credit to the demand side*, leaving the supply side dynamics unrevealed.

This section first reviews conventional interpretations about the credit - housing price interaction, and summarizes insights from extant literature regarding the idea of credit disaggregation. Then, we extend the convention by introducing a credit disaggregation strategy in the housing market, through which the interaction is truly uncovered via separately-identified housing demand and supply credit-circulation channels, respectively. A succinct view of the key literature is summarized in Table A.1 in Appendix A.

2.1 Conventional interpretation

The extant literature shows that houses (or properties) are often regarded as collateral associated with bank lending, while house prices can positively affect both the demand and supply of bank credit to housing buyers through the channel of 'wealth effects'. Such a mechanism is determined by moral hazard and adverse selection, both of which arise in the event of asymmetric information in the credit markets (see for example, Bernanke and Gertler, 1989; Bernanke et al., 1999; Kiyotaki and Moore, 1997). Specifically, due to the underlying feature of 'a lagged appreciation of current housing prices' (Muellbauer and Murphy, 2008; Murphy, 2018), an increase in current prices tends to induce an optimistic expectation of further price appreciations from housing market participants (Kuang, 2014).

With regard to commercial banks, current property price fluctuations can impact their capital conditions and thus their credit lending capacities will change either directly through market valuations of bank holdings of real estate assets, or indirectly through changes in the volume of non-performing loans (Gerlach and Peng, 2005). Thus, during rising housing prices, credit lending to housing buyers will expand due to 'wealth effects' as banks' perceived wealth tends to increase. Moreover, due to an expectation of future housing price appreciations and an intention of maximizing perceived wealth with a lower cost, credit demand of housing buyers will also boost to meet their currently increasing housing demand.

Alternatively, through the medium of 'collateral effects', a rise in collateralized asset prices will expand credit supply to housing buyers as banks are expecting lower mortgage default risk and higher profitability. Meanwhile, it will also induce a boom in credit demand given that lending margins are constant as exogenous (Ling et al., 2016), and encourage individuals to borrow and spend more, for example on housing transactions, thanks to the improvement of their borrowing capacity (Gounopoulos et al., 2019). Thus, following the housing demand side argument, changes in housing prices could lead to variations of both the demand and supply of bank credit in the same direction through the channels of 'wealth effects' and 'collateral effects', respectively.

The question now is what specific mechanism can provide a robust explanation of the effects of credit on the housing market dynamics? Through the lens of a demand-supply channel, a simple interpretation can be given. We know that greater/less access to bank credit can affect housing prices by shifting the housing demand. First, through the perspective of credit demand, the increase of credit demand will indeed stimulate individuals to spend money in buying properties due to 'wealth effects' (Muellbauer and Murphy, 2008). Given a fixed housing supply in the short-run (due to a relatively long-time period for the provisions of new property), both housing demand and housing prices will subsequently increase. Although housing supply can be adjusted by increasing its levels in the long-run, housing prices tend to remain persistent due to a sticky and heightening housing price even in face of a signal of housing supply increase (Oikarinen, 2009).[5]

Second, many researchers argue that an increase in housing prices should be ultimately attributed to an expansion of credit supply rather than credit demand (Duca et al., 2011; Favara and Imbs, 2015; Justiniano et al., 2019; Ling et al., 2016; Mian and Sufi, 2009). The liberalization of credit markets, reflected by a credit supply expansion, stimulates an increase in housing prices. On the one hand, lower collateral requirements possibly due to the implementation of quantitative easing (QE) monetary policies can boost credit demand of households by loosening their borrowing constraints against the collateral values given that the households are borrowing-constrained (Kiyotaki and Moore, 1997). This can raise housing demand and then housing prices following the mechanism discussed above. On the other hand, the expansion of bank credit supply (liquidity) can lower the levels of loan interest rates and increase current values of the mortgage properties (the discounted future cash flows of property returns) by influencing the discount rate.

On the whole, existing research has highlighted the mutually reinforcing positive interaction between housing prices and bank credit on the demand side. However, interpretation of the interaction on the supply side is nevertheless ignored. Thus, the paper aims to fill the gap by segregating credit via both the housing demand and supply sides, and then respectively investigating their distinct impacts on housing price dynamics.

2.2 Does segregation of credit unravel the true effects?

The idea of credit 'disaggregation' can be traced back to Keynes (1930). He notes that credit/money should be split into 'industrial' and 'financial' circulations to offer insights into how credit impacts output growth and financial asset appreciations, respectively. This idea provides a conceptual underpinning of a *more differentiated equation of exchange*, showing that only credit flowing to the 'industrial' circulation, i.e. real economy, drives economic growth, while the one to the 'financial' circulation raises asset prices instead.

Despite the importance of disaggregating credit from the aggregate level, the literature is sparse in this strategy when investigating the credit impact on the economy, particularly the housing market. As an exception, Bezemer and Grydaki (2014) segregate credit into components to non-financial sectors and to real estate and financial sectors, through which their roles in generating financial fragility are identified. Particularly, growth in credit to real estate and financial sectors is driven more by its past values and less by output growth, providing an indication of rising financial fragility. In the same vein, Bezemer et al. (2016) find positive impacts of credit to non-financial sectors on growth, while coefficients of mortgages and credit to other asset markets are shown to be insignificant or negative. They further point out that financial development since 1990 was primarily led by growth in credit to real estate and financial markets; in turn, hampering economic growth.

Jordà et al. (2016) undertake a cross-country analysis and use division of credit to show that mortgage credit possesses significant implications for business cycles and financial stability risks, whereas non-mortgage credit only plays a negligible role. Unger (2017) investigates the interrelationship between domestic credit and the current account balance in European countries. By segregating credit as components flowing into financial and non-financial private sectors, an increase in credit to non-financial private sectors is checked to be one of the main reasons for growing current account imbalances. Yan (2018) segregates total capital flows into components at the sectoral level by using a disaggregation strategy, through which the potentially heterogeneous impacts of hot money in different individual financial sectors are discussed.

In the light of the credit disaggregation strategy, we segregate bank credit as *credit to the real economy* and *credit to the asset markets*, through which credit impacts on dynamics of the real economy/asset markets are separately quantified; and the validity of a *more differentiated equation of exchange* are further examined. Importantly, these two credit components are also able to effectively proxy *the credit components flowing into the housing demand and supply circulations*. The following subsection will introduce how we specifically represent the two segregated credit components so that credit impacts on housing prices through the demand and supply sides are gauged, respectively.

2.3 Identification of demand and supply credit-circulation channels

In addition to the demand side dynamics as already discussed, the availability of credit to housing developers is also a powerful instrument that determines housing prices; greater access to finance encourages developers to supply more houses, thereby potentially influencing the direction of housing prices. One way to understand this is to *segregate* total credit lending into *(i) credit to the real economy (cr)* and *(ii) credit to the asset markets (cf)*. It is the latter that demonstrates whether and how credit provided to housing developers affects housing prices through the supply side. Hence, an important question arises: how does one define *credit to the real economy* (cr) and *credit to the asset markets* (cf) to proxy credit lending to the housing demand and supply sides, respectively? We explore them below.

(a) cr and housing demand

Conventionally, cr denotes credit associated with all GDP transactions, and its holders include all the non-financial sector including households, non-profit institutions serving households and private-/public-owned businesses, etc. However, this conventional definition is not a good proxy for credit to the housing demand as it contains not only credit to the house buyers or individuals, but also credit to the house developers in the primary real estate market, viz. the residential construction industry. Thus, to serve as a qualified approximation for credit to the housing demand and distinguish from *credit to the asset markets (cf)* (a proxy for credit to the housing supply), we refine the conventional definition by using credit to the households and non-profit institutions serving households to represent cr. As discussed in Subsection 2.2, cr and housing prices should depict a positive relationship.

(b) cf and housing supply

Similarly, cf conventionally denotes credit for non-GDP transactions, viz. credit to other financial corporations including the real estate holding companies, which serves as the main housing suppliers to operate the rental and sales businesses in the secondary housing markets. Moreover, it is well-known that most of the properties purchased especially in industrialized countries occur in the secondary markets, viz. the second-hand housing transactions (Best and Kleven, 2018).[6] Thus, in our study, cf provides a convenient way to proxy the amount of credit lending to the secondary housing suppliers, viz. the real estate holding companies.

Led by the above, we argue that by segregating credit into cr and cf, we are able to unravel the distinct impacts of credit shocks from the housing demand and supply sides on housing price dynamics, respectively. Meanwhile, we are also able to examine the rationale of a *more differentiated quantity theory of credit* by investigating how the two components of credit (viz., cr and cf) individually influence economic growth.

3 Methodology and Estimation Issues

3.1 Panel VAR model

Noting that our empirical objective is to use a dataset involving observations in a time-country domain, to capture and model dynamic interdependence between credit, housing prices, and macroeconomic variables, we estimate a reduced form representation of our conceptual model and undertake estimations using a panel vector autoregressive (PVAR) model. As widely applied in finance and real estate related literature (see, for instance, Fassas and Papadamou, 2018; Saffi and Vergara-Alert, 2020), PVAR model performs well in estimating how temporal lags of incorporated variables affect their corresponding contemporaneous counterparts across countries over a specified period of time.

Following Abrigo and Love (2016), the general specification of an order p panel vector autoregressive (PVAR) model is presented as

$$Y_{it} = \sum_{p=1}^{P} Y_{it-p}\alpha_p + u_i + \epsilon_{it} \tag{1}$$

$i = 1, \ldots, N; t = 1, \ldots, T; p = 1, \ldots, P.$

Where Y_{it} stands for a $(1 \times K)$ row vector of dependent variables where K is the number of endogenous variables included in the model system, u_i is a $(1 \times K)$ row vector of panel-specific fixed effects and ϵ_{it} is a row vector of the error terms ($1 \times K$), where $\epsilon_{it} \sim iidN(0, \sigma^2)$. α is a $K \times K$ coefficient matrix, viz. $\alpha_1, \alpha_2, ..., \alpha_p$, and p is the order of time lags included on the right hand side of (1). Moreover, the potentially-existing heterogeneous country specific fixed effects are modelled and captured by u_i in the PVAR.

$$\underset{(1\times 6)}{\begin{pmatrix} dlcpi_{it} \\ dlcr_{it} \\ dlcf_{it} \\ dlngdp_{it} \\ dlhpi_{it} \\ dirate_{it} \end{pmatrix}'} = \underset{(1\times 6)}{\begin{pmatrix} dlcpi_{it-1} \\ dlcr_{it-1} \\ dlcf_{it-1} \\ dlngdp_{it-1} \\ dlhpi_{it-1} \\ dirate_{it-1} \end{pmatrix}'} \underset{(6\times 6)}{\begin{pmatrix} a_{11} & a_{12} & \cdots & a_{16} \\ a_{21} & a_{22} & \cdots & a_{26} \\ a_{31} & a_{32} & \cdots & a_{36} \\ a_{41} & a_{42} & \cdots & a_{46} \\ a_{51} & a_{52} & \cdots & a_{56} \\ a_{61} & a_{62} & \cdots & a_{66} \end{pmatrix}} + \underset{(1\times 6)}{\begin{pmatrix} u_{1i} \\ u_{2i} \\ u_{3i} \\ u_{4i} \\ u_{5i} \\ u_{6i} \end{pmatrix}'} + \underset{(1\times 6)}{\begin{pmatrix} \epsilon_{1it} \\ \epsilon_{2it} \\ \epsilon_{3it} \\ \epsilon_{4it} \\ \epsilon_{5it} \\ \epsilon_{6it} \end{pmatrix}'} \tag{2}$$

Specifically in our empirical exercise, we use six variables in the estimation (see details in Section 4), viz. consumer price index (cpi), credit to the real economy (cr), credit to the asset markets (cf), nominal GDP ($ngdp$), nominal house prices (hpi), and interest rates ($irate$). By setting lag order $p = 1$, we re-express equation (1) in a compact form shown in (2) where $Y_{it} = \begin{pmatrix} dlcpi_{it} & dlcr_{it} & dlcf_{it} & dlngdp_{it} & dlhpi_{it} & dirate_{it} \end{pmatrix}$; α is a 6×6 coefficient matrix of Y_{it-1}; $u_i = \begin{pmatrix} u_{1i} & u_{2i} & u_{3i} & u_{4i} & u_{5i} & u_{6i} \end{pmatrix}$ and $\epsilon_{it} = \begin{pmatrix} \epsilon_{1i} & \epsilon_{2i} & \epsilon_{3i} & \epsilon_{4i} & \epsilon_{5i} & \epsilon_{6i} \end{pmatrix}$ are the panel specific fixed effects and error terms of each endogenous variable in Y_{it}, respectively.

Overall, the panel VAR model can capture the potential multiple dynamic interactions among the target economic variables and depict a *system-wide* effect rather than individual country-specific effect that 'shuns the intra/inter-country movements of shocks'. In addition, identifying the fixed effects helps us account for the idiosyncratic effects from each individual country and capture the heterogeneity in the panel data. However, OLS estimators of the PVAR could be biased even after eliminating the fixed effects due to the endogeneity issue induced by the inclusion of lagged dependent variables on the right hand side (RHS) of the PVAR.[7] In order to address this problem, we transform the PVAR and then estimate it using the technique of the generalized method of moments (GMM).

3.2 Endogeneity issues and estimation

It is well known that GMM estimators of the PVAR model result in consistent estimates and mitigate endogeneity problems due to the presence of lagged variables in the model (Abrigo and Love, 2016). There are two different data transformation methods available in the GMM estimation, viz., first difference (FD) and forward orthogonal deviation (FOD), respectively to remove the time-invariant effects (panel-specific fixed effects) from the PVAR model. The FD method transforms each variable in (1) by using its first time-differenced value, while the transformed variables are instrumented by the differences and levels of untransformed variables in Y_{it} from earlier time periods. However, the FD transformation would widen the time-period gap, especially in the context of the unbalanced panel dataset, and its minimum required time period is also larger than that required by the FOD transformation for the same PVAR model (Abrigo and Love, 2016).

Indeed, the FOD method is able to avoid the weaknesses of the FD method (Arellano and Bover, 1995). Rather than using the observations in the earlier periods to undertake transformation, the FOD method subtracts the average value of all available future observations from each untransformed variable. Hence, the loss of data points can be minimized. Moreover, the valid instruments for each FOD transformed variable on the RHS of (1) can even include its un-transformed variable at the same time period because the past observations are not involved during the transformation, indicating less time periods required in the FOD transformation than that in the FD transformation.

In addition, the efficiency of the GMM estimation can be improved by using more time-lagged dependent variables as instruments. However, this would give rise to the problem of missing observations, while selecting a reasonable set of instruments based on data availability and then substituting corresponding missing observations by zeros could be a remedy (Holtz-Eakin et al., 1988). Moreover, GMM estimators based on the FOD transformation are known to be consistent given that the fraction N/T is a positive constant, which is less than or equal to two (Alvarez and Arellano, 2003). Our dataset (to be introduced in Section 4) conforms to the above requirement to ensure the accuracy of GMM estimators.

In light of the PVAR model specification with untransformed variables shown in (1), we provide below, for ease of understanding, the steps to obtain its transformed version (equation (3)) and to study how the GMM estimator can control for the endogeneity problem.

$$Y^*_{it} = \widetilde{Y}^*_{it} A + \epsilon^*_{it} \tag{3}$$

Each variable and parameter in (3) can be explicitly presented in a matrix form.

$$Y^*_{it} = \begin{bmatrix} y^*_{1it} & y^*_{2it} & \cdots & y^*_{K-1it} & y^*_{Kit} \end{bmatrix} \tag{4}$$

$$\widetilde{Y}^*_{it} = \begin{bmatrix} Y^*_{it-1} & Y^*_{it-2} & \cdots & Y^*_{it-P+1} & Y^*_{it-P} \end{bmatrix} \tag{5}$$

$$A' = \begin{bmatrix} A'_1 & A'_2 & \cdots & A'_{P-1} & A'_P \end{bmatrix} \tag{6}$$

$$\epsilon^*_{it} = \begin{bmatrix} \epsilon^*_{1it} & \epsilon^*_{2it} & \cdots & \epsilon^*_{K-1it} & \epsilon^*_{Kit} \end{bmatrix} \tag{7}$$

Where Y^*_{it} on the left hand side (LHS) of (3) is a $(1 \times K)$ row vector to represent transformed Y_{it} in (1); $\widetilde{Y}^*_{it}$ on the right hand side (RHS) of (3) is the $(1 \times KP)$ row vector of transformed $\sum_{p=1}^{P} Y_{it-p}$ in (1); A is the $(KP \times K)$ coefficient matrix, which needs to be estimated; ϵ^*_{it} is the $(1 \times K)$ row vector of the transformed error terms (ϵ_{it}). Overall, variables with an asterisk superscript in (3) are the transformed version of the same variables in (1) by using either the FD or the FOD transformation. Regarding our empirical exercise, FOD transformation is applied and any transformed variable, h^*_{it} in (3) can be expressed as

$$h^*_{it} = (h_{it} - \overline{h}_{it})\sqrt{O_{it}/O_{it} + 1} \tag{8}$$

Where h^*_{it} is the transformed variable and h_{it} is its untransformed counterpart; $\overline{h}_{it}$ is the average value of h_{it} of all available future observations for cross-section i at time t; O_{it} is the total number of future observations. Hence, (3) can be expanded and re-formulated in algebraic form as

$$Y_{it}^{*} = Y_{it-1}^{*}A_1 + Y_{it-2}^{*}A_2 + \cdots + Y_{it-P}^{*}A_P + \epsilon_{it}^{*} \tag{9}$$

$$Q = \begin{bmatrix} Y_{it-1} & Y_{it-2} & \cdots & Y_{it-P+1} & Y_{it-P} \end{bmatrix} \tag{10}$$

Where M instruments of variables on the RHS of (9) are included in the common instrument set (Q); Q is a $1 \times M$ row vector and $M \geq KP$. [8] By assuming that target variables are predetermined variables, viz. weakly exogenous, in the PVAR system, the set of instrumental variables of $Y_{it-\alpha}^{*}$ is: $Q_\alpha = \begin{bmatrix} Y_{it-\alpha} & Y_{it-\alpha-1} & \cdots & Y_{it-P+1} & Y_{it-P} \end{bmatrix}$; $\alpha = 1, \ldots, P$. This implies that the un-transformed variable can still be a valid instrument of its transformed form in the same time period, viz. $Y_{it-\alpha}$ is a valid instrument of $Y_{it-\alpha}^{*}$. Hence, $cov(Q'_\alpha, \epsilon_{it}^{*}) = 0$, indicating no correlation between the instruments and the error terms in (9). Indeed, the GMM estimator is able eliminate the endogeneity problem in the PVAR model.

Finally, with regard to the GMM estimator in the FOD-transformed PVAR presented in (9), suppose observations in the data are stacked over panels and then over time. The GMM estimator is consistent given $\mathrm{E}\,(Q'\epsilon_{it}^{*}) = 0$ and rank ($\mathrm{E}\,(\widetilde{Y^{*}}'_{it}Q)$)=$KP$ (Abrigo and Love, 2016). Thus, the specification of the GMM estimator can be eventually presented in the following matrix form.

$$A = (\widetilde{Y^{*}}'Q\widehat{W}Q'\widetilde{Y^{*}})^{-1}(\widetilde{Y^{*}}'Q\widehat{W}Q'\widetilde{Y^{*}}) \tag{11}$$

Where $\widehat{W}$ is a $(M \times M)$ weighted matrix, which is assumed to be nonsingular, symmetric, and positive semidefinite. The weighted matrix $\widehat{W}$ is chosen so as to maximize efficiency of the GMM estimation (Hansen, 1982).

3.3 Identification strategies

We adopt a two-pronged strategy to identify the clear effects of cr and cf on housing prices. First, for the model parameter identification, we use four widely-used analytical tools associated with the PVAR model, viz. Model and Moment Selection Criterion (MMSC), Granger causality test, generalized impulse response function (IRF) and forecasting error variance decomposition (FEVD). Second, given the generality of the problem, we restrict our PVAR system by setting the parameters related to cr or cf to zero in two separate estimations so that dynamic effects of cr or cf do not bias the inference on other model parameters, especially the effects of cf or cr on housing prices in these two estimations, respectively. In other words, through the estimation with restrictions, shocks to cr or cf would not influence the covariance matrix when measuring the effect of cf or cr separately in these two estimations.

Specifically, to determine the PVAR model specification, we first confirm the optimal lag order and the moment condition of the model, which is conducted by applying MMSC to the GMM estimator of the PVAR model (Andrews and Lu, 2001). MMSC is constructed based on the Hansen's J statistic regarding overidentifying restrictions (Hansen, 1982). Similar to the widely-used information criterion system, MMSC includes modified Akaike information criteria (MMSC$_{AIC}$), modified Bayesian information criteria (MMSC$_{BIC}$), and Hannan-Quinn information criteria (MMSC$_{HQIC}$) (Abrigo and Love, 2016). Hence, the optimal model lag can be selected as the one with the minimum value of MMSC statistics, and the model parameters are checked to be well-identified when the corresponding J statistic is large.

Regarding the Granger causality test, given that the equation system of the PVAR model is jointly estimated by the GMM technique, we can use a Wald test to perform hypothesis testing for any a given specific parameter (Abrigo and Love, 2016). The null hypothesis is that coefficients/effects of temporal lags of a given variable y_1 from all equations on a specific variable y_2 are jointly equal to zero. Moreover, to gauge how target variables react to an isolated unit shock to a specific variable, a generalized impulse response function

(IRF) summarizes the responses. Rather than reporting averaged coefficient estimates of the PVAR, IRF plot enables us to observe the predictive behaviors of each target variable in future periods.

The fourth tool we employ is to forecast the error variance decomposition (FEVD) of target variables. It predicts the contribution of a specific variable to the error variance of target variables in a predefined-period ahead. Finally, to correctly identify the effects of cr and cf on housing prices, we re-estimate the PVAR system using two restricted model specifications where the parameters of cr and cf, which are denoted as α_{2k} and α_{3k} in (2), are imposed to be zero (as exogenous), respectively. $k = 1, \ldots, K$, and K denotes numbers of variables in the PVAR system. Results from restricted panel VAR are reported in Subsection 5.3.3.

4 Data

We use a quarterly panel dataset for nine industrialized countries, including Australia, Belgium, Canada, France, Germany, Japan, Spain, Switzerland, and United Kingdom, over the period from 1990Q1 to 2014Q2.[9] We use six economic variables in our estimation: consumer price index (cpi), credit to the real economy (cr), credit to the asset markets (cf), nominal GDP ($ngdp$), nominal house prices (hpi), and interest rates ($irate$).[10]

Note further that each variable is transformed in logarithms to express as the rate of growth and avoid any domestic currency effect, except interest rates ($irate$), which is described in levels. Moreover, all variables, except interest rates, are seasonally adjusted through X-12-ARIMA method. For interest rates we could not detect any seasonal peaks in its spectrum. Variable descriptions and corresponding data sources can be seen in Table 1, and detailed descriptions of data information are further provided in Appendix B. Nominal GDP ($ngdp$) and nominal housing prices (hpi) are our main variables, where their interactions with disaggregate bank credit (both cr and cf) will be investigated. Other macroeconomic variables are assumed to endogenously govern the dynamics of the interaction, for instance, through the lead-lag effects of financial costs and inflation. Preliminary observations regarding the data dynamics and stationarity checks are provided in Appendix C.

[Table 1 about here.]

5 Main Results

In this section, we present the results from panel VAR estimation for the benchmark models and the robustness exercises. Our benchmark results comprise of estimations with business cycles and without business cycles. For the latter, we employ the Hamilton filter and perform the estimation on the de-cycled series. A series of robustness checks are then undertaken to study the sensitivity of our benchmark results.

5.1 Benchmark results

5.1.1 Untreated data: Estimation in the presence of business cycles

To identify the VAR structure, we begin with the optimal lag order selection of the model. We use the Model and Moment Selection Criterion (MMSC) for the purpose (see Table 2). The validity of up to five lags in the PVAR model, including four quarters given the quarterly frequency of our sample plus an extra lag for the instrumentation, is examined. Meanwhile, we further substitute the missing observations due to the use of instrumental variables by zeros, in order to minimize the data loss while ensuring the efficiency of the estimation (Holtz-Eakin et al., 1988). Hence, in light of Table 2, the first-order panel VAR is preferable over others due to the smallest values of the modified BIC (MBIC) and QIC (MQIC). Based on the first lag, the Hansen *J*-statistic is 228.74 with a p-value of 0.000, implying rejection of an over-identified model. Instead, the first order PVAR model is checked to be well identified.

[Table 2 about here.]

(a) Main findings from the PVAR estimation

Table 3 presents the results of the first order PVAR estimation by using original data in the presence of business cycles. The key findings are summarized as follows. First, all six variables display - as expected - significant positive autoregression, implying temporal dependence of the current value of each variable on the past. Second, in line with the quantity theory of credit (the post-Keynesian school of thought), credit to the real economy ($dlcr$) significantly boosts economic growth ($dlngdp$) that a 1% increase in cr in the previous period exerts a 0.112% increase in $ngdp$. Whereas the effect of credit to the asset markets ($dlcf$) on $dlngdp$ is found to be expected and negligible, the effect could become significant in the analysis of impulse response function with the explanation provided in the next section.

[Table 3 about here.]

Third, in terms of the effects of disaggregate credit ($dlcr$ and $dlcf$) on housing prices ($dlhpi$), credit to the real economy ($dlcr$) exerts a positive impact where its elasticity of housing prices is 1.735, which is significantly greater than its elasticity of nominal GDP ($dlngdp$) (0.112). Credit to the asset markets ($dlcf$) has a negative effect on housing prices ($dlhpi$) although insignificant. We will demonstrate in Section 5.1.2 that the effect of $dlcf$ becomes significant and positive once removing potential business cycles in the raw data. Corresponding explanations in this regard will be discussed in Section 5.2.

Fourth, both housing prices ($dlhpi$) and nominal GDP ($dlngdp$) depict significant and positive interactions with credit to the real economy ($dlcr$); the elasticities are positive and are 0.008 and 0.103, respectively. However, both nominal GDP and housing prices evince a uni-directional effect on credit to the asset markets ($dlcf$) with positive elasticities 0.225 and 0.008, respectively. Fifth, regarding the impacts of macroeconomic factors, the appreciation of inflation ($dlcpi$) can also be regarded as a driving force of nominal GDP ($dlngdp$), viz., a 1% increase of CPI leads to a 0.384% increase of nominal GDP, while CPI only exerts an insignificant impact on housing prices. Furthermore, interest rates negatively affect both nominal GDP and housing prices, and the corresponding semi-elasticities are -0.392 and -6.841 respectively.

(b) Response to shocks

Next we present the results from impulse-response function (IRF) analysis. Corresponding IRF plots presented in Figure 1a to 1d are consistent with our expectations. In particular, as shown in Figure 1b, it is clear that due to a unit shock to credit to the asset markets ($dlcf$), the response of housing prices ($dlhpi$) depicts a pattern of decline in a very short-run before witnessing a rise throughout the rest of the periods. It is worth noting that its insignificant and negative impacts at the beginning periods tend to disappear once we remove business cycles from the raw series (as presented later in Figure 2b).

[Figure 1 about here.]

As depicted in Figure 1a, a unit shock to credit to the real economy ($dlcr$) impacts significantly and positively on all variables lasting for around 10 periods (except for CPI ($dlcpi$) with an insignificant effect). Specifically, a unit shock to $dlcr$ impacts both housing prices ($dlhpi$) and nominal GDP ($dlngdp$) positively as expected; the effect on $dlhpi$ peaks at 1.7, which is much greater than that for $dlngdp$ (0.11). Interestingly, the effect of credit to the asset markets ($dlcf$) on $dlngdp$ is insignificant in most of the 40-periods (see Figure 1b), whereas it turns to be significant over a short period from the 5th to 8th period. In addition, as evident in Figures 1c and 1d, the impacts of $dlhpi$ and $dlngdp$ on both disaggregate credit ($dlcr$ and $dlcf$) are shown to be significant and positive, respectively. Moreover, we further check the causality among target variables through the Granger causality test and forecast how the error variance of each variable is determined by other variables including itself through the error variance decomposition (FEVD) analysis. The corresponding findings are consistent with the coefficient estimates reported in Table 3.[11]

5.1.2 Estimation after treatment: The effects of business cycles removal

It is well-established that macroeconomic variables and housing prices often suffer from business cycle fluctuations, i.e., periodic fluctuations, that occur repeatedly throughout the trajectory of the growth of these variables.[12] To accurately model the dynamic interdependence among target variables, it is necessary to control for these periodic movements, a failure of which may give rise to biased inferences in interpreting the lead-lag relationship between them. The Hodrick-Prescott (H-P) filter is one of the widely-used methods to remove business cycles. However, its validity is questioned due largely to its imposed assumption of a smoothly-varying trend component, and its cyclical component tends to depict an autoregressive property, which is only a feature of having applied the H-P filter rather than a reflection of the true dynamics of the Data Generating Process (DGP) (Hamilton, 2018).

[Table 4 about here.]

To avoid these fundamental weaknesses, Hamilton (2018) develops a new filtering method, which is demonstrated to be a better replication of the real Data Generation Process (DGP). Specifically, it is able to decompose any a given non-stationary series by extracting a stationary part as its cyclical component, defining business cycles as the transient shocks lasting over specified time periods, which tend to disappear in the long-run. The remaining part is defined then as the trend component. In this section, we remove business cycles by filtering out cyclical components from the raw series using the Hamilton's filter and then re-estimate the PVAR with the same variables as used in the above section while they are *treated/de-cycled*. Following Hamilton (2018), a two-year horizon is set to recognize business cycles in the raw series. The corresponding results, including coefficient estimates and impulse response function (IRF) plots are presented in Table 4 and Figure 2, respectively. The results of Granger causality test and variance decompositions are presented in Tables D.1 and D.2, respectively, in Appendix D.

Overall, our results based on the *treated/de-cycled* data are broadly consistent with that from the *untreated* data as reported in Section 5.1.1. On top of that, several important findings emerge. First, in terms of the impacts of credit on nominal GDP ($dlngdp$), as shown in Table 4, we find that credit to the real economy ($dlcr$) presents an expected and significant positive effect on $dlngdp$, which is 0.077, in contrast to the insignificant effect of credit to the asset markets ($dlcf$). Interestingly, as for the IRF plots, the response of $dlngdp$ in the face of a unit shock to $dlcf$ can be significant although lasting for a short duration, which could be attributed to the composition of credit to asset markets (cf) in levels employed in our case.

Following European Central Bank (2020), in our paper, cf is represented by credit to financial corporations other than monetary financial institutions (MFI), including real estate holding companies. Although the majority of cf belongs to credit for non-GDP transactions, the real estate holding companies included within the scope of cf not only engage in selling existing properties but also involve in property leasing services. Furthermore, the holding companies can also engage in housing development acting as owners of their investment projects (Romainville, 2017). Thus, an increase in cf raises credit to the supply of existing properties and credit to other asset markets, both of which have no direct contribution to economic growth. At the same time, a rising cf can also increase credit to the supply of property rental services and housing constructions, both of which are known to boost growth (Landefeld et al., 2008). The above discussion identifies and clarifies the two components in cf that exert insignificant and significant impacts on growth, respectively.

With regard to the impact of credit on housing prices ($dlhpi$), conforming to theoretical expectations, we find that $dlcr$ holds a bidirectional and positive relationship with $dlhpi$. Importantly, the effect of $dlcf$ on $dlhpi$ is significant and positive when using the de-cycled data, in contrast to the insignificant and negative impact obtained from the untreated (raw) data. As shown in Table 4, a 1% unit change of cf induces a 0.062% change of hpi in the same direction, while $dlhpi$ in turn affects $dlcf$ with its elasticity as 0.271. Moreover, the corresponding IRF plot (Figure 2b) further confirms the significant and positive effect of $dlhpi$ on $dlcf$. The negative and insignificant result obtained earlier from the estimation with 'untreated' data could be due to the contamination of short-run periodic disturbances, misleading the real impacts of credit components on housing prices. Explanations for this key relationship between credit components and housing prices will be elaborated in the next section.

[Figure 2 about here.]

How does the interest rate impact economic activities in our panel VAR system? The interest rate ($dirate$), in our work, exhibits a negative impact on economic growth ($dlngdp$) as depicted from both the estimation results (Table 4) and the corresponding IRF plot (Figure 2e). This is consistent with expectations that a monetary policy contraction represented by the rising price of money would suppress economic activities and the wealth of nations, leading to a fall in GDP (Sousa, 2010). Conversely, $dlngdp$ also exerts an expected negative impact on $dirate$ although weakly significant as shown in Figure 2d. Indeed, an economic boom results in optimistic economic expectations, subsequently stimulating credit expansions in the economy (Chen, 2020; Muellbauer and Murphy, 2008). Moreover, regarding the impact of interest rates ($dirate$) on credit components ($dlcr$ and $dlcf$), $dirate$ exerts a positive effect on $dlcr$ and a negative but less significant effect on $dlcf$. As further depicted in corresponding IRF Figure 2e, the negative impact of $dirate$ on $dlcf$ tends to be only short-lasting and negligible, while its impacts on both credit components are shown to be overall positive. These findings provide empirical evidence of the distinct arguments co-existing in extant literature in this regard.

Specifically, via the 'bank-lending channel' of monetary policy transmissions, Jordà et al. (2015) suggest that tightening monetary conditions represented by higher short-term rates make home buying less accessible, leading to downward pressure of the housing demand and prices, as well as weakened availability of mortgage loans. Duan et al. (2019) point out that increasing short-term rates also raise the financing cost of housing supply. Through the argument of 'portfolio behavior of bank loans', a monetary tightening demonstrates differential impacts: it could reduce the supply of long-term credit and raise the relatively short-term less risky one (Den Haan et al., 2007). DellAriccia et al. (2014) add that a loose policy indication, i.e. a falling short-term interest rate, would even decrease the long-term mortgage loans as captured by $dlcr$ when the agent is highly leveraged with a fixed capital structure. Thus, these two arguments provide a theoretical interpretation for the impacts of interest rates on the two credit components ($dlcr$ and $dlcf$).

In turn, the impact pattern of different credit components (i.e. $dlcr$ and $dlcf$) on $dirate$ could also be distinct. In our case, as shown in Table 4 and IRF Figures 2a and 2b, credit to households ($dlcr$) exerts a positive effect on $dirate$, while credit to housing developers ($dlcf$) could have a negative impact. This conforms to our expectations and may be caused by the interplay between the 'liquidity effect' and 'Fisher effect' (Mishkin, 1982). Specifically, through the 'liquidity effect', an increase in credit lending, which represents the money supply for transactions through 'credit creation theory' (Li and Wang, 2020), could lower price of money, i.e. nominal interest rates ($dirate$) (Michis, 2015; Modigliani, 1974). In parallel, via the medium of the 'Fisher effect', $dirate$ could increase in response to rising money growth due to an increase in inflationary expectations (Friedman, 1968; Thornton, 2004). Thus, the direction of credit impacts on interest rates would depend on which of the two effects is dominating.

Furthermore, an increase in $dirate$ could either raise or drop housing prices ($dlhpi$) by suppressing the housing supply or demand, respectively (Arestis and Gonzalez-Martinez, 2016; Duan et al., 2018, 2019). As shown in Table 4, the impact from the housing supply outweighs that from the demand, leading to an increasing $dlhpi$ in our case. Conversely, an increase in $dlhpi$ could expand credit demand and supply due to both wealth and collateral effects to be discussed in the next section, which in turn would either raise or drop $dirate$ depending upon whether the 'Fisher effect' or the 'liquidity effect' is dominating as previously discussed. In addition, in line with the extant literature (See, e.g. Goodhart and Hofmann, 2008), a unit shock to inflation ($dlcpi$) induces a rise in target economic factors in normal terms as shown in IRF Figure 2f.

Finally, as presented in Table 4 and IRF Figure 2c, a rising housing prices ($dlhpi$) boosts economic growth ($dlngdp$). Through both housing wealth and collateral effects, a higher housing price stimulates consumption of households while enhancing their borrowing capacity; it could also expand residential investment, thus, in turn, leading to higher economic growth (Goodhart and Hofmann, 2008). Conversely, the response of $dlhpi$ when facing a unit shock to $dlngdp$ tends to be weakly definite, depicting a negative response at first followed by a positive move thereafter, as shown in IRF Figure 2d. This is attributed to the interplay between forces from the housing demand and supply sides. On the one hand, higher growth could be caused by rising residential investment, resulting in an increase in the housing supply and then a fall in housing prices (Aastveit et al., 2019; Green, 1997). On the other hand, a heightening economic output demonstrates an increasing buying power of households, raising the housing demand and then housing prices (Duan et al., 2018, 2019).

To summarize, results based on 'treated/decycled' data provide robust empirical evidence of the dynamics of credit - housing price - macroeconomy interactions that conforms to the extant literature and our expectations.[13] The removal of business cycles helps reconcile the seemingly-contradictory findings previously reported by the IRF plots using 'untreated/raw' data regarding pair relationships between target variables (e.g., between the interest rate and growth). It is argued that such the seemingly-contradictory results are caused by the contamination of periodic disturbances, demonstrating the importance of removing business cycles in the raw data prior to estimation.

5.2 Theoretical implications of results

In this section, we discuss effect transmissions from credit to housing price dynamics via demand and supply channels of housing. The interactive mechanism between credit and housing prices via the two channels is illustrated in Figures 3a and 3b, respectively. Specifically, in terms of the demand side, as discussed in Section 2.1, credit to the housing demand (cr) is known to depict a positive interaction with housing prices, governed through the medium of wealth and collateral effects, respectively. However, existing discussions on the supply-side dynamics remain surprisingly sparse. This section fills the gap by explaining the positive relationship between credit to the housing supply (cf) and housing prices.

[Figure 3 about here.]

Specifically, based on the demand and supply dynamics in the housing market, cf is assumed to display a positive effect on housing prices although through a more complex mechanism. Specifically, in the short-run period, the disequilibrium condition of the real estate market is featured by the insufficient housing supply and relatively excess housing demand. It implies that housing supply tends to be less elastic relative to the housing demand. In other words, the response of housing supply is smaller and slower than that of housing demand when there is a unit percent change in housing prices.[14] Hence, given a fixed housing demand, an increase in credit to the housing supply (cf) may not immediately raise the housing supply, indicating that an increase in cf has a negligible effect on the increase of housing supply and the deflation of housing prices in the short-run.

In the long-run, although housing suppliers can accordingly adjust the housing supply by providing more housing units, appropriate adjustments of housing demand can be also made. Having perceived the declining tendency in housing prices, housing demand will also increase, while its positive effect on raising housing prices tends to be stronger than the negative effect of the increasing housing supply. This is due to the inelastic housing supply in contrast to the relatively elastic housing demand. In addition, our theoretical discussions regarding the interaction between housing prices and credit on the supply side are illustrated in Figure 3b. Please see the positive effect of cf on housing prices drawn in black colour solid lines and its limited negative effect drawn in black colour dashed lines.

Thus, the above theoretical discussions support our empirical results that the effect of *credit to the housing supply* on housing prices is negative but negligible and can be a short-run phenomenon; the effect will be offset and dominated by an increasing housing demand, eventually becoming positive and significant in the long-run. Similar explanations are also provided by Arestis and Gonzalez-Martinez (2016).[15] The positive credit impact on housing prices on the supply side can explain the simultaneous phenomenon of overvalued housing prices and expanded housing stocks in the US as reported by Muellbauer and Murphy

(2008). A similar positive relation between them has also been found by Jordà et al. (2016). Moreover, this is consistent with Barker (2006), suggesting that a housing supply shortage in the face of excess housing demand is found to be a root cause of overvalued housing prices in the UK.

In turn, with regard to the effect of housing prices on cf, similar with its effect on credit to the housing demand (cr), an increase in housing prices will expand banks' credit supply to housing suppliers through both channels of 'wealth effects' and 'collateral effects'. Moreover, housing suppliers will also be inclined to enlarge their housing inventories for higher profitability with a lower borrowing cost. Hence, the credit demand of housing suppliers will eventually get a boost as well.

5.3 Robustness

In this section, we conduct additional analyses to demonstrate that our main results remain robust to a series of changes in the research design, such as the impact of economic policy uncertainty (EPU), the structural break (i.e. global financial crisis (GFC)), restrictions on the channel of credit shocks, correcting for interdependence and heteroskedasticity, and controlling for the price level, respectively.[16]

5.3.1 Accounting for the effects of economic policy uncertainty

Baker et al. (2016), among others, point out that economic policy uncertainty could lead to fluctuations in the real economy, suggesting that a heightening uncertainty gives rise to periods of sustained volatility, which invariably incur negative psychological effects among investors. According to the index of economic policy uncertainty (EPU), the global EPU has experienced an average annual growth of 6.51% since 1990s (Baker et al., 2016). Therefore, the rise in the uncertainty level might deter the credit flow to the real economy and the asset markets due to negative perceptions of market participants, which can further impact operations of the overall economic and financial system.

To examine the impact of uncertainty on the relationship between credit components, the housing market and growth, we introduce the EPU index (denoted by $uncer$) [17] and re-estimate the PVAR model.[18] The estimation results are reported in Table E.1 in Appendix E. It is clear that considering uncertainty does not alter our main conclusions drawn from the benchmark estimations (as in Table 4). In particular, it is worth noting that the interactions between both disaggregate credit ($dlcr$ and $dlcf$) and $dlhpi$ become more pronounced after controlling for uncertainty ($dluncer$) in the PVAR. Overall, we conclude that considering uncertainty does not alter our main conclusions, rather adds overall statistical power to the impact of credit classes on housing prices.

5.3.2 The effect of the global financial crisis

The intervention of the Global Financial Crisis (GFC) is known to slow down the growth of key economic fundamentals across countries. Arguably the largest impact has been felt in the housing market as it was measurably affected by information cascades and weak lending restrictions. A visual inspection of Figure C.1 also reveals the negative impacts of the outbreak of the GFC on economic factors. Following National Bureau of Economic Research (2020), the trough period of the GFC is defined to start from the beginning of 2008, i.e. 2008Q1 in our sample. To test the suitability of this definition in our case and the stability of model parameters in the interaction between the target variables when facing the outbreak of the GFC, we first perform a Chow test following Correa (2012) to confirm this structural break. The corresponding null hypothesis of the parameter stability is rejected at 5% level of significance, since the χ^2 statistic is 32.6. This test result is also consistent with the ones from alternative structural break tests (both in mean and variance).[19]

Thus, to account for the structural break, we accordingly split our sample into two sub-sample periods, viz. before and after the outbreak of the GFC starting from 2008Q1. Results of the PVAR estimation using the two sub-sample periods are presented in Tables E.2 and E.3 respectively in Appendix E. While the outbreak of the GFC tends to alter the associations between target variables, signs and magnitudes of the estimated coefficients remain similar in both the whole- and sub-sample periods. Specifically, credit components ($dlcr$ and $dlcf$) demonstrate an overall positive impact on housing prices ($dlhpi$). $dlcr$ exerts a positive effect on economic growth, while the impact of $dlcf$ is found to be insignificant. In a nutshell, our main findings drawn from the full sample are broadly consistent with those from the two sub-samples.

5.3.3 Restrictions on credit demand and supply shocks

Simultaneous inclusions of credit provisions to the housing demand side (cr) and the housing supply side (cf) in the same estimation could bias the estimated results - thanks to the possibility of the correlation of errors with both cr and cf, respectively. Therefore, to separately identify the effects of these two credit components, we re-estimate the PVAR model by imposing appropriate restrictions within the VAR system. Specifically, we restrict credit demand (cr) or credit supply (cf) shocks to zero (as exogenous) in specific PVAR models when estimating the impacts of cf or cr, respectively. This strategy could help 'free' the variance-covariance matrix (containing shocks to target variables) from possible 'noise' due to the inclusion of a related variable in the estimation and correlation with the error term. PVAR estimates with restrictions on credit demand and supply shocks are respectively reported in Tables E.4 and E.5, respectively. Overall, we find that the impacts of $dlcr$ when restricting $dlcf = 0$ (similarly, the impacts of $dlcf$ when restricting $dlcr = 0$) are consistent with their counterparts in the benchmark model. Moreover, the consistency of our main conclusions is also confirmed by identification strategies associated with the PVAR model, such as impulse response function, Granger causality test, and variance decomposition.

5.3.4 Correcting for interdependence and heteroskedasticity

The dynamics of macroeconomic variables can depict an interdependent pattern in both cross-sectional and temporal dimensions (Bailey et al., 2016; Duan et al., 2018). Specifically, the cross-sectional interconnection can emerge due to global common shocks that exert heterogeneous impacts across regions/countries (i.e. the strong form of dependence) and local spillover effects among neighbouring locations (i.e. the weak form of dependence) (Chudik et al., 2011). At the same time, macroeconomic variables are also known to be dependent with their own temporal lagged terms (Fuhrer, 2017), leading to the presence of autocorrelation in the corresponding model residuals due to potential variable omissions in the estimation. A failure to account for the interdependence in both dimensions could lead to unreliable estimation (Duan et al., 2021a; Huang, 2008; Huang et al., 2021).

Accordingly, we relax the independent identically distributed ($i.i.d.$) assumption of the model residuals, and improve the GMM estimator by considering a heteroskedasticity and autocorrelation consistent (HAC) weight matrix (i.e. W in Equation (11)) constructed using the Bartlett Kernel following Giacomini et al. (2020). Moreover, we follow Levin et al. (2002) by subtracting the cross-sectional averages from our data, through which the potential cross-sectional dependence can be further controlled by accounting for the time-specific effects. Through these, along with consideration of the panel specific fixed-effects (i.e. u_i in Equation (1)), our improved PVAR estimation captures the interdependence of target variables in both cross-sectional and temporal dimensions. Accordingly, we re-estimate the PVAR model with its coefficient estimates reported in Table E.6 in Appendix E. It is clear that the results mimic that of our benchmark estimation after removing business cycles (See in Table 4), confirming the robustness of our main findings.

5.3.5 Controlling for the price level

Since the relationship among variables in nominal terms might be affected due to variations in the price level, i.e. inflation, to further examine robustness of our conclusions, we remove the price level component from target variables in nominal terms and convert them into real variables. Simultaneously, we have also incorporated inflation into the estimation to examine the impact of the price level on target variables. Through this, the actual relationship among credit components, housing prices, and growth could be investigated. It can be seen that results of the PVAR estimation with the price level being controlled (in Table E.7 in Appendix E) are consistent with their counterparts in the benchmark estimation (in Table 4).

6 Conclusions

In light of the post-Keynesian arguments on the credit disaggregation strategy, this paper proposes a conceptual construct to argue that this strategy helps untangle the distinct effects of the two defined credit components on housing prices and economic growth, respectively. Moreover, asymmetric information arising from persistence in economic policy uncertainty could alter the relationship of credit with housing prices and economic growth. We also shed light on a likely bias in the estimation with cycle-unadjusted data because the latter often displays varied convergence processes and non-synchronized paths of co-movements of the temporal variables within a system. Our three-pronged strategy, viz., disaggregation of credit, explicit treatment of economic policy uncertainty, and cyclical adjustment of target variables, identifies and measures the exact effects of credit on both the short-run and long-run movements of housing prices as well as economic growth.

Consistent with our theoretical expectations, the main conclusions of the paper are summarized as follows. *Credit-to-the-real-economy* engages in a dynamic and mutually positive reinforcing relationship with housing prices, whereas *credit-to-the-asset-markets* and housing prices tend to be intertwined and appear to affect each other through a more complex mechanism. Specifically, *credit-to-the-asset-markets* is found to leave a negligible negative effect on housing prices in the very short-run and a strong positive effect in the long-run. Regarding the effect of credit on economic growth, only *credit-to-the-real-economy* rather than *credit-to-the-asset-markets* is found to significantly contribute towards nominal GDP growth. Moreover, the interactions between the credit components and housing prices become more pronounced once the effects of economic policy uncertainty are controlled for. The uncertainty level gives rise to significant negative effects on key economic variables such as housing prices and nominal GDP. The robustness checks add further credence to our findings.

Our findings possess valuable insights for policy. First, since *aggregate* credit presents only 'averaged out' real effects of its *components*, policymakers may like to minimize significant loss of microlevel information by using *disaggregate* credit so that distinct effects of the credit components flowing into different circulations on impacting housing prices and economic growth can be well interpreted. Thus, an appropriate monetary policy intervention regarding the credit distribution to different housing market participants can be made, while a sensible credit rationing to the real economy and the financial/asset markets can be also allocated. Accordingly, such knowledge can help policymakers implement a balanced strategy to limit the risk of 'overheating in housing markets and the real economy'. Second, uncertainty is a persistent phenomenon in modern economic and financial systems and its detrimental role cannot be overlooked when modeling dynamic interactions among macro-financial variables, asset markets and the real economy in general, and credit markets, housing markets and economic growth in particular.

Notes

[1]Throughout the paper, the term credit is used as synonymous with bank credit.

[2]See Table A.1 for a summary of the key literature.

[3]Recent applications of credit disaggregation notably include, for instance, Bezemer and Grydaki (2014); Bezemer et al. (2016), among others.

[4]In Section 2.2, we present a modified definition of cr and cf and explain how they can represent credit to the demand and supply sides of housing, respectively.

[5]In the paper, we conceptually define both short-run and long-run to describe the specific time periods when a target variable reacts to an exogenous shock. These definitions neither involve nor consider formations of the equilibrium status of the housing market. They will be estimated and tested through the impulse response function plot in our empirical analysis.

[6]Authors' calculation according to the data from the National Association of Realtors and the US Bureau of the Census, the ratio of numbers of existing/second-hand home sales to the numbers of total home sales in the US between March 2017 and March 2018 is 99.05%. In the UK, this ratio is 90.25% between January 2007 and December 2016 (Data source: Office for National Statistics). Moreover, the ratio of the amount of existing home transactions to the total amount of home transactions in 2018 is 98.31% (Data source: HM Land Registry Open Data).

[7]While it is known that the endogeneity issue can be alleviated by incorporating the time-lagged term of explanatory variables, i.e. predetermined variables (Duan et al., 2021b), it does not apply in a VAR setting

where all variables in the system are considered as dependent variables.

[8] $M = KP$, if and only if the instrument of each transformed variable is it's untransformed variable at the same time period.

[9] Due to data unavailability on disaggregate bank credit, our empirical research is restricted to the nine countries.

[10] The short-term interest rate is applied as the monetary policy indicator (DellAriccia et al., 2014; Jordà et al., 2015) and it measures the marginal cost of banks for the purpose of liquidity and lending businesses. Moreover, the short-term interest rate is a recognized approach to stand for 'the price of money' (Woodford, 2011). It along with with 'the quantity of money' (i.e. cr and cf) capture the monetary policy transmission mechanism. In the paper, we follow the extant literature by representing the short-term rate using the three-month interbank rate (Borio and Gambacorta, 2017; Goodhart and Hofmann, 2008). Altering the proxy of short-term rates using the overnight interest rate would not change our main findings. Results of the PVAR estimation with overnight rates are available from the authors upon request.

[11] Due to limited space, the results of the Granger causality test and variance decomposition are available from the authors upon request.

[12] There can be many sources of these fluctuations, and important ones are technological changes, changes in policy regime and/or financial regulations.

[13] To examine the validity of our findings regarding the relationships between credit components, housing prices, and macroeconomic variables as shown in Figure 2, we test whether our findings are still held in a standard PVAR model that only considers classical macroeconomic variables (i.e. economic growth, the interest rate, and inflation). Results of the standard PVAR estimation regarding the relationship between the three macroeconomic variables mimic the counterparts in our benchmark estimations, confirming the validity of our findings. The standard PVAR estimation results are available from the authors upon request.

[14] Recent phenomena provide strong support for this finding (see empirical examples, Kuenzel and Bjornbak, 2008, among others). Housing supply is inelastic especially in those regions where the supply appears to be unresponsive and ineffective in the face of fast rising housing prices (Glaeser et al., 2012). It is because housing is so durable that the market cannot quickly adjust the housing supply (Green et al., 2005). Instead, the provision of new housing supply needs a considerably long duration of preparation including the planning process and the construction period, whereas the response of housing demand tends to be relatively faster and greater. Moreover, limited land availability and high land values could be another reason why housing supply is less elastic (Saiz, 2010). A forward-looking behaviour of housing builders could also lead to a strong reduction in the elasticity of supply, especially during periods of housing booms (Murphy, 2018).

[15] In the light of Arestis and Gonzalez-Martinez (2016), an increase in credit to the housing supply could

induce a falling housing price in the short run but this downward tendency might be limited due to the inelastic supply in the short-run. In the long-run, housing prices would increase as a result of dominant and positive impacts of the increasing demand against relatively inelastic and negative impacts of the increasing supply.

[16]Due to limited space, we report results of PVAR estimates for each additional analysis in Appendix E to check robustness of our main findings. Further evidence of robustness from the Impulse response function (IRF) plot, the Granger causality test, and the variance decomposition is available from the authors upon request.

[17]For each country except Switzerland, the EPU index is available from http://www.policyuncertainty.com/. The Swiss EPU index can be downloaded through https://www.kof.ethz.ch/en/forecasts-and-indicators /indicators/kof-uncertainty-indicator.html. Moreover, we have to exclude Belgium as its EPU index is currently not available.

[18]Given the superiority of the de-cycled data to the raw data, we present results using the de-cycled data.

[19]In addition to imposing a known breakpoint, we also perform a sequential break point test, i.e Sup-Wald test, following Andrews (1993). The test statistic is greater than 5% significance level provided by Andrews (2003) in the iteration of 2008Q1, but lower than in the next iteration, indicating the break at 2008Q1. Moreover, the result is further confirmed by endogenously detecting the potential break in variance of the key economic factors in our sample using the iterative cumulative sum of squares algorithm (ICSS) (Dungey and Gajurel, 2015; Inclan and Tiao, 1994).

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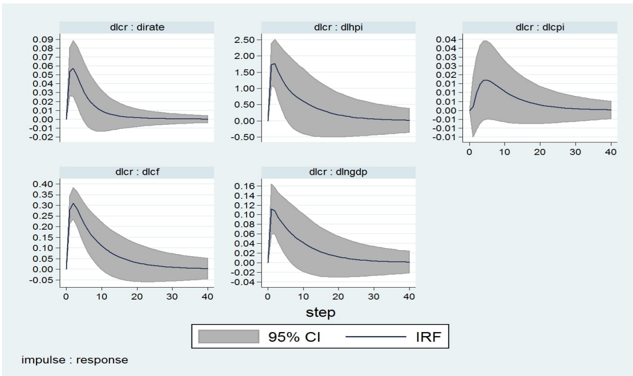
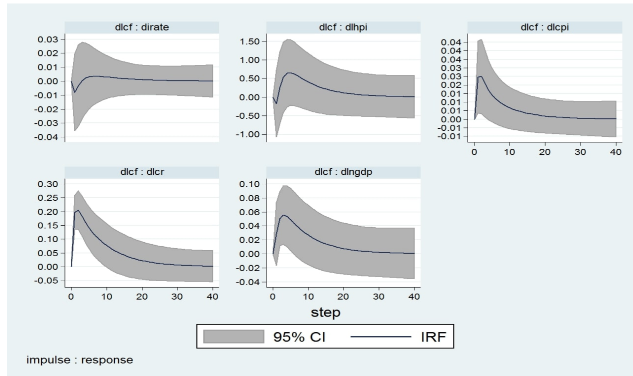
Figures

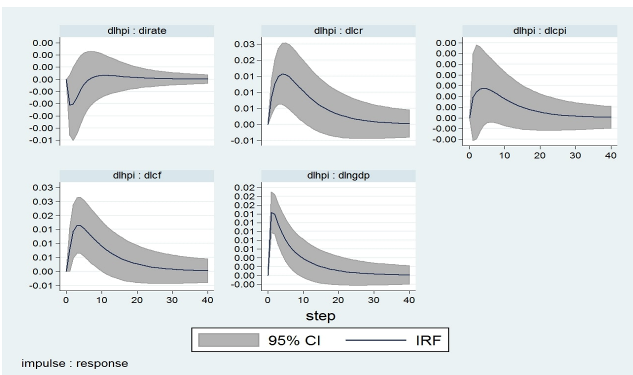
(a) A unit shock to $dlcr$



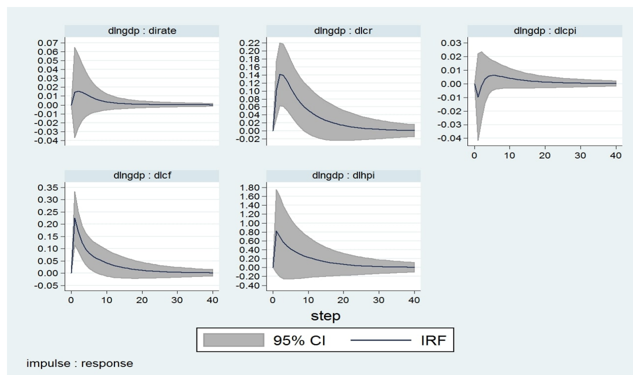
(b) A unit shock to $dlcf$



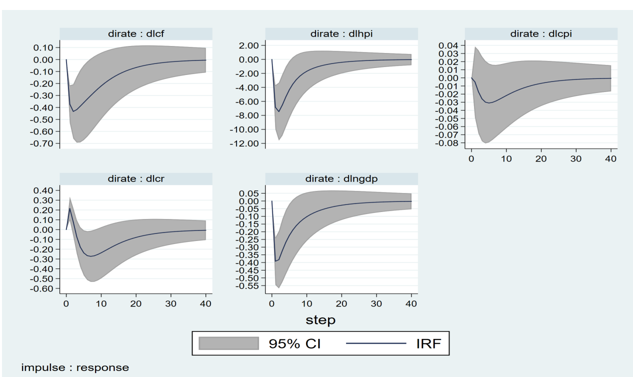
(c) A unit shock to $dlhpi$



(d) A unit shock to $dlngdp$



(e) A unit shock to $dirate$



(f) A unit shock to $dlcpi$

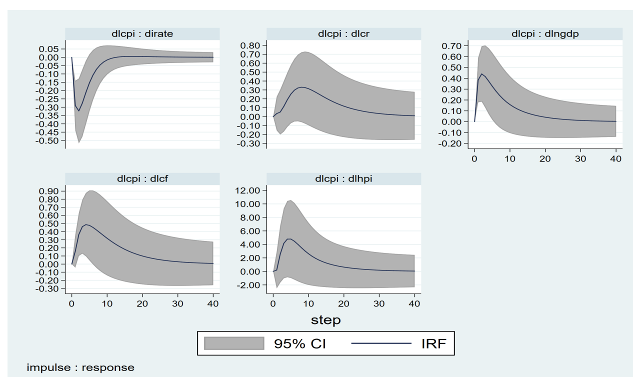
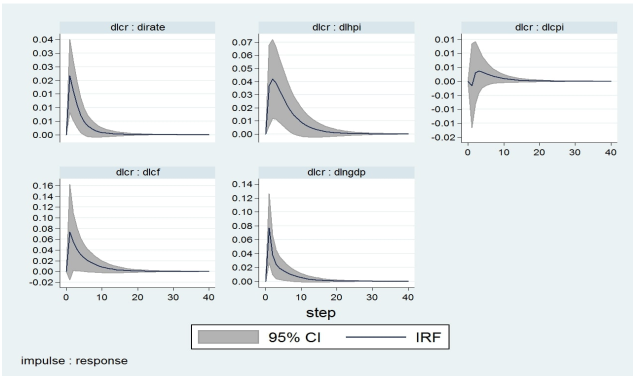


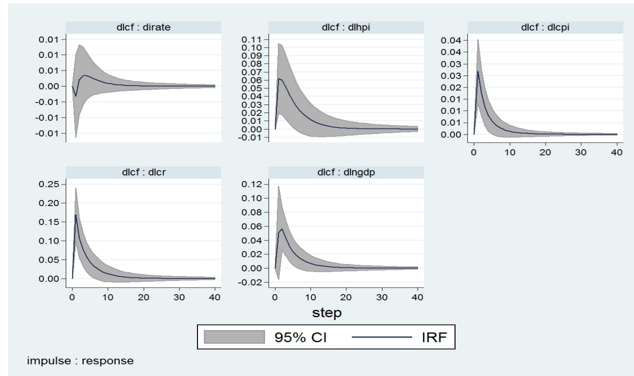
Figure 1: **Generalized IRF plots - Non de-cycled data**

Note: Figure 1 demonstrates the results of impulse response function (IRF) plots from the PVAR estimation with 'untreated/raw' data. Each subfigure reports the response of variables to a unit shock to the impulse variable that is used to name the subfigure. cpi denotes consumer price index; $ngdp$ denotes nominal GDP; hpi denotes nominal housing prices; cf denotes credit to the asset markets; cr denotes credit to the real economy; $irate$ denotes the short-run interest rate. Variables in the first-differenced logarithms begin with a prefix 'dl'.

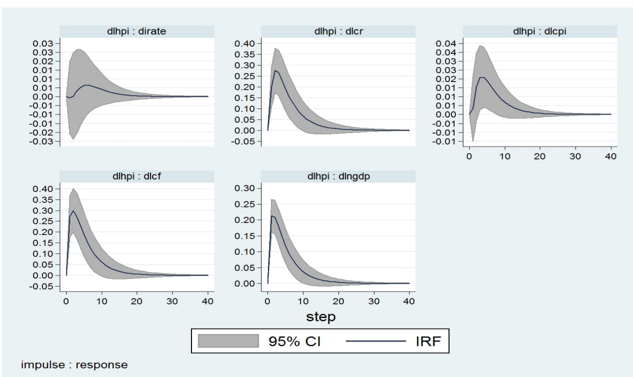
(a) A unit shock to $dlcr$



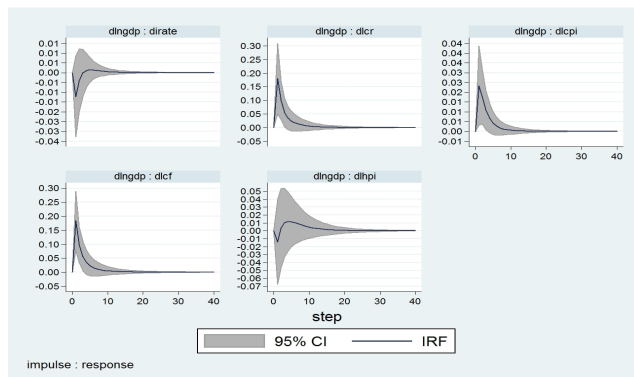
(b) A unit shock to $dlcf$



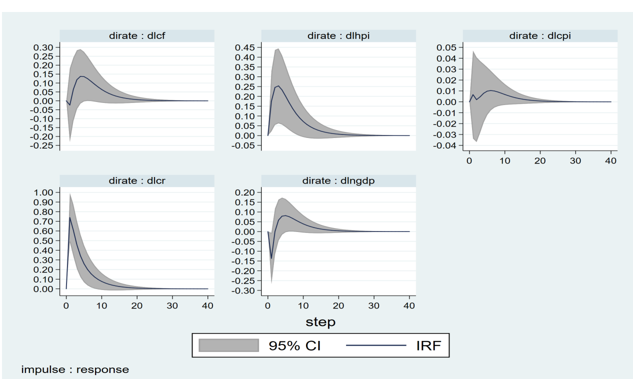
(c) A unit shock to $dlhpi$



(d) A unit shock to $dlngdp$



(e) A unit shock to $dirate$



(f) A unit shock to $dlcpi$

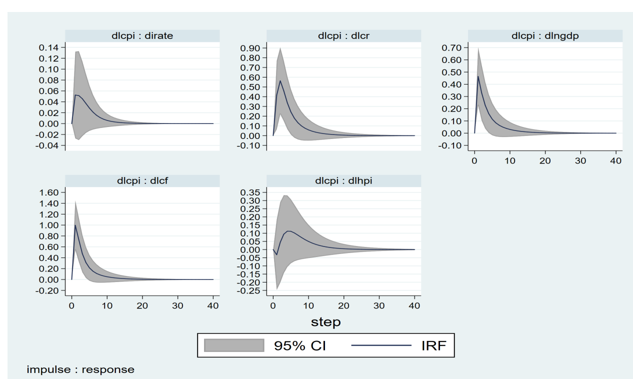
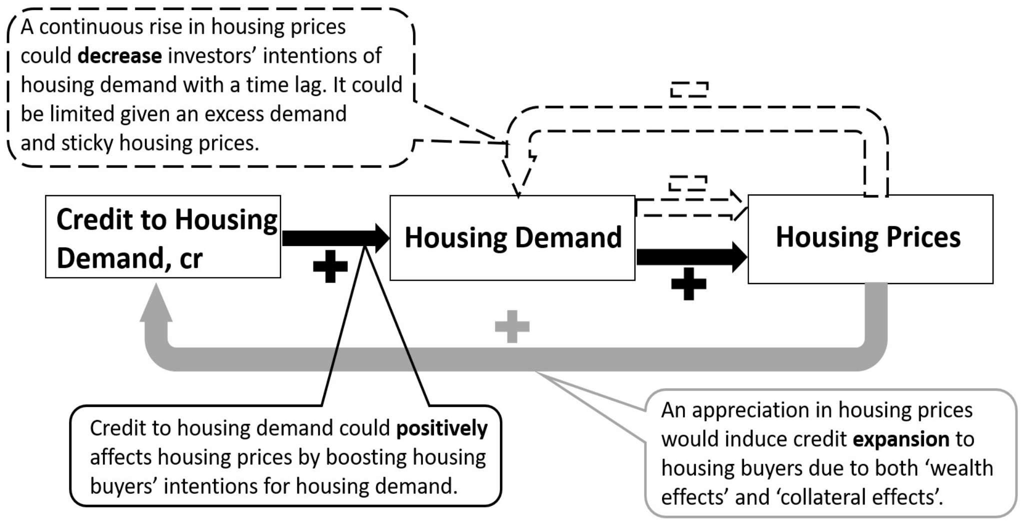


Figure 2: **Generalized IRF plots - De-cycled data**

Note: Figure 2 demonstrates the results of impulse response function (IRF) plots from the PVAR estimation with 'treated/decycled' data. Each subfigure reports the response of variables to a unit shock to the impulse variable that is used to name the subfigure. cpi denotes consumer price index; $ngdp$ denotes nominal GDP; hpi denotes nominal housing prices; cf denotes credit to the asset markets; cr denotes credit to the real economy; $irate$ denotes the short-run interest rate. Variables in the first-differenced logarithms begin with a prefix 'dl'.

(a) The Housing Demand Credit Circulation Channel



(b) The Housing Supply Credit Circulation Channel

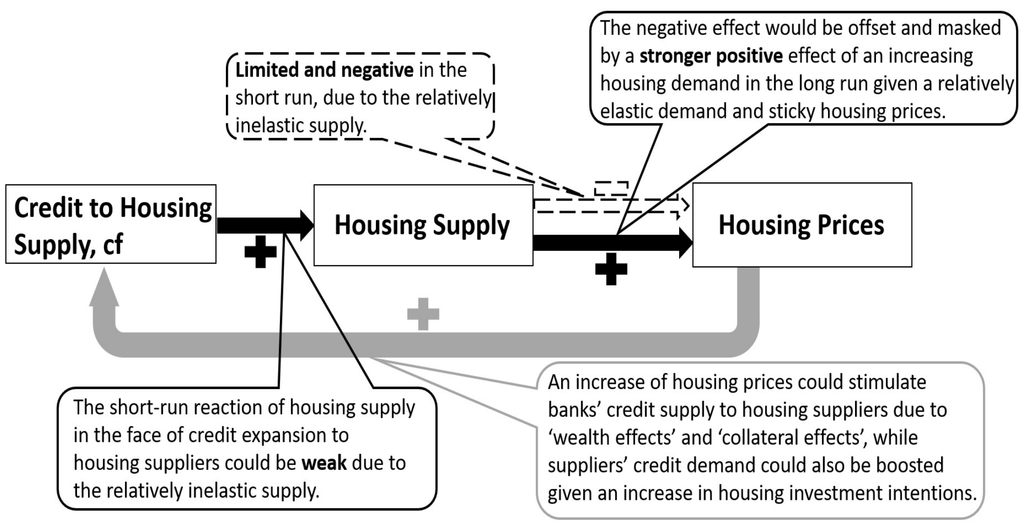


Figure 3: **Housing prices - credit interactions**

Note: Figures 3a and 3b illustrate how disaggregate credit interacts with housing prices through the credit circulation channels on the housing demand and supply sides, respectively, after controlling for the mediating role of macroeconomic fundamentals.

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Tables

Table 1: **Data description**

Variable	Definition	Data Source
Consumer price index (cpi)	The price changes of a basket of goods and services purchased by a reference population overtime	OECD Main Economic Indicators (MEI)
Credit to the real economy (cr)	Nominal credit lending to households and the non-profit institutions serving households (Millions of national currency)	The asset/liability side of the consolidated balance sheets of money issuers/borrowers
Credit to the asset markets (cf)	Nominal credit lending to other financial corporations including the real estate holding companies (Millions of national currency)	The asset/liability side of the consolidated balance sheets of money issuers/borrowers
Nominal GDP ($ngdp$)	Nominal gross domestic product (Millions of national currency)	OECD Main Economic Indicators (MEI)
Nominal housing prices (hpi)	Nominal price index of different types of dwellings nationwide	The Bank for International Settlements (BIS)
Interest rates ($irate$)	Nominal three-month interbank rates	OECD Main Economic Indicators (MEI)

Table 2: **Model and moment selection criterion**

Lag order	J statistic	J p-value	MBIC	MAIC	MHQIC
1	228.7439	0.000	-729.0825	-59.25614	-316.9739
2	154.3506	0.002	-564.0192	-61.64942	-254.9377
3	101.7399	0.012	-377.1732	-42.26006	-171.1189
4	61.79143	0.005	-177.6652	-10.20857	-74.638

Note: This table reports results of the lag order selection based on the Model and Moment Selection Criterion (MMSC). MMSC statistics for each tested lag, i.e. modified Akaike information criterion (MAIC), modified Bayesian information criterion (MBIC), and modified Hannan-Quinn information criterion (MHQIC), are calculated based on Hansen's J statistic for the over-identification restriction test (Hansen, 1982). The optimal lag order should be selected as the one with the minimum value of MMSC statistics.

Table 3: **The benchmark estimation (with business cycles)**

$dlcpi$		$dlngdp$		$dlhpi$		$dlcf$		$dlcr$		$dirate$	
L.$dlcpi$	0.599***	L.$dlcpi$	0.384***	L.$dlcpi$	0.198	L.$dlcpi$	0.158	L.$dlcpi$	0.034	L.$dlcpi$	-0.291***
	(0.058)		(0.104)		(1.321)		(0.109)		(0.097)		(0.081)
L.$dlngdp$	-0.01	L.$dlngdp$	0.223***	L.$dlngdp$	0.821	L.$dlngdp$	0.225***	L.$dlngdp$	0.103**	L.$dlngdp$	0.014
	(0.016)		(0.048)		(0.533)		(0.053)		(0.04)		(0.026)
L.$dlhpi$	0.001	L.$dlhpi$	0.014***	L.$dlhpi$	0.578***	L.$dlhpi$	0.008**	L.$dlhpi$	0.008***	L.$dlhpi$	-0.002
	(0.001)		(0.002)		(0.045)		(0.004)		(0.003)		(0.001)
L.$dlcf$	0.025**	L.$dlcf$	0.029	L.$dlcf$	-0.173	L.$dlcf$	0.413***	L.$dlcf$	0.197***	L.$dlcf$	-0.008
	(0.011)		(0.024)		(0.408)		(0.044)		(0.033)		(0.014)
L.$dlcr$	0.002	L.$dlcr$	0.112***	L.$dlcr$	1.735***	L.$dlcr$	0.280***	L.$dlcr$	0.627***	L.$dlcr$	0.054***
	(0.009)		(0.025)		(0.351)		(0.034)		(0.034)		(0.013)
L.$dirate$	-0.005	L.$dirate$	-0.392***	L.$dirate$	-6.841***	L.$dirate$	-0.373***	L.$dirate$	0.215***	L.$dirate$	0.530***
	(0.022)		(0.075)		(1.65)		(0.085)		(0.066)		(0.058)

Note: Table 3 reports the GMM estimation of the first-order PVAR model by using raw data in the presence of business cycles. Regarding incorporated variables, cpi denotes consumer price index; $ngdp$ denotes nominal GDP; hpi denotes nominal housing prices; cf denotes credit to the asset markets; cr denotes credit to the real economy; $irate$ denotes the short-run interest rate. The symbol 'L.' denotes the first temporal lag of the variable, and variables in the first-differenced logarithms begin with a prefix '*dl*'. *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level. Standard errors are in parentheses.

Table 4: **The benchmark estimation (business cycles removal)**

$dlcpi$		$dlngdp$		$dlhpi$		$dlcf$		$dlcr$		$dirate$	
L.$dlcpi$	0.418***	L.$dlcpi$	0.464***	L.$dlcpi$	-0.032	L.$dlcpi$	0.997***	L.$dlcpi$	0.416**	L.$dlcpi$	0.052
	(0.051)		(0.125)		(0.101)		(0.214)		(0.168)		(0.041)
L.$dlngdp$	0.023**	L.$dlngdp$	0.143***	L.$dlngdp$	-0.014	L.$dlngdp$	0.184***	L.$dlngdp$	0.180***	L.$dlngdp$	-0.012
	(0.011)		(0.037)		(0.026)		(0.054)		(0.067)		(0.011)
L.$dlhpi$	0.003	L.$dlhpi$	0.213***	L.$dlhpi$	0.692***	L.$dlhpi$	0.271***	L.$dlhpi$	0.202***	L.$dlhpi$	-0.001
	(0.009)		(0.025)		(0.037)		(0.048)		(0.043)		(0.011)
L.$dlcf$	0.027***	L.$dlcf$	0.05	L.$dlcf$	0.062***	L.$dlcf$	0.206***	L.$dlcf$	0.170***	L.$dlcf$	-0.003
	(0.007)		(0.035)		(0.022)		(0.058)		(0.036)		(0.007)
L.$dlcr$	-0.002	L.$dlcr$	0.077***	L.$dlcr$	0.037**	L.$dlcr$	0.074*	L.$dlcr$	0.251***	L.$dlcr$	0.022***
	(0.007)		(0.026)		(0.017)		(0.043)		(0.040)		(0.007)
L.$dirate$	0.007	L.$dirate$	-0.137**	L.$dirate$	0.175**	L.$dirate$	-0.024	L.$dirate$	0.739***	L.$dirate$	0.556***
	(0.021)		(0.064)		(0.078)		(0.109)		(0.117)		(0.046)

Note: Table 4 reports the GMM estimation of the first-order PVAR model by using the transformed data with potential cyclical component removed. Regarding incorporated variables, cpi denotes consumer price index; $ngdp$ denotes nominal GDP; hpi denotes nominal housing prices; cf denotes credit to the asset markets; cr denotes credit to the real economy; $irate$ denotes the short-run interest rate. The symbol 'L.' denotes the first temporal lag of the variable, and variables in the first-differenced logarithms begin with a prefix '*dl*'. *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level. Standard errors are in parentheses.

Appendix A Summary of the Key Literature

Table A.1: **Summary of the key literature**

Authors	Data	Key Variables	Main findings
Werner (1997)	Japan (1981Q1-1991Q1)	GDP, credit to the real economy and credit to the asset markets	Split credit into credit to the real economy and credit to the asset markets. Only credit to the real economy is significant to economic growth.
Senhadji and Collyns (2002)	Eight Eastern Asian countries (1990M1-2001M1)	Real housing prices, real credit to private sector, and real GDP per person	Credit and GDP positively affect housing prices. Financial crisis weakens the effect of credit on housing prices.
Hofmann (2003)	20 industrialized countries (1985Q1-2001Q4)	Real housing prices, real aggregate bank credit, and real GDP	Unidirectional effect of housing prices on credit in the short-term, while bidirectional in the long-term.
Gerlach and Peng (2005)	Hong Kong (1980Q4-2001Q4)	Real housing prices, GDP, and Real aggregate credit	Unidirectional effect of housing prices on credit. Housing prices are driven by the economic fundamentals.
Almeida et al. (2006)	26 countries (1970-1999)	Housing prices, GDP, Loan-to-value ratio	Housing prices are more sensitive to GDP in countries with greater LTV ratios.
Fitzpatrick and McQuinn (2007)	Ireland (1980Q1-2002Q4)	Housing prices, mortgage credit, and other fundamental variables	Bidirectional effect of housing prices on credit in the long-run, while unidirectional in the short run. Housing prices are driven by the fundamental variables.
Goodhart and Hofmann (2008)	17 industrialized countries (1970Q1-2006Q4)	Housing prices, broad money lending, bank credit to the private sector, real GDP	Multi-directional interactions between the money supply, credit to the private sector, housing prices, and GDP.
Mian and Sufi (2009)	US (1991-2007)	Mortgage credit, housing prices	Mortgage credit is driven by the credit supply, while the growth of housing prices is explained by credit expansions.
Duca et al. (2011)	US (1981Q1-2007Q2)	Loan-to-value (LTV) ratio, price-to-rent, mortgage rate, and taxation on property	Both exogenous mortgage supply and LTV ratio positively affect the price to rent ratio. House price cycles stem from the credit supply cycles.
Abdallah and Lastrapes (2013)	43 US States (1976Q2-2008Q4)	Real personal disposable income, Real housing prices, real consumption per capita	Consumption in the state with greater opportunities to home equity as collateral is more sensitive to a housing demand shock than the state with few opportunities.
Arslan et al. (2015)	US (1992Q2-2013Q2)	Housing prices and foreclosures	The feedback mechanism between the dip in housing prices and the increase in foreclosure rates enlarges the influence of defined macroeconomic shocks.
Favara and Imbs (2015)	US (1994-2005)	Housing prices, branching deregulation, mortgage loans, and loan to income ratio	Credit supply increases housing prices in regions with inelastic housing supply, while it increases housing stock in regions with elastic housing supply.
Justiniano et al. (2019)	US (1990-2006)	Credit constraints, collateral requirements, house prices, GDP, and mortgage rate	Unlike credit demand, an increase in credit supply drives the boom in housing prices.
Jordà et al. (2016)	17 advanced economies (1870-2011)	Mortgage credit, non-mortgage credit, and, GDP	The dynamics of mortgage credit are synchronized with the boom-bust behaviors of economic growth, while the growth has been argued to be the source of financial fragility.
Ling et al. (2016)	US (1992Q2-2013Q2)	Commercial housing prices market liquidity credit availability	Credit constraints to the housing demand side provide the negative effect on housing price behaviors especially in the markets which are highly levered and relatively illiquid.
Unger (2017)	11 European countries in the euro area (1999-2013)	Domestic bank credit to the non-financial private sector, external debt claims of domestic banks, current account balance	The increase of bank credit to the non-financial private sectors, along with a loss in competitiveness, are the intrinsic reasons for the build-up of the current account imbalances.

Appendix B Data Information

This appendix describes the data employed in our analysis. In light of the 2008 System of National Accounts (United Nations, 2009), credit is defined as net lending claimed by money issuers, i.e. monetary financial institutions (MFIs); and it also denotes the outstanding amount that money borrowers are liable to repay. MFIs are financial institutions whose businesses are to receive deposits from and grant credit on their own accounts to entities other than MFIs (i.e. non MFIs), and they include the central bank and other deposit-taking corporations, such as commercial banks, credit unions, saving institutions, money market mutual funds and etc. Following our discussions in Section 2.3, credit to the real economy (cr) is defined as the credit lending by MFIs to households and non-profit institutions serving households; credit to the asset markets (cf) denotes the credit lending by MFIs to other financial corporations (OFCs) that are defined as financial corporations other than depository corporations including the real estate holding companies.

The consumer price index (cpi) is defined as the price changes of a basket of goods and services that are typically purchased by a reference population; Nominal GDP ($ngdp$) denotes the gross domestic product in nominal terms; Interest rates ($irate$) denote nominal three-month interbank rates; the corresponding data are collected from the OECD Main Economic Indicators (MEI). The variable of house prices (hpi) is represented by the price index of various types of dwellings nationwide and the data are from the Bank for International Settlements (BIS).

Appendix C Preliminary Observations

C.1 Understanding the data dynamics

In Figures C.1 and C.2, we present dynamic patterns of target variables in growth rates and their corresponding standard deviations, respectively. Figure C.1 shows that both credit components (i.e. cr and cf) presented mostly positive and high growth rates before the outbreak of the global financial crisis in 2008, and growth rates of the interest rate ($irate$) were relatively small and fluctuated across zero before the crisis. These phenomena conform to key features in the 'Great Moderation (1984-2007)', which is particularly indicated as a falling tendency of the volatility of real output growth preceding the recession of 2008 as illustrated in Figure C.3. Specifically, the Great Moderation is mainly characterized by high stability in the macroeconomy, credit expansion, and a shift of credit distribution towards financial and real estate sectors (Bezemer and Grydaki, 2014; Grydaki and Bezemer, 2019).

Moreover, nominal GDP ($ngdp$) and inflation (cpi) exhibited a similar pattern that demonstrates relatively stable and modest growth rates except for an obvious drop during the crisis. Housing prices (hpi) first experienced a rapid growth before the crisis following by a dramatic decline thereafter. Furthermore, as reported in Figure C.2, the standard deviation of the growth rate of each variable was within a small range, indicating limited dispersion from its mean values, while its dynamics depicted a relatively fluctuating pattern during the crisis.

C.2 Identifying non-stationarity

The presence of a unit root in the included variables can cause problems of weak instrumentation in the GMM estimation for the PVAR model (Blundell and Bond, 1998). To ensure stationarity of all variables before the PVAR estimation, we perform a series of unit root tests for our panel dataset, viz., IPS test (Im et al., 2003) and PESCADF test (Pesaran, 2020). Table C.1 presents these results. We find that except for interest rates ($irate$), other variables in levels are not stationary as we fail to reject the null hypothesis of a unit root. Moreover, after first difference, all variables turn to be stationary. Therefore, all variables are first-differenced to meet the stationarity requirements and measure the impacts of variables in increments in the PVAR estimation.

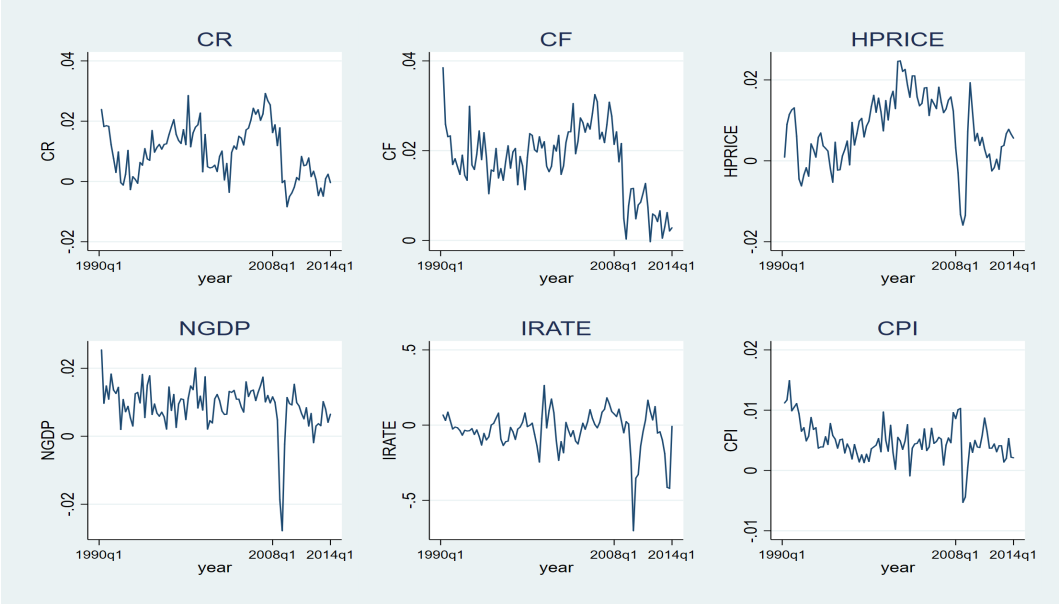

Figure C.1: **Variables in growth rates**

Note: Figure C.1 demonstrates dynamics of the cross-country growth rate of each target variable. cpi denotes consumer price index; $ngdp$ denotes nominal GDP; hpi denotes nominal housing prices; cf denotes credit to the asset markets; cr denotes credit to the real economy; $irate$ denotes the short-run interest rate. The variables are in growth rates and averaged among countries overtime. Cross-country growth rates of a variable X ($AveReturn(X)$) in each time period are calculated through:$AveReturn(X_t) = \left(\sum_{i=1}^{N} \Delta Log(X_{it})\right)/N$. The time period is from 1990Q1 to 2014Q2. Variable descriptions and data sources can be seen in Table 1.

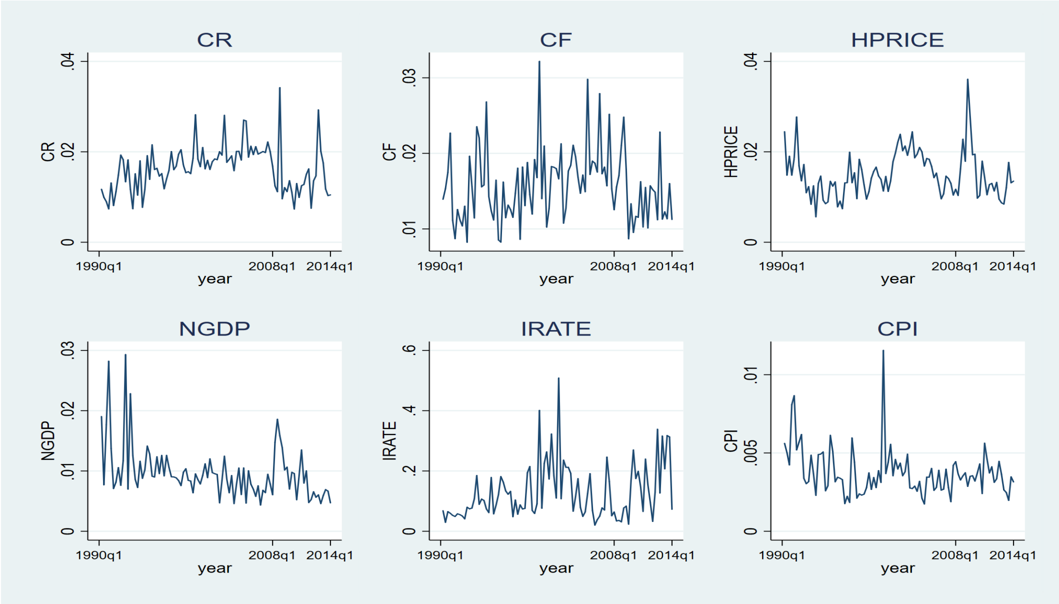

Figure C.2: **The standard deviation**

Note: Figure C.2 demonstrates dynamics of cross-country standard deviations of the variables in growth rates. The variables are transformed in a return format and are country-averaged over time. The time period is from 1990Q1 to 2014Q2. Variable descriptions and data sources are explained in Table 1.

Figure C.3: **The standard deviation of growth of the real GDP**

Note: Figure C.3 demonstrates dynamics of cross-country standard deviations of growth of the real GDP (1990Q1-2014Q2)

Table C.1: **Panel unit root test**

	Test/Variable		$lhpi$	lcr	lcf	$lcpi$	$lngdp$	$irate$
d=0								
	IPS	Demean	1.80	0.61	-1.01	1.88	-0.09	-5.89***
		Demean & Trend	2.19	2.42	0.8	-0.41	3.29	-5.18***
	PESCADF	No Trend	-1.88	-0.45	-1.40	-2.63***	-1.2	-3.18***
		Trend	-1.94	-1.31	-2.14	-2.74*	-1.96***	-3.39***
d=1								
	IPS	Demean	-7.61***	-6.13***	-5.51***	-13.01***	-17.68***	-15.81***
		Demean & Trend	-7.01***	-5.35***	-6.63***	-13.02***	-21.05***	-15.45***
	PESCADF	No Trend	-3.22***	-2.70***	-3.18***	-5.84***	-6.59***	-12.96***
		Trend	-3.26***	-2.95**	-3.80***	-5.29***	-5.90***	-12.65***

Note: Table C.1 reports the results of panel unit root tests for each incorporated variable. The tests are conducted using two methods, i.e. IPS test (Im et al., 2003) and PESCADF test (Pesaran, 2020). IPS test is applied to both demeaned data (i.e. Demean) and demeaned data with its temporal trend identified (i.e. Demean & Trend); PESCADF is applied to the data with and without trend being identified, i.e. Trend and No Trend, respectively. Regarding incorporated variables, cpi denotes consumer price index; $ngdp$ denotes nominal GDP; hpi denotes nominal housing prices; cf denotes credit to the asset markets; cr denotes credit to the real economy; $irate$ denotes the short-run interest rate. *: significance at 10% level; **: Significance at 5% level; ***: Significance at 1% level. 'd=0' denotes variables are in levels; 'd=1' denotes variables are in first-difference format; the logarithmic variables begin with a prefix 'l'. The number of lags included in each unit root test are chosen based on the information criteria.

Appendix D Benchmark Results (Business Cycles Removal)

Table D.1: **Granger causality test: Benchmark (business cycles removal)**

Equation Variable	Excluded variable	χ^2	P-value	Equation Variable	Excluded Variable	χ^2	P-value
$dlcpi$				$dlcf$			
	$dlngdp$	4.463	0.035		$dlcpi$	21.772	0.000
	$dlhpi$	0.118	0.731		$dlngdp$	11.567	0.001
	$dlcf$	15.310	0.000		$dlhpi$	32.064	0.000
	$dlcr$	0.047	0.829		$dlcr$	2.881	0.090
	dirate	0.096	0.757		dirate	0.048	0.827
$dlngdp$				$dlcr$			
	$dlcpi$	13.762	0.000		$dlcpi$	6.164	0.013
	$dlhpi$	71.302	0.000		$dlngdp$	7.299	0.007
	$dlcf$	2.131	0.144		$dlhpi$	22.200	0.000
	$dlcr$	8.906	0.003		$dlcf$	21.880	0.000
	dirate	4.571	0.033		dirate	39.851	0.000
$dlhpi$				$dirate$			
	$dlcpi$	0.099	0.753		$dlcpi$	1.622	0.203
	$dlngdp$	0.285	0.594		$dlngdp$	1.312	0.252
	$dlcf$	8.293	0.004		$dlhpi$	0.003	0.957
	$dlcr$	4.695	0.030		$dlcf$	0.225	0.635
	dirate	5.080	0.024		$dlcr$	8.745	0.003

Note: Table D.1 reports the Granger causality test results for the benchmark PVAR estimation using transformed data with the cyclical component removed. The excluded variable is concluded to Granger-cause the equation variable if the corresponding P-value of the test is small, indicating the rejection of the null hypothesis regarding no Granger causality. The test statistic follows the Chi-square (χ^2) distribution. Regarding incorporated variables, cpi denotes consumer price index; $ngdp$ denotes nominal GDP; hpi denotes nominal housing prices; cf denotes credit to the asset markets; cr denotes credit to the real economy; $irate$ denotes the short-run interest rate. Variables in the first-differenced logarithms begin with a prefix 'dl'.

Table D.2: **Variance decomposition: Benchmark (business cycles removal)**

Response variable	Period	Impulse Variable $dlcpi$	$dlngdp$	$dlhpi$	$dlcf$	$dlcr$	$dirate$
$dlcpi$							
	1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	10	0.9501	0.0108	0.0172	0.0202	0.0010	0.0006
	20	0.9489	0.0108	0.0181	0.0203	0.0011	0.0007
	30	0.9489	0.0108	0.0181	0.0203	0.0011	0.0007
	40	0.9489	0.0108	0.0181	0.0203	0.0011	0.0007
$dlngdp$							
	1	0.0242	0.9758	0.0000	0.0000	0.0000	0.0000
	10	0.0571	0.7841	0.1243	0.0167	0.0129	0.0049
	20	0.0571	0.7814	0.1264	0.0169	0.0130	0.0053
	30	0.0571	0.7813	0.1264	0.0169	0.0130	0.0053
	40	0.0571	0.7813	0.1264	0.0169	0.0130	0.0053
$dlhpi$							
	1	0.0000	0.0109	0.9891	0.0000	0.0000	0.0000
	10	0.0055	0.0134	0.9330	0.0154	0.0115	0.0212
	20	0.0060	0.0136	0.9311	0.0157	0.0118	0.0219
	30	0.0060	0.0136	0.9311	0.0157	0.0118	0.0219
	40	0.0060	0.0136	0.9311	0.0157	0.0118	0.0219
$dlcf$							
	1	0.0002	0.0000	0.0095	0.9903	0.0000	0.0000
	10	0.0810	0.0314	0.1393	0.7334	0.0103	0.0046
	20	0.0810	0.0314	0.1419	0.7302	0.0105	0.0051
	30	0.0810	0.0314	0.1419	0.7301	0.0105	0.0051
	40	0.0810	0.0314	0.1419	0.7301	0.0105	0.0051
$dlcr$							
	1	0.0009	0.0143	0.0005	0.0121	0.9722	0.0000
	10	0.0477	0.0428	0.1035	0.0465	0.7017	0.0578
	20	0.0478	0.0428	0.1063	0.0465	0.6984	0.0582
	30	0.0478	0.0428	0.1064	0.0465	0.6983	0.0582
	40	0.0478	0.0428	0.1064	0.0465	0.6983	0.0582
$dirate$							
	1	0.0106	0.0003	0.0003	0.0016	0.0170	0.9703
	10	0.0221	0.0006	0.0012	0.0017	0.0392	0.9352
	20	0.0221	0.0006	0.0014	0.0018	0.0392	0.9349
	30	0.0221	0.0006	0.0014	0.0018	0.0392	0.9349
	40	0.0221	0.0006	0.0014	0.0018	0.0392	0.9349

Note: Table D.2 reports the contribution of each 'Impulse Variable' to the error variance of each 'response variable' in a predefined period ahead. The applied data are transformed data with the potential cyclical component removed. Regarding incorporated variables, cpi denotes consumer price index; $ngdp$ denotes nominal GDP; hpi denotes nominal housing prices; cf denotes credit to the asset markets; cr denotes credit to the real economy; $irate$ denotes the short-run interest rate. Variables in the first-differenced logarithms begin with a prefix 'dl'.

Appendix E Results of the Robustness Check

Table E.1: **The PVAR estimation: Robustness check (Considering Uncertainty)**

dlcpi		*dlngdp*		dlhpi		*dlcf*		*dlcr*		*dirate*		*dluncer*	
L.*dlcpi*	0.389***	L.*dlcpi*	0.407***	L.*dlcpi*	-0.196*	L.*dlcpi*	1.134***	L.*dlcpi*	0.687***	L.*dlcpi*	0.137***	L.*dlcpi*	1.301***
	(0.047)		(0.113)		(0.111)		(0.222)		(0.152)		(0.033)		(0.227)
L.*dlngdp*	0.007	L.*dlngdp*	0.012	L.*dlngdp*	-0.037*	L.*dlngdp*	0.270***	L.*dlngdp*	0.161***	L.*dlngdp*	-0.007	L.*dlngdp*	0.067
	(0.010)		(0.025)		(0.019)		(0.055)		(0.062)		(0.008)		(0.062)
L.dlhpi	0.008	L.dlhpi	0.234***	L.dlhpi	0.745***	L.dlhpi	0.339***	L.dlhpi	0.291***	L.dlhpi	0	L.dlhpi	-0.009
	(0.008)		(0.021)		(0.031)		(0.042)		(0.033)		(0.008)		(0.058)
L.*dlcf*	0.022***	L.*dlcf*	0.036	L.*dlcf*	0.065***	L.*dlcf*	0.209***	L.*dlcf*	0.206***	L.*dlcf*	0.005	L.*dlcf*	-0.115***
	(0.005)		(0.022)		(0.018)		(0.053)		(0.029)		(0.005)		(0.042)
L.*dlcr*	0.005	L.*dlcr*	0.098***	L.*dlcr*	0.050***	L.*dlcr*	0.052	L.*dlcr*	0.167***	L.*dlcr*	0.023***	L.*dlcr*	0.012
	(0.006)		(0.022)		(0.013)		(0.041)		(0.033)		(0.006)		(0.050)
L.*dirate*	-0.002	L.*dirate*	-0.328***	L.*dirate*	0.323***	L.*dirate*	0.689***	L.*dirate*	0.766***	L.*dirate*	0.468***	L.*dirate*	-0.941***
	(0.021)		(0.056)		(0.075)		(0.132)		(0.110)		(0.036)		(0.155)
L.*dluncer*	0.006	L.*dluncer*	-0.036***	L.*dluncer*	-0.046***	L.*dluncer*	-0.021	L.*dluncer*	-0.012	L.*dluncer*	0.001	L.*dluncer*	-0.107***
	(0.004)		(0.011)		(0.012)		(0.022)		(0.019)		(0.003)		(0.031)

Note: Table E.1 reports the PVAR estimation using the decycled data (considering uncertainty). *cpi* denotes consumer price index; *ngdp* denotes nominal GDP; *hpi* denotes nominal housing prices; *cf* denotes credit to the asset markets; *cr* denotes credit to the real economy; *irate* denotes the short-run interest rate; *uncer* denotes the level of economic policy uncertainty. 'L.' denotes the first temporal lag of the variable, and variables in the first-differenced logarithms begin with a prefix '*dl*'. *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level. Standard errors are in parentheses.

Table E.2: **The PVAR estimation: Robustness check (Before the GFC)**

dlcpi		*dlngdp*		*dlhpi*		*dlcf*		*dlcr*		*dirate*	
L.*dlcpi*	0.450***	L.*dlcpi*	0.686***	L.*dlcpi*	0.074	L.*dlcpi*	0.863***	L.*dlcpi*	0.549***	L.*dlcpi*	0.004
	(0.059)		(0.189)		(0.119)		(0.229)		(0.176)		(0.047)
L.*dlngdp*	0.010	L.*dlngdp*	0.041	L.*dlngdp*	0.003	L.*dlngdp*	0.108**	L.*dlngdp*	0.170**	L.*dlngdp*	-0.021**
	(0.009)		(0.049)		(0.026)		(0.048)		(0.073)		(0.011)
L.*dlhpi*	-0.016	L.*dlhpi*	0.224***	L.*dlhpi*	0.722***	L.*dlhpi*	0.257***	L.*dlhpi*	0.218***	L.*dlhpi*	0.006
	(0.010)		(0.030)		(0.042)		(0.048)		(0.046)		(0.012)
L.*dlcf*	0.021***	L.*dlcf*	0.037	L.*dlcf*	0.072***	L.*dlcf*	0.025	L.*dlcf*	0.046	L.*dlcf*	-0.018**
	(0.008)		(0.030)		(0.028)		(0.054)		(0.033)		(0.008)
L.*dlcr*	0.0003	L.*dlcr*	0.092***	L.*dlcr*	0.038**	L.*dlcr*	0.018	L.*dlcr*	0.206***	L.*dlcr*	0.015**
	(0.007)		(0.032)		(0.019)		(0.046)		(0.040)		(0.007)
L.*dirate*	-0.013	L.*dirate*	-0.204**	L.*dirate*	0.151*	L.*dirate*	-0.437***	L.*dirate*	0.518***	L.*dirate*	0.545***
	(0.024)		(0.080)		(0.092)		(0.135)		(0.100)		(0.052)

Note: Table E.2 reports the PVAR estimation using the decycled data (before the global financial crisis (GFC)). Detailed table notes refer to that in Table E.1.

Table E.3: **The PVAR estimation: Robustness check (After the GFC)**

dlcpi		*dlngdp*		*dlhpi*		*dlcf*		*dlcr*		*dirate*	
L.*dlcpi*	0.406***	L.*dlcpi*	0.105	L.*dlcpi*	-0.555**	L.*dlcpi*	2.100***	L.*dlcpi*	0.291	L.*dlcpi*	0.083
	(0.088)		(0.233)		(0.226)		(0.432)		(0.397)		(0.052)
L.*dlngdp*	0.044*	L.*dlngdp*	0.245***	L.*dlngdp*	-0.123**	L.*dlngdp*	0.07	L.*dlngdp*	0.067	L.*dlngdp*	0.004
	(0.023)		(0.081)		(0.061)		(0.108)		(0.101)		(0.016)
L.*dlhpi*	0.041*	L.*dlhpi*	0.265***	L.*dlhpi*	0.737***	L.*dlhpi*	0.267**	L.*dlhpi*	0.244***	L.*dlhpi*	-0.038**
	(0.021)		(0.056)		(0.050)		(0.104)		(0.062)		(0.019)
L.*dlcf*	0.007	L.*dlcf*	-0.055	L.*dlcf*	-0.006	L.*dlcf*	0.167*	L.*dlcf*	0.294***	L.*dlcf*	0.021***
	(0.011)		(0.053)		(0.034)		(0.096)		(0.076)		(0.008)
L.*dlcr*	-0.006	L.*dlcr*	0.077**	L.*dlcr*	0.080*	L.*dlcr*	0.133*	L.*dlcr*	0.339***	L.*dlcr*	0.057***
	(0.017)		(0.036)		(0.044)		(0.074)		(0.081)		(0.014)
L.*dirate*	0.032	L.*dirate*	-0.391***	L.*dirate*	-0.013	L.*dirate*	0.049	L.*dirate*	0.338	L.*dirate*	0.474***
	(0.048)		(0.102)		(0.150)		(0.306)		(0.236)		(0.065)

Note: Table E.3 reports the PVAR estimation using the decycled data (after the global financial crisis (GFC)). Detailed table notes refer to that in Table E.1.

Table E.4: **The estimations: Robustness check (Exclusion of cr)**

dlcpi		dlngdp		dlhpi		dlcf		dirate		dluncer	
L.$dlcpi$	0.397***	L.$dlcpi$	0.341***	L.$dlcpi$	-0.223*	L.$dlcpi$	1.259***	L.$dlcpi$	0.079**	L.$dlcpi$	0.955***
	(0.048)		(0.109)		(0.118)		(0.234)		(0.035)		(0.239)
L.$dlngdp$	0.016*	L.$dlngdp$	0.056***	L.$dlngdp$	-0.027	L.$dlngdp$	0.243***	L.$dlngdp$	0.006	L.$dlngdp$	0.064
	(0.009)		(0.022)		(0.020)		(0.073)		(0.007)		(0.065)
L.$dlhpi$	0.016**	L.$dlhpi$	0.239***	L.$dlhpi$	0.739***	L.$dlhpi$	0.345***	L.$dlhpi$	-0.001	L.$dlhpi$	-0.054
	(0.008)		(0.020)		(0.032)		(0.045)		(0.009)		(0.060)
L.$dlcf$	0.014***	L.$dlcf$	0.033	L.$dlcf$	0.038**	L.$dlcf$	0.174***	L.$dlcf$	0.011**	L.$dlcf$	-0.05
	(0.005)		(0.020)		(0.018)		(0.052)		(0.005)		(0.044)
L.$dirate$	0.065***	L.$dirate$	-0.062	L.$dirate$	0.388***	L.$dirate$	0.912***	L.$dirate$	0.510***	L.$dirate$	-1.622***
	(0.020)		(0.055)		(0.078)		(0.145)		(0.033)		(0.192)
L.$dluncer$	0.001	L.$dluncer$	-0.046***	L.$dluncer$	-0.048***	L.$dluncer$	-0.02	L.$dluncer$	0.002	L.$dluncer$	-0.121***
	(0.004)		(0.011)		(0.012)		(0.023)		(0.004)		(0.034)

Note: Table E.4 reports the PVAR estimation using the decycled data (exclusion of cr). Detailed table notes refer to that in Table E.1.

Table E.5: **The estimations: Robustness check (Exclusion of cf)**

dlcpi		dlngdp		dlhpi		dlcr		dirate		dluncer	
L.$dlcpi$	0.416***	L.$dlcpi$	0.376***	L.$dlcpi$	-0.355***	L.$dlcpi$	0.715***	L.$dlcpi$	0.147***	L.$dlcpi$	0.881***
	(0.053)		(0.108)		(0.131)		(0.168)		(0.030)		(0.240)
L.$dlngdp$	0.027***	L.$dlngdp$	0.01	L.$dlngdp$	-0.024	L.$dlngdp$	0.178***	L.$dlngdp$	-0.012	L.$dlngdp$	0.054
	(0.010)		(0.023)		(0.021)		(0.066)		(0.008)		(0.077)
L.$dlhpi$	0.004	L.$dlhpi$	0.195***	L.$dlhpi$	0.744***	L.$dlhpi$	0.335***	L.$dlhpi$	0.005	L.$dlhpi$	-0.064
	(0.009)		(0.020)		(0.032)		(0.037)		(0.008)		(0.061)
L.$dlcr$	0.005	L.$dlcr$	0.097***	L.$dlcr$	0.066***	L.$dlcr$	0.209***	L.$dlcr$	0.028***	L.$dlcr$	0.005
	(0.006)		(0.020)		(0.014)		(0.037)		(0.006)		(0.049)
L.$dirate$	0.039*	L.$dirate$	-0.209***	L.$dirate$	0.422***	L.$dirate$	0.859***	L.$dirate$	0.464***	L.$dirate$	-1.264***
	(0.021)		(0.051)		(0.085)		(0.131)		(0.041)		(0.184)
L.$dluncer$	0.003	L.$dluncer$	-0.046***	L.$dluncer$	-0.040***	L.$dluncer$	-0.009	L.$dluncer$	0.002	L.$dluncer$	-0.139***
	(0.004)		(0.011)		(0.012)		(0.020)		(0.003)		(0.032)

Note: Table E.5 reports the PVAR estimation using the decycled data (exclusion of cf). Detailed table notes refer to that in Table E.1.

Table E.6: **The estimations: Robustness check (Correcting for interdependence and heteroskedasticity)**

$dlcpi$		$dlngdp$		$dlhpi$		$dlcf$		$dlcr$		$dirate$	
L.$dlcpi$	0.338***	L.$dlcpi$	0.213***	L.$dlcpi$	-0.099***	L.$dlcpi$	0.306***	L.$dlcpi$	0.100**	L.$dlcpi$	0.058***
	(0.019)		(0.033)		(0.031)		(0.042)		(0.044)		(0.012)
L.$dlngdp$	0.021***	L.$dlngdp$	0.034***	L.$dlngdp$	-0.018**	L.$dlngdp$	0.134***	L.$dlngdp$	0.105***	L.$dlngdp$	-0.025***
	(0.003)		(0.012)		(0.009)		(0.012)		(0.019)		(0.003)
L.$dlhpi$	0.003	L.$dlhpi$	0.176***	L.$dlhpi$	0.585***	L.$dlhpi$	0.119***	L.$dlhpi$	0.147***	L.$dlhpi$	-0.020***
	(0.003)		(0.007)		(0.015)		(0.013)		(0.012)		(0.003)
L.$dlcf$	0.014***	L.$dlcf$	-0.007	L.$dlcf$	0.030***	L.$dlcf$	0.017	L.$dlcf$	0.097***	L.$dlcf$	-0.012***
	(0.002)		(0.012)		(0.006)		(0.019)		(0.011)		(0.002)
L.$dlcr$	0.004*	L.$dlcr$	0.060***	L.$dlcr$	0.043***	L.$dlcr$	0.054***	L.$dlcr$	0.228***	L.$dlcr$	0.032***
	(0.002)		(0.009)		(0.005)		(0.011)		(0.016)		(0.003)
L.$dirate$	-0.002	L.$dirate$	-0.116***	L.$dirate$	0.055**	L.$dirate$	0.154***	L.$dirate$	0.300***	L.$dirate$	0.409***
	(0.006)		(0.021)		(0.022)		(0.029)		(0.027)		(0.012)

Note: Table E.6 reports the PVAR estimation using the decycled data (after correction). Detailed table notes refer to that in Table E.1.

Table E.7: **The estimations: Robustness check (Controlling for the price level)**

$dlcpi$		$dlrgdp$		$dlrhpi$		$dlrcf$		$dlrcr$		$drirate$	
L.$dlcpi$	0.398***	L.$dlcpi$	0.604***	L.$dlcpi$	0.689***	L.$dlcpi$	1.770***	L.$dlcpi$	1.752***	L.$dlcpi$	0.341***
	(0.047)		(0.155)		(0.142)		(0.301)		(0.283)		(0.060)
L.$dlrgdp$	0.026***	L.$dlrgdp$	0.141***	L.$dlrgdp$	-0.029	L.$dlrgdp$	0.185***	L.$dlrgdp$	0.137*	L.$dlrgdp$	-0.032***
	(0.010)		(0.037)		(0.029)		(0.067)		(0.072)		(0.012)
L.$dlrhpi$	-0.003	L.$dlrhpi$	0.234***	L.$dlrhpi$	0.709***	L.$dlrhpi$	0.330***	L.$dlrhpi$	0.245***	L.$dlrhpi$	0.014
	(0.009)		(0.027)		(0.039)		(0.054)		(0.051)		(0.014)
L.$dlrcf$	0.027***	L.$dlrcf$	0.013	L.$dlrcf$	0.025	L.$dlrcf$	0.174***	L.$dlrcf$	0.122***	L.$dlrcf$	-0.018**
	(0.007)		(0.038)		(0.024)		(0.061)		(0.041)		(0.009)
L.$dlrcr$	-0.003	L.$dlrcr$	0.066***	L.$dlrcr$	0.034*	L.$dlrcr$	0.046	L.$dlrcr$	0.225***	L.$dlrcr$	0.026***
	(0.007)		(0.024)		(0.018)		(0.045)		(0.042)		(0.010)
L.$drirate$	0.009	L.$drirate$	0.037	L.$drirate$	0.281***	L.$drirate$	0.443***	L.$drirate$	1.005***	L.$drirate$	0.548***
	(0.022)		(0.078)		(0.088)		(0.128)		(0.164)		(0.051)

Note: Table E.7 reports the PVAR estimation using the decycled data (controlling for the price level). Detailed table notes refer to that in Table E.1.