

Is Housing the Business Cycle? A Multi-resolution Analysis for OECD Countries

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Abstract

Fluctuations in the housing market have long been recognized by academics and practitioners as leading indicators of general economic activities. Recently, Leamer (2007, 2015) claims that housing activities both predict and cause national business cycles in the US. We investigate his claims for a larger set of countries. We also examine the predictive relationship in multiple resolutions or time scales, namely short-run and long-run variations of business cycles. Structural vector auto-regression (SVAR) models are estimated to test his more contentious causal claim. Our results show that: (1) housing indicators lead business cycles in most countries; (2) such leading relationship is the most prominent in the long-run. In addition, our SVAR results for the US indicate that housing factors are likely independent drivers of business cycles. Housing starts predict short-run variations in business cycles, while housing prices predict long-run variations better. The cross-country evidences are less certain. Generally, our findings on time-scale based relationships between housing and macro economy put restrictions on future models of monetary transmissions.

Key Words: Housing Cycles; Monetary Transmission Mechanism; Wealth Effect; Collateral Constraint; Wavelet Analysis; Frequency Domain Analysis

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1. Introduction

Business activities in the housing market, such as building permits and housing starts, have long been recognized as leading indicators of the aggregate economy (Green, 1997; Coulson and Kim, 2000). They are regularly mentioned in the news media when people comment on stock market movements or macro-economic conditions. Leamer (2007, 2015) offers a much more provocative proposition, claiming “Housing Is the Business Cycle” in the United States. He suggests that the relationship between fluctuations in the housing market and business cycles are both predictive and causal. In our paper, we investigate this empirical regularity and Leamer’s claims through a set of exploratory analyses.

In the first part of this paper, we expand Leamer (2007, 2015)’s analysis on the predictive power of housing factors in three directions. Firstly, the relationship between housing and macro economy is analyzed in multiple time scales. In other words, the strength or even the direction of the predictive relationship can vary as the time horizon involved changes. Time scales are differentiated by wavelet multi-resolution analysis, a tool useful for both the time-domain and the frequency-domain analysis. Intuitively, wavelet analysis decomposes the original time series into its trend component and many time scales, which in turn represent more and more details of the original data. In this sense, wavelet multi-resolution analysis can be thought of as an alternative to the time series filters in business cycle analysis, such as Hodrick and Prescott (1997) and Baxter and King (1999).

Secondly, we analyze a larger set of countries, namely the OECD countries. Expanding the analysis to multiple countries not only tests the robustness of Leamer (2007, 2015)’s claims but also opens a window to discover the underlying mechanism. Some cross-country studies have investigated the mechanisms. A few studies use institutional details in mortgage markets to explain inter-country differences in how housing and the economy interact, e.g. Rubio (2011), Calza, Monacelli, and Stracca (2013), and Garriga, Kydland, and Sustek (2017). In our paper, we aim to describe the predictive relationship across countries. We do not offer a specific explanation, however. These results are left for model builders to interpret and to work on.

Thirdly, we utilize a larger set of indicators for both the housing sector and the macro economy. Specifically, we include housing permits, housing starts, housing price indexes, and residential investments as housing-related indicators. In terms of macro economy, we include GDP, industrial production index, and unemployment rate. Inclusion of alternative measures tests robustness of the predictive relationship. It may also help reveal deeper mechanisms for why housing indicators lead the macro-economy. Kydland, Rupert, and Sustek (2016) offer an important insight in this respect. Because housing investments require time to materialize and to be recorded by statistical agencies, housing starts are more likely to lead the economy than residential investments. Their model shows how institutional factors help explain why lead-lag relationships between housing and macro economy vary across countries.

These extensions enable a more complete characterization of the relationship between housing and business cycles. Time scale decomposition is essential. On an intuitive level, time horizons matter for both the real estate industry and the macro-economy because both involve short-term decisions as well as long-term planning. The distinction between short-run and long-run is common in many other economic applications, yet it is mostly ad hoc and imprecise. The frequency-domain analysis rigorously generalizes this distinction. The seminal paper of Engle (1974) uses band spectrum regression, a frequency-domain tool, to test the permanent income hypothesis. Wavelet method, which is closely related to spectral analysis, is used in this paper as well as some other papers, e.g. Ramsey and Lampart (1998a) and Ramsey and Lampart (1998b).

We find that housing factors indeed predict business cycles. First, the contemporaneous correlation between housing indicators and business activities becomes stronger as the time scales increase. Such a result is robust to alternative measures of housing and economic variables. Second, most housing indicators are found to lead business activities in a majority of OECD countries. Moreover, such a leading relationship is more prominent in the long-term of business cycles. Last, housing permits and housing starts predict business activities more strongly than other indicators, such as residential investments and housing prices. This result shows that timing of real estate development due to institutional differences across countries likely generates inter-country differences in lead-lag relationship between housing and business cycles.

In the second part of our paper, we investigate the second and more controversial causal claim of Leamer (2007, 2015). Causality is difficult to establish in empirical macroeconomics (Nakamura and Steinsson, 2017). The main counter argument to Leamer (2007, 2015) comes from Smets (2007) and Kydland, Rupert, and Sustek (2016), who claim that housing indicators are unlikely driving forces of business cycles because they are themselves determined by changes in nominal interest rate as a part of the monetary transmission mechanism. We shed some light on this debate by employing structural vector auto-regressions (Structural VARs or SVARs). We allow housing market to respond to monetary shocks, i.e. interest rate shocks, by modeling user costs of housing investments as functions of contemporaneous and past values of interest rates and other variables. In other words, we adopt a simple recursive identification scheme commonly used in the literature. Additionally, we differentiate between long-run and short-run variations within business cycles, thus offering a multiresolution SVAR analysis.

Studies most similar to ours, e.g. Goodhart and Hofmann (2008), Jarocinski and Smets (2008), Ghent and Owyang (2010), Musso, Neri, and Stracca (2011), and Cesa-Bianchi (2013), normally select a recursive identification scheme without referring to a particular economic mechanism. We differ from them in that we distinguish among four competing mechanisms, which in turn are associated with four sets of endogenous variables and recursive structures. We draw theoretical relationships among key macroeconomic variables from the now rich literature on housing and the business cycle.² Mishkin (2007) provides a comprehensive yet intuitive discussion of these mechanisms. We focus on four main channels: (1) the neoclassical model of housing investment and monetary transmission; (2) wealth effects of housing price shocks on consumption; (3) collateral effects on households balance sheets and their consumption; (4) collateral effects on balance sheets of financial institutions and hence credit supply. We link our choices of variables and their sequencings in the SVARs to these four mechanisms respectively. Again, we consider

² Detailed references are discussed in Section 2.3.

user cost as the crucial link between monetary and housing variables, differing from the existing literature that mostly omits user cost in their SVAR specifications.

The results on SVARs resonate with our findings in the first part. For the US and G7 countries, housing factors are likely autonomous driving forces of business cycles. In other words, housing market is not a mere channel through which monetary shocks propagate. More interestingly, housing supply indicators such as housing starts or housing permits better predict short-term business activities, while housing prices seem to predict long-term variations in the macro-economy. However, the evidence of a larger set of countries is less conclusive. Overall, a comparison of the predictive ability of interest rate versus housing factors demonstrates an independent role of housing shocks in business cycles. Additionally, housing prices seem to predict business activities in the long-term in many countries.

To the best of our knowledge, we are the first to apply wavelet multiresolution analysis to investigate the relationship between housing and business cycles. The seminal papers by Ramsey and Zhang (1997), Ramsey and Lampart (1998a, 1998b) are among the first few papers that apply wavelet methods to economics. In particular, Yogo (2008) describes US business cycles using wavelet multiresolution analysis. Other applications in economics include but are not limited to Gençay, Selçuk and Whitcher (2005), Andersson (2011), and Dowd, Cotter, and Loh (2011).

In the real estate literature, the most related studies include earlier papers such as Green (1997) and Coulson and Kim (2000) and recent papers such as Kim (2004) for South Korea, Chen, Guo, and Zhu (2011) for China, and Ren and Yuan (2014) for the US. All of these papers focus on the leading role of housing indicators on macroeconomic performance. A related but different literature analyzes the organizations of housing supply, particular attention has been paid to building permits, housing starts, and housing completions and their relationships, e.g. Coulson (1999), Somerville (2001), Falk and Lee (2004), and Chinloy and Wu (2013). These studies are complementary to Kydland, Rupert, and Sustek (2016)'s model

of residential time-to-build. Our study contributes to this literature by offering both a cross-country perspective and a multi-timescale description of the housing-economy link.

The rest of this paper is organized as follows. Section 2 describes the data, the wavelet multiresolution analysis, and the SVAR methodology. Section 3 shows the empirical results for the lead-lag relationships between housing variables and macroeconomics variables across 34 OECD countries. Section 4 reports standard results of SVARs such as impulse responses and forecast variance decompositions for the US and other OECD countries. Section 6 concludes.

2. Data and Methodology

2.1 Data and Variable Construction

The dataset comprises a set of macroeconomic and housing variables for all the OECD countries. To ensure consistent definitions of these variables across countries, we download most data series from the Organization for Economic Cooperation and Development (OECD) database. When certain variables are not available in the OECD database, we find supplementary information from other sources. Details on data sources and variable constructions are reported in Table 1.³ All the time series are quarterly; and they end at 4th quarter of 2016. The starting dates of included time series vary due to data availability.⁴ In the end, we obtain an unbalanced panel data. The list of countries, the starting dates of the series, and their availability are reported in Table A.1.

[Table 1 about here]

³ To be comparable with existing studies, e.g. Jarocinski and Smets (2008) and Kydland, Rupert and Sustek. (2016), we preprocess the variables before applying wavelet decomposition or running regressions. Indicators, such as GDP, industrial production index, all the housing variables, private final consumption, household wealth and mortgage balance, are transformed by taking log differences with respect to the original series. Indicators measured as ratios or percentages, such as unemployment rate and interest rates, are transformed by taking simple differences.

⁴ Wavelet analysis requires sufficient data points to provide reliable estimates. A typical business cycle consists of a contraction phase of 6 quarters and an expansion phase of 8 quarters. The literature conventionally consider variations from 6 to 32 quarters as the cyclical component. We therefore require the data to be available at least 2 full cycles, i.e. $32 \times 2 = 64$ quarters, for inclusion in the analysis. As a practical matter, we drop all series who are available only after 2000Q1.

To achieve our research objectives, three types of variables are considered. The first category of variables are those describing economic activities in the housing sector. We therefore include both housing price indexes and volume indicators, namely building permits, housing starts, and residential investments.⁵ Building permits are perhaps the leading indicator of the other two. If more building permits are issued in a quarter, we expect more construction activities and residential investments to appear in the following quarters. If more housing units are started, residential investments are likely to accumulate and grow in the future. Considerable time lags exist among the three key milestones for a residential project: obtaining a permit, start of construction, and completion. According to US Census Bureau's Survey of Construction, the average lag between authorizations and starts is 2 months for multi-unit buildings and 0.9 month for single-unit buildings in 2016. Since residential investments are recorded as building structures are put in place, residential investments lag starts and precede completions. Kydland et al. (2016) claim that time-to-build of residential projects pushes residential investments towards being coincident with the output even if housing starts and housing permits consistently precede output.

The second category of variables relate to measurements of business cycles. Business cycle research studies the recurrent expansions and contractions of aggregate economic activities. The obvious choice is Gross Domestic Product (GDP). We also use Industrial Production as a substitute measure because it is reported for longer time periods than GDP in most countries. Another important indicator of aggregate economic fluctuations is unemployment. Many business cycle models attempt to explain cyclical behavior of unemployment using labor market frictions. Liu, Miao, and Zha (2016), in particular, model the connection between land/housing shocks and unemployment. We also characterize the relationship between unemployment and housing indicators.

The last category of variables are those included in our Structural VAR analysis. These variables are associated with particular transmission mechanisms of monetary policy shocks. These mechanisms are

⁵ Housing completions are another indicator describing housing activities. However, they are only available in a few countries. We therefore do not include them in our analysis.

explored in more depth in Section 2.3. Here, we intuitively explain the rationale for including these variables. We consider short-term interest rates as indicating the policy stances of central banks because most central banks in OECD countries target base rates when implementing their monetary policies. Long-term interest rates, on the other hand, are equilibrium outcomes given demand and supply conditions in the financial market. Aggregate household gross wealth and aggregate final private consumption of households are collected to show the ramifications of housing shocks on the general economy. Mortgage balance gauges not only the supply of credit to the housing market but also the overall credit supply in the economy. Credit spread is measured as the yield differential between corporate bonds⁶ and short-term government bonds. This yield differential also reflects aggregate credit supply. But it is more related to the balance sheets of financial institutions affected by housing market and other macroeconomic shocks.

Besides all the above variables, user cost of housing capital is calculated to connect monetary variables with housing indicators. User costs, in fact, appear in all of our SVAR specifications. The central role of user costs in our framework is consistent with practice in macroeconomic policy modeling (Mishkin, 2007) and the real estate literature on housing investment and macro economy, e.g. Poterba (1984). The existing cross-country studies have mostly ignored user costs, substituting them by long-term interest rates sometimes. We follow the simple formula of Himmelberg, Mayer and Sinai. (2005) and calculate user costs as follows

$$u_c = (1 - t) * d * i - \pi_h^e + \delta, \quad (1)$$

where i is the long-term mortgage interest rate, t is the marginal income tax rate, d is the percentage of mortgage interest that is deductible for income tax, π_h^e is the expected housing price appreciation, and δ denotes depreciation and maintenance costs. We cannot find long-term mortgage interest rates for a majority of the countries. We use instead long-term government bond yield plus 1% risk premium. This choice is supported by Kydland, Rupert, and Sustek (2016), who find that nominal long-term mortgage

⁶ For Canada, we use the Bank of America Merrill Lynch Canada Corporate Index. For US, the Moody's corporate bond index is used.

rates move closely with yields of government bonds with comparable maturities. Table A.2 reports the marginal income tax rates and the percentages of tax-deductible interest payments for all the OECD countries. OECD (2016)'s⁷ report on taxation is used to calculate most of the statistics in Table A.2. The rest of statistics are collected from relevant government websites. The depreciation or maintenance cost δ is set at 2.5%. One of the key variables in calculation user cost is the expected price appreciation π_h^e . We assume that consumers have extrapolative expectations, i.e. π_h^e equals the realized price appreciation in the most recent quarter.

2.2 Methodology: Wavelet Multiresolution Analysis

In characterizing business cycles, wavelet-based filtering offers a promising alternative to popular filters in business cycle research, such as Hodrick and Prescott (HP) (1997), Baxter and King (BK) (1999), Christiano and Fitzgerald (CF) (2003), and Corbae and Ouliaris (CO) (2006). HP, BK, and CF are all time-domain filters approximating the ideal frequency domain bandpass filters. Baxter and King (1999) argue that frequency domain analysis is not suitable for filtering economic time series for two reasons: (1) many economic time series are non-stationary and require ad hoc detrending before applying Fourier analysis; (2) sample size changes will alter the filtered series significantly. Corbae and Ouliaris (2006) resolves the first problem by offering a frequency domain filter that can be applied to non-stationary time series. However, the technique works only for time series that are integrated of order 1.

Wavelet analysis is well suited to analyze non-stationary data, which may include outliers, structural breaks, and non-recurring events (Percival and Walden, 2006). Therefore, wavelet filtering is not subject to the first criticism of Baxter and King (1999).⁸ Since wavelet analysis preserves localized time domain features (Yogo, 2003), the second critique of Baxter and King (1999) is also not applicable. Lastly, wavelet transform naturally decomposes an economic time series into various time scales, and hence the name of

⁷ The title for the report is "PH2.2 Tax Relief for Access to Home Ownership", which can be retrieved from <https://www.oecd.org/els/family/PH2-2-Tax-relief-for-home-ownership.pdf>

⁸ To be comparable with other studies, we still take either log differences or simple differences with respect to the data series. In principle, we could omit this preprocessing in applying wavelet filtering techniques.

multi-resolution analysis.⁹ Its multi-resolution capability enables a rigorous distinction between long-run versus short-run properties of the data. We are not aware of any macroeconomics models of housing markets that generate explicit time-scale based predictions. Future macroeconomic models will be more credible if they can match these fine empirical features differentiated by time scales.

Generally, there are two main types of wavelet transforms: Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). We use DWT in our paper for its simplicity and comparability with existing filtering techniques. Specifically, an extended version of DWT or maximum-overlap DWT (MODWT) is used to decompose the time series into several time scales. After that, both simultaneous correlation and cross-correlations (lead-lag relationship) are calculated to explore linkages between housing indicators and macroeconomic variables for two time scales, i.e. scale of 8-16 quarters and scale of 16 – 32 quarters. The decomposed time series are then used to estimate the SVARs.

The fundamental building blocks for wavelet analysis are wavelet bases or basic wavelets. We can think of each class of wavelet basis as composed of father wavelet $\varphi(t)$ and mother wavelet $\psi(t)$. Father wavelet describes the smooth or trend component of a time series. Mother wavelet, on the other hand, represents the deviations from the smooth component. They satisfy the following conditions:

$$\int \varphi(t)dt = 1 \text{ and } \int \psi(t)dt = 0.$$

Moreover, each wavelet is compact in the time domain and hence the name wavelet. They are defined in the time domain by two indexes: the translation index k and the scale index $j \in \{1,2, \dots, J\}$, where J is the maximum scale sustainable by the length of data or the maximum scale selected by a researcher. More specifically, father wavelet and mother wavelets are defined as follows:

$$\varphi_{J,k}(t) = \frac{1}{\sqrt{2^J}} \varphi\left(\frac{t-2^J k}{2^J}\right),$$

⁹ Good introductions of wavelet multiresolution analysis include Ramsey and Lampart (1998a), Ramsey (2002), and Crowley (2007). An excellent treatment of wavelet filtering as compared with other filtering methods is offered by Gencay, Selcuk, and Whitcher (2001).

$$\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}} \psi\left(\frac{t-2^j k}{2^j}\right) \text{ for } j \in \{1, 2, \dots, J\}.$$

These wavelets can be thought of as a series of compact functions defined in the time domain. They are dilated by the scaling factor 2^j . They are shifted or translated by the translation index k . A time series $x(t)$ can be described by a sequence of projections onto the father and mother wavelets:

$$x(t) = \sum_k c_{J,k} \varphi_{J,k}(t) + \sum_j \sum_k d_{j,k} \psi_{j,k}(t), \quad (2)$$

where $c_{J,k}$ and $d_{j,k}$ with $j \in \{1, 2, \dots, J\}$ are called wavelet coefficients. They are given by the following equations:

$$c_{J,k} = \int x(t) \varphi_{J,k}(t) dt, \text{ and } d_{j,k} = \int x(t) \psi_{j,k}(t) dt.$$

We can express Equation (2) more succinctly to demonstrate the concept of multiresolution analysis:

$$x(t) = S_J + D_J + D_{J-1} + \dots + D_1, \quad (3)$$

where $S_J = \sum_k c_{J,k} \varphi_{J,k}(t)$, and $D_j = \sum_k d_{j,k} \psi_{j,k}(t)$ for $j \in \{1, 2, \dots, J\}$. Equation (3) is termed the multiresolution decomposition of $x(t)$, or MRD. S_J is called the smooth or trend component, while $\{D_j\}$ is called the detailed component of scale j , reflecting the deviation from the trend at scale j .

Although DWT is simple and intuitive, it requires the data sample to have dyadic length, i.e. length of 2^T with T being an integer equal to or greater than the maximum scale J . DWTs are also very sensitive to the starting point of the data. Furthermore, DWT is not suitable for cross-correlation analyses because the transformed series experience phase shifts. To overcome the above drawbacks, we use maximal-overlap DWT (MODWT) instead. The detailed mathematics of MODWT are presented by Gencay, Selcuk, and Whitcher (2001) and Percival and Walden (2006). Unlike DWT, MODWT does not have orthogonal bases. Instead, it is redundant and uses an approximate zero-phase-shift filter to produce a representation of a time series. The wavelet coefficients have the same length of original time series $x(t)$ and hence not sensitive to the choice of starting point.

Both DWT and MODWT multiresolution analyses can decompose a time series into various levels of resolution. These levels of decompositions are referred to as time scales. The interpretation of scales in this

study is listed below. We use Daubechies wavelet class 2 (db2), which can account for possible asymmetries in the data. As the shortest sample length is 64 quarters, the highest scale we can attain is six ($2^6 = 64$). According to Crowley (2007), it is advisable to select a maximum scale smaller than 5. Since business cycle conventionally spans across frequencies of 6-32 quarters, we select the maximum scale as 4, corresponding to 32 quarters. The details are shown below.

Scales	Quarterly Frequency Resolution
Scale 1	2-4 Quarters
Scale 2	4-8 Quarters
Scale 3	8-16 Quarters
Scale 4	16-32 Quarters
Trend Component	>32 Quarters

2.3 Methodology: Structural VARs and Monetary Transmission Mechanisms

Given the strong leading role of housing indicators with respect to GDP across countries¹⁰, we ask further whether housing factors can predict business cycles even after we control for the effects of monetary policy instruments. More specifically, could housing independently drive the economic boom and bust, instead of simply acting as an intermediary to transmit shocks in interest rates? If the answer is yes, Leamer (2007, 2015)'s second claim will be more credible. Monetary authorities should also take more seriously Leamer's advices to monitor and dampen overbuilding early on.

To explore further how housing sector affects the broader economy, we firstly introduce the four mechanisms through which housing absorbs and transmits monetary policy shocks and subsequently influences the final output (Mishkin, 2007). Structural VARs are set up to fit these monetary transmission

¹⁰ Results are shown in Section 3.3.

mechanisms respectively. Existing cross-country studies also use SVARs. For example, Goodhart and Hofmann (2008) carry out a cross-country study using a panel VAR approach. Jarocinski and Smets (2008) focus on the US monetary policy and housing prices and use Bayesian SVARs. Ghent and Owyang (2010) analyze US cities and explore further nonlinearities in the data. Musso, Neri, and Stracca (2011) cover US and EU countries and also employ structural VARs. Igan et al. (2011) explore the lead-lag relationship between housing and other macroeconomic variables without estimating SVARs.

The main difference of our approach from existing studies lies in associating SVARs with individual monetary transmission mechanism. Previous studies select a certain identification scheme without attaching it to a particular theory. In the following, we follow Mishkin (2007)'s narrative descriptions of these mechanisms in specifying the sequencing of variables in SVARs. Additionally, user cost plays a central role in all SVARs in our analysis. Previous studies do not include user costs in their models. User costs, which incorporate mortgage interest rate, past housing price movement, and inter-country difference in tax treatment of mortgage interests, offer the necessary link between monetary and housing variables.

(1) Investment Channel: User Cost and Housing Investment

User cost of capital lies at the center of the neoclassical model of housing investment, e.g. Poterba (1984). With a decrease of short-term interest rate after easing of money supply, the long-term interest rate will also go down due to expected declines in future short-term interests. As a result, the user cost of residential capital also drops. It becomes less expensive for people to hold residential capital. Housing demand then rises. On the supply side, higher demand leads to larger amount of residential investments, which then spill over to other sectors of the economy. On the other hand, the decrease in interest rate also reduces financing costs of housing supply. If housing supply is relatively inelastic, housing price will increase when interest rate shocks are negative. User cost of capital is also reduced as housing price is expected to rise. This enables a more interesting dynamic relationship among key variables. Monetary policy changes can therefore alter expectation of future housing price changes directly, which then feedback to current housing demand through the user cost. It is clear that user cost plays a central role in linking macroeconomic

outcomes with housing market outcomes. The set of endogenous variables we include in the VAR are short-term interest rate, long-term interest rate, user cost, housing supply indicators,¹¹ and GDP. The sequencing or the recursive identification scheme also follows that order.

(2) Wealth Channel: Housing Price and Wealth Effect

Apart from the direct effect on the housing demand and supply, monetary policy can also be transmitted through the housing wealth effect. The lifecycle model of consumption and savings provides the theoretical foundation for this mechanism. As the net wealth of an individual increases, he may spend more in expectation of liquidating his accumulated wealth later. This propensity to consume is due to people's tendency to smooth consumption over the life cycle. This mechanism is a built-in feature of the macroeconomic forecasting model of the US Federal Reserve (Mishkin, 2007). Empirical studies also confirm and estimate this marginal propensity to consume wealth, e.g. Case, Quigley, and Shiller (2005) and Campbell and Cocco (2007). Specifically, if interest rate and user cost are lower, housing demand increases, leading to higher housing prices. As aggregate housing wealth increases, aggregate consumption also increases, leading to overall expansion of the economy. The sequencing of variables in SVAR is hence short-term interest rate, user cost, housing price, aggregate household wealth, aggregate household consumption, and GDP.

(3) Collateral Channel: Housing Price and Borrowing Constraint

With lower base interest rate and rising housing prices, credit constraints faced by consumers and firms are reduced because the collateral values of their housing assets increase. Credit constraints are usually due to information asymmetry faced by banks in deciding whom to lend to. Higher housing collateral value alleviates information asymmetry and hence reduces loan risk. If the collateral value increases, both the available loan amount and the terms for borrowers improve. The aggregate leverage in the economy hence increases. In other words, housing amplifies the initial easing of credit. In addition, housing price

¹¹ Building permits, housing starts, and residential investments are not always available for all the countries. We select one indicator sequentially from the previous list. In other words, we select building permits if they are available. If permits are unavailable, we select starts. If both starts and permits are unavailable, we are left with residential investments.

appreciation also enable homeowners to withdraw cash through home equity loans or other financial instruments more easily. Both effects stimulate consumption and GDP. Many empirical studies have found evidence for collateral effect, e.g. Mian and Sufi (2011), Mian, Rao, and Sufi (2013), and Agarwal and Qian (2017). Theoretical models of collateral effect have appeared in recent years, e.g. Kiyotaki and Moore (1997), Iacoviello (2005), Iacoviello and Neri (2010), Liu, Wang, and Zha (2013). The sequencing of variables in SVAR is hence short-term interest rate, user cost, housing price, aggregate mortgage balance, aggregate household consumption, and GDP.

(4) Credit Channel: Housing Price and Credit Supply

The last mechanism relates housing price shocks, especially negative shocks, to stability of the financial market. Rising housing prices increase the values of housing collaterals on the book of banks and other financial institutions. Bank lending becomes less risky, resulting in loose lending standards. On the contrary, if housing prices drop significantly, the balance sheets of financial institutions deteriorate. Banks tend to become more conservative and raise their lending standards. This cyclical movement of credit supply with collateral assets has been modeled by Fostel and Geanakoplos (2008) and Brunnermeier and Pedersen (2008). A narrative development of this theory is also offered by Mishkin (2007). When monetary shocks lead to decrease in housing prices, bank lending is reduced or even completely frozen under certain circumstances. Lack of credit supply in the economy then adversely affects consumption and GDP. The sequencing of variables is hence: short-term interest rate, user cost, housing price, credit spread, aggregate consumption, and GDP. We use credit spread to proxy for the availability of bank credit.

We use the estimated SVARs to gauge the relative contributions of housing factors compared with those of the monetary variables, i.e. interest rates. Only two-quarters lagged variables are included in SVARs. We report impulse response functions (IRF) and forecast error variance decompositions (FEVD). The former traces out how current and future values of the targeted variables respond to one-shot increase in the current value of an impulse variable while keeping shocks to other variables at zeros. The forecast error variance decompositions measure the percentage contribution of a variable in forecasting another variable at

particular forecasting horizons. Since identification of SVARs crucially depends on the short-run restrictions implied by individual monetary transmission channels, our findings are valid only if these theoretical channels and our formulations of them in the SVARs are valid.

3. Wavelet Multiresolution Analysis

3.1 Wavelet Decomposition of Housing and Macro Indicators in the US

The wavelet multiresolution analysis is demonstrated using US data. Figure 1, which contains three panels, shows the decomposed time series of GDP, housing starts, and housing price index. The shaded time periods represent recessions identified by National Bureau of Economic Research (NBER). Wavelet decomposition reveals interesting dynamics of these series hidden in the original data. Graphs of scales 3 and 4 in Figure 1a show that the troughs in the decomposed GDP series correspond closely to recessions defined by NBER. However, there seem to be more frequent ups and downs in the wavelet-decomposed series. These findings are also featured in Yogo (2008). After the mid-1980s until 2008, or during the great moderation period, the volatilities of most series in Figure 1a drop, especially for scales 1 and 2. During the 2008 global financial crisis, the volatilities of the series increase substantially. Afterwards, however, the volatilities stabilize to some extent. Interestingly, scale 4 GDP component experiences no significant change either after 1985 or during and after the global financial crisis.

[Figures 1 & 2 about here]

Figure 1b illustrates the same decomposition for housing starts. Scale 3 and scale 4 subplots present an interesting and robust finding. Almost all recessions are preceded by troughs in the cyclical movements of housing starts. The decreases in variability in housing starts are not as obvious as those for the GDP series. For housing price index series shown in Figure 1c, the troughs in the cycles do not correspond clearly to US recessions, in contrast to results on housing starts. Overall, housing starts are much more volatile than housing prices and GDP. These findings are consistent with Leamer (2007)'s claim that cyclical movement in housing markets should be characterized as “volume cycles” not “price cycles”.

Figure 2 compares the wavelet decompositions with other popular filtering methods. Again, three key indicators are shown, namely GDP, housing starts, and housing price index. In addition to the widely used BK and CF filters, an additional naïve filtering method is also reported. We apply an 8-quarter centered moving average filter (MA8) on the three time series, which are detrended by a linear time trend. The wavelet-based series are the sum of scales 3 and 4 as reported in Figure 1. Clearly, wavelet-based series are more comparable to BK and CF results. The MA8 results are much more volatile than other more sophisticated methods.

3.2 Correlation: Housing and Macro Indicators in OECD Countries

The average contemporaneous correlations between housing indicators and macroeconomic variables are reported for all OECD countries in Table 2. Four housing indicators are analyzed: building permits, housing starts, residential investment, and housing price index. Three macroeconomic indicators are included, namely GDP, industrial production index, and unemployment rate. Due to space limitations, only averages across all the countries reported. Table 2 describes both correlation coefficients for the original time series and correlation coefficients for decomposed series at various time scales. Generally speaking, all housing indicators are positively related to aggregate output; but they are negatively related to unemployment rate. These signs certainly are consistent with our expectations.

[Table 2 about here]

Comparing across scales for each pair of variables, we observe a very strong pattern. As the scales of the decomposed variables increase, the correlation coefficients rise steadily. In other words, there is a stronger dependence between housing market and macro economy in 16-32 and 8-16 quarter cycles than that in shorter time frames. This pattern of dependency remains hidden without the multiresolution capability of wavelet analysis. These findings also suggest that we should pay more attention to business cycle periodicity of 8 – 32 quarters in our latter analysis.

Comparing across different indicator-pairs, we find some additional patterns. First, residential investments and housing price indexes are more strongly correlated with macroeconomic variables than housing starts or building permits are. This finding is not surprising in light of findings of Kydland, Rupert, and Sustek (2016). Housing starts and building permits tend to precede the other two housing indicators and hence tend to lead rather than correlate contemporaneously with outputs. Second, the raw correlations distort our view of housing starts and building permits more than those for investments and housing prices. The correlations between macro indicators and housing starts or building permits for cycles of 8 -16 quarters and 16 -32 quarters are more than double the raw correlations, while those of investments and prices increase by about 50% relative to raw correlations. Lastly, across macroeconomic indicators, the results do not differ systematically. Overall, we find strong correlations between housing and macro variables, especially for business cycle scales.

3.3 Lead-Lag Relationships: Housing and GDP in OECD Countries

We further explore the lead-lag relationships between housing and macroeconomic indicators. We restrict our analysis to scales 3 and 4, namely cyclical variations of 8 - 16 and 16 - 32 quarters. The sum of scales 3 and 4, in turn, represents the cyclical variations from 8 to 32 quarters, the periodicity normally associated with business cycles. Furthermore, we put the results on unemployment and industrial production index to the Appendix (Tables A.3 and A.4) as these results are similar to those reported in Table 3 for GDP. The number in each cell denotes the leading or lagging period at which the correlation coefficient between GDP and the relevant housing indicator achieves its maximum value. If housing variable leads GDP, the value in the cell is positive, and vice versa. Zero in a cell means housing and GDP achieve their maximum correlation coefficient contemporaneously. We also indicate, using a star, whether the maximum correlation achieved is statistically significant at 5% level.

[Table 3 about here]

Most previous studies analyze one housing indicator, e.g. building permits (Ghent and Owyang, 2010) and residential investments (Igan et al., 2011). We analyze multiple housing indicators in light of the time-to-build argument in Kydland, Rupert, and Sustek (2016). We expect building permits and housing starts to precede residential investments and housing prices. These expectations are partially supported by Table 2. Table 3 provides a more complete picture. Take the overall business cycle variation, or the sum of scale 3 and scale 4, as an example. Building permits are found to lead in 52% of the available countries. Housing starts' lead are even stronger with 75% available countries. Residential investments, as expected, are found to lead GDP in only 35% countries. Surprisingly, housing prices lead GDP in about 60% of the countries. To reconcile these findings for different housing indicators, considerable variations must exist among countries in the lead-lag relationships between equilibrium price levels and housing supply variables. Further investigation is hence warranted but beyond the scope of this paper.

Moving to the decomposed scales, the results are essentially unchanged with the exception of building permits for scale 3. For scale 3, building permits only lead in 32% of the countries. Fortunately, most of the leading correlations are statically significantly, while others are not significant. Firstly, more of the maximum correlation coefficients start to become statistically significant in the multi-scale results. This implies that the traditional filtering method, which focuses on the overall variations from 6 to 32 quarters frequencies, may have overlooked some interesting details. Secondly and more importantly, the leading effects of housing supply variables become stronger in the long-run than those in the short-run. The number of leading periods increases in many cases. Interestingly, the reverse patterns emerges for housing prices, i.e. the leading effects are stronger in the short-run than those in the long-run. This pattern is robust to the macro indicators used. Tables A.3 and A.4 show the essentially the same patterns. As several monetary transmission channels we analyze involve either housing supply indicators or housing prices, this finding has interesting implications for theoretical modelling of monetary transmissions.

The lead-lag patterns vary considerably across countries as we should expect. Among G7 countries, whose economies are large enough to be resilient to international shocks, we expect a more robust lead-lag

relationship between housing and macro economy (Leamer, 2007). Indeed, housing factors are found to lead macro indicators consistently across all scales in Canada, France, Germany, UK, and US. Generally speaking, those countries with stronger leading results of housing factors tend to have longer time series in housing and macro variables. In combination with previous findings, cross-country difference in housing and macroeconomic institutions need to be accounted for in macroeconomic models of housing and business cycles.

4. Structural Vector Auto-Regressions

Our main objective in this section is to disentangle the relationships among housing variables, interest rates or monetary shocks, and GDP. Due to the large number of countries and four monetary transmission mechanisms, we are forced to focus on the three key variables mentioned above. For the case of US, we are able to report more detailed analysis, including impulse responses and forecast error variance decompositions. For other OECD countries, we are only reporting variance decompositions.

4.1 Impulse Responses: the US

Figures 3-6 depict how housing variables, GDP, and interest rates respond to shocks in one another for the respective four channels of monetary transmission. Only original data series are used due to space limitations again. Among all figures, two subplots in the left column show how GDP respond to shocks in interest rates and housing supply/price. The right column illustrates the interactions between interest rates, which represent monetary policy shocks, and housing variables. Figure 3 selects housing starts to represent housing supply in the theoretical channel. Figures 4-6 use housing price indexes to describe housing conditions because prices are associated with the other channels. The shaded areas illustrate the 95% confidential intervals of the responses.

[Figures 3, 4, 5, 6 about here]

With respect to how interest rate shocks affect GDP, all the figures show similar results. GDP initially drops sharply in the first two quarters. The trend reverses very quickly. By the 4th quarter after the initial shock in interest rate, its effect almost completely dissipates. Monetary policy tightening does adversely affect GDP. Its impact is only temporary. In contrast, the effect of housing shocks on GDP seem to last much longer. For the user-cost channel depicted in Figure 3, it takes about 5 quarters for the impact to dissipate. For the other channels depicted in Figures 4 – 6, it takes much longer, about 24 quarters, for the impact to dissipate. Even though their impact lasts for less time, housing supply shocks seem to have stronger effects than housing price shocks do. In this sense, different housing indicators indeed may represent different underlying mechanisms for the connections between housing and the macro economy.

In terms of the interactions between housing variables and interest rates, we also find consistent patterns across the four figures. Through this analysis, we hope to shed light on the debate about whether housing factors are autonomous. First, Figure 3 shows that housing starts do respond negatively to interest rate hikes. The effects, however, last only for about 2 – 3 quarters. On the other hand, housing supply shocks seem to have a temporarily positive effect on interest rate. Second, Figures 4 – 6 show that housing prices are unresponsive to interest rate shocks, while interest rate response to housing price shocks tend to be long-lasting and significant. Recall that the last three channels work through accumulation of aggregate mortgage balances or aggregate wealth, which supposedly will have long-term ramifications on the economy.

4.2 Forecast-Error Variance Decompositions: the US

Forecast-error variance decompositions are complementary tools to impulse response functions. They summarize the relative contributions of respective variables to forecasting a certain variable of interest. Tables 4 - 7 report these decompositions for the US. We are able to distinguish among the four channels as well as time scales. Forecast horizons analyzed are 2, 8, 16 and 32 quarters, corresponding to the very short-term and the several horizon cutoffs related to our identified time scales. The series to be forecasted are

listed in rows, while all the variables in SVARs are listed in columns. We report the decomposition results for GDP, interest rate, and housing indicators only.

[Tables 4, 5, 6, 7 about here]

Panel A in each table reports for the original data. Interest rate is always the most important factor in predicting itself across all tables. It accounts for more than 80% of the forecast error variances of itself for all the horizons and mechanisms. Similarly, housing variables generally also demonstrate strong self-predicting ability. The self-explanatory powers of housing prices, which are close to 90% in Tables 5 - 7, are stronger than that of housing starts, which is shown in Table 4 as about 70%. Short-term interest rate is the second most important factor in explaining variations in housing supply. It accounts for about 20% of its variation in the investment channel. For other channels, interest rate only accounts for less than 5% variations in housing. It is hardly true that housing factors are primarily driven by interest rate variations or monetary shocks. Among the three key variables, GDP has the weakest self-explanatory power. In Table 4, it accounts for about 70% of variation in itself. In Tables 5 – 7, this self-explanatory fraction becomes much lower at 30% to 50%. Housing is much more important than interest rate in explaining variation in GDP for channel 1. For other channels, the two factors have comparable explanatory powers.

Panels B and C report for time scales 3 and 4, representing the short-run and long-run variations within business cycles. Comparing scales 3 and 4 with the original series, the self-explained portions of the variance decompositions drop quickly as the forecast horizons increase from 2 quarters to 32 quarters for all three indicators. This highlights the importance of filtering in business cycle analysis. Both transitory variations below 8 quarters and trend component above 32 quarters are removed from the analysis. The trend component likely explains the persistent self-explanatory power of the three key variables. Removing this component enables a more accurate depiction of the dynamic relationships.

Compared with traditional filtering method, the multi-scale analysis offers an additional advantage in its distinction between short-run and long-run variations within business cycles. As we switch from the short-

run to the long-run business cycles, an interesting pattern emerges. The explanatory power of interest rate with respect to GDP decreases under the investment channel. For the other three channels, interest rate becomes more prominent in explaining variations in GDP. In other words, if channel 1 is at work, we should expect interest rate to be more important for short-run variations in GDP. Otherwise, interest rate should matter more for long-run variations in GDP. This unique feature of US data puts restrictions on future theoretical work that has time-scale based predictions.

The explanatory role of housing variables with respect to GDP also follows an interesting pattern. As we change from the short-run to the long-run, their explanatory power decreases for the investment channel, while it increases for the other three channels. In other words, housing starts seem to matter more for short-run variations of GDP, while housing prices are more relevant for long-run variations in GDP. Moreover, as the forecast horizons increase, the portions of housing variables in the variance decomposition increase consistently. These features of the data, especially those associated with particular time scales, require model builders to consider when they formulate their theoretical frameworks.

4.3 International Evidence

Given the substantial differences in industrial compositions, sizes, and political and economic institutions of OECD countries, we expect the relationship between housing and macro economy to vary significantly across countries.¹² Tables 8 to 11 report forecast error variance decompositions of GDP in OECD countries for which the required variables are available. For the collateral and credit channels, only a limited number of countries are available. Therefore, our cross-country comparisons mainly focus on the first two channels. As our main objective is to test whether housing factors are autonomous, we only report short-term interest rate and housing variables as the explanatory factors. Interest rate is used as the basis of comparison for housing variables because short-term interest rates are normally set by the monetary authorities. We also

¹² These heterogeneous characteristics make us less willing to carry out a panel VAR analysis. Panel VAR requires the underlying mechanisms to have at least some common features in order for the system to be identified. We don't want to make these assumptions. Instead, we report VAR results for individual countries.

use US results to benchmark other countries. To offer some preliminary potential explanations to the findings in Tables 8 – 11, we summarize in Table 12 a few stylized facts for the housing/household wealth/mortgage market development status for OECD countries. All the values are the averages across available time periods for these variables.

[Table 8, 9, 10, 11, 12 about here]

Results on the investment channel are reported in Table 8. This mechanism is not directly related to the housing finance system. Specifically, the mechanism characterizes how monetary policy shocks, through their effect on housing supply, can spill over to the general economy. Presumably, the relative size of housing sector will reinforce the strength of this mechanism. Indeed, countries in which residential investments account for larger fractions of GDP tend to show a bigger role of housing in predicting variations in GDP, e.g. Canada, Greece, Ireland, Switzerland, and the US. In these cases, housing is more important than interest rate in explaining GDP in both the original series and the decomposed scales. We also observe some idiosyncratic differences for the decomposed scales as well as the original series. In many cases, though, housing plays a role as important as, if not more important than, the role played by short-term interest rate. Compared with the US, not many countries show stronger effect of housing on GDP.

Table 9 shows the results on the wealth channel. Naturally, countries with higher wealth to GDP ratios and countries whose economies are more dependent on consumption are likely to offer stronger results for the importance of housing price shocks. Among G7 countries, Canada, France, Norway, UK, and the US show some positive results. These four countries indeed have more than average wealth-to-GDP and consumption-to-GDP ratios. Other countries whose housing sectors are shown to be important are Greece, Netherland, New Zealand, and Sweden. These countries do not differ systematically in terms of wealth to GDP ratios or consumption shares of GDP from other countries. More in-depth empirical investigation of the institutional or other factors that drive these results is certainly necessary. Comparing across scales, we

note that the prominence of housing price shocks increases as the time frame changes from short-run to long-run variations. Some idiosyncratic cases do exist even though the general pattern is clear. Compared to other countries, the importance of housing price shocks in the US under the wealth channel is not particularly strong. Many countries, e.g. UK, Norway, and France, have much stronger results. These features of the data should be useful for future theoretical models.

Tables 10 and 11 report the forecast error variance decompositions for the collateral channel and the credit channel. At the center of these two channels is the operation of the financial market, especially the institution of housing finance. Real estate accounts for a large fraction of total wealth. It is also widely used as collateral assets by both households and firms. For the collateral channel, most of available countries show strong roles of housing price shocks. The ratio between aggregate mortgage balance and GDP in these countries tend to be high. In the multiscale analysis, other OECD countries seem to differ from the US. Although both scales 3 and 4 matter for the US, housing price seems to matter more for scale 3 in other countries. This suggests that collateral effect, if present, is more prominent in the short-run, in contrast to the wealth effect whose presence in the long-run seems to be more conspicuous. This finding can put time-scale restrictions on theoretical models of these closely related channels. As for the credit channel, both Canada and the US show that housing price shocks are important determinants of GDP fluctuations. We should note that conclusions in these tables are only tentative as we only have a few countries in our data.

In summary, we fail to find overwhelming evidence to support the causal claim made by Leamer (2007, 2015). These findings contrast with the clear evidence shown in Section 3 that housing factors lead business cycles. Some OECD countries, especially the G7 countries, do offer support for an autonomous role played by housing factors. In these cases, housing price shocks are more important if not as important as shocks in monetary policy in predicting GDP. The distinction among the four channels of monetary transmission and that between short-run and long-run cycles enable a more complete depiction of dynamic relationships between housing and macroeconomic indicators. The investment channel seems to work in both short-run and long-run. The wealth channel works more strongly in the long-run, while collateral and credit channels

work more strongly in the short-run. These tentative findings raise more questions than they answer. They certainly put some restrictions on future theories of housing and macro economy. We also relate country-specific characteristics to the heterogeneous results in Tables 8 – 11. This is in line with the active literature on institutional explanations of the housing-macro link, e.g. Calza, Monacelli, and Stracca (2012). A complete cross-country analysis of these issues is beyond the scope of our paper.

5. Conclusion

In this paper, we investigate the claims made by Leamer (2007, 2015) that housing indicators both predict and cause macroeconomic fluctuations. We carry out two sets of analyses for OECD countries. First, we adopt a wavelet approach to characterize the lead-lag relationship between housing and macroeconomic indicators in multiple time scales. In most countries, housing variables do lead the economy. Such a result becomes stronger as we switch from the 8-16 quarters to 16-32 quarters, i.e. housing becomes a more important indicator for the relative longer term within cycles. This finding is robust to different measurements of housing and macroeconomic indicators.

The second part of our analysis focuses on the “causal” claim made by Leamer (2007, 2015). We build standard Structural VARs motivated by four popular theories about how housing affects the economy: the neoclassical theory of housing investment, wealth effects of housing assets, collateral effects of housing on consumption, and housing collateral effects on credit supply. Our results generally support an independent role of housing in amplification of business cycles at least in large G7 countries. However, the evidence is not strong enough to confirm or refute Leamer (2007, 2015)’s causal claim. In some OECD countries, housing seems to play a minor role in economic fluctuations. Heterogeneous country characteristics likely contribute to these findings.

To the best of our knowledge, we are the first to characterize the relationship between housing and business cycles using wavelet multiresolution analysis.¹³ We have found strong evidence for time scales to matter in both the US and other OECD countries. Depending on the monetary transmission channels, the effect of housing can become stronger or weaker in the long-run versus the short-run. This paper provides several stylized findings for researchers working with macroeconomic models that distinguish among time scales, among which Kydland, Rupert, and Sustek (2016) is a good example.

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¹³ We only know one empirical paper by Igan et al. (2010) on housing and macro economy that differentiates between time scales. They use the Corbae and Ouliaris (2006) filter and analyze the lead-lag relationships mainly. Our paper analyzes both lead-lag relationships and SVARs motivated by theories of monetary transmission mechanisms.

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Table 1. Variable description

Category	Variables	Abbr.	Subject	Dataset
Macroeconomy Indicators	GDP	GDP	B1_GE: Gross domestic product - expenditure approach	OECD_Quarterly National Accounts
	Industrial Production Index	IDP	Industrial production, s.a.	OECD_Key Short-Term Economic
	Unemployment Rate	UNE	Harmonised unemployment rate: all persons, s.a.	OECD_Key Short-Term Economic Indicators
Housing Indicators	Permits Issued for Dwellings	PMT	Permits issued for dwellings, s.a.	OECD_Key Short-Term Economic
	Work Started for Dwellings	STA	Work started for dwellings sa, Index	OECD_Industry and Services_Production and Sales (MEI)
	Residential Investment	INV	P51N1111: Dwellings s.a	OECD_Quarterly National Accounts
	Residential Property Price Indices(RPPIs)	PRC	Nominal house price indices, s.a.	OECD_Analytical house prices indicators
Channel Indicators	Long-term interest rates	LTR	Long-term interest rates, Per cent per annum	OECD_Monthly Monetary and Financial Statistics (MEI)
	Short-term interest rates	STR	Short-term interest rates, Per cent per annum	OECD_Monthly Monetary and Financial Statistics (MEI)
	Private Final Consumption_Household	PFC	Final consumption expenditure of households	OECD_Quarterly National Accounts
	Household Wealth	HHW	Household Sector_Gross Wealth	DataStream_Oxford Economics
	Mortgage balance	MTB	Loans for house purchasing	OECD_Households' Financial Assets and
	Marginal Tax Rate	MTR	Marginal tax rates and wedges (Combined central and sub-central government)	OECD_Marginal Personal Income Tax and Social Security Contribution Rates on Gross Labour Income

Table 2. Scale-by-scale correlations

Macroeconomy Indicators	Housing Indicators	Correlation	Scale 1: 2Q-4Q	Scale 2: 4Q-8Q	Scale 3: 8Q-16Q	Scale 4: 16Q-32Q	Trend Component: larger than 32Q
GDP	Permits Issued for Dwellings	0.11	0.01	0.11	0.20	0.25	0.44
	Work Started for Dwellings	0.13	0.06	0.16	0.30	0.39	0.34
	Residential Investment	0.37	0.16	0.27	0.45	0.61	0.71
	Residential Property Price Indices(RPPIs)	0.38	0.06	0.18	0.38	0.52	0.59
Industrial Production Index	Permits Issued for Dwellings	0.14	0.04	0.12	0.24	0.33	0.55
	Work Started for Dwellings	0.14	0.04	0.17	0.30	0.41	0.41
	Residential Investment	0.21	0.07	0.20	0.37	0.52	0.44
	Residential Property Price Indices(RPPIs)	0.17	0.04	0.17	0.27	0.29	0.29
Unemployment Rate	Permits Issued for Dwellings	-0.14	-0.05	-0.03	-0.17	-0.23	-0.51
	Work Started for Dwellings	-0.15	-0.08	-0.13	-0.23	-0.25	-0.42
	Residential Investment	-0.28	-0.02	-0.15	-0.34	-0.50	-0.57
	Residential Property Price Indices(RPPIs)	-0.33	-0.06	-0.17	-0.35	-0.44	-0.48

Table 3. Lead-Lag relationships between GDP and housing variables

Country	Abbr.	Scale 3: 8Q-16Q Cycle Component				Scale 4: 16Q-32Q Cycle Component				Scale 3+4: 8Q-32Q Cycle Component			
		Permits Issued for Dwellings	Work Started for Dwellings	Residential Investment	Residential Property Price Indices	Permits Issued for Dwellings	Work Started for Dwellings	Residential Investment	Residential Property Price Indices	Permits Issued for Dwellings	Work Started for Dwellings	Residential Investment	Residential Property Price Indices
Austria	AT	+2*	+2*	+1*	+2*	+4	+3	+1	+1*	+3	+2	+1	+2
Australia	AU	NA	NA	-1*	+3	NA	NA	0	+3	NA	NA	-1	+3
Belgium	BG	-7	+1	NA	-1	+6	+3	NA	0	-7	-8	NA	-1
Canada	CA	+2*	+1	+1	+1	+4	+4	+2	+1	+2	+1	+1	+1
Chile	CH	-4	NA	NA	NA	-3	NA	NA	NA	-3	NA	NA	NA
Czech Republic	CZ	-4	+2	0	NA	-1	-2	+1*	NA	0	-2	0	NA
Denmark	DM	0	NA	-1	0*	+3	NA	+1	+1	0	NA	-1	+1
Estonia	ES	+2	NA	+2	NA	+3	NA	+1*	NA	+2	NA	+2	NA
Finland	FL	+3*	NA	+1*	+3*	+5	NA	+2	+4	+3	NA	+1*	+2
France	FR	+1	+2*	0*	0*	+3	+3	+1*	+3*	+2	+2	0*	0
Germany	GM	+9	NA	+1	0	+6	NA	+1*	0	+8	NA	+1	0
Greece	GR	-7	NA	0	+5	-8	NA	+1	+4	-7	NA	0	+5
Hungary	HG	-3	NA	NA	NA	-4	NA	NA	NA	-3	NA	NA	NA
Iceland	IC	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Ireland	IR	-3	NA	0	0	-4	NA	0	-2	-1	NA	+1	+1
Israel	IS	NA	+1*	+2	+1	NA	+3	-10	-10	NA	+9	-10	-9
Italy	IT	NA	NA	0	-1*	NA	NA	+1	0	NA	NA	+1	-1
Japan	JP	NA	+7	NA	-1*	NA	0	NA	-2	NA	+7	NA	-1
Korea	KR	0*	NA	+2	0*	0	NA	0	-1	0	NA	+2	0
Luxembourg	LB	0	NA	-1	NA	+2	NA	-2	NA	+1	NA	0	NA
Mexico	MX	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Netherlands	NL	-1	NA	-1*	0*	-3	NA	-1	0	-1	NA	-2	-1*
Norway	NW	0	NA	0	+1*	+2	NA	0	0	-10	NA	0	+1
New Zealand	NZ	+1	-1	-4	+3	+1	+1	0	0	+1	-1	-2	+2
Poland	PL	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Portugal	PT	0*	NA	-1	+2*	+1	NA	+1	+2	+1	NA	-2	+2
Sweden	SD	NA	NA	-6	NA	NA	NA	-5	NA	NA	NA	-4	NA
Spain	SP	-10	NA	-1*	NA	+2	NA	-1	NA	-10	NA	-1	NA
Slovak Republic	SR	+2	+2*	0*	+1*	+4	+3	+1*	+2	+3	+2	0*	+1
Slovenia	SV	-10	0	0*	+2*	+4	+3	+1*	+1	+2	+2	0*	+2
Switzerland	SW	-8	NA	0	+6	+6	NA	+2	+5	+7	NA	-1	+7
Turkey	TK	-9	NA	NA	NA	+6	NA	NA	NA	-9	NA	NA	NA
United Kingdom	UK	0	+2*	-1*	0*	+3	+3*	0	+2	+1	+2*	-1	0
United States	US	NA	+2*	+1	+1	NA	+4*	+3	+1*	NA	+2*	+2	+2
Number of Available Series		25	12	26	23	25	12	26	23	25	12	26	23
Percentage of LEAD		32.00	83.33	30.77	56.52	72.00	83.33	57.69	56.52	52.00	75.00	34.62	60.87
Percentage of LAG		44.00	8.33	34.62	13.04	24.00	8.33	19.23	17.39	36.00	25.00	38.46	21.74
Percentage of Coincidence		24.00	8.33	34.62	30.43	4.00	8.33	23.08	26.09	12.00	0.00	26.92	17.39

Notes:

- * represents significant correlation at 5% level
- + represents housing variable is a leading indicator for macro economy and – represents a lagging relationship. Leading relationship is marked with light blue color, lagging with light yellow while contemporaneous relation is shown with light green.
- Numbers shown the lag/lead term at which correlation reach the maximum absolute value
- NA represents the unavailability of these data pair

Table 4. Forecast error variance decompositions for the US: Investment channel

Panel A: Original Series						
Decomposed Series	Forecast Horizon	Short-term Interest Rate	Long-term Interest Rate	User Cost of Capital	Housing Supply	GDP
Short-term Interest Rate	2	94%	2%	0%	3%	0%
	8	87%	4%	0%	5%	4%
	16	87%	4%	0%	5%	4%
	32	87%	4%	0%	5%	4%
Housing Supply	2	20%	1%	2%	76%	0%
	8	23%	2%	2%	69%	4%
	16	23%	2%	2%	69%	4%
	32	23%	2%	2%	69%	4%
GDP	2	3%	6%	0%	14%	77%
	8	6%	7%	0%	20%	67%
	16	6%	7%	0%	20%	67%
	32	6%	7%	0%	20%	67%

Panel B: Scale 3 (8Q-16Q Cycle Component)						
Decomposed Series	Forecast Horizon	Short-term Interest Rate	Long-term Interest Rate	User Cost of Capital	Housing Supply	GDP
Short-term Interest Rate	2	98%	1%	1%	0%	0%
	8	77%	10%	3%	7%	2%
	16	63%	8%	4%	19%	6%
	32	44%	7%	3%	37%	10%
Housing Supply	2	4%	1%	1%	95%	0%
	8	17%	15%	1%	63%	4%
	16	21%	14%	2%	53%	10%
	32	16%	12%	3%	56%	14%
GDP	2	18%	3%	1%	23%	55%
	8	11%	2%	2%	36%	48%
	16	6%	3%	5%	41%	45%
	32	6%	3%	6%	50%	35%

Panel C: Scale 4 (16Q-32Q Cycle Component)						
Decomposed Series	Forecast Horizon	Short-term Interest Rate	Long-term Interest Rate	User Cost of Capital	Housing Supply	GDP
Short-term Interest Rate	2	99%	0%	0%	0%	0%
	8	90%	0%	7%	2%	0%
	16	69%	5%	12%	5%	9%
	32	42%	12%	12%	18%	15%
Housing Supply	2	22%	7%	6%	65%	0%
	8	43%	7%	2%	48%	0%
	16	44%	8%	6%	38%	4%
	32	49%	4%	13%	24%	10%
GDP	2	4%	12%	5%	9%	70%
	8	1%	8%	12%	26%	53%
	16	2%	22%	17%	24%	35%
	32	11%	21%	19%	27%	22%

Table 5. Forecast error variance decompositions for the US: Wealth channel

Panel A: Original Series							
Decomposed Series	Forecast Horizon	Short-term Interest Rate	User Cost of Capital	Housing Price	Household Asset	Final Private Consumption	GDP
Short-term Interest Rate	2	92%	1%	2%	3%	1%	1%
	8	84%	1%	4%	5%	2%	4%
	16	83%	1%	5%	5%	2%	4%
	32	83%	1%	5%	5%	2%	4%
Housing Price	2	4%	0%	93%	0%	1%	1%
	8	2%	0%	95%	0%	1%	1%
	16	2%	1%	96%	0%	1%	1%
	32	2%	1%	96%	0%	0%	1%
GDP	2	9%	1%	2%	8%	40%	40%
	8	13%	1%	9%	12%	34%	30%
	16	13%	1%	15%	11%	32%	28%
	32	12%	1%	17%	11%	31%	27%
Panel B: Scale 3 (8Q-16Q Cycle Component)							
Decomposed Series	Forecast Horizon	Short-term Interest Rate	User Cost of Capital	Housing Price	Household Asset	Final Private Consumption	GDP
Short-term Interest Rate	2	98%	0%	0%	1%	1%	0%
	8	72%	2%	4%	8%	9%	5%
	16	41%	3%	5%	20%	18%	13%
	32	29%	4%	10%	22%	17%	19%
Housing Price	2	0%	5%	94%	0%	1%	0%
	8	2%	4%	77%	7%	10%	1%
	16	6%	4%	51%	23%	15%	1%
	32	11%	9%	25%	46%	9%	1%
GDP	2	26%	2%	2%	16%	41%	13%
	8	15%	2%	7%	30%	37%	9%
	16	8%	3%	7%	49%	25%	7%
	32	10%	5%	8%	49%	20%	8%
Panel C: Scale 4 (16Q-32Q Cycle Component)							
Decomposed Series	Forecast Horizon	Short-term Interest Rate	User Cost of Capital	Housing Price	Household Asset	Final Private Consumption	GDP
Short-term Interest Rate	2	100%	0%	0%	0%	0%	0%
	8	86%	6%	7%	0%	1%	0%
	16	75%	11%	11%	1%	1%	1%
	32	47%	18%	15%	12%	2%	7%
Housing Price	2	5%	21%	74%	0%	0%	0%
	8	12%	31%	52%	2%	3%	1%
	16	20%	26%	33%	16%	5%	1%
	32	26%	25%	23%	16%	8%	2%
GDP	2	44%	5%	0%	41%	7%	2%
	8	38%	2%	13%	43%	2%	2%
	16	34%	5%	25%	32%	2%	3%
	32	23%	18%	36%	19%	1%	3%

Table 6. Forecast error variance decompositions for the US: Collateral channel

Panel A: Original Series							
Decomposed Series	Forecast Horizon	Shortterm Interest Rate	User Cost of Capital	Housing Price	Mortgage Balance	Final Private Consumption	GDP
Short-term Interest Rate	2	95%	1%	0%	1%	1%	2%
	8	85%	2%	2%	1%	2%	7%
	16	84%	2%	4%	1%	2%	7%
	32	84%	2%	4%	1%	2%	7%
Housing Price	2	2%	4%	93%	0%	0%	1%
	8	1%	2%	93%	0%	1%	2%
	16	1%	2%	93%	0%	2%	2%
	32	1%	2%	93%	0%	2%	2%
GDP	2	5%	1%	1%	5%	40%	49%
	8	10%	1%	14%	4%	39%	33%
	16	9%	1%	23%	3%	35%	29%
	32	9%	1%	26%	3%	33%	28%
Panel B: Scale 3 (8Q-16Q Cycle Component)							
Decomposed Series	Forecast Horizon	Shortterm Interest Rate	User Cost of Capital	Housing Price	Mortgage Balance	Final Private Consumption	GDP
Short-term Interest Rate	2	100%	0%	0%	0%	0%	0%
	8	91%	1%	1%	3%	3%	1%
	16	72%	2%	3%	9%	11%	3%
	32	45%	2%	13%	12%	23%	5%
Housing Price	2	3%	1%	96%	1%	0%	0%
	8	3%	1%	75%	10%	11%	0%
	16	4%	1%	41%	27%	26%	1%
	32	7%	5%	21%	29%	35%	4%
GDP	2	14%	1%	1%	5%	61%	19%
	8	8%	2%	4%	7%	62%	17%
	16	5%	3%	11%	8%	60%	14%
	32	5%	3%	25%	6%	50%	10%
Panel C: Scale 4 (16Q-32Q Cycle Component)							
Decomposed Series	Forecast Horizon	Shortterm Interest Rate	User Cost of Capital	Housing Price	Mortgage Balance	Final Private Consumption	GDP
Short-term Interest Rate	2	100%	0%	0%	0%	0%	0%
	8	97%	0%	2%	0%	0%	0%
	16	85%	1%	13%	1%	1%	0%
	32	56%	9%	26%	5%	2%	1%
Housing Price	2	13%	4%	83%	0%	0%	0%
	8	13%	2%	81%	1%	2%	1%
	16	16%	4%	67%	4%	7%	2%
	32	13%	15%	44%	10%	13%	5%
GDP	2	33%	10%	0%	7%	41%	9%
	8	19%	6%	21%	7%	36%	9%
	16	17%	16%	32%	6%	21%	7%
	32	8%	11%	52%	12%	10%	7%

Table 7. Forecast error variance decompositions for the US: Credit channel

Panel A: Original Series							
Decomposed Series	Forecast Horizon	Shortterm Interest Rate	User Cost of Capital	Housing Price	Credit Spread	Final Private Consumption	GDP
Short-term Interest Rate	2	90%	0%	2%	3%	6%	0%
	8	85%	0%	6%	3%	6%	0%
	16	83%	0%	8%	3%	6%	0%
	32	82%	0%	9%	3%	5%	0%
Housing Price	2	2%	1%	95%	0%	0%	0%
	8	2%	1%	94%	0%	2%	1%
	16	2%	1%	93%	0%	2%	1%
	32	2%	1%	93%	0%	2%	1%
GDP	2	13%	2%	2%	6%	38%	40%
	8	10%	1%	15%	6%	35%	32%
	16	9%	1%	24%	6%	31%	29%
	32	9%	1%	27%	6%	30%	28%

Panel B: Scale 3 (8Q-16Q Cycle Component)							
Decomposed Series	Forecast Horizon	Shortterm Interest Rate	User Cost of Capital	Housing Price	Credit Spread	Final Private Consumption	GDP
Short-term Interest Rate	2	98%	0%	0%	0%	2%	0%
	8	70%	1%	5%	1%	22%	2%
	16	36%	2%	8%	2%	47%	5%
	32	31%	3%	13%	2%	44%	7%
Housing Price	2	2%	0%	97%	0%	1%	0%
	8	2%	9%	61%	5%	23%	0%
	16	4%	17%	30%	8%	40%	1%
	32	12%	12%	20%	16%	38%	2%
GDP	2	5%	14%	3%	0%	68%	10%
	8	2%	14%	7%	1%	72%	4%
	16	4%	11%	9%	4%	70%	2%
	32	10%	9%	12%	11%	56%	2%

Panel C: Scale 4 (16Q-32Q Cycle Component)							
Decomposed Series	Forecast Horizon	Shortterm Interest Rate	User Cost of Capital	Housing Price	Credit Spread	Final Private Consumption	GDP
Short-term Interest Rate	2	96%	2%	0%	1%	0%	0%
	8	59%	7%	6%	15%	10%	4%
	16	39%	25%	4%	16%	12%	4%
	32	33%	29%	3%	25%	8%	3%
Housing Price	2	3%	36%	58%	2%	1%	0%
	8	27%	7%	35%	17%	9%	4%
	16	24%	20%	19%	26%	7%	3%
	32	27%	16%	12%	36%	5%	3%
GDP	2	0%	12%	7%	5%	71%	5%
	8	2%	55%	5%	3%	32%	3%
	16	14%	44%	7%	9%	24%	2%
	32	18%	44%	7%	21%	9%	2%

Table 8. Forecast error variance decompositions for all available countries: Investment channel

Response Variable: GDP			Original Series				Scale 3 (8Q-16Q Cycle Component)				Scale 4 (16Q-32Q Cycle Component)			
			Forecast Horizon				Forecast Horizon				Forecast Horizon			
Country	Abbr.	Impulse Variable	2	8	16	32	2	8	16	32	2	8	16	32
Australia	AU	Short-term IR	3%	3%	3%	3%	7%	9%	18%	28%	17%	10%	10%	6%
Australia	AU	Housing	6%	11%	11%	11%	7%	9%	11%	12%	2%	1%	1%	4%
Austria	AT	Short-term IR	23%	22%	22%	22%	58%	32%	27%	25%	68%	83%	41%	23%
Austria	AT	Housing	5%	5%	5%	5%	1%	3%	4%	6%	15%	4%	19%	17%
Belgium	BG	Short-term IR	19%	3%	18%	3%	64%	53%	38%	39%	17%	9%	17%	26%
Belgium	BG	Housing	0%	1%	1%	1%	10%	15%	22%	20%	15%	11%	22%	25%
Canada	CA	Short-term IR	0%	1%	1%	1%	2%	2%	2%	2%	12%	22%	12%	10%
Canada	CA	Housing	14%	19%	19%	19%	34%	40%	42%	41%	31%	30%	16%	15%
Denmark	DM	Short-term IR	9%	14%	14%	14%	22%	45%	47%	39%	3%	27%	24%	54%
Denmark	DM	Housing	1%	7%	7%	7%	7%	6%	9%	15%	36%	8%	29%	17%
Finland	FL	Short-term IR	1%	2%	2%	2%	13%	11%	14%	25%	68%	56%	48%	46%
Finland	FL	Housing	4%	9%	9%	9%	2%	5%	6%	7%	0%	1%	4%	7%
France	FR	Short-term IR	0%	1%	1%	1%	45%	38%	32%	28%	26%	42%	30%	23%
France	FR	Housing	1%	1%	1%	1%	0%	0%	1%	2%	19%	13%	8%	9%
Germany	GM	Short-term IR	20%	20%	20%	20%	8%	3%	3%	3%	3%	2%	3%	8%
Germany	GM	Housing	0%	1%	1%	1%	10%	8%	6%	5%	19%	5%	3%	11%
Greece	GR	Short-term IR	1%	3%	3%	3%	7%	4%	4%	12%	29%	34%	33%	37%
Greece	GR	Housing	8%	7%	7%	7%	5%	9%	19%	17%	22%	33%	29%	28%
Hungary	HG	Short-term IR	1%	3%	3%	3%	14%	8%	41%	34%	5%	12%	11%	40%
Hungary	HG	Housing	4%	6%	6%	6%	7%	5%	4%	6%	3%	11%	13%	17%
Ireland	IR	Short-term IR	6%	6%	6%	6%	5%	3%	3%	20%	4%	1%	2%	7%
Ireland	IR	Housing	11%	18%	18%	18%	2%	42%	61%	27%	11%	1%	10%	10%
Israel	IS	Short-term IR	8%	8%	8%	8%	6%	13%	30%	40%	2%	6%	4%	1%
Israel	IS	Housing	6%	6%	6%	6%	31%	37%	28%	23%	7%	17%	38%	32%
Italy	IT	Short-term IR	19%	16%	16%	16%	49%	59%	47%	32%	61%	31%	14%	16%
Italy	IT	Housing	13%	11%	11%	11%	0%	9%	20%	16%	7%	29%	16%	14%
Japan	JP	Short-term IR	5%	5%	5%	5%	2%	2%	7%	31%	63%	28%	15%	11%
Japan	JP	Housing	16%	15%	15%	15%	22%	16%	14%	9%	1%	4%	47%	35%
Luxembourg	LB	Short-term IR	3%	4%	4%	4%	20%	9%	8%	11%	78%	60%	47%	61%
Luxembourg	LB	Housing	16%	16%	16%	16%	39%	23%	14%	25%	2%	5%	4%	3%
Netherlands	NL	Short-term IR	35%	31%	31%	31%	84%	73%	58%	50%	57%	12%	18%	22%
Netherlands	NL	Housing	0%	0%	0%	0%	1%	1%	3%	4%	20%	5%	13%	11%
New Zealand	NZ	Short-term IR	4%	6%	6%	6%	0%	2%	8%	10%	9%	1%	2%	3%
New Zealand	NZ	Housing	3%	4%	4%	4%	6%	3%	8%	24%	0%	0%	1%	2%
Norway	NW	Short-term IR	0%	1%	1%	1%	0%	0%	3%	9%	7%	4%	4%	12%
Norway	NW	Housing	1%	1%	1%	1%	3%	8%	24%	34%	59%	60%	47%	43%
Portugal	PT	Short-term IR	7%	10%	11%	11%	38%	34%	29%	22%	74%	58%	48%	27%
Portugal	PT	Housing	7%	9%	9%	9%	3%	9%	18%	19%	3%	0%	4%	8%
Spain	SP	Short-term IR	15%	6%	6%	6%	39%	19%	12%	9%	55%	7%	25%	21%
Spain	SP	Housing	1%	9%	8%	8%	0%	20%	31%	42%	10%	10%	8%	7%
Sweden	SD	Short-term IR	25%	23%	23%	23%	48%	32%	24%	18%	34%	29%	19%	13%
Sweden	SD	Housing	4%	5%	5%	5%	8%	17%	25%	21%	18%	14%	25%	30%
Switzerland	SW	Short-term IR	11%	9%	9%	9%	3%	8%	13%	12%	77%	79%	80%	77%
Switzerland	SW	Housing	3%	15%	15%	15%	21%	23%	24%	25%	2%	3%	4%	7%
United Kingdom	UK	Short-term IR	5%	6%	6%	6%	14%	16%	17%	23%	0%	5%	6%	8%
United Kingdom	UK	Housing	6%	5%	5%	5%	7%	6%	8%	14%	0%	0%	0%	0%
United States	US	Short-term IR	3%	6%	6%	6%	18%	11%	6%	6%	4%	1%	2%	11%
United States	US	Housing	14%	20%	20%	20%	23%	36%	41%	50%	9%	26%	24%	27%

Table 9. Forecast error variance decompositions for all available countries: Wealth channel

Response Variable: GDP			Original Series				Scale 3				Scale 4			
			Forecast Horizon				Forecast Horizon				Forecast Horizon			
Country	Abbr.	Impulse Variable	2	8	16	32	2	8	16	32	2	8	16	32
Austria	AT	Short-term IR	20%	15%	15%	15%	83%	57%	44%	36%	2%	3%	5%	9%
Austria	AT	Housing	7%	5%	5%	5%	7%	21%	22%	20%	49%	3%	11%	14%
Canada	CA	Short-term IR	0%	2%	2%	2%	6%	2%	3%	3%	29%	21%	14%	10%
Canada	CA	Housing	3%	4%	4%	4%	39%	24%	14%	11%	27%	15%	37%	33%
Denmark	DM	Short-term IR	3%	16%	16%	16%	17%	17%	24%	25%	15%	34%	32%	18%
Denmark	DM	Housing	9%	8%	8%	8%	13%	18%	25%	33%	0%	1%	7%	31%
Finland	FL	Short-term IR	29%	28%	28%	28%	68%	31%	24%	46%	93%	68%	74%	68%
Finland	FL	Housing	10%	18%	18%	18%	26%	41%	42%	20%	0%	1%	1%	3%
France	FR	Short-term IR	12%	11%	12%	12%	54%	20%	19%	45%	85%	71%	73%	58%
France	FR	Housing	14%	19%	20%	21%	21%	20%	17%	10%	6%	2%	3%	13%
Germany	GM	Short-term IR	23%	21%	21%	21%	50%	44%	31%	23%	48%	42%	43%	30%
Germany	GM	Housing	4%	6%	7%	8%	1%	3%	8%	15%	7%	5%	4%	6%
Greece	GR	Short-term IR	2%	3%	3%	3%	18%	34%	45%	47%	20%	16%	17%	14%
Greece	GR	Housing	16%	31%	35%	36%	5%	4%	11%	13%	25%	32%	31%	43%
Italy	IT	Short-term IR	17%	18%	20%	20%	74%	72%	63%	59%	44%	12%	8%	9%
Italy	IT	Housing	6%	10%	10%	10%	7%	10%	14%	12%	0%	3%	8%	17%
Netherlands	NL	Short-term IR	40%	28%	25%	24%	74%	58%	42%	41%	11%	78%	74%	84%
Netherlands	NL	Housing	7%	25%	31%	34%	2%	13%	17%	11%	21%	5%	4%	5%
New Zealand	NZ	Short-term IR	6%	6%	6%	6%	34%	41%	42%	44%	11%	15%	8%	10%
New Zealand	NZ	Housing	8%	11%	11%	11%	28%	26%	26%	27%	21%	18%	15%	13%
Norway	NW	Short-term IR	0%	9%	9%	9%	7%	5%	6%	4%	68%	70%	66%	45%
Norway	NW	Housing	12%	15%	15%	15%	3%	6%	19%	28%	14%	7%	7%	6%
Portugal	PT	Short-term IR	6%	14%	16%	16%	4%	20%	31%	30%	53%	81%	76%	76%
Portugal	PT	Housing	1%	8%	8%	8%	1%	16%	14%	16%	16%	12%	10%	7%
Spain	SP	Short-term IR	3%	16%	20%	21%	19%	18%	12%	12%	2%	4%	13%	24%
Spain	SP	Housing	10%	13%	12%	12%	1%	13%	17%	24%	7%	1%	1%	6%
Sweden	SD	Short-term IR	9%	11%	11%	11%	52%	24%	21%	43%	71%	12%	35%	32%
Sweden	SD	Housing	19%	20%	20%	20%	3%	21%	19%	14%	0%	6%	4%	10%
United Kingdom	UK	Short-term IR	1%	4%	4%	4%	18%	17%	16%	38%	29%	7%	7%	12%
United Kingdom	UK	Housing	3%	16%	17%	17%	14%	13%	12%	9%	22%	22%	17%	10%
United States	US	Short-term IR	9%	13%	13%	12%	26%	15%	8%	10%	44%	38%	34%	23%
United States	US	Housing	2%	9%	15%	17%	2%	7%	7%	8%	0%	13%	25%	36%

Table 10. Forecast error variance decompositions for all available countries: Collateral channel

Response Variable: GDP			Original Series				Scale 3				Scale 4			
			Forecast Horizon				Forecast Horizon				Forecast Horizon			
Country	Abbr.	Impulse Variable	2	8	16	32	2	8	16	32	2	8	16	32
Canada	CA	Short-term IR	0%	1%	1%	1%	21%	14%	12%	9%	31%	8%	16%	18%
Canada	CA	Housing	7%	10%	10%	10%	28%	16%	8%	9%	17%	4%	9%	6%
Denmark	DM	Short-term IR	1%	18%	18%	18%	15%	6%	6%	8%	3%	6%	21%	11%
Denmark	DM	Housing	19%	20%	20%	20%	6%	3%	2%	34%	25%	23%	18%	35%
Germany	GM	Short-term IR	29%	27%	26%	26%	68%	26%	24%	19%	7%	3%	5%	5%
Germany	GM	Housing	2%	4%	5%	5%	14%	52%	51%	52%	6%	1%	1%	4%
Israel	IS	Short-term IR	6%	6%	6%	6%	8%	9%	15%	18%	18%	69%	53%	63%
Israel	IS	Housing	7%	6%	6%	6%	18%	39%	27%	26%	5%	18%	21%	18%
New Zealand	NZ	Short-term IR	6%	7%	7%	7%	32%	33%	31%	33%	20%	33%	25%	23%
New Zealand	NZ	Housing	9%	13%	13%	13%	54%	47%	45%	40%	3%	2%	4%	5%
Spain	SP	Short-term IR	5%	16%	19%	20%	34%	32%	36%	15%	0%	1%	10%	13%
Spain	SP	Housing	6%	12%	15%	16%	23%	29%	21%	12%	21%	2%	7%	8%
United States	US	Short-term IR	5%	10%	9%	9%	14%	8%	5%	5%	33%	19%	17%	8%
United States	US	Housing	1%	14%	23%	26%	1%	4%	11%	25%	0%	21%	32%	52%

Table 11. Forecast error variance decompositions for all available countries: Credit channel

Response Variable: GDP			Original Series				Scale 3				Scale 4			
			Forecast Horizon				Forecast Horizon				Forecast Horizon			
Country	Abbr.	Impulse Variable	2	8	16	32	2	8	16	32	2	8	16	32
Canada	CA	Short-term IR	1%	1%	1%	1%	18%	8%	8%	11%	9%	13%	13%	11%
Canada	CA	Housing	3%	5%	5%	5%	29%	26%	18%	16%	2%	4%	3%	4%
United States	US	Short-term IR	13%	10%	9%	9%	5%	2%	4%	10%	0%	2%	14%	18%
United States	US	Housing	2%	15%	24%	27%	3%	7%	9%	12%	7%	5%	7%	7%

Table 12. Characteristics of national housing/household/consumption/mortgage market

Country	Residential Investment/GDP	Household Wealth/GDP	Final Consumption Expenditure of Household/GDP	Outstanding Mortgage Balance/GDP
Austria	0.05	7.45	0.52	2.65
Australia	0.05	6.52	NA	1.32
Belgium	NA	NA	0.51	NA
Canada	0.06	9.31	0.54	1.78
Chile	NA	NA	0.61	NA
Czech Republic	0.03	NA	0.49	NA
Denmark	0.05	8.82	0.47	3.82
Estonia	0.04	NA	0.53	1.24
Finland	0.06	4.08	0.49	NA
France	0.06	7.24	0.55	1.38
Germany	0.06	6.14	0.55	1.67
Greece	0.07	5.52	0.65	1.33
Hungary	NA	3.52	0.51	0.33
Iceland	NA	NA	NA	NA
Ireland	0.07	6.27	NA	NA
Israel	0.06	NA	0.54	0.84
Italy	0.05	9.15	0.60	0.92
Japan	NA	12.00	0.55	1.46
Korea	0.05	6.71	0.55	NA
Luxembourg	0.03	NA	0.35	1.51
Mexico	NA	1.94	NA	NA
Netherlands	0.05	10.21	0.47	4.01
Norway	0.05	9.31	0.57	NA
New Zealand	0.04	4.05	0.44	1.73
Poland	NA	3.25	0.61	0.58
Portugal	0.05	7.29	0.63	NA
Sweden	0.03	6.50	0.55	NA
Spain	0.03	NA	0.54	0.52
Slovak Republic	0.08	NA	0.58	1.89
Slovenia	0.03	7.65	0.45	2.42
Switzerland	0.10	13.47	NA	NA
Turkey	NA	NA	NA	0.18
United Kingdom	0.03	9.85	0.62	NA
United States	0.04	12.13	0.63	1.52

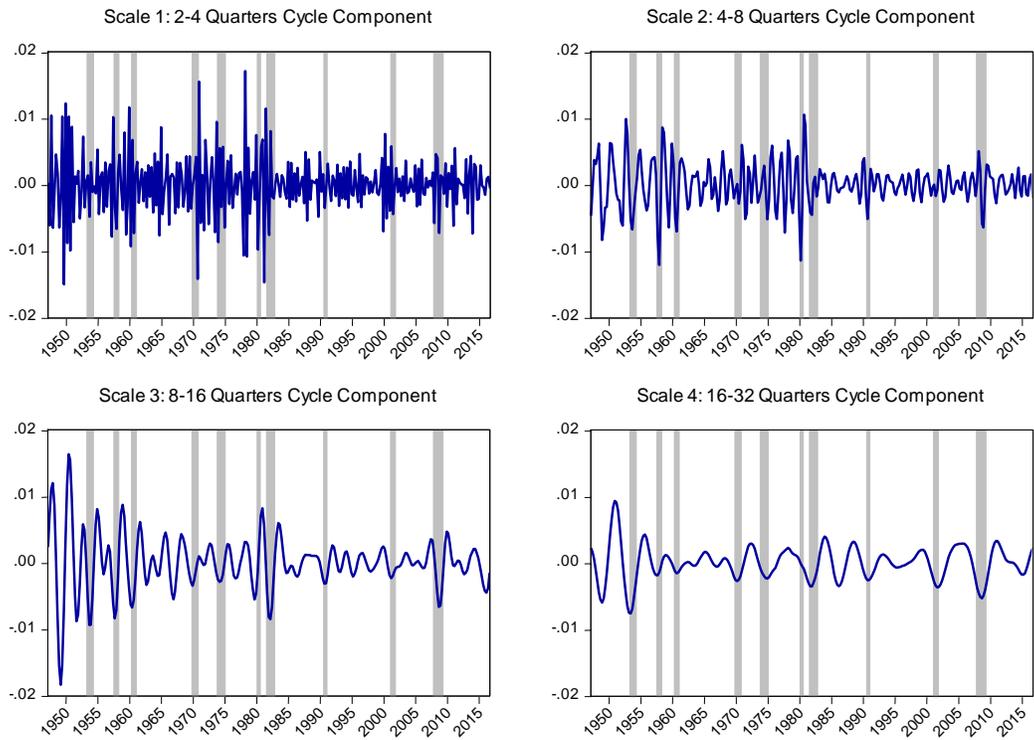


Figure 1a. Cycle component of US GDP (log-difference)

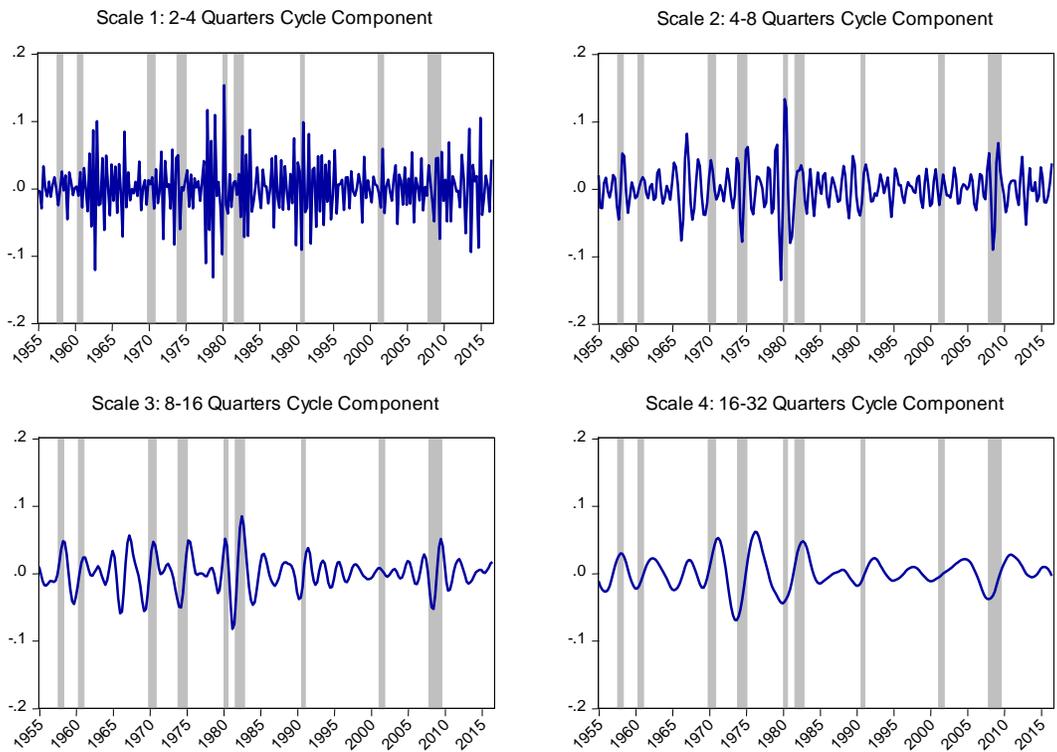


Figure 1b. Cycle component of US work started for dwellings (log-difference)

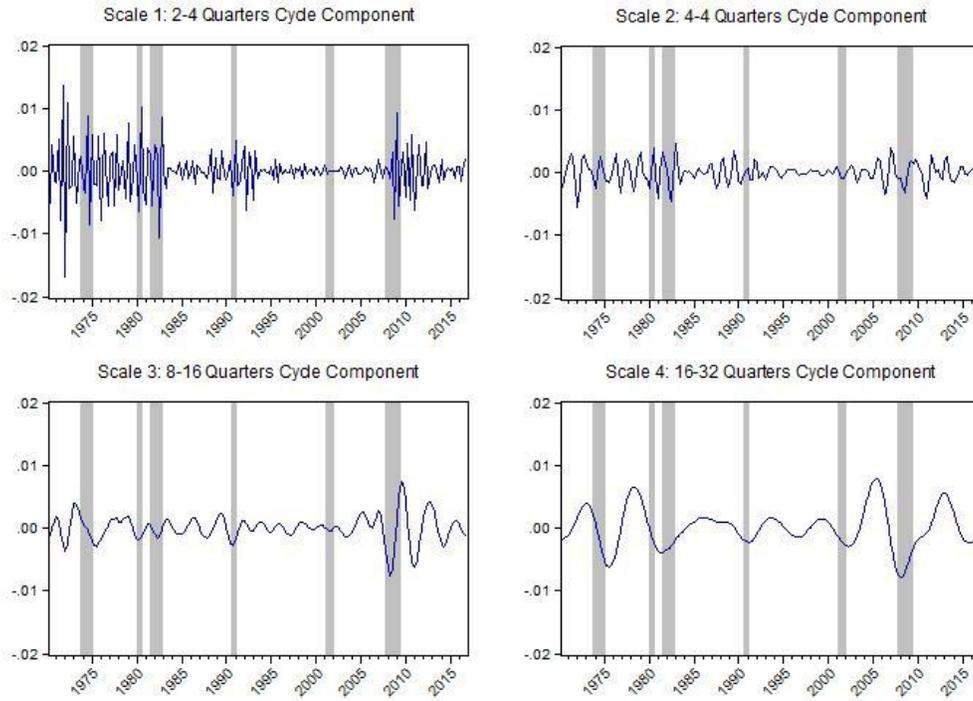


Figure 1c. Cycle component of US housing price index (log-difference)

Figure 1. Multiresolution decomposition of US GDP, work started for dwellings and housing price index

(*Shaded regions are NBER recessions.)

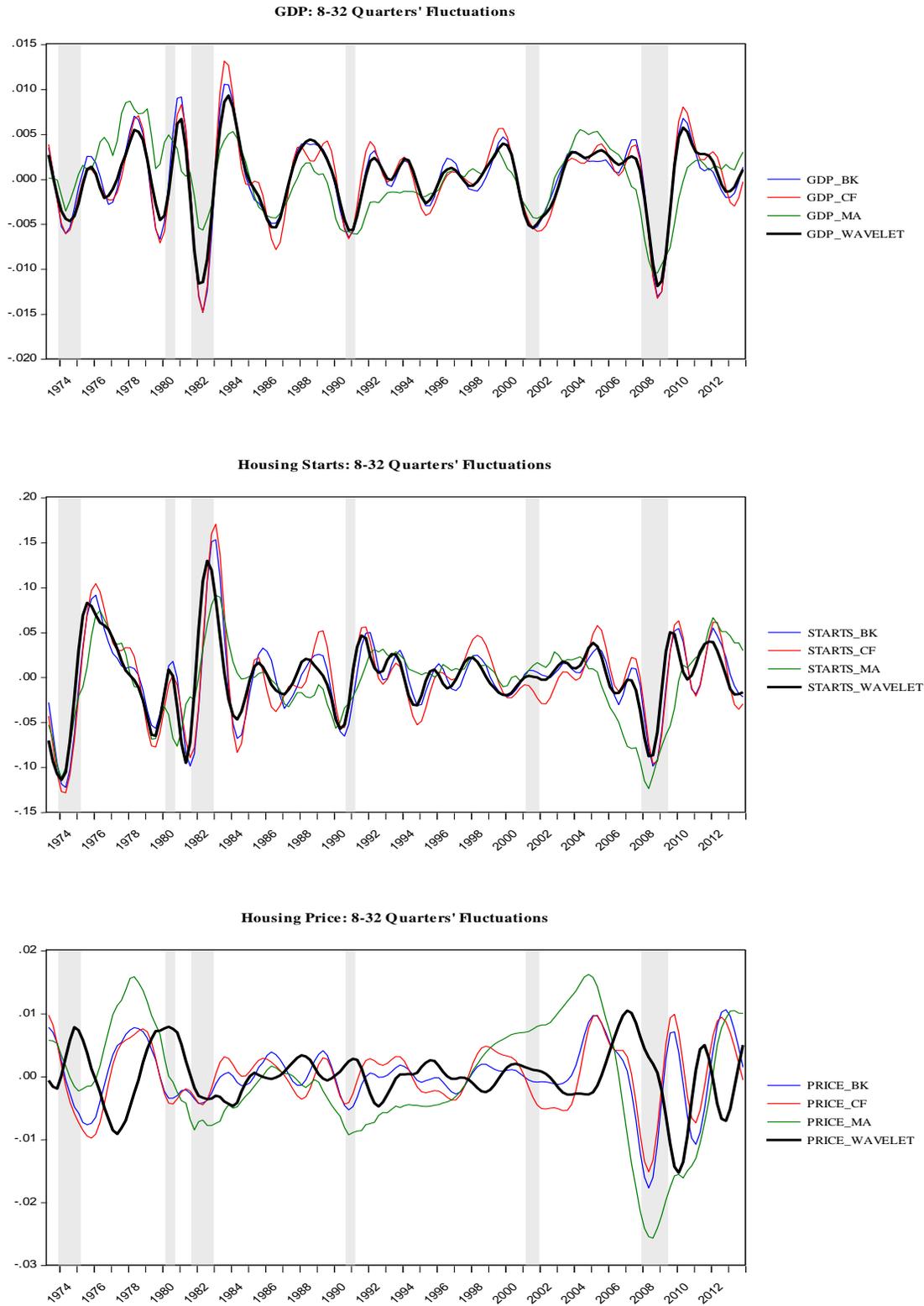
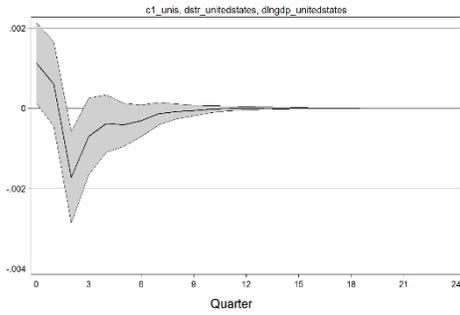
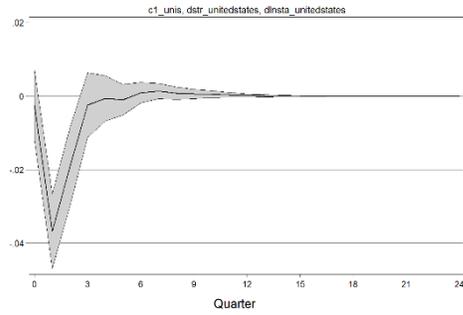


Figure 2. Filters Comparison for US GDP, work started for dwellings and housing price index

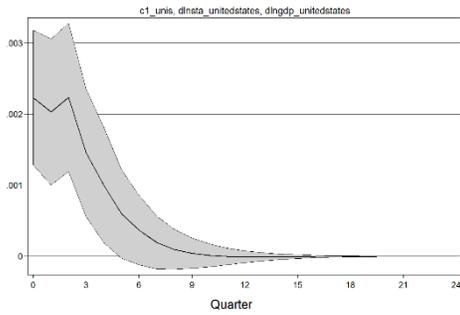
(*Shaded regions are NBER recessions.)



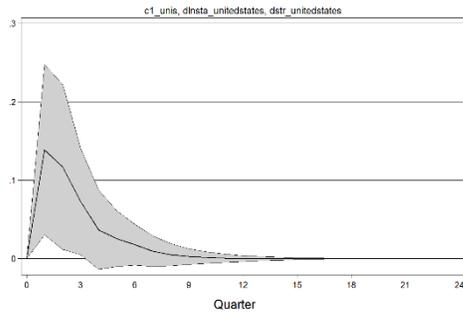
3a. GDP Responses to Short-term Interest Rate Shocks



3b. Housing Supply Responses to Short-term Interest Rate Shocks

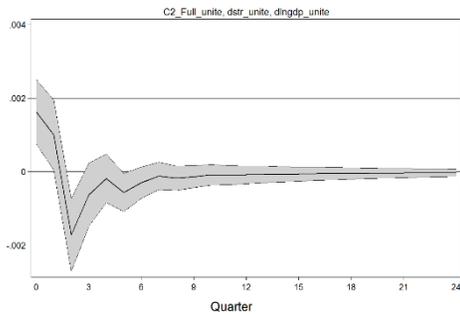


3c. GDP Responses to Housing Supply Shocks

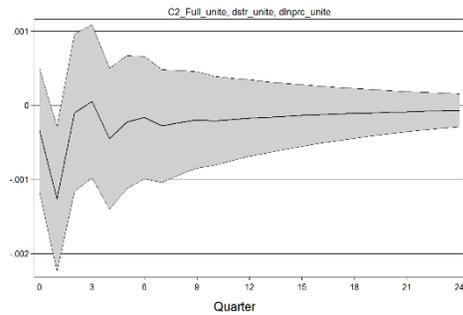


3d. Short-term Interest Rate Responses to Housing Supply Shocks

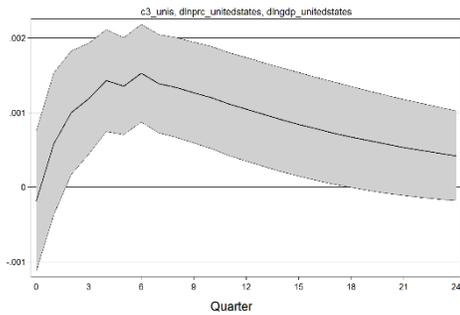
Figure 3. Impulse responses of interest rate, GDP, and housing starts: Investment channel



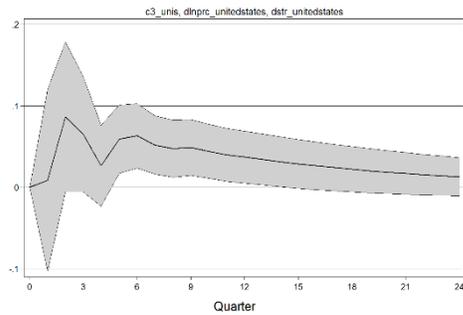
4a. GDP Responses to Short-term Interest Rate Shocks



4b. Housing Price Responses to Short-term Interest Rate Shocks

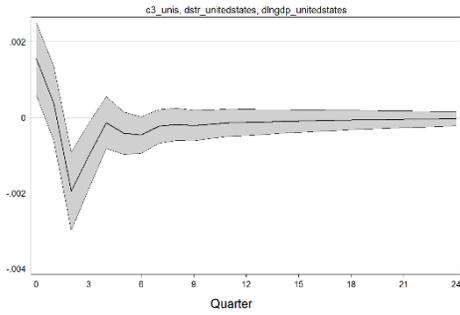


4c. GDP Responses to Housing Price Shocks

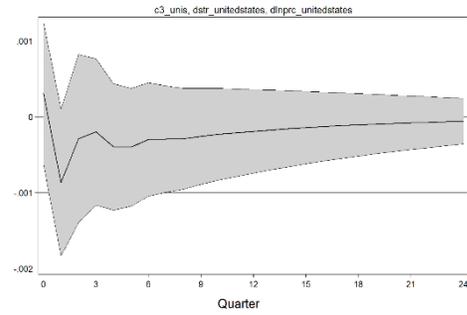


4d. Short-term Interest Rate Responses to Housing Price Shocks

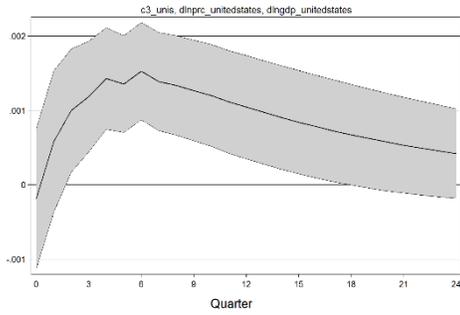
Figure 4. Impulse responses of interest rate, GDP, and housing prices: Wealth channel



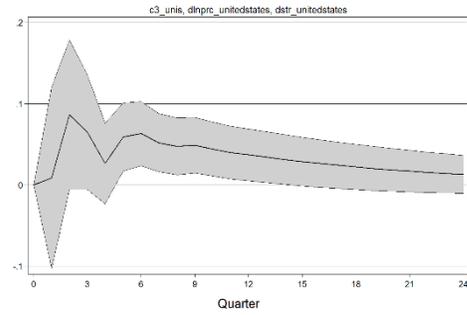
5a. GDP Responses to Short-term Interest Rate Shocks



5b. Housing Price Responses to Short-term Interest Rate Shocks

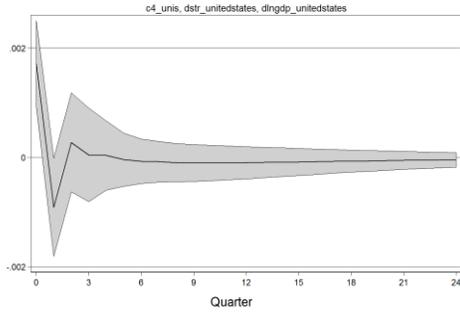


5c. GDP Responses to Housing Price Shocks

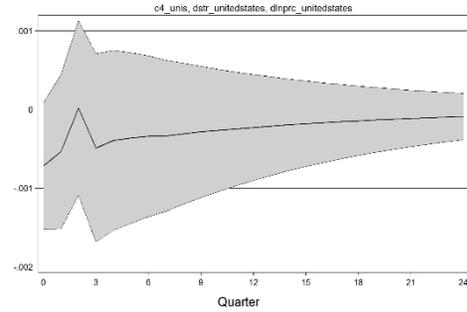


5d. Short-term Interest Rate Responses to Housing Price Shocks

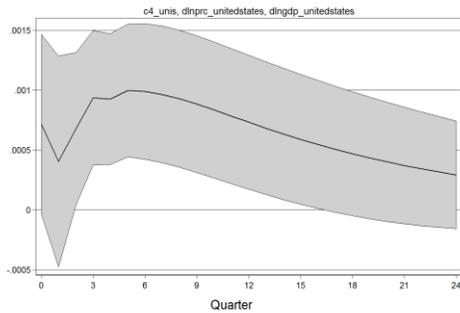
Figure 5. Impulse responses of interest rate, GDP, and housing prices: Collateral channel



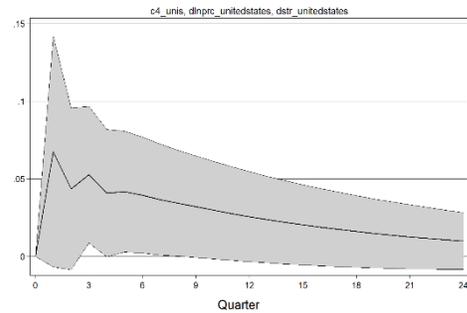
6a. GDP Responses to Short-term Interest Rate Shocks



6b. Housing Price Responses to Short-term Interest Rate Shocks



6c. GDP Responses to Housing Price Shocks



6d. Short-term Interest Rate Responses to Housing Price Shocks

Figure 6. Impulse responses of interest rate, GDP, and housing prices: Credit channel

Appendix

Table A.1: Country list with sample starting time point

Country	Abbr.	GDP	Industrial Production Index	Unemployment Rate	Permits Issued for Dwellings	Work Started for Dwellings	Residential Investment	Residential Property Price Indices	Short-term Interest Rate	Long-term Interest Rate	Personal Final Consumption	Household Wealth	Mortgage Balance	User Cost	Credit Spread
Austria	AT	Q3-1959	Q3-1974	Q3-1966	Q1-1955	Q3-1965	Q3-1959	Q1-1970	Q1-1968	Q3-1969	NA	Q2-1988	Q1-1995	Q4-1969	Q2-2004
Australia	AU	Q1-1996	Q1-1955	Q1-1993	NA	NA	Q1-1996	Q1-2000	Q3-1989	Q1-1990	Q1-1996	Q4-1980	Q1-2006	Q2-1990	NA
Belgium	BG	Q1-1995	Q1-1955	Q1-1983	Q1-1968	Q1-1968	NA	Q1-1970	Q1-1958	Q1-1955	Q1-1995	NA	NA	Q2-1956	NA
Canada	CA	Q1-1981	Q1-1961	Q1-1955	Q1-1948	Q1-1956	Q1-1981	Q1-1970	Q1-1956	Q1-1955	Q1-1981	Q1-1990	Q1-1990	Q2-1956	Q2-1992
Chile	CH	Q1-1996	Q1-1991	Q1-1986	Q1-1991	NA	NA	Q1-2002	Q3-1997	Q3-2004	Q1-1996	Q1-2004	NA	Q4-2004	NA
Czech Republic	CZ	Q1-1995	Q1-1990	Q1-1993	Q1-1999	Q1-1996	Q1-1995	Q1-2008	Q1-1993	Q2-2000	Q1-1995	NA	NA	Q3-2000	NA
Denmark	DM	Q1-1995	Q1-1974	Q1-1983	Q1-1955	NA	Q1-1995	Q1-1970	Q1-1987	Q1-1987	Q1-1995	Q4-1994	Q3-2000	Q2-1987	NA
Estonia	ES	Q1-1995	Q1-1998	Q1-1997	Q1-1998	NA	Q1-1995	Q1-2005	Q1-1996	NA	Q1-1995	NA	Q1-2004	NA	NA
Finland	FL	Q1-1990	Q1-1958	Q1-1988	Q2-1955	NA	Q1-1990	Q1-1970	Q1-1987	Q1-1988	Q1-1990	Q4-1995	NA	Q2-1988	NA
France	FR	Q1-1949	Q1-1956	Q1-1983	Q1-1955	Q1-1974	Q1-1980	Q1-1970	Q1-1970	Q1-1960	Q1-1949	Q4-1994	Q1-2003	Q2-1960	NA
Germany	GM	Q1-1991	Q1-1958	Q1-1991	Q1-1979	NA	Q1-1991	Q1-1970	Q1-1960	Q3-1956	Q1-1991	Q1-1980	Q1-1999	Q4-1956	NA
Greece	GR	Q1-1995	Q1-1962	Q2-1998	Q1-1995	NA	Q1-1995	Q1-1997	Q2-1994	Q3-1997	Q1-1995	Q4-1995	Q1-2005	Q4-1997	NA
Hungary	HG	Q1-1995	Q1-1985	Q1-1996	Q1-1998	NA	NA	Q1-2007	Q1-1991	Q2-1999	Q1-1995	Q1-1991	Q4-1989	Q3-1999	NA
Iceland	IC	Q1-1997	Q1-1998	Q1-2003	NA	NA	NA	Q1-2005	Q1-1988	Q1-1994	Q1-1997	NA	NA	Q2-1994	NA
Ireland	IR	Q1-1997	Q3-1975	Q1-1983	Q1-1992	NA	Q1-1997	Q1-1970	Q1-1984	Q1-1971	Q1-1997	Q1-2002	NA	Q2-1971	NA
Israel	IS	Q1-1995	Q1-1990	Q1-1995	Q1-2002	Q1-1995	Q1-1995	Q1-1994	Q1-1992	Q1-1997	Q1-1995	NA	Q1-2001	Q2-1997	NA
Italy	IT	Q1-1995	Q1-1955	Q1-1983	NA	NA	Q1-1995	Q1-1970	Q4-1978	Q2-1991	Q1-1995	Q1-1980	Q1-2008	Q3-1991	NA
Japan	JP	Q1-1994	Q1-1955	Q1-1955	NA	Q1-1955	NA	Q1-1960	Q2-2002	Q1-1989	Q1-1994	Q1-1980	Q1-1998	Q2-1989	Q2-2002
Korea	KR	Q1-1960	Q1-1989	Q1-1990	Q1-1990	NA	Q1-1970	Q1-1986	Q1-1991	Q4-2000	Q1-1970	Q4-2002	Q4-2008	Q1-2001	NA
Luxembourg	LB	Q1-1995	Q1-1955	Q1-1983	Q1-1991	NA	Q1-1995	Q1-2007	Q1-1999	Q4-1993	Q1-1995	NA	Q1-2002	Q1-1994	NA
Mexico	MX	Q1-1993	Q1-1980	Q1-1987	NA	NA	NA	Q1-2005	Q1-1997	Q4-2001	NA	Q4-2000	NA	Q1-2002	NA
Netherlands	NL	Q1-1995	Q1-1956	Q1-1983	Q1-1995	NA	Q1-1995	Q1-1970	Q1-1986	Q1-1959	Q1-1995	Q4-1990	Q4-2005	Q2-1959	NA
Norway	NW	Q2-1987	Q2-1977	Q1-1986	Q2-1973	NA	Q2-1987	Q1-1970	Q1-1974	Q1-1970	Q2-1987	Q4-1998	Q4-1998	Q2-1970	NA
New Zealand	NZ	Q1-1978	Q1-1955	Q1-1989	Q1-1990	Q1-1955	Q1-1978	Q1-1970	Q1-1979	Q1-1985	Q1-1978	Q4-1995	NA	Q2-1985	NA
Poland	PL	Q1-2002	Q1-1985	Q1-1997	Q1-2000	Q1-2001	NA	Q1-2010	Q3-1991	Q1-2001	Q1-2002	Q4-1995	Q1-2004	Q2-2001	NA
Portugal	PT	Q1-1995	Q1-1955	Q1-1983	Q1-1994	NA	Q1-1995	Q1-1988	Q4-1985	Q3-1993	Q1-1995	Q4-1995	NA	Q4-1993	NA
Sweden	SD	Q1-1995	Q1-1991	Q1-1998	NA	NA	Q1-1995	Q1-2005	Q3-1995	Q4-2000	Q1-1995	Q4-1995	NA	Q1-2001	NA
Spain	SP	Q1-1995	Q1-1992	Q1-1996	Q1-1999	NA	Q1-1995	Q1-2007	Q1-2002	Q2-2002	Q1-1995	NA	Q4-2004	Q3-2002	NA
Slovak Republic	SR	Q1-1995	Q1-1965	Q2-1986	Q1-1992	Q1-1972	Q1-1995	Q1-1971	Q1-1977	Q1-1980	Q1-1995	Q4-1980	Q3-1997	Q2-1980	NA
Slovenia	SV	Q1-1993	Q1-1959	Q1-1983	Q1-1996	Q1-1965	Q1-1993	Q1-1970	Q1-1982	Q1-1987	Q1-1993	Q1-1996	Q3-2010	Q2-1987	NA
Switzerland	SW	Q1-1980	Q1-1959	Q2-1999	Q1-1994	NA	Q1-1980	Q1-1970	Q1-1974	Q1-1955	NA	Q4-1999	Q4-1999	Q2-1956	NA
Turkey	TK	Q1-1998	Q1-1985	Q1-2005	Q1-1982	NA	NA	Q1-2010	NA	NA	NA	NA	Q4-2005	NA	NA
United Kingdom	UK	Q1-1955	Q1-1956	Q1-1983	Q1-1966	Q1-1990	Q1-1995	Q2-1968	Q1-1978	Q1-1960	Q1-1955	Q1-1980	NA	Q2-1960	NA
United States	US	Q1-1947	Q1-1919	Q1-1955	NA	Q1-1955	Q1-1995	Q1-1970	Q3-1964	Q2-1953	Q1-1947	Q1-1980	Q1-1952	Q2-1956	Q1-1983

Table A.2: Summarized information for tax-deductibility of mortgage interests

CountryList	Tax_Deductible	Percentage
Australia	No	0
Austria	Yes	1
Belgium	No	0
Canada	No	0
Chile	Yes	1
Czech Republic	No	0
Denmark	Partially	33%
Estonia	Yes	1
Finland	Partially	31%
France	No	0
Germany	No	0
Greece	NA	0
Hungary	No	0
Iceland	No	0
Ireland	Yes	1
Israel	NA	0
Italy	Partially	19%
Japan	Yes	1
Korea	No	0
Luxembourg	Yes	1
Mexico	No	0
Netherlands	Partially	44.50%
New Zealand	No	0
Norway	Partially	25%
Poland	Yes	1
Portugal	Yes	1
Slovak Republic	NA	0
Slovenia	No	0
Spain	Yes	1
Sweden	Partially(22%-30%)	26%
Switzerland	No	0
Turkey	NA	0
United Kingdom	NA	1
United States	Yes	1

Table A.3: Lead-Lag relationship between unemployment and housing variables

Country	Abbr.	Permits Issued for Dwellings	Work Started for Dwellings	Residential Investment	Residential Property Price Indices	Permits Issued for Dwellings	Work Started for Dwellings	Residential Investment	Residential Property Price Indices	Permits Issued for Dwellings	Work Started for Dwellings	Residential Investment	Residential Property Price Indices
		Scale 3: 8Q-16Q Cycle Component				Scale 4: 16Q-32Q Cycle Component				Scale 3+4: 8Q-32Q Cycle Component			
Austria	AT	+2*	+2*	+1*	+1*	+3*	+3*	+2*	+1	+2*	+2*	+1*	+2*
Australia	AU	NA	NA	0	-9	NA	NA	0	+3	NA	NA	0	-8
Belgium	BG	-10	+2	NA	+3	+10	+10	NA	+4	+3	+2	NA	+3
Canada	CA	+2*	+2*	+2*	+1*	+4	+5	+3	-1	+2*	+2*	+2	+1*
Chile	CH	+1	NA	NA	NA	0	NA	NA	NA	-3	NA	NA	NA
Czech Republic	CZ	-1	-2	+1	NA	-1	-1	+2	NA	-1	-2	+2	NA
Denmark	DM	+1	NA	+1	+1	+5	NA	+3	+3*	+1	NA	0	+1
Estonia	ES	+6	NA	+3	NA	+3	NA	+1	NA	+4	NA	+3	NA
Finland	FL	+3	NA	+1*	+2	+6	NA	+3	+3	+4	NA	+2	+3
France	FR	+2	+2*	+1*	+1*	+6	+5	+3*	+3	+2	+2	+1*	+1
Germany	GM	+3	NA	+2	+1	+8	NA	+2	0	+10	NA	+2	0
Greece	GR	+10	NA	-4	0	+10	NA	+4	+4	+5	NA	-3	0
Hungary	HG	-1	NA	NA	NA	-3	NA	NA	NA	-3	NA	NA	NA
Iceland	IC	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Ireland	IR	-3	NA	-1	0*	-1	NA	0	-1*	-2	NA	-1	0*
Israel	IS	NA	+1	+10	+2	NA	+7	+10	+8	NA	0	+10	+9
Italy	IT	NA	NA	+3	-3	NA	NA	+1	+1	NA	NA	+2	-1
Japan	JP	NA	+3	NA	0*	NA	+4*	NA	-1*	NA	+3	NA	0*
Korea	KR	0*	NA	-7	0*	0	NA	-5*	-4	0	NA	-7	0
Luxembourg	LB	+8	NA	-4	NA	+7	NA	-5	NA	+10	NA	-3	NA
Mexico	MX	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Netherlands	NL	+1	NA	0*	+1*	+9	NA	+1	0	0	NA	0	+1
Norway	NW	+2	NA	+1	+2	+3	NA	+2	+1	+3	NA	+2	+2
New Zealand	NZ	+5	+4	-1	+2	+5	+4	+3	+2	+1	0	-1	+2
Poland	PL	+2	NA	NA	NA	+2	NA	NA	NA	+2	NA	NA	NA
Portugal	PT	+2	NA	-1	+2*	+4	NA	0	0	+3	NA	-1	+3
Sweden	SD	NA	NA	-9	NA	NA	NA	-4	NA	NA	NA	-2	NA
Spain	SP	-9	NA	0	NA	+3	NA	0	NA	+4	NA	0	NA
Slovak Republic	SR	+1	+1*	-1	+1*	+2*	+2	-1	+1	+1	+1	-1	0
Slovenia	SV	-10	+1	+1*	+2*	+5	-3	+2	-1*	+3	+1	+1	+2
Switzerland	SW	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Turkey	TK	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
United Kingdom	UK	+2*	+2*	0	+2*	4	+3	+1	+2*	+2	+2	0	+2*
United States	US	NA	+2*	+2	+1	NA	+4*	+3	-1*	NA	+3*	+2	+2
Number of available series		24	12	25	22	24	12	25	22	24	12	25	22
Percentage of LEAD		70.83	91.67	52.00	72.73	79.17	83.33	68.00	59.09	75.00	75.00	48.00	63.64
Percentage of LAG		20.83	8.33	32.00	9.09	12.50	16.67	16.00	27.27	16.67	8.33	32.00	9.09
Percentage of Coincidence		8.33	0.00	68.00	18.18	8.33	0.00	16.00	13.64	8.33	16.67	20.00	27.27

Notes:

1. * represents significant correlation at 5% level
2. + represents housing variable is a leading indicator for macro economy and – represents a lagging relationship. Leading relationship is marked with light blue color, lagging with light yellow while contemporaneous relation is shown with light green.
3. Numbers shown the lag/lead term at which correlation reach the maximum absolute value
4. NA represents the unavailability of these data pairs

Table A.4: Lead-Lag relationship between industrial production index and housing variables

Country	Abbr.	Permits Issued for Dwellings	Work Started for Dwellings	Residential Investment	Residential Property Price Indices	Permits Issued for Dwellings	Work Started for Dwellings	Residential Investment	Residential Property Price Indices	Permits Issued for Dwellings	Work Started for Dwellings	Residential Investment	Residential Property Price Indices
Scale 3: 8Q-16Q Cycle Component					Scale 4: 16Q-32Q Cycle Component				Scale 3+4: 8Q-32Q Cycle Component				
Austria	AT	+2	+1	0	+1	+2	+2	0	-1	+1	+1	0	0
Australia	AU	NA	NA	-1	+4	NA	NA	-1	+3	NA	NA	-1	+3
Belgium	BG	-7	0	NA	-1*	+3	+2	NA	0	-7	+1	NA	-1
Canada	CA	+2*	+1*	+2*	+1*	+3	+3	+1	-10	+2*	+2	+2	+1
Chile	CH	0	NA	NA	NA	0*	NA	NA	NA	-1	NA	NA	NA
Czech Republic	CZ	-4	-4	0	NA	-3	-4	-1	NA	-3	-4	0	NA
Denmark	DM	+1*	NA	-1	+1*	+2*	NA	+1	+1*	+1	NA	-1	+1
Estonia	ES	+1	NA	+1	NA	+1	NA	0	NA	+1	NA	+1	NA
Finland	FL	+2*	NA	0*	+2*	+4	NA	+1	0	+3	NA	0*	+2
France	FR	+1*	+1*	0	-1*	+2*	+2*	0*	0	+1*	+1	0*	0
Germany	GM	+8	NA	0	-5	+5	NA	0*	-2	+8	NA	+1	-6
Greece	GR	+9	NA	0	+5	+7	NA	0	+3	-6	NA	-2	+5
Hungary	HG	-3	NA	NA	NA	-6	NA	NA	NA	-4	NA	NA	NA
Iceland	IC	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Ireland	IR	-4	NA	0	0	0	NA	+2	-1	-1	NA	+1	0
Israel	IS	NA	+1	-7	-7	NA	+4	+9	+7	NA	-4	+9	+8
Italy	IT	NA	NA	0*	-2*	NA	NA	+1	-4	NA	NA	0	-4
Japan	JP	NA	0	NA	-1*	NA	+2*	NA	-2*	NA	+1	NA	-1*
Korea	KR	0*	NA	-7	-1	-2	NA	-8	-10	0	NA	-7	-1
Luxembourg	LB	+10	NA	-2	NA	+2	NA	-3	NA	0	NA	0	NA
Mexico	MX	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Netherlands	NL	-2	NA	-3*	-1	-7	NA	-4	+1	-3	NA	-3	-1
Norway	NW	+1*	NA	+1*	0	+1*	NA	0*	-10	+1	NA	+1	+1
New Zealand	NZ	0	+4	+4	-10	+6	+6	+5	-8	+5	+4	+4	-8
Poland	PL	0	NA	NA	NA	-1	NA	NA	NA	-1	NA	NA	NA
Portugal	PT	-1	NA	-3	+2	+1	NA	+4	+3	0	NA	-3	+1
Sweden	SD	NA	NA	-4	NA	NA	NA	-4	NA	NA	NA	-4	NA
Spain	SP	-10	NA	-1	NA	0	NA	-3	NA	-10	NA	-2	NA
Slovak Republic	SR	0*	0*	-1*	0*	+1*	+1*	-1	0	+1	0*	-1	0
Slovenia	SV	-10	+1	0	+2*	+3*	+2	+1*	0	-10	+1	0	+1
Switzerland	SW	-9	NA	-1	0	+4	NA	0	-1	+6	NA	-1	-1
Turkey	TK	-2	NA	NA	NA	0	NA	NA	NA	-2	NA	NA	NA
United Kingdom	UK	+2*	+2*	-1*	+1*	+4*	+2*	-1	-2	+2	+2*	-1	0
United States	US	NA	+2*	+1	-9	NA	+3*	+2	-2	NA	+3*	+1	+2
Number of available series		26	12	26	23	26	12	26	23	26	12	26	23
Percentage of LEAD		42.31	66.67	19.23	39.13	65.38	91.67	38.46	26.09	46.15	75.00	30.77	43.48
Percentage of LAG		38.46	8.33	46.15	43.48	19.23	8.33	34.62	52.17	42.31	16.67	42.31	34.78
Percentage of Coincidence		19.23	25.00	34.62	17.39	15.38	0.00	26.92	21.74	11.54	8.33	26.92	21.74

Notes:

- * represents significant correlation at 5% level
- + represents housing variable is a leading indicator for macro economy and – represents a lagging relationship. Leading relationship is marked with light blue color, lagging with light yellow while contemporaneous relation is shown with light green.
- Numbers shown the lag/lead term at which correlation reach the maximum absolute value
- NA represents the unavailability of these data pairs