Disaggregated Bank Credit and Housing Price Movements: Disentangling the Real Effects

Abstract

When disentangling the real effects of bank credit in the demand-supply dynamics of both the asset market and the real economy, it is disaggregate bank credit, which holds quantitatively important information. This is all the more relevant when persistent economic policy uncertainty dominates the demand-supply equilibrium in these markets. To examine this in the context of the international housing market, we develop an empirically testable framework and perform a panel VAR estimation for a unique quarterly dataset consisting of nine industrialized countries. We find that credit to the real economy and housing prices depict mutually reinforcing relationships. Moreover, we find that there is a negligible negative effect of credit to the asset market on housing prices in the short-run, and such effects are positive over the long-run. Alternatively, the effect of housing prices on credit to the asset market is positive in both the short- and long-run. Moreover, the dynamic interdependent effects of housing prices and credit to the asset market are more pronounced when economic policy uncertainty and the global financial crisis are respectively accounted for in our estimation. Finally, a battery of robustness checks confirms our predictions.

Key Words: Disaggregated bank credit; Housing price movements; Uncertainty; Panel vector autoregressive model **JEL Classifications:** E3; E5; R3

1 Introduction

Recent research has demonstrated that the role of bank credit is paramount to our understanding of the sources and magnitudes of real economic fluctuations. An imposing issue important to both academics and practitioners in particular, is the way that bank credit determines the price behaviour in the housing market (Bernanke, 2007), and reflects the complex interplay of financial, macroeconomic, and psychological factors in real-estate markets, depicting one of the most challenging demand-supply equilibrium dynamics. However, competing theories and mixed empirical evidence have so far inhibited conclusions on the exact nature of the impact of (the composition of) bank credit.¹ Despite some progress, surprisingly, the extant theory and empirics mainly consider credit in the aggregate form only. As a result, the evidence that bank credit impacts economic activities (positively/negatively) remains mixed.² Such results can often be seen as an artifact of non-robust methodological tools and/or sample variations. However, recent research in the post-Keynesian tradition of the credit-business cycle relationship (viz., Jordà et al., 2016; Unger, 2017) have demonstrated that it is disaggregate credit, i.e., credit to the real economy and credit to the asset market, which might explain the theoretically expected impact on real economic activities.³

Most conflicting empirical evidence can be reconciled by looking at the effect of the two components of credit on economic activities. For instance, if we disregard disaggregation, it is possible that for a panel of countries, the impact of credit on economic activities may be negative for some periods, positive for some, and insignificant for others. This is not because of sample sensitivity and its persistent behavior as promulgated by existing studies. Rather, the hidden effects may have been locked in the aggregation of credit. It is possible that credit to the real economy may have a large positive effect on growth, whereas credit to the financial market can have a similar effect on housing market. Thus, the aggregate effect of credit may wrongly depict positive/negative effects on aggregate economic behavior. It is for this reason, our research attempts to disentangle the real effects of disaggregated credit on economic activities. Our conceptual model owes its foundation to the small open-economy macroeconomic model, where cross-country housing price movements are examined by controlling for a number of economic growth and financial factors, in particular, credit to the real economy and credit to the asset market. But, why is credit (in both aggregate and disaggregate forms) so important to the housing market? The next subsection seeks

¹Conventional theory regards credit as negative financial frictions and as resource constraints for obtaining optimum welfare, empirical practices often fail to recognize the micro perspective of credit for delivering definitive positive/negative effects.

² In the case of housing price dynamics, some researchers argue that the effects of credit on housing prices can be positive (See for instance, Gerlach and Peng, 2005; Oikarinen, 2009; Valverde and Fernández, 2010), while others find negative or even insignificant impacts (See for instance, Coleman et al., 2008; Gimeno and Martinez-Carrascal, 2010).

³The conceptual foundation of our idea follows Keynes (1930) who first suggested - following the economic prosperity in the 1920s - that the aggregate deposit-money flow should be split by the differences in circulation channels, viz., the 'industrial' circulation and the 'financial' circulation. To study these distinct effects of the components of the aggregate bank credit, we split it into *credit to the real economy* (i.e., credit to non-financial corporations and for consumption) and *credit to the asset market* (i.e., credit to domestic real estate or financial assets) respectively. Specifically, the former includes mortgage credit for new-builds to personal households, etc, while the latter contains credit to financial or property holding corporations, and commercial mortgages or loans to purchase existing assets, such as the property, etc.

to shed some light on this question.

1.1 Importance of credit in the housing market

Existing research puts forward a number of arguments to explain why the study of the interdependence between housing and the credit markets is so important.⁴ First, the growth of credit is known to exert measurable effects on housing prices following an increase in residential investment. This tends to provide a strong contribution to a boom in economic growth (Corradin and Fontana, 2013). Second, the bust of housing prices also forces a decline in the profitability of banks by increasing the probability of mortgage defaults (Allen et al., 2009; Gan, 2007). This could also result in a depression of the financial markets as well as for the economy as a whole (Ghent and Owyang, 2010). Third, housing prices exert a measurable impact on the composition of household wealth by impacting investment in the real estate market. Fourth, the rise of housing prices can always be regarded as an indicator of the boom of credit supply, which also misleads the housing market participants to have further optimistic expectations of housing price appreciation in the future (Muellbauer and Murphy, 2008). On the whole, housing finance serves as the crucial channel to transmit the impacts of housing price variations on the behaviors of the aggregate economy (Muellbauer and Murphy, 2008).

Furthermore, the absence of the role of bank credit in conventional macroeconomic models and empirical applications can also be seen as a possible reason why there was a failure to predict the outbreak of global financial crisis and the subsequent collapse of the real estate market (Ryan-Collins et al., 2016). In a nutshell, due to the various evidence of close interactions between housing market and bank credit, it is very important to undertake a rigorous study of the dynamic interrelationships between bank credit and housing prices. Evidently, there is a clear lack of rigorous theoretical and empirical research that investigates how housing prices and bank credit are intertwined and how they impact relevant policy.

1.2 Housing prices-credit dynamics: What does theory say?

Bank credit and housing prices have experienced a close interaction in both developed and developing countries financial markets. In terms of the effect of housing prices on bank credit, the houses (or properties) are often regarded as collateral associated with the bank lending, while the prices affect both supply and demand of bank credit through the channel of wealth effects. Such a mechanism can be governed by the influence of either moral hazard or adverse selection owing to asymmetric information in the credit markets (see for example, Bernanke and Gertler, 1989; Bernanke et al., 1999; Kiyotaki and Moore, 1997).⁵ In addition, property prices influence

⁴Both Kindleberger (1978) and Minsky (2015) highlight the important role of credit availability standards in the valuations of assets.

⁵Specifically, due to the feature of lagged appreciation of current housing prices (Muellbauer and Murphy, 2008), the increase of its current prices would induce the expectation of further price appreciations by housing market participants, banks, and etc. In particular, given that housing prices experience upward movements, the supply of bank credit will rise. This is because banks tend to have relatively lower mortgage default risks and higher profitabilities

the capital conditions and thus the credit lending capacities of the banks either directly, viz., the market valuations of bank holdings of real estate assets, or indirectly, viz., the changes in the volume of non-performing loans (Gerlach and Peng, 2005). Thus, changes in housing prices could theoretically lead to variations of both demand and supply of bank credit in the same direction.

The next question is, what specific mechanism can provide a robust explanation of the effects of credit on the housing market equilibrium? Through the lens of a demand-supply channel, a simple example can be given. We know that greater/lower access to bank credit can shift housing demand. First, through the perspective of credit demand, the liberalization of credit markets can stimulate a positive impact on housing prices (Muellbauer and Murphy, 2008). Broadly speaking, following Kiyotaki and Moore (1997), lower requirements of the collateral could boost the credit demand of the households by loosing their borrowing limits (constraints) against the value of the real estate. Thanks to the wealth effects, this ultimately stimulates both housing demand and housing prices.

Second, some researchers argue that an increase of housing prices should be attributed to the expansion of credit supply instead of credit demand (Duca et al., 2011; Favara and Imbs, 2015; Justiniano et al., 2015; Mian and Sufi, 2009, among others.). On the one hand, the expansion of bank credit supply (liquidity) can lower the levels of loan interest rates and increase current (discounted future) values of the mortgage property directly by influencing the discount rate. On the other hand, due possibly to the implementation of quantitative easing (QE) monetary policies, the credit supply (expansions) could drive an increase in housing prices by directly accelerating housing demand (Mian and Sufi, 2009). On the whole, it can be concluded that bank credit holds a central role in the determination of housing prices by directly controlling the demand of house buyers. Meanwhile, the lack of existing research regarding how bank credit affects housing prices through housing supply side motivates us to disaggregate the aggregate bank credit and explore the real role of bank credit through not only the housing demand side but also the housing supply side. Indeed, despite theoretical predictions, the nascent empirical work have produced conflicting evidence of the nature of the impact of bank credit on the housing market. It may well be attributed to the aggregate nature of bank credit data. Disaggregated bank credit may help researchers identify the proper channel through which credit affects the real economy and the financial markets respectively.

1.3 Segregate or aggregate?

While the extant literature has stressed on the availability of credit as an important determinant of the demand side of the housing market, the role of credit in housing supply has been less emphasized. This is possibly one of the reasons why the components of credit have been overlooked in understanding the real effects of credit on housing price dynamics. It is well-known that availabil-

under such circumstance, while the demand for bank credit will be subsequently boosted as the housing buyers will feel more comfortable and easy to borrow money from the banks to afford the increasing housing prices. Moreover, the boom of bank credit demand will be converted to the boom of housing demand as the housing buyers are willing to spend more money in purchasing properties due to the increase of their perceived wealth.

ity of credit to the housing developers is 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 how credit supply to developers determine housing market is to actually *segregate* credit to (*i*) *credit to the real economy, cr* and (*ii*) *credit to the asset market, cf*. It is the latter form of credit, which can demonstrate whether bank credit provided to housing developers can affect housing prices through the housing supply side. Indeed, credit in aggregate form can mask the true effect because a large amount of credit to the real economy can offset the positive/negative effects of credit to the financial market on housing prices.

Overall, cf theoretically depicts a positive relationship with housing prices due to the following three reasons.⁶ First, based on the quantity theory of credit from the post-Keynesian school of thought, only money used for GDP transactions (cr) drive the evolutions of economic growth, while the specific part of money used for non-GDP transactions (cf) can determine the appreciation of financial assets including properties. Second, the increase of credit to the financial markets can expand the house buyers' credit availability for the purpose of purchasing existing properties. Thus, as earlier discussed, it could result in the boom of both housing demand and housing prices. Lastly, through the idea of market disequilibrium, due to the imbalance in the housing market as excess demand outweighs shortage of supply, the increase of housing supply driven by credit expansions to housing developers and the boom of housing prices tend to exist simultaneously.

Theoretically, under market clearing condition, housing prices should exert a negative effect on housing supply. Plus, the expansions of housing finance will directly boost the housing supply and decrease housing prices then.⁷ However, facing disequilibrium situation in the housing market, the excess demand and insufficient supply seldom disappear especially in the short-term, resulting in housing prices exerting a positive correlation on housing finance to developers and then on housing supply. This leads to an interesting phenomenon that housing prices keep increasing regardless of the simultaneous increase of credit availability.⁸ This has given rise to the simultaneous presence of increasingly overvalued housing prices and expansions of the housing stock, especially in the US (Muellbauer and Murphy, 2008). This is also consistent with the studies of Barker (2004, 2006) for the case of the UK where a housing supply shortage in the face of excess housing demand is a root cause of strong overvalued housing prices and leads to a housing affordability problem.

In light of these developments, the main purpose of this paper is to study the interdependence between housing prices and different components of aggregate bank credit, and investigate if bank credit markedly affects the determination of housing prices through a macroeconomic perspective. On the basis of the quarterly panel dataset of nine advanced economies during the pe-

⁶The interaction between housing prices and cr has already been discussed in the last subsection where cr can be regarded as the credit provided through the housing demand side.

⁷The property holding companies could obtain more money/credit to develop the real estate

⁸ On the basis of our panel dataset of nine industrialized countries in our empirical study, the simultaneously increasing growth rates overtime of credit to the asset market and housing prices can be observed in figure 1. A similar positive correlation has also been reported by Jordà et al. (2016).

riod 1990Q1-2014Q2, we mainly examine the multi-directional interdependence between housing prices and disaggregate credit (credit either to the real economy or to the asset markets). During the empirical study, we employ a panel vector autoregressive (VAR) model, which is estimated by using generalized method of moments (GMM) to control for potential endogeneity problems. In addition, to the best of our knowledge, our research is possibly among the first to rigorously investigate the role of disaggregate bank credit in housing market fluctuations.

We contribute to the literature in a number of ways. First, we expand on the current knowledge on credit-housing market relationship by explicitly modeling 'credit' so that its micro-dynamic effects can be studied in a macroeconomic context. Contrary to conventional thus, instead of ignoring the important role of bank credit or only considering bank credit in the aggregate format, we explicitly investigate the heterogeneous effects of all different components of aggregate bank credit in analyzing housing price equilibrium. Second, we study the predictive power of disaggregate bank credit in housing price variations. For this purpose, we employ a panel vector autoregressive (PVAR) so that a 'systemic' perspective of housing variations can be studied due to shocks in bank credit. This approach overcomes the strict limitation of single country study where it is not possible to truly understand the dynamic multi-directional interdependence between housing prices and macroeconomic fundamentals. Indeed, a shock that originates in one country could be both a cause and consequence of the shocks emerging from the neighboring countries (that is, the countries which are considered within a common economic/geographic system). The system perspective also helps us understand the average effect of credit shocks on housing prices and macroeconomic fundamentals by fully considering the interdependencies among countries.

Third, to delve deeply into the dynamic effects of credit, we introduce the role of economic policy uncertainty, which not only affects economic growth *per se*, but also affects credit to both the real economy and the financial market as well as other key economic factors. It is argued that during a period of persistent uncertainty, credit is rationed to the financial market measurably, which affects the short and long-run housing price behaviors. By introducing uncertainty in our empirical setting, we intend to control for the effect of exogenous shocks that can make the 'credit supply' vulnerable, and study if the existence of uncertainty can seriously bias the interdependence between bank credit, housing prices and other key economic factors.

The rest of paper is structured as follows. Section 2 summarizes relevant literature. Section 3 introduces the empirical methodology, data, and discusses preliminary results. Section 4 discusses our main estimation results and presents robustness tests. Finally, section 5 concludes with the main findings of the paper.

2 Insight from the literature

In this section we summarize the extant literature by focusing on (disaggregate) bank credit and housing market interactions. Table 1 presents a non-exhaustive list of key references and summarizes the broad implications from these studies.

2.1 Credit and housing prices

It is often argued that the '*Quantitative Easing*' policy could result in rapid expansion of credit loans to households and thus an increase in housing prices can be triggered. This can be summarized in what is known as wealth effects (Ryan-Collins et al., 2016). Taking the case of Hong Kong, Gerlach and Peng (2005) use an aggregate credit route and demonstrate that there is a unidirectional effect of housing prices on bank credit. Such an effect became less sensitive in the early 1990s, which might be due to the tightened credit standards from the banks and prudential regulations from the government so as to control for the potential risk of great credit demand and excessive market booming. In addition, by using the variables in the real terms, the authors also suggest that the dynamics of credit are also positively affected by GDP growth, while the growth of housing prices can be negatively explained by the changes of unemployment rate. This research explicitly distinguishes the direction of causality between housing prices and bank credit.

Similarly, investigating this credit-housing market channel between 1996 and 2002 in the case of Ireland, Fitzpatrick and McQuinn (2007) find a bidirectional reinforcing effects between housing prices and credit standards in the long-run term. The authors posit that such mutual effects might be because of economic prosperity, net flow of migration, and rigidities of housing supply. While the effect of credit on housing prices is unidirectional in the short-run term, denoting credit exerts a positive impact on housing prices, the latter does not markedly affect the former. Moreover, in the long-run term, other economic fundamental factors, such as interest rate, personal disposable income, demographic factors, and housing stock, also trigger significantly expected effects on housing price variations. They also study the short-term shocks of the exogenous variable, personal disposable income, on both housing prices and credit, which are significantly positive.

In the context of the USA, Mian and Sufi (2009) use county level data and demonstrate that the expansions of sub-prime mortgage credit are better explained by the supply-driven hypothesis, which means that the credit expansions are pushed by an outward shift in the mortgage credit by the lenders. Relatedly, using quarterly data for the US, Duca et al. (2011) criticizes the omitted effect of credit standards in the existing research relevant to housing prices. As opposed to the popular viewpoint that driven by the loosening lending constraints, credit demand expansions trigger the housing boom leading up to the financial crisis in 2008, the authors suggest that easing the credit supply tends to be the real reason. Justiniano et al. (2015) also point out that the increase of credit supply due to the implementation of quantitative easing monetary policies is the fundamental driver in a housing boom, which is in line with four empirical observations, such as the surges of both housing prices and mortgage debt, the stable mortgage ratios between values of mortgage and real estate, and the decline of mortgage rate. Consistent with the very recent research on the US housing market from Favilukis et al. (2017), Favara and Imbs (2015) offer a narrative for the markedly positive impact of credit supply on housing price.

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Authors	Data	Key Variables	Main findings
Werner (1997)	Japan (1981Q1-1991Q1)	GDP, credit to the real economy and credit to the asset markets	Disaggregating credit aggregates to either the real economy or the asset markets. Only credit to the real economy significantly drive the 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	The 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 the countries with greater LTV ratios.
Fitzpatrick and McQuinn (2007)	Ireland (1980Q1-2002Q4)	Housing prices, mortgage credit, and other fundamental variables	The 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, bank credit to the private sector, real GDP	The expected multi-directional interactions between 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 such 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 price to rent ratio. The house price cycles stem from the credit supply cycles.
Justiniano et al. (2015)	US (1990-2006)	Credit constraints, collateral requirements, house prices, GDP, and mortgage rate	Instead of credit demand, the increase of credit supply provides the fundamental driven forces to the boom of housing price.
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 instead in regions with elastic housing supply.
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 bust-boom behaviors of economic growth, while its growth also has been argued as the source of financial fragility.
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 the loss in competitiveness, are the intrinsic reasons of the build-up of the current account imbalances.

Table 1: Summary of The Key Literature

Based upon US interstate data sample, they define the exogenous credit supply shock by ruling out the demand-based explanations, which provides the causal interpretation on housing prices. By setting up the branching deregulation as an instrumental variable of the credit expansion due to shocks of credit supply, different measures of the credit expansion, such as the number of loans, loan volumes, and loan to income ratio, trigger the increases of both housing demand and price in counties where housing supply is inelastic. Alternatively, the housing stock rises in counties where housing supply is elastic.

Instead of the single country context, there also exist a number of studies that investigate the dynamics between housing prices and bank credit at the cross-country context and use spatiotemporal methods to study the relationship. For instance, Senhadji and Collyns (2002) study the interactions between credit, housing prices and financial crisis in the late of 1990s for Eastern Asian countries. They argue that the the expansions of credit to the private sector significantly boost the housing prices.⁹ Moreover, the outbreak of financial crisis markedly weakens the positive effect of credit on housing prices. Apart from credit, they also find that GDP per capita triggers positive effect on housing prices as expected, while interest rate's effect is not statistically significant. However, the explanatory variables they considered regarding housing prices are only GDP per capita, credit, and interest rate, although the variables in the supply side have not been considered due to the inelastic assumption they made. This might possibly cause the endogeneity problem of variable omissions.

On the direction of causality, Hofmann (2003) studies the two-sided causality relationship between real housing prices and real credit in the case of 20 industrialized countries during 1985Q1-2001Q4. In the short-run term, the dynamics of real housing prices trigger the unidirectionally positive impacts on the standards of real aggregate bank credit, while such effects perform to be two-sided in the long-run term. This is supported with the research from Goodhart and Hofmann (2008), who find the multi-directional interactions between money supply, credit to the private sector, housing prices, and GDP in an international dataset of 17 industrialized countries over the period 1970-2006. In addition, the current shocks to money supply and credit tend to demonstrate greater impacts on housing prices in the booming period of house prices. Besides, credit constraints through the credit demand perspective could affect the relationship between housing prices and economic growth. Under the international context, Almeida et al. (2006) find that housing prices in countries with greater down-payment constraints, viz., maximum loan-to-value (LTV) ratio, are more sensitive to the shocks of aggregate income, viz., GDP.

To sum up, most of the literature have studied the bidirectional causality between bank credit and housing prices. The variables they mostly use to stand for bank credit are at the aggregate level. Moreover, there is still no clear and definitive research to define the real dynamics of the interactions between housing prices and bank credit. Research considering disaggregate credit in examining international housing price dynamics is sparse.

⁹Both 'credit to the private sector' and 'aggregate bank credit' are used interchangeably in our paper. Based on the definition from OECD Glossary of Statistical Terms, 'the private sector' comprises private corporations, households and non-profit institutions serving households.

2.2 Disaggregated bank credit

A number of studies recently have argued that the components of aggregate bank credit can have heterogeneous effects on real economic fluctuations. Indeed, motivated by the original idea in Keynes (1930), credit-money should be split into either the 'industrial' circulation or the 'financial' circulation, in order to better study the economic output growth and the appreciation of financial assets respectively. It is also worth noting that the simultaneous upward trends of both booming financial markets and increasing asset prices in the 1980s can also be regarded as a good demonstration for the quantity theory of credit from the post-Keynesian school of thought. All of these lead us to build a theoretical foundation and empirical model which edifice rest on disaggregate credit, viz., *credit to the real economy* and *credit to the asset markets*.

In studying the linkage between bank credit and economic growth, it has been observed that the effects of aggregate credit on economic growth stem from disaggregate credit for GDP transactions, viz., credit to the real economy. Werner (1997) divides the money supply into either GDP transactions(the real economy) or non-GDP transactions (the asset market), and finds that only credit to GDP transactions contributes to economic growth, while the increase of credit to non-GDP transactions would only cause the appreciation of financial assets such as in the case of Japan. Such recent empirical results demonstrate the rationale of the quantity theory of credit from the post-Keynesian school of thought. Moreover, it is also consistent with the recent empirical result from Ryan-Collins et al. (2016) in the case of the UK that credit to the financial markets only exerts an indirect effect on the economic growth, which will be more likely to cause asset inflation instead of generating new GDP-transactions.

Moreover, through disaggregate credit and based on a long-period dataset for 17 developed countries over the period 1870-2011, Jordà et al. (2016) document the central role of housing finance, viz., mortgage credit, on determining business cycles and financial stability risks, whereas the other component of aggregate credit, viz., non-mortgage credit, only plays a negligible role. In other words, the dynamics of mortgage credit, which is a part of aggregate credit, are synchronized with the bust-boom behaviors of economic growth, while its growth also has been argued as the source of financial fragility. Moreover, the share of mortgage credit in aggregate credit has markedly increased in target advanced economies, while the ratio of mortgage credit to housing values have experienced an increasing tendency especially in the UK and US, regardless of the ascent of housing prices. It denotes the simultaneous rising movements of both housing prices and mortgage credit to the households, while the latter grows even faster than the former. This research is to some extent consistent with the viewpoint of Stiglitz (2011) who points out that conventional macroeconomic models should recognize the importance of the financial sector, which will help improve the accurate forecast of the financial crisis. He also studies the close linkage between bank credit the housing price dynamics and finds the strong relationship of the credit expansion in both US and UK housing markets. Another empirical application of disaggregate credit is from Unger (2017) in studying the real interrelationship between the growth of domestic credit and the current account balance. On the basis of the panel dataset of eleven European countries within the euro area over the period 1999-2013, the author especially investigates the root cause of current account imbalances in the deficit countries within the euro area. He disaggregates the aggregate bank credit into either financial or non-financial private sectors, and finds that the increase of bank credit to the non-financial private sectors (i.e. non-financial firms and households), along with the loss in competitiveness, are the intrinsic reason of the build-up of the current account imbalances by using a panel error correction model.

Overall, although the above literature mainly studies the importance of disaggregate credit to the real economy on economic growth, little of them devotes to explicitly investigating the pure contributions of different components of aggregate credit to the variations of housing prices - despite the paramount role of housing finance on the macroeconomy that has been studied by Jordà et al. (2016) in detail. All of which deeply motivate us to further study the interdependence of housing prices, disaggregate credit, and other economic factors.

3 Methodology and data description

3.1 Panel VAR model

To capture and model 'system' characteristics, we model the relationship between components of bank credit, housing prices, economic policy uncertainty, and relevant macroeconomic factors in a panel vector autoregressive (VAR) framework. This approach enables us to investigate how temporal lags of incorporated variables affect their corresponding contemporaneous counterparts across countries and over a period of time. The general specification of panel vector autoregressive (PVAR) model with panel-specific fixed effects¹⁰ can be given by:

$$Y_{it} = \sum_{p=1}^{P} Y_{it-p} \alpha_p + X_{it} \beta + u_i + \epsilon_{it}$$
(1)

Where *p* is the number of order; Y_{it} stands for the *K* endogenous variables and it can be also regarded as the $1 \times K$ row vector; X_{it} is the factor represents the individually exogenous shocks; u_i is the vector of panel-specific fixed effects and ϵ_{it} indicates error terms following the identical independent distribution process with zero mean and constant variance. The coefficients α_p and β are parameters, which need to be estimated. In addition, t = 1, ..., T; i = 1, ..., N.

The strengths of using a panel model is that it significantly improves the efficiency and explanatory power of our estimates by accounting for more observations. Otherwise, individually estimating the time-series model for each country would result in the problem of loss of degree of freedom. Second, the estimation results from panel VAR model could explicitly unfold the multiple dynamic interactions among the target economic variables (Muellbauer and Murphy, 2008) and depict a system-wide effect rather than individual country-specific effect by 'shunning the intra/inter-country movements of shocks'. In addition, identifying the fixed effects enable us

¹⁰For simplicity and without loss of generality, we remove the existence of exogeneity, and study the autoregressive property of panel VAR model in our empirical research by following Abrigo and Love (2016).

to account for the idiosyncratic effects from each individual country in order to better capture the heterogeneity among different panels. In terms of the estimation technique, some literature selects ordinary least squares (OLS) to estimate panel VAR model, whereas it would trigger biased estimations¹¹ due to the failure to control the endogeneity problems of simultaneity/additional endogeneity variables. Alternatively, our paper is going to use the estimators of generalized method of moments (GMM), which enables to especially eliminate such endogeneity problems.

3.2 Identification strategies and robustness

In this subsection, we introduce the analytical tools related to panel VAR estimation applied in our empirical research, which include optimal lag order selection process, Granger causality test, generalized impulse response function (IRF) and forecasting error variance decomposition (FEVD). In terms of selecting the optimal lag order for panel VAR model, we follow the technique of order selection criteria¹² proposed by Andrews and Lu (2001) based on the GMM estimations. Specifically, the optimal number of lag order can be obtained by minimizing information criteria statistics. Besides, we employ the Granger causality test to study the causality relationship between incorporated variables. In order to gauge the causal relationship that how the target variable responds in the future after receiving an isolated unit shock of other certain variables, we employ the technique of generalized impulse response function (IRF). Instead of observing the averaged effects by coefficient estimates, this technique enables us to explicitly study the behaviors of each target variable in both short-run and long-run periods. In terms of forecasting the error variance decomposition (FEVD), it enables us to study to what extent the forecast of error variance of each target variable can be interpreted by the exogenous shocks provided by other incorporated variables.

3.3 Data

We use a hand collected quarterly dataset for nine industrialized countries, including Austria, Belgium, Canada, France, Germany, Japan, Spain, Switzerland, and United Kingdom, over 1990Q1 to 2014Q2.¹³ In our research, six economic variables are incorporated such as consumer price index (*cpi*), credit to the real economy (*cr*), credit to asset markets (*cf*), nominal GDP (*ngdp*), nominal house prices (*hpri*), and interest rate (*irate*). While all variables are transformed in logarithms, in order to approximately express the growth rates and avoid any negative effects from domestic currencies, except interest rate, which is less-possible to take logarithms of this variable in levels. In addition, by using the X-12-ARIMA model via NumXL Excel software, any potential seasonal

¹¹Coefficient estimates are still biased even if the sample size is large (Judson and Owen, 1999; Nickell, 1981).

¹²The order selection criteria of a panel VAR model is based on the technique of information criteria such as Akaike information criteria (AIC), Bayesian information criteria (BIC) and Hannan-Quinn information criteria (HQIC) (Abrigo and Love, 2016).

¹³Due to data availability on disaggregate bank credit, we are restricted to only nine countries in our empirical research.

effects in the included variables can be deseasonalized.¹⁴ In addition, the detailed variable descriptions and corresponding data sources can be seen in table 2.

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Variable	Definition	Data Source
Consumer price index (cpi)	The price changes of a basket of goods and	OECD Main Economic Indicators
	services overtime required by a reference population	(MEI)
Credit to the real economy (cr)	Nominal bank credit to the real economy	Central Bank data on Monetary
	(Millions of national currency)	Financial Institutions' assets
Credit to the asset markets (cf)	Nominal bank credit to the asset markets,	Central Bank data on Monetary
	e.g., real estate markets and financial markets (Millions of national currency)	Financial Institutions' assets
Nominal CDP (made)	Nominal Cross Domostic Product	OFCD Main Economic Indicators
Noniniai GDI (<i>ngap</i>)	(Millions of national currency)	(MEI)
	х У/	
Nominal housing prices (hpri)	Nominal price index of different types of dwellings at different geographical locations	The Bank of International Settlements (BIS)
Interest rate (<i>irate</i>)	Nominal three-month or 90-day interbank rate	OECD Main Economic Indicators (MEI)

Table 2: Data Description

3.4 Preliminary observations

3.4.1 Descriptive statistics

We present here descriptive statistics for all variables to uncover distributional patterns of these variables and if these might reflect on the uniqueness or exception of some results we might obtain in the panel VAR estimation. Among variables, nominal GDP $(lngdp)^{15}$ and nominal housing prices (lhpri) are our main variables, where the impact of disaggregate bank credits will be studied. Other macroeconomic variables are used as various predictors but assumed to endogenously determine housing prices, for instance, through the lead-lag effects of bank credit and income. Each variable is expressed in the rate of growth through logarithmic transformation except interest rate (irate), which is described in levels. The sub-figure (a) of figure 1 shows the moving tendency regarding the growth rate of the disaggregate credit (both to the real economy (lcr) and to the asset market (lcf)), nominal GDP (lngdp), and housing prices (lhpri). Broadly speaking, the growth rates of both *lcr* and *lcf* behaved the similar movements over time with that of *lngdp* and *lhpri*. In particular, it is worth noting to highlight that the growth rate of housing prices (lhpri) demonstrates the simultaneous increasing tendency with that of different components of aggregate bank credit, viz., both *lcr* and *lcf* respectively.

¹⁴Due to no significant seasonal peaks found in the spectrum of the variables of interest rates from the X-12-ARIMA model, there is no need to do seasonal adjustment for this variable.

¹⁵The logarithmic transformed variables begin with a prefix l'.



Figure 1: The Cross-country Mean

(a) Disaggregate credit, Nominal GDP, and Housing prices



(b) CPI, Interest rate, Nominal GDP, and Housing prices

Note: (i) the variables except interest rate transformed in logarithms are cross-country averaged overtime; (ii) cross-country logarithmic variables (AveLog(X)) in each time period in each sub-figure are calculated through the following formula: $AveLog(X_t) = (\sum_{i=1}^N Log(X_{it}))/N$; (iii) the quarterly data time period is from 1990Q1 to 2014Q2; (iv) data sources can be seen in table 2.



Figure 2: Standard Deviation

(a) Disaggregate credit, Nominal GDP, and Housing prices



(b) CPI, Interest rate, Nominal GDP, and Housing prices

Note: (i) the values shown in each sub-figure are the standard deviations for cross-cross averaged logarithmic variables calculated in figure 1; (ii) the quarterly data time period is from 1990Q1 to 2014Q2; (iii) data sources can be seen in table 2.

Moreover, the sub-figure (b) of figure 1 describes the rates of growth of consumer price index (*lcpi*), interest rate (*irate*), nominal GDP (*lngdp*), and housing prices (*lhpri*) over the period 1990-2014. The rates of growth of both lcpi and lngdp exhibited the similar increasing slope. Besides, although *irate* behaved an increasing momentum at the year of 2008, it experienced a more volatile decrease since 2009 onwards and reached zero lower bound shortly thereafter. The occurrence of such a phenomenon might be due to the relative long period of aggressive monetary policy during 'Great Moderation (1995-2005)' followed by the more prudential monetary policy during 'Great Recession (2007-2016)'. In addition, due to the outbreak of global financial crisis, the growth rates of all variables except lcf depicted a decrease especially after 2008, while the increasing velocity of *lcf* became more flat after that. In other words, the global financial crisis markedly exerted negative impacts on the changes of all variables either in logarithms or in levels. Overall, from figure 1, we could intuitively capture some evidence to argue that disaggregate credit and CPI demonstrate positive co-movement behaviors with nominal GDP and housing prices, while interest rate shows negative relations. Besides, it also can be seen that variables in logarithms exhibit a more linear moving tendency than the variable in levels, such as interest rate, due to the role of logarithmic transformation.

Furthermore, the temporal movements of corresponding standard deviation can be clearly seen in figure 2. Similarly, the dispersions of 'disaggregate credit' (*lcr* and *lcf*), nominal GDP, and CPI tended to be smaller overtime, whereas housing prices experienced a reverse trend, which became more volatile from 1990 onwards. The standard deviation of interest rate witnessed a relative more fluctuated movements. In addition, the outbreak of global financial crisis markedly affect the movements of variables' standard deviations, especially for CPI, interest rate, and housing prices.

To summarize, we can conclude that all components of disaggregate credit tend to be synchronized with that of nominal GDP and housing prices. In particular, credit to the asset market, especially to the property holding companies, evinces an increasing movement in the face of booming housing prices. This could provide a general inference to support our earlier theoretical arguments regarding both the market disequilibrium theory (excess housing demand and insufficient housing supply in the short-term) and the quantity theory of credit from the post-Keynesian school of thought (the expansions of credit to the asset market induces the appreciations of asset price) in the context of the international housing market during 1990Q1-2014Q2.

3.4.2 Stationarity

In order to guarantee the stationarity of all included variables in the panel VAR model, we perform the following panel unit root tests, viz., IPS test (Im et al., 2003) and PESCADF test (Pesaran, 2004), by considering different conditions such as demeaning, and considering the trend term, etc. From the results of the panel unit test shown in table 3, except interest rate (*irate*), other variables in levels are non-stationary, which means we can not reject the null hypothesis that there exits a unit root. Moreover, after differencing once (first difference), all included variables turn out to be stationary. Hence, due to the stationary requirement in our following empirical research, the variables included are exhibited either in first-differenced logarithms to express the changes of growth rates, such as housing prices (*dlhpri*), credit to the real economy (*dlcr*), credit to the asset market (*dlcf*), consumer price index (*dlcpi*), and nominal GDP (*dlngdp*), or in first-differences to express the absolute increments, such as interest rate (*dirate*).

				r				
	Test/Variable		lhpri	lcr	lcf	lcpi	lngdp	irate
<i>d</i> =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***
<i>d</i> =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***

Table 3: Results of panel unit root test

Note: (i) * significance at 10% level; ** Significance at 5% level; *** Significance at 1% level; (ii) d=0 denotes variables are in levels; d=1 denotes variables are in first-difference format; the logarithmic variables begin with a prefix 'l'; (iii) the number of lags included into each unit root test are chosen based on information criteria (IC).

4 Empirical results

In this section, we first build a benchmark model by regressing our whole dataset covering nine industrialized countries from 1990Q1 to 2014Q2, then a series of robustness checks are conducted to examine the accuracy of our main estimates.

4.1 Main estimation

4.1.1 Benchmark estimation results

Since our benchmark model is characterized as the panel VAR structure, we first use the order selection criteria to determine the optimal lag order of the model. In addition, up to four lags are examined due to the quarterly data frequency of our data sample, and one more lag is necessary as instrumental variables (five lags in total) in order to maximize the estimation efficiency and minimize the data loss simultaneously (Abrigo and Love, 2016). Hence, from table 4, the first-order panel VAR has been demonstrated to be preferable than others due to the overlapping results regarding both the greatest J value and the smallest values of information criteria (IC).

Since large degrees of freedom would be lost with the increasing lags in the instrumental variables of the panel VAR model, we follow the idea from Holtz-Eakin et al. (1988) to substitute those missing observations with zero in order to ensure the efficiency of GMM estimators. Table

No.lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.8695122	228.7439	8.84E-06	-729.0825	-59.25614	-316.9739
2	0.9052584	154.3506	0.0022986	-564.0192	-61.64942	-254.9377
3	0.9260017	101.7399	0.012061	-377.1732	-42.26006	-171.1189
4	0.9228213	61.79143	0.0047538	-177.6652	-10.20857	-74.638

Table 4: Order Selection Criteria

5 presents the estimated coefficients of the first-order panel VAR model.¹⁶ 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 from the post-Keynesian school of thought, the disaggregate credit to the real economy significantly boosts the economic growth in that a 1% increase in credit to the real economy in the previous period exerts an approximately 0.112% increase in nominal GDP, whereas the effect of disaggregate credit to the asset market on nominal GDP is found to be negligible.

Third, in terms of the effects of disaggregate credit (dlcr and dlcf) on housing prices, credit to the real economy exerts a positive impact and the elasticity of housing prices with respect to credit to the real economy is 1.735, which is significantly greater than the elasticity of nominal GDP (0.112). The significant effect of credit to the real economy on housing prices could be supported by our earlier theoretical arguments that the increase of credit availability to the house buyers could directly boost the housing demand and thus housing prices. In addition, credit to the asset market tends to behave negative effects on housing prices, while insignificant. As mentioned in Section 1, there mainly exist two different theoretical viewpoints to explain the relationship between these two variables.

On the one hand, based on the equilibrium theory of the real estate market, the greater access and availability of credit to the real-estate developers stimulates the housing supply and subsequently impedes the housing prices. In most likelihood, due to the current scenario of excess demand and the relative shortage of supply - in the short-run - the negative effect of credit to the asset market on housing prices is insignificant, regardless of the simultaneous increase in the growth rates of these two variables as earlier shown in figure 1.¹⁷ However, we expect that such an effect will be significantly positive in the long-run (to be demonstrated by studying the impulse response function (IRF)).¹⁸

¹⁶As discussed above, we use first-differenced interest rates, and all other variables are in first-differenced logarithms.

¹⁷This negative insignificant effect also may be in line with the viewpoint that the positive correlation between housing prices and credit to the asset markets shown in figure 1 can not be regarded as a direct proof of causality relationship between them in the same direction (Valverde and Fernández, 2010).

¹⁸From the subsequently specific IRF plots when dlcf is regarded as the impulsed variable in figure 4, 8, and 13, the trajectory of the effect of credit to the asset market on housing prices can be clearly observed. It exerts negative but negligible effect in the extremely short run period at the beginning, whilst it turns to be positive for the rest of the period. Such negative disturbances at the beginning help explain the reason why the corresponding estimated coefficient in the benchmark estimation results is negative.

dlcpi		dlngdp		dlhpri		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.dlhpri	0.001	L.dlhpri	0.014^{***}	L.dlhpri	0.578***	L.dlhpri	0.008**	L.dlhpri	0.008***	L.dlhpri	-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***
	(600.0)		(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)

Table 5: The Benchmark Estimations

Note: (i) * significance at 10% level; ** significance at 5% level; *** significance at 1% level; (ii) *cpi* for consumer price index, *ngdp* for nominal GDP, *hpri* for nominal house price, *cr* for bank credit to the real economy, *cf* for bank credit to the asset markets, and *irate* for interest rate; (iii) The signal 'L.' denotes the first temporal lag of the variable, and variables in the first-differenced logarithms begin with a prefix '*dl*'.

Moreover, such phenomenon also is in line with the idea of Arestis and Gonzalez-Martinez (2016) that credit expansions to the housing developers will decrease the housing prices in the short-run, while increase the falling prices in the long run, due to the increase of housing demand in the face of the continued low prices in the short-run. Specifically, owing to the boom of housing supply by the credit expansions, the inelastic housing supply gradually becomes more elastic in the long-run, denoting its impacts on housing prices tend to be more significant. In particular, in the long-run, the theoretically negative effect of housing supply will be masked by the positive effect of subsequent increasing housing demand, and eventually demonstrates significantly positive effect on housing prices. The generalized impulsed response function (IRF) plots later on respectively show how housing prices behave in the face of the simultaneous expansion of both housing supply and demand.¹⁹

On the other hand, based on the quantity theory of credit from the post-Keynesian school of thought, the increase in credit associated with the asset market would lead to the corresponding increase in the asset prices as well. Indeed, from the corresponding IRF plots (Figures 4, 8, and 13), as we will investigate shortly, the effect of credit to the asset market on housing prices are observed to be positive, which is theoretically expected. This positive effect tends to be sharper and more significant after accounting for uncertainty and global financial crisis respectively. Overall, one can conclude that credit to the real economy and housing prices are mutually reinforcing in both short- and the long-run. The effect of credit to the asset market on housing prices tends to be negative in the very short-run period, while such effect becomes positive in the long-run.

Fourth, both housing prices and nominal GDP evince mutually reinforcing interactions with credit to the real economy; the elasticities are 0.008 and 0.103, respectively. However, both nominal GDP and housing prices only depict unidirectional effect on credit to the asset markets. Once again, the elasticities are 0.225 and 0.008, respectively. Specifically, in the case of housing markets, one possible reason regarding the dynamics of credit can be attributed to the economic boom and the growth of main macroeconomic variables, such as nominal GDP and housing prices. This could result in the increasing optimistic attitudes/expectations of economic situations from housing market participants, banks and etc., which will lead to the expansions of credit demand and supply (Gerlach and Peng, 2005; Muellbauer and Murphy, 2008). Fifth, the appreciations of inflation can also be regarded as a driven force of nominal GDP, viz., 1% increase of CPI leads to 0.384% increase of nominal GDP, while CPI does not exert any significant impact on housing prices. Furthermore, interest rate tends to negatively affect both nominal GDP and housing prices, and the corresponding semi-elasticities are -0.392 and -6.841 respectively. Besides, we further conduct the Granger causality test to study the causal relationships between all equation variables. Overall, the results of Granger causality test shown in table 6 are consistent with the estimated coefficients in table 5.

¹⁹Consistent with Arestis and Gonzalez-Martinez (2016), we can observe the more obvious results, after accounting for economic policy uncertainty and global financial crisis respectively, that credit to the housing supply side (*dlcf*) exerts insignificant negative effect in the short-run, while it turns to become significant positive in the long-run.

Equation	Excluded	χ^2	P-value	Equation	Excluded	χ^2	P-value
Variable	variable			Variable	Variable		
dlcpi				dlcf			
	dlngdp	0.363	0.547		dlcpi	2.093	0.148
	dlhpri	0.976	0.323		dlngdp	18.123	0
	dlcf	5.413	0.02		dlhpri	4.805	0.028
	dlcr	0.045	0.831		dlcr	66.244	0
	dirate	0.051	0.821		dirate	19.252	0
dlngdp				dlcr			
	dlcpi	13.58	0		dlcpi	0.126	0.722
	dlhpri	35.535	0		dlngdp	6.584	0.01
	dlcf	1.442	0.23		dlhpri	9.712	0.002
	dlcr	20.609	0		dlcf	36.649	0
	dirate	26.987	0		dirate	10.795	0.001
dlhpri				dirate			
	dlcpi	0.022	0.881		dlcpi	12.832	0
	dlngdp	2.375	0.123		dlngdp	0.286	0.593
	dlcf	0.179	0.672		dlhpri	2.016	0.156
	dlcr	24.464	0		dlcf	0.334	0.563
	dirate	17.178	0		dlcr	16.094	0

Table 6: Granger Causality Test

Figure 3: Generalized IRF of *dlcr*





Figure 4: Generalized IRF of *dlcf*

Figure 5: Generalized IRF of *dlhpri*





Figure 6: Generalized IRF of *dlngdp*

To study the predictive behavior of response variable due to an isolated unit shock of other impulse variables especially in the long-run, we use generalized impulse response function (IRF) so that the results are robust to the variables' ordering.²⁰ Moreover, IRF can also help us to shed in-depth look at the behaviors of included variables in both short run and long run, while the results of coefficient estimates in table 5 only provide the average effects. As shown in figure 3, a current shock of credit to the real economy (*dlcr*) demonstrates significantly positive effects on all the other variables in a relatively long-run period (around 10 periods) except the insignificant effect to CPI (*dlcpi*). In particular, one unit shock to *dlcr* exerts significantly positive effects on both *dlhpri* and *dlngdp* respectively, while the effect on *dlngdp* peaks at 1.6, which is much greater than that on dlngdp (0.11). Interestingly, from figure 4, broadly consistent with our main estimates, the effect of credit to the asset market (dlcf) on nominal GDP (dlngdp) is insignificant in most of the entire period, whereas it tends to become significant within a relatively short-term from the 5th period to the 8th period. Furthermore, although the impulsed effect of credit to the asset market on housing prices is insignificant²¹, it first exerts negative effect in an extremely short period and turns to become expected positive then in the long-run, which is consistent with the theoretical mechanisms earlier discussed.

In addition, the effects of both housing prices (*dlhpri*) and nominal GDP (*dlngdp*) on other

²⁰To save space, we only show the IRF plots when specific variables (*dlcr*, *dlcf*, *dlhpri*, and *dlngdp*) are regarded as the impulse variables respectively. The rest of IRF plots are available from the authors upon request.

²¹We will discuss later that such an effect should be significantly positive after accounting for either economic policy uncertainty or global financial crisis.

economic variables, especially disaggregate credit have been presented in figures 5 and 6. As expected, one standard deviation shock of either housing prices or nominal GDP gives rise to positive effect on the dynamics of all components of disaggregate credit (*dlcr* and *dlcf*). Moreover, housing prices can be regarded as one of determinants of nominal GDP, which depicts significant positive effect, while the latter also positively affect the former although the magnitudes are insignificant. Table 11 shown in appendix expresses the results regarding FEVD. The previous lags of each variable itself contribute the largest part of error variance. In particular, the contributions of credit to the real economy and credit to the asset market to changes of nominal GDP are 2.70% and 4.54% respectively, while the contributions of disaggregate credit to housing prices are 1.7% and 4.6% respectively. In addition, housing prices tend to explain 10.26% and 8.10% changes of credit to the real economy and credit to the asset market, which are all greater than the corresponding contributions of nominal GDP.

To sum up, our benchmark estimations demonstrate mutually reinforcing interactions between credit to the real economy with either housing prices or nominal GDP, whereas credit to the asset markets has no significant impact on nominal GDP. Moreover, as observed from the respective IRF plots, credit to the asset markets has negative effect on housing prices in the very short-run, while it exerts the expected positive effect in the long-run although being statistically insignificant. Besides, both housing prices and nominal GDP exhibit significantly positive effects on credit to the asset markets.

4.2 Robustness check

In this section, we introduce the role of economic policy uncertainty (EPU) and global financial crisis for robustness exercise. The latter is assumed to act as a structural break point; hence, we will investigate the sensitivity of results before and after the break-point.

4.2.1 Accounting for the effects of economic policy uncertainty

Economic policy uncertainty (EPU) has been shown in the fast growing literature that real economic fluctuations respond measurably and significantly to its upward or downward movements. Researchers have argued that heightened uncertainty gives rise to periods of sustained volatility and that it invariably manifests a negative psychological effects among investors (see Baker et al., 2016, and the references therein). Due to the robust empirical evidences and sound theoretical foundation of the role of uncertainty in real economic variations, it won't be a-theoretical to assume that persistent uncertainty can produce asymmetric information in the economic system. As a result, how much credit should be supplied to the real economy and the financial markets also becomes a policy question. At the same time, due to this uncertainty, real-estate investors may not be willing to invest a big amount in the property market, while the buyers' perception also experience a depressing trend. Moreover, in recent years, it has been shown that global economic policy uncertainty has been rising at an alarming level.²²

We introduce the EPU index²³ in our estimation as a form of robustness study. Our aim is that controlling for uncertainty within the estimation of this credit-real economic fluctuations may shed light on the true effects of the relationship. We add this variable to our benchmark model. The corresponding estimation results, such as estimated coefficients, Granger causality test, and variance decomposition, have been described in tables 7, 8, and 12 respectively. Broadly speaking, from table 7, the estimation results after adding uncertainty are consistent with the earlier benchmark estimations (see in table 5). Specifically, as expected, credit to the real economy (*dlcr*) exerts significant positive effects on both nominal GDP (*dlngdp*) and housing prices (*dlhpri*), which are 0.089 and 1.375 respectively, while such effects are also bidirectional. Interestingly, compared with the insignificant counterpart in the benchmark estimations, the positive effect of credit to the asset market (*dlcf*) on nominal GDP tends to become weakly significant after accounting for uncertainty, while its effect on *dlhpri* turns to be positive although still insignificant.

Moreover, nominal GDP and housing prices demonstrate significantly positive effects on disaggregate credit (*dlcr* and *dlcf*), and corresponding magnitudes are similar either in direction or in size compared with the benchmark estimations. In particular, housing prices keep offering significantly positive effect on determining nominal GDP, while the latter does not significantly affect the former. In addition, it is also noteworthy to mention that EPU index (*dluncer*) imparts a significant negative effect on key macroeconomic variables, such as nominal GDP, housing prices, which might indicate an inference that the increasing uncertainty would depress the economic activities due to the fall of confidence. The increase of uncertainty also tends to negatively affect credit aggregates, while such influence is significant to credit to the asset markets and insignificant to credit to the real economy. In particular, 1% change of uncertainty could lead to 0.051% changes of credit to the asset market in the opposite direction.

²²Using EPU index of Baker et al. (2016) at the global level, we find that the EPU has experienced an average annual growth of 6.51%. The upward movement of the global EPU from 1997 to 2017 can also be observed in figure 17 in appendix.

²³For each country except Switzerland, EPU index is available from http://www.policyuncertainty.com/. The Swiss EPU index can be downloaded from KOF Swiss Economic Institute through https://www.kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-uncertainty-indicator.html. Moreover, we have to exclude Belgium as the EPU index of Belgium is currently not available.

		0.593**	(0.241)	0.243^{**}	(0.097)	-0.001	(0.007)	-0.192***	(0.065)	0.197^{***}	(0.069)	-0.786***	(0.166)	-0.185***	(0.032)
	dluncert	L.dlcpi		L.dlngdp		L.dlhpri		L.dlcf		L.dlcr		L.dirate		L.dluncert	
		-0.362***	(0.078)	0.011	(0.023)	-0.003**	(0.001)	-0.033**	(0.013)	0.089***	(0.015)	0.559***	(0.065)	-0.005	(0.005)
וויל דוומרעל	dirate	L.dlcpi		L.dlngdp		L.dlhpri		L.dlcf		L.dlcr		L.dirate		L.dluncert	
		0.217^{**}	(0.105)	0.078^{*}	(0.041)	0.009***	(0.002)	0.276^{***}	(0.033)	0.568^{***}	(0.033)	0.293***	(0.077)	-0.018	(0.014)
ginner	dlcr	L.dlcpi		L.dlngdp		L.dlhpri		L.dlcf		L.dlcr		L.dirate		L.dluncert	
		0.601^{***}	(0.169)	0.206***	(0.057)	0.009**	(0.004)	0.272***	(0.047)	0.442^{***}	(0.042)	-0.771***	(0.127)	-0.051***	(0.018)
	dlcf	L.dlcpi		L.dlngdp		L.dlhpri		L.dlcf		L.dlcr		L.dirate		L.dluncert	
TVC9 MTC9.		9.145***	(1.977)	-0.494	(0.599)	0.678^{***}	(0.04)	0.07	(0.389)	1.375^{***}	(0.362)	-6.217***	(1.455)	-0.392**	(0.161)
OULLIAUTOIL	dlhpri	L.dlcpi		L.dlngdp		L.dlhpri		L.dlcf		L.dlcr		L.dirate		L.dluncert	
		0.418^{***}	(0.109)	0.197^{***}	(0.045)	0.015^{***}	(0.002)	0.054^{**}	(0.021)	0.089***	(0.026)	-0.479***	(0.065)	-0.031***	(0.011)
-	dp bulp	L.dlcpi		L.dlngdp		L.dlhpri		L.dlcf		L.dlcr		L.dirate		L.dluncert	
		0.545***	(0.058)	-0.008	(0.017)	0.001	(0.001)	0.024^{***}	(0.00)	0.007	(0.01)	-0.003	(0.024)	0.002	(0.005)
	dlcpi	L.dlcpi		L.dlngdp		L.dlhpri		L.dlcf		L.dlcr		L.dirate		L.dluncert	

Table 7: Estimation Results: Robustness Check (Adding Uncertainty Index)

Note: (i) * significance at 10% level; ** significance at 5% level; *** significance at 1% level; (ii) *cpi* for consumer price index, *ngdp* for nominal GDP, *hpri* for nominal house price, *cr* for bank credit to the real economy, *cf* for bank credit to the asset markets, *irate* for interest rate, and *uncert* for EPU index; (iii)The signal 'L.' denotes the first temporal lag of the variable, and variables in the first-differenced logarithms begin with a prefix 'dl'.

Equation	Excluded	Chi2	P-value	Equation	Excluded	Chi2	P-value
Variable	Variable			Variable	Variable		
dlcpi				dlcr			
	dlngdp	0.228	0.633		dlcpi	4.253	0.039
	dlhpri	1.382	0.24		dlngdp	3.679	0.055
	dlcf	6.77	0.009		dlhpri	13.332	0
	dlcr	0.473	0.492		dlcf	71.145	0
	dirate	0.013	0.909		dirate	14.406	0
	dluncert	0.128	0.72		dluncert	1.602	0.206
dlngdp				dirate			
	dlcpi	14.716	0		dlcpi	21.521	0
	dlhpri	41.389	0		dlngdp	0.226	0.634
	dlcf	6.403	0.011		dlhpri	4.195	0.041
	dlcr	11.679	0.001		dlcf	6.299	0.012
	dirate	53.743	0		dlcr	37.554	0
	dluncert	7.696	0.006		dluncert	0.818	0.366
dlhpri				dluncert			
	dlcpi	21.407	0		dlcpi	6.053	0.014
	dlngdp	0.682	0.409		dlngdp	6.202	0.013
	dlcf	0.032	0.857		dlhpri	0.026	0.872
	dlcr	14.404	0		dlcf	8.712	0.003
	dirate	18.261	0		dlcr	8.075	0.004
	dluncert	5.921	0.015		dirate	22.517	0
dlcf							
U U	dlcpi	12.623	0				
	dlngdp	13.274	0				
	dlhpri	5.598	0.018				
	dlcr	110.01	0				
	dirate	36.605	0				
	dluncert	8.059	0.005				

Table 8: Granger Causality Test: Robustness Check (Adding Uncertainty Index)

Furthermore, the corresponding results of Granger causality test (in table 8) are consistent with the estimated coefficients in table 7 and these roughly mimic the results of Granger causality test of the benchmark model (table 6). From table 8, credit to the real economy Granger cause both nominal GDP and housing prices respectively, and such causal relationships are bidirectional. As expected, housing prices Granger cause credit to the asset market although unidirectional. Besides, uncertainty Granger causes both nominal GDP, housing prices and credit to the asset markets. In terms of impulse response function (IRF), as shown from figures 7 to 10, the consistent results, especially regarding the impulsed shocks from *dlcr*, *dlcf*, *dlhpri*, and *dngdp*, obtained from both the benchmark estimations and the estimations after considering uncertainty can be well studied. Specifically, these impulsed shocks demonstrate expected effect in relatively 10 periods and gradually return to be zero in the long-term period. In particular, it is worth noting that the effect from credit to the asset market on housing prices initially is insignificant negative within an extremely short-run period, while such effect turns to be significantly positive since then in the long-run period; it is in line with our earlier theoretical discussions that credit to the asset market should demonstrate expected positive effect on housing prices.



Figure 7: Generalized IRF of *dlcr*







Figure 9: Generalized IRF of *dhpri*







Figure 11: Generalized IRF of *dluncert*

Besides, uncertainty (dluncer) plotted in figure 11 demonstrates significantly negative effect on determining nominal GDP, housing prices, and credit to the asset market. Uncertainty does not significantly affect credit to the real economy in the beginning (around 2 periods), whereas such negative effect turns to become significant since the 2nd period until the 10th period. This could help explain the reason of corresponding insignificant estimated coefficient shown in table 7. Regarding the results of variance decomposition after adding economic uncertainty index, it broadly mimics the results from the benchmark model. In particular, the contributions from uncertainty to the changes of key economic variables, such as housing prices, nominal GDP, and disaggregate credit (dlcr and dlcf) are relatively tiny, although they are all significant. Overall, it can be generally concluded that the estimation results after considering uncertainty are consistent with our benchmark estimations. Importantly, it can also be well studied that economic policy uncertainty (EPU) index is an important factors on determining the interdependence between disaggregate credit, housing prices, and other key economic variables.

4.2.2 The Effect of the global financial crisis

The intervention of Global Financial Crisis (GFC) is known to have slowed down the growth of key economic fundamental almost at every corner of the globe. The largest impact has been felt in the housing market as it was affected by information cascades and the weak lending restrictions. Our structural break test (Chow test: the detailed results not reported here) confirms that the p-values for rejecting the null hypothesis of no break point effect in 2008 on the series is close to

zero for each country.²⁴ Such an exogenous break point is confirmed for the housing price series leading us to re-estimate the PVAR model for the sub-samples (before and after the break-point).

Following the idea from Ferretti and Razin (2000) and Kroszner et al. (2007), we introduce a time dummy variable (fc) to capture the outbreak of financial crisis, where the value of 1 at each quarter of 2008 depict the presence of break point, and zero otherwise. In tables 9, 10, and 13 respectively, we have presented the results of the re-estimation PVAR regression by accounting for the effect of the crisis. Our broad conclusions from these results remain consistent with the benchmark regression; there is no significant differences between the estimations before and after the intervention of the global financial crisis. In other words, adding such a time dummy does not considerably alter our conclusions of the effects of credit shocks on housing prices and other real variables. One notable conclusion emerges from this regression: the global financial crisis tends to remarkably dampen the dynamics of both nominal GDP and housing prices.

Specifically, as expected from our main estimates, credit to the real economy (dlcr) depicts bidirectional positive interactions with both nominal GDP and housing prices, whereas credit to the asset market (dlcf) has no significant effect on nominal GDP. Moreover, a result consistent with our earlier discussions. The impulse of dlcf to housing prices remains positive and significant for a relatively long period, although it is negative but insignificant in the extremely short period at the beginning.²⁵ Furthermore, consistent with above benchmark estimations, both nominal GDP and housing prices exert significant and positive effects on credit to the asset market; housing prices exhibit the unidirectional positive effect on nominal GDP.

In particular, on the basis of the IRF plot in figure 16, apart from the negative influences provided by the outbreak of financial crisis on main economic variables during the entire time period, it appears to exert counterfactually positive effect on both components of disaggregate credit in the very short period at the beginning, while such effect turns out to be negative in the remaining periods. By studying the Granger causality test (in table 10) and variance decomposition (in table 13) along with the corresponding impulse response function plots from figures 12 to 16²⁶, we conclude that the results are largely consistent with the benchmark estimation. Both the introduction of uncertainty and GFC, while sharpened the results of disaggregate credit-real variables interactions, the broad results remain consistent across addition of variables and sample stratification.

²⁴In fact, a visual inspection of figure 1 also reveals the potential negative impact of outbreak of global financial crisis on the included economic variables.

²⁵See more details in figures 4, 8, and 13 respectively.

²⁶To save space, the IRF plots of other variables are available from the authors upon request.

	Iable y:	Esumau	un ivesuit	cs: Kobus	thess Che	eck (Con	sidering	GIODAL J	rinancial	Crisis		
	dpgulp		dlhpri		dlcf		dlcr		dirate		fc	
	L.dlcpi	0.396***	L.dlcpi	-4.195***	L.dlcpi	0.163^{*}	L.dlcpi	0.288***	L.dlcpi	-0.294***	L.dlcpi	0.019**
		(0.078)		(1.141)		(0.099)		(0.091)		(0.05)		(0.007)
	L.dlngdp	0.233***	L.dlngdp	1.158^{**}	L.dlngdp	0.227***	L.dlngdp	0.122^{***}	L.dlngdp	0.014	L.dlngdp	0.010***
		(0.038)		(0.469)		(0.048)		(0.036)		(0.021)		(0.003)
	L.dlhpri	0.010^{***}	L.dlhpri	0.433***	L.dlhpri	0.006*	L.dlhpri	0.012***	L.dlhpri	0	L.dlhpri	-0.000*
		(0.002)		(0.039)		(0.003)		(0.003)		(0.001)		(0)
	L.dlcf	0.026	L.dlcf	-0.06	L.dlcf	0.458^{***}	L.dlcf	0.192^{***}	L.dlcf	-0.007	L.dlcf	-0.009***
		(0.021)		(0.343)		(0.041)		(0.03)		(0.011)		(0.002)
	L.dlcr	0.117^{***}	L.dlcr	1.818^{***}	L.dlcr	0.275***	L.dlcr	0.639***	L.dlcr	0.065***	L.dlcr	0.004
		(0.021)		(0.332)		(0.032)		(0.033)		(0.012)		(0.003)
	L.dirate	-0.364***	L.dirate	-4.144***	L.dirate	-0.417***	L.dirate	0.056	L.dirate	0.428^{***}	L.dirate	-0.008**
		(0.063)		(1.085)		(0.087)		(0.064)		(0.039)		(0.003)
*	L.fc	-1.101^{***}	$\mathrm{L.}fc$	-42.287***	$\mathrm{L.}fc$	0.262	$\mathrm{L.}f_{C}$	1.406^{***}	L.fc	1.288^{***}	L.fc	0.768***
		(0.165)		(2.396)		(0.185)		(0.17)		(0.059)		(0.02)

in Cain Clobal E: • 7 Ś ÷ ť 4 ÷ è 1 è ì ÷ μ ġ Table *Note:* (i) * significance at 10% level; ** significance at 5% level; *** significance at 1% level; (ii) cpi for consumer price index, ngdp for nominal GDP, hpri for nominal house price, cr for bank credit to the real economy, cf for bank credit to the asset markets, irate for interest rate, and fc for the global financial crisis; (iii)The signal 'L.' denotes the first temporal lag of the variable, and variables in the first-differenced logarithms begin with a prefix 'dl'.

Equation	Excluded	Chi2	P-value	Equation	Excluded	Chi2	P-value
Variable	Variable			Variable	Variable		
dlcpi				dlcr			
	dlngdp	1	0.317		dlcpi	9.896	0.002
	dlhpri	0.293	0.588		dlngdp	11.624	0.001
	dlcf	2.641	0.104		dlhpri	20.679	0
	dlcr	0.237	0.627		dlcf	39.875	0
	dirate	3.366	0.067		dirate	0.768	0.381
	fc	175.093	0		fc	68.249	0
dlngdp				dirate			
	dlcpi	25.695	0		dlcpi	34.807	0
	dlhpri	23.263	0		dlngdp	0.428	0.513
	dlcf	1.5	0.221		dlhpri	0.083	0.774
	dlcr	31.405	0		dlcf	0.432	0.511
	dirate	33.075	0		dlcr	31.561	0
	fc	44.4	0		fc	480.305	0
dlhpri				fc			
	dlcpi	13.513	0		dlcpi	6.366	0.012
	dlngdp	6.092	0.014		dlngdp	9.46	0.002
	dlcf	0.031	0.861		dlhpri	3.611	0.057
	dlcr	29.98	0		dlcf	15.382	0
	dirate	14.577	0		dlcr	2.418	0.12
	fc	311.493	0		dirate	6.141	0.013
dlcf							
	dlcpi	2.743	0.098				
	dlngdp	22.701	0				
	dlhpri	3.705	0.054				
	dlcr	71.944	0				
	dirate	22.983	0				
	fc	2.015	0.156				

 Table 10: Granger Causality Test: Robustness Check (Considering Global Financial Crisis)



Figure 12: Generalized IRF of *dlcr*







Figure 14: Generalized IRF of *dlhpri*







Figure 16: Generalized IRF of fc

5 Concluding remarks

In this paper we developed a conceptual and empirical foundation for understanding the way disaggregate bank credit might determine housing market fluctuations at the international level. We show that the mechanism of disaggregating bank credit is important in understanding if credit can affect housing prices positively/negative and under what conditions such effects may disappear. Our main conclusion is that credit to the real economy engages in a mutually reinforcing relationships with housing prices, whereas credit to the asset market and housing prices tends to be intertwined and affect each other. Specifically, housing prices demonstrate a positive effect on credit to the asset market in both the short-run and long-run periods. Conversely, credit to the asset market has a negligible negative effect on housing prices in an extremely short-run period, and a positive effect in the long-run. More importantly, when we respectively introduce the role of economic policy uncertainty and global financial crisis into the interplay of credit-housing market fluctuations, the net effect of disaggregated credit to the asset market on housing prices appears sharper and more significant, and are of theoretically expected signs (positive), especially in the long-run period.

Both uncertainty and the global financial crisis give rise to significantly negative effects on the main economic variables, such as housing prices and nominal GDP. Moreover, our findings are also consistent with the post-Keynesian school of thought on credit-cycle relationship, especially

on the aspects of the quantity theory of credit. We found that bank credit lending to the real economy depicts a bidirectionally positive effect on economic growth, whereas bank credit lending to the asset market evinces an insignificant effect. Finally, robustness checks confirm our findings.

References

- Abrigo, M. R. and Love, I. (2016), 'Estimation of panel vector autoregression in Stata', *Stata Journal* **16**(3), 778–804.
- Allen, M., Madura, J. and Wiant, K. (2009), 'Commercial bank exposure and sensitivity to the real estate market', *Journal of Real Estate Research*.
- Almeida, H., Campello, M. and Liu, C. (2006), 'The financial accelerator: Evidence from international housing markets', *Review of Finance* 10(3), 321–352.
- Andrews, D. W. and Lu, B. (2001), 'Consistent model and moment selection procedures for gmm estimation with application to dynamic panel data models', *Journal of Econometrics* **101**(1), 123–164.
- Arestis, P. and Gonzalez-Martinez, A. R. (2016), 'House prices and current account imbalances in OECD countries', *International Journal of Finance & Economics* **21**(1), 58–74.
- Baker, S. R., Bloom, N. and Davis, S. J. (2016), 'Measuring economic policy uncertainty', *The Quarterly Journal of Economics* **131**(4), 1593–1636.
- Barker, K. (2004), 'Review of housing supply: Delivering stability: Securing our future housing needs', *HM Treasury*, *London*.
- Barker, K. (2006), *Barker Review of Land Use Planning: Interim Report-Analysis*, Stationery Office published with the permission of HM Treasury.
- Bernanke, B. and Gertler, M. (1989), 'Agency costs, net worth, and business fluctuations', *The American Economic Review* pp. 14–31.
- Bernanke, B. S. (2007), Housing, housing finance, and monetary policy: A symposium sponsored by the Federal Reserve Bank of Kansas City: Opening remarks, Federal Reserve Bank of Kansas City, pp. 1–20.
- Bernanke, B. S., Gertler, M. and Gilchrist, S. (1999), 'The financial accelerator in a quantitative business cycle framework', *Handbook of Macroeconomics* **1**, 1341–1393.
- Coleman, M., LaCour-Little, M. and Vandell, K. D. (2008), 'Subprime lending and the housing bubble: Tail wags dog?', *Journal of Housing Economics* **17**(4), 272–290.

- Corradin, S. and Fontana, A. (2013), House price cycles in Europe, Technical report, European Central Bank No. 1613.
- Davis, S. J. (2016), An index of global economic policy uncertainty, Technical report, National Bureau of Economic Research.
- Duca, J. V., Muellbauer, J. and Murphy, A. (2011), 'House prices and credit constraints: Making sense of the US experience', *The Economic Journal* **121**(552), 533–551.
- Favara, G. and Imbs, J. (2015), 'Credit supply and the price of housing', *The American Economic Review* 105(3), 958–992.
- Favilukis, J., Ludvigson, S. C. and Van Nieuwerburgh, S. (2017), 'The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium', *Journal of Political Economy* **125**(1), 140–223.
- Ferretti, G. M. M. and Razin, A. (2000), Current Account Reversals and Currency Crises: Empirical Regularities, *in* 'Currency crises', University of Chicago Press, pp. 285–323.
- Fitzpatrick, T. and McQuinn, K. (2007), 'House prices and mortgage credit: Empirical evidence for Ireland', *The Manchester School* **75**(1), 82–103.
- Gan, J. (2007), 'The real effects of asset market bubbles: Loan-and firm-level evidence of a lending channel', *Review of Financial Studies* **20**(6), 1941–1973.
- Gerlach, S. and Peng, W. (2005), 'Bank lending and property prices in Hong Kong', *Journal of Banking & Finance* **29**(2), 461–481.
- Ghent, A. C. and Owyang, M. T. (2010), 'Is housing the business cycle? Evidence from US cities', *Journal of Urban Economics* **67**(3), 336–351.
- Gimeno, R. and Martinez-Carrascal, C. (2010), 'The relationship between house prices and house purchase loans: The Spanish case', *Journal of Banking & Finance* **34**(8), 1849–1855.
- Goodhart, C. and Hofmann, B. (2008), 'House prices, money, credit, and the macroeconomy', *Ox*ford Review of Economic Policy **24**(1), 180–205.
- Hofmann, B. (2003), Bank lending and property prices: Some international evidence, Technical report, HKIMR Working Paper No. 22/2003.
- Holtz-Eakin, D., Newey, W. and Rosen, H. S. (1988), 'Estimating vector autoregressions with panel data', *Econometrica: Journal of the Econometric Society* pp. 1371–1395.
- Im, K. S., Pesaran, M. H. and Shin, Y. (2003), 'Testing for unit roots in heterogeneous panels', *Journal of Econometrics* 115(1), 53–74.

- Jordà, Ô., Schularick, M. and Taylor, A. M. (2016), 'The great mortgaging: Housing finance, crises and business cycles', *Economic Policy* 31(85), 107–152.
- Judson, R. A. and Owen, A. L. (1999), 'Estimating dynamic panel data models: A guide for macroeconomists', *Economics Letters* **65**(1), 9–15.
- Justiniano, A., Primiceri, G. E. and Tambalotti, A. (2015), Credit supply and the housing boom, Technical report, National Bureau of Economic Research.
- Keynes, J. M. (1930), Treatise on Money: Pure Theory of Money Vol. I, Macmillan, London.
- Kindleberger, C. (1978), Manias, Panics and Crashes: A History of Financial Crises, *in* C. Kindleberger and J. Laffarge, eds, 'Financial crises: Theory, history and policy', Cambridge University Press, Cambridge.
- Kiyotaki, N. and Moore, J. (1997), 'Credit cycles', Journal of Political Economy 105(2), 211–248.
- Kroszner, R. S., Laeven, L. and Klingebiel, D. (2007), 'Banking crises, financial dependence, and growth', *Journal of Financial Economics* 84(1), 187–228.
- Mian, A. and Sufi, A. (2009), 'The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis', *The Quarterly Journal of Economics* **124**(4), 1449–1496.
- Minsky, H. P. (2015), Can "It" Happen Again?: Essays on Instability and Finance, M.E. Sharpe.
- Muellbauer, J. and Murphy, A. (2008), 'Housing markets and the economy: The assessment', *Ox*ford Review of Economic Policy **24**(1), 1–33.
- Nickell, S. (1981), 'Biases in dynamic models with fixed effects', *Econometrica: Journal of the Econometric Society* pp. 1417–1426.
- Oikarinen, E. (2009), 'Interaction between housing prices and household borrowing: The Finnish case', *Journal of Banking & Finance* **33**(4), 747–756.
- Pesaran, M. H. (2004), General diagnostic tests for cross section dependence in panels, Technical report, Cambridge Working Papers in Economics No. 435, University of Cambridge, and CESifo Working Paper Series No. 1229.
- Ryan-Collins, J., Werner, R. A. and Castle, J. (2016), 'A half-century diversion of monetary policy? An empirical horse-race to identify the UK variable most likely to deliver the desired nominal GDP growth rate', *Journal of International Financial Markets, Institutions and Money*.
- Senhadji, A. S. and Collyns, C. (2002), Lending booms, real estate bubbles and the Asian crisis, Technical report, IMF Working paper No. 02/20.
- Stiglitz, J. E. (2011), 'Rethinking macroeconomics: What failed, and how to repair it', *Journal of the European Economic Association* **9**(4), 591–645.

- Unger, R. (2017), 'Asymmetric credit growth and current account imbalances in the euro area', *Journal of International Money and Finance* **73**, 435–451.
- Valverde, S. C. and Fernández, F. R. (2010), The relationship between mortgage markets and house prices: Does financial instability make the difference?, Technical report, CenFIS Working Paper, Federal Reserve Bank of Atlanta, February 2010.
- Werner, R. A. (1997), 'Towards a new monetary paradigm: A quantity theorem of disaggregated credit, with evidence from Japan', *Kredit und Kapital* **30**(2), 276–309.

Appendix

Response	Period			Impulse	Variable		
variable		dlcpi	dlngdp	dlhpri	dlcr	dlcf	dirate
dlcpi							
	1	1	0	0	0	0	0
	5	0.9743286	0.0010372	0.006063	0.0137311	0.0031709	0.001669
	10	0.9532161	0.0030206	0.0118609	0.0181699	0.0087411	0.0049914
dlngdp							
	1	0.0509745	0.9490255	0	0	0	0
	5	0.1145927	0.6735948	0.0857204	0.0173003	0.03478	0.0740119
	10	0.1334329	0.6067768	0.1014608	0.0269794	0.0453593	0.0859908
dlhpri							
	1	0.0002672	0.0236994	0.9760334	0	0	0
	5	0.0217398	0.04144	0.7686186	0.007898	0.0373087	0.1229948
	10	0.0530881	0.0431748	0.7038702	0.0176544	0.0463722	0.1358404
dlcf							
	1	0.0009242	0.0041531	0.01609	0.9788328	0	0
	5	0.0319198	0.0690989	0.0730653	0.6488191	0.1322995	0.0447973
	10	0.0596461	0.0720872	0.1026292	0.5500685	0.1539267	0.0616423
dlcr							
	1	0.0014624	0.0113805	0.0004431	0.0143447	0.9723694	0
	5	0.002945	0.0587923	0.0460683	0.1087883	0.7778201	0.0055859
	10	0.0186563	0.0689895	0.0810867	0.1206557	0.6896216	0.0209903
dirate							
	1	0.0000629	0.0000303	0.0067498	0.0008236	0.0026837	0.9896497
	5	0.1203697	0.0025696	0.0145168	0.0008878	0.0487511	0.8129051
	10	0.1330255	0.0036501	0.0142468	0.0014079	0.0559244	0.7917453

Table 11: Variance Decomposition (Benchmark Estimations)

Note: To save space, we only report the results in the 1st, 5th, and 10th future periods. The results of other periods are available from the authors upon request.

Response	Period		-	In	npulse Variał	ole		
variable		dlcpi	dlngdp	dlhpri	dlcf	dlcr	dirate	dluncert
dlcpi								
	1	1	0	0	0	0	0	0
	5	0.9557131	0.0016889	0.0145081	0.0173132	0.007495	0.003055	0.0002269
	10	0.9086753	0.0040942	0.0349841	0.0267837	0.0143208	0.0106774	0.0004645
dlngdp								
	1	0.0727219	0.9272782	0	0	0	0	0
	5	0.2238145	0.4841236	0.1480398	0.0335529	0.0132646	0.0922237	0.0049809
	10	0.3003344	0.3607067	0.172586	0.0444955	0.0162483	0.1015392	0.0040898
dlhpri								
	1	0.0062745	0.0260112	0.9677144	0	0	0	0
	5	0.2255059	0.0155147	0.6546102	0.0195476	0.0118977	0.0699426	0.0029812
	10	0.3129506	0.0150196	0.5328076	0.0352025	0.0156973	0.0857558	0.0025665
dlcf								
	1	0.0001474	0.014426	0.0381755	0.9472511	0	0	0
	5	0.1709826	0.0466046	0.1270274	0.4672039	0.1090213	0.0736308	0.0055292
	10	0.274534	0.0388634	0.1699864	0.3351175	0.0929728	0.0840601	0.0044658
dlcr								-
	1	0.000402	0.0133275	0.0007131	0.024988	0.9605694	0	0
	5	0.0702788	0.0502899	0.0879461	0.167243	0.6099795	0.0100378	0.0042248
	10	0.1919191	0.0454903	0.154773	0.156296	0.4123268	0.0350434	0.0041513
dirate								-
	1	0.0007881	0.0003144	0.037161	0.0038	0.0004512	0.9574853	0
	5	0.1683381	0.0012672	0.0540309	0.0061877	0.0638305	0.7058069	0.0005388
	10	0.1871915	0.0022293	0.0531195	0.0066229	0.0724208	0.6777872	0.0006287
dluncert			0.001000-	0.010001	0 0000 (0 000 05-	0.000	
	1	0.0097696	0.0010035	0.0130216	0.0000574	0.0000255	0.0002609	0.9758615
	5	0.0347433	0.00/1592	0.0154481	0.0066952	0.0061541	0.0191989	0.9106012
	10	0.0409505	0.0071571	0.0175239	0.0071839	0.0061309	0.0206881	0.9003657

Table 12: Variance Decomposition:	Robustness Check	(Adding U	Incertainty Index)

Note: To save space, we only report the results in the 1st, 5th, and 10th future periods. The results of other periods are available from the authors upon request.

Response	Period	Impulse Variable							
variable		dlcpi	dlngdp	dlhpri	dlcf	dlcr	dirate	fc	
dlcpi	1	1	0	0	0	0	0	0	
	5	0.8867563	0.0027436	0.0002924	0.0097452	0.0021863	0.001552	0.0967242	
	10	0.8534376	0.0027253	0.0020215	0.0150581	0.0057362	0.0020357	0.1189857	
dlngdp									
	1	0.031546	0.968454	0	0	0	0	0	
	5	0.0719966	0.5896935	0.04755	0.0204995	0.028458	0.0579137	0.1838887	
	10	0.0598288	0.4844661	0.0501547	0.034636	0.0326639	0.0544968	0.2837537	
dlhpri									
	1	0.0001918	0.0019505	0.9978577	0	0	0	0	
	5	0.0147142	0.0033686	0.5507885	0.0128048	0.0250849	0.0483765	0.3448626	
	10	0.0142263	0.0028197	0.461307	0.0246717	0.0267888	0.0479333	0.4222531	
dlcf									
	1	0.0021234	0.0055411	0.0090894	0.9832461	0	0	0	
	5	0.0364311	0.0577267	0.0487398	0.6523134	0.1227204	0.0520687	0.0299998	
	10	0.0397964	0.0466113	0.0612115	0.5243567	0.1329579	0.0549527	0.1401137	
dlcr									
	1	0.0029688	0.0201153	0.0031927	0.0206268	0.9530964	0	0	
	5	0.0259113	0.0736559	0.0375732	0.1146635	0.72381	0.0086697	0.0157165	
	10	0.0397579	0.066769	0.0569561	0.1317437	0.6121593	0.0225051	0.0701089	
dirate									
	1	0.0028391	0.0030221	0.0373369	0.0001492	0.0080732	0.9485796	0	
	5	0.0480024	0.0275186	0.0246557	0.0002352	0.0548049	0.559953	0.2848302	
	10	0.0512997	0.032308	0.0227643	0.0004055	0.0595322	0.5108905	0.3227997	
fc									
	1	0.0007637	0.0085437	0.0012447	0.0002063	0.0000147	0.0117232	0.9775038	
	5	0.0262219	0.0193617	0.0057801	0.0086198	0.000964	0.0075802	0.9314724	
	10	0.0326308	0.0188018	0.0070651	0.0101325	0.0009811	0.0082996	0.922089	

Table 13: Variance Decomposition: Robustness Check (Considering Global Financial Crisis)

Note: To save space, we only report the results in the 1st, 5th, and 10th future periods. The results of other periods are available from the authors upon request.



Figure 17: Increasing Tendency of Global Economic Policy Uncertainty (GEPU)

Note: (i) this figure shows the increasing dynamics of global EPU index over the period 1997M1-2017M5; (ii) GEPU is weighted by PPP (purchasing power parity)-adjusted GDP (see details about the method from Davis, 2016); (iii) the dash line in black color is a polynomial trendline of GEPU with order two; (iv) data sources can be accessed in footnote 23.