EMPIRICAL STUDIES ON HOUSING AND THE MACROECONOMY

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Diese Dissertation besteht aus drei Arbeitspapieren, von denen ein in Zusammenarbeit mit einer Koautorin entstanden ist.

- Lee, Tsung-Hsien Michael und Chen, Wenjuan (2015) :
  "Is There an Asymmetric Impact of Housing on Output?",
  SFB 649 Discussion Paper 2015-020.

- Lee, Tsung-Hsien Michael (2016) :
  "Housing Market Spillovers: Identifying Housing Demand Shocks Using Sales Variable",
  Freie Universität Berlin, Berlin.

- Lee, Tsung-Hsien Michael (2016) :
  "Can We Predict Housing Price Downturns?",
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Contents

Overview

Before the turn of the century, macroeconomics and housing research seemed to have only little overlap. On the housing side, macroeconomic variables had mostly been treated as exogenous control variables. On the macro side, housing was often undifferentiated from the other consumption goods, or neglected in the analysis (see Leung (2004) for further discussions). At best, housing sector had merely been thought of as a link in the transmission of macro shocks.

Since the last boom and the subsequent collapse in the U.S. real estate market, housing has attracted unprecedented levels of attention from academics, media and policymakers, as it was generally believed to be responsible for the outbreak of the global financial crisis. Recent researches suggest that housing developments do not solely reflect the macroeconomic activity, but can be an important driving source of the macroeconomic fluctuations.

The changing role of housing may be due to advancements in financial market and globalization. Financial innovations and deregulations open up new possibilities for housing to be further connected to the broader economy. For instance, credit market liberalization can alter households' borrowing and consumption behaviors via the reduction of down-payment constraint, or the use of homes as collateral. Moreover, the liberalization of capital flows makes real estate an attractive investment vehicle, and thus renders the housing market a volatile sector in the economy.

Despite the growing recognition of housing as an important factor in the macroeconomic dynamics, there remain, nevertheless, a number of interesting questions, the answers to which enable us to better understand the macro-housing nexus. This thesis particularly focuses on the following questions. First, given the weight placed by the recent theories (see, for instance, Iacoviello (2005) and Iacoviello and Neri (2010)) on housing demand shock for driving the housing and business cycles, how do researchers identify this housing-specific shock and evaluate the responses of economic aggregates to this shock in the data? In addition, how to identify the channel through which housing is linked to the macroeconomy? Second, there is no consensus on whether housing market is a forerunner of the business cycles, would it be because the macro-housing nexus is subject to the state of the economy? Finally, as fluctuations in home values have shown to exert large impact on the real economic activity and financial stability, is it possible to develop a method to predict large movements in home values?

This thesis consists of three papers and contributes to the burgeoning macro-housing literature by providing empirical evidence to the research questions. Several econometric models, such as vector autoregression model and probit model, serve as the principal tools to unravel the relationship between housing and the macroeconomy. In the following the main contributions and results of each individual paper are briefly summarized.

- ***Paper 1:*** *Is There an Asymmetric Impact of Housing on Output?*

  In this paper we use a Markov-switching vector autoregression model to investigate whether there is an asymmetric relationship between housing and the overall economic activity. The answer to the research question may allow us to explain the mixed views on housing's leading role in the economy.

Regime dependent causality analysis suggests that housing affects output only in the regime associated with the contraction phase in both the housing and business cycles. Our findings are not only in line with the argument that housing market leads the business cycles, but also show that it has time-varying leading effects on the overall economy.

- ***Paper 2:*** *Housing Market Spillovers: Identifying Housing Demand Shocks Using Sales Variable*

  Previous studies have shown that the effects of housing demand shocks on the economy are inconclusive. The key issue arising in these empirical researches might be the inability of housing prices to timely reflect changes in market demand. This paper revisits the literature on housing spillovers by suggesting a new way to identify housing demand shocks and to assess its effects on the aggregate economy.

  Based on a housing theory that explores the responses of housing prices and sales following shifts in demand, we propose housing sales as a better measure of housing demand. We find that sales shocks in a vector autoregression model have the interpretation of housing demand shocks, driving not only the housing dynamics but also the overall economic activity. Evidence suggests collateral channel as the principal link between housing and the broader economy.

- ***Paper 3:*** *Can We Predict Housing Price Downturns?*

  This paper investigates whether housing price downturns are predictable. We first use a nonparametric approach to identify downturns in the housing price series. Then, we select the forecasting variables based on economic theories. In the forecasting exercise, a probit model is applied in such a way that the performance of each predictor is compared with that of the others.

Empirical evidence shows that housing sales growth holds vast forecasting power for the price correction episodes both in-sample and out-of-sample, and that it outperforms the other conventional macroeconomic variables. Moreover, we find that an augmented probit model with further lags of sales growth can consistently and accurately predict price downturns, suggesting that this variable serves as a simple and reliable indicator of future housing price corrections.

Zusammenfassung

Vor der Jahrhundertwende schienen die Makroökonomie und die Forschung zu Immobilienmärkten nur wenig Überschneidung zu haben. Letztere behandelte makroökonomische Größen meist als exogene Kontrollvariablen, während die Makroökonomie Immobilien häufig ähnlich wie andere Konsumgüter analysierte oder kaum berücksichtigte (siehe Leung (2004)). In wenigen Fällen wurde dem Immobiliensektor immerhin eine Rolle in der Übertragung von Makro-Schocks zugesprochen, jedoch ohne selbst Treiber solcher Shocks zu sein.

Seit dem letzten Boom und dem nachfolgenden Zusammenbruch des US-Immobilienmarktes hat der Immobilienmarkt noch nie dagewesene Aufmerksamkeit von Wissenschaftlern, Medien und Politikern auf sich gezogen. Der Grund dafür war, dass der Immobilienmarkt für den Ausbruch der globalen Finanzkrise weithin verantwortlich gemacht wurde. Neuere Forschungen weisen darauf hin, dass die Immobilienentwicklung nicht nur die Wirtschaftsaktivität widerspiegelt, sondern auch makroökonomische Schwankungen in großem Maße verursachen kann.

Die sich wandelnde Rolle des Immobilienmarktes lässt sich auf die Finanzmarktentwicklung sowie die Globalisierung zurückführen. Finanzinnovationen und Deregulierungen eröffnen neue Möglichkeiten für den Immobilienmarkt mit der Gesamtwirtschaft stärker verbunden zu sein. Beispielsweise kann die Liberalisie-

rung des Kreditmarktes das Konsumverhalten und die Kreditaufnahme des Haushaltes ändern - durch verringerte Einschränkungen der Anzahlungsbedingungen oder der Verwendung der Immobilie als Sicherheit. Darüber hinaus macht die Liberalisierung der Kapitalmärkte Immobilien zu einem attraktivem Anlageinstrument, und somit den Immobilienmarkt zu einem volatilem Wirtschaftssektor.

Trotz der wachsenden Anerkennung des Immobilienmarktes als wesentlichen Faktor der makroökonomischen Dynamik, bleibt doch eine Reihe von interessanten Fragen offen, deren Antworten uns ein besseres Verständnis des Makro-Häuser-Nexus ermöglicht. Diese Arbeit konzentriert sich vor allem auf die folgenden Fragen. Erstens, angesichts der neuen Wichtigkeit eines Immobilien-Nachfrageschocks (siehe zum Beispiel Iacoviello (2005) und Iacoviello and Neri (2010)) als Treiber des Konjunktur- und Immobilienzyklus, wie identifizieren Forscher solch einen Schock in den Daten, und wie bewerten sie die Reaktion der Wirtschaftsaggregate auf diesen Schock? Zusätzlich, wie kann man den Kanal, über welchen der Immobilienmarkt mit der Gesamtwirtschaft verbunden ist, identifizieren? Zweitens, im Hinblick darauf, dass es keine Übereinstimmung über die Lead-Lag-Beziehung des Immobilienmarktes und des Konjunkturzyklus gibt, liegen die Gründe dafür darin, dass die Verknüpfung des Immobilienmarktes mit der restlichen Volkswirtschaft vom gegebenen Wirtschaftszustand abhängig ist? Abschließend, da gezeigt wurde, dass Schwankungen des Wertes von Immobilien große Auswirkungen auf realwirtschaftliche Aktivitäten und die Finanzstabilität haben können, ist es möglich, ein Verfahren zu entwickeln, welches große Schwankungen in Immobilienwerten vorhersagt?

Diese Forschungsarbeit besteht aus drei Studien, und trägt zur wachsenden Literatur zur Verbindung der Makroökonomie mit dem Immobilienmarkt bei, indem sie empirische Befunde zu den oben genannten Fragestellungen liefert. Verschiedene ökonometrische Modelle, wie die Vektorautoregression und Probit Modelle, dienen als grundsätzliche Mittel, um die Beziehungen zwischen den Variablen zu entwirren. Im Folgenden werden die wichtigsten Beiträge und Ergebnisse der einzelnen Studien kurz zusammengefasst.

- ***Studie 1:*** *Is There an Asymmetric Impact of Housing on Output?*

  In dieser Arbeit verwenden wir ein Markov-Switching Vektorautoregressionsmodell um zu untersuchen, ob es ein asymmetrisches Verhältnis zwischen dem Immobilienmarkt und der gesamtwirtschaftlichen Aktivität gibt. Die Antwort auf diese Fragestellung könnte es uns ermöglichen, die gemischten Ansichten bezüglich der Rolle des Häusermarktes in der Ökonomie zu erklären.

  Eine regimeabhängige Kausalitätsanalyse lässt darauf schließen, dass der Häusermarkt den Output ausschließlich in der Phase der Kontraktion des Immobilien- sowie Konjunkturzyklus beeinflusst. Unsere Ergebnisse zeigen nicht nur, dass die Entwicklungen auf dem Häusermarkt dem Konjunkturzyklus zeitlich vorausgehen, sondern auch, dass die Immobilienmarktentwicklungen zeitvariierende Auswirkungen auf die gesamtwirtschaftliche Aktivität haben.

- ***Studie 2:*** *Housing Market Spillovers: Identifying Housing Demand Shocks Using Sales Variable*

  Frühere Studien finden keinen eindeutigen Effekt von Immobilien-Nachfrageschocks auf die Gesamtwirtschaft. Das zentrale Problem in der empirischen Literatur liegt dabei darin, dass Immobilienpreise die Veränderungen der Marktnachfrage nur verzögert widerspiegeln. Die vorliegende Arbeit schlägt eine neue Methode zur Identifizierung von Immobilien-Nachfrageschocks vor und analysiert ihre Effekte auf die Gesamtwirtschaft.

Basierend zu theoretischen Ergebnissen zu den Reaktionen von Immobilienpreisen und -umsätze auf Nachfrageverschiebungen schlagen wir die Verkaufszahlen von Immobilien als ein besseres Maß der Immobiliennachfrage vor. Wir finden, dass in einem Vektorautoregressiven Modell Verkaufsschocks als Immobilien-Nachfrageschocks interpretiert werden können, welche nicht nur die Dynamik des Häusermarktes treibt, sondern auch die gesamtwirtschaftliche Aktivität. Die Ergebnisse legen den collateral channel als Hauptverbindung zwischen dem Häusermarkt und der Gesamtwirtschaft nahe.

- ***Studie 3:*** *Can We Predict Housing Price Downturns?*

  Diese Arbeit untersucht, ob Abschwünge in Immobilienpreisen prognostizierbar sind. Wir verwenden zunächst einen nichtparametrischen Ansatz um Abschwünge in Immobilienpreisen zu identifizieren. Dann wählen wir die Prognosevariablen basierend auf ökonomischen Theorien aus. Das Prognoseverfahren basierend auf einem Probit-Modell läuft dermaßen ab, das die Güte jedes Prädiktors mit der der anderen vergleichbar ist.

  Die empirischen Ergebnisse zeigen, dass das Wachstum in Immobilienverkäufe eine starke Prognosefähigkeit für Preisveränderungen sowohl in- als auch out-of-Sample hat, und dass es eine erhöhte Vorhersagekraft als die üblichen makroökonomischen Variablen besitzt. Darüber hinaus finden wir, dass ein um weitere Verzögerungen des Verkaufswachstums erweitertes Probit-Modell Preisabschwünge konsistent und präzise vorhersagt, was darauf hindeutet, dass diese Variable als ein einfacher und zuverlässiger Indikator für künftige Immobilienpreisveränderungen dienen kann.

Chapter 1

Is There an Asymmetric Impact of Housing on Output?

1.1 Introduction

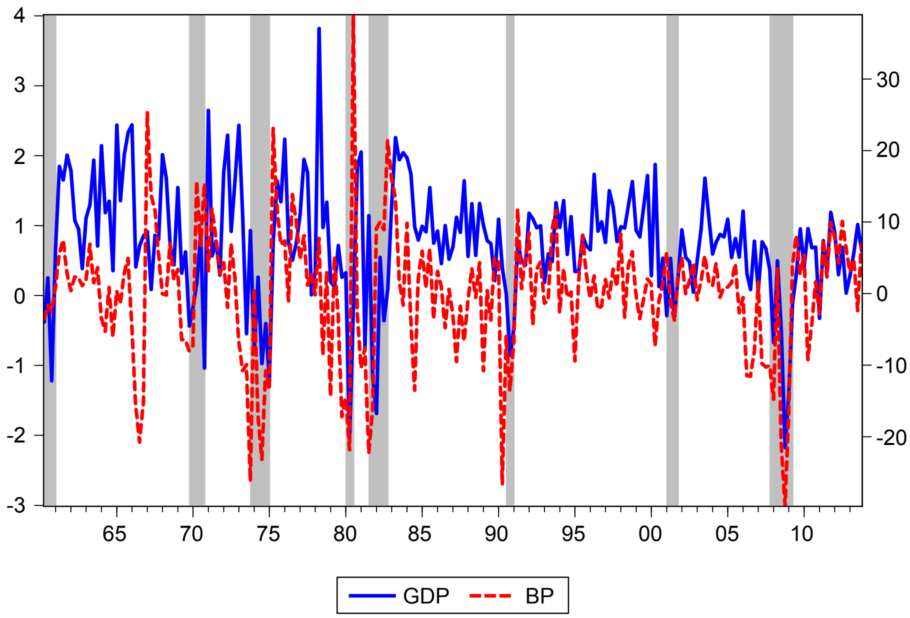
Since the beginning of the financial crisis, housing has gained more attention from academics and practitioners than ever. In fact, there has long been a discussion about housing's role in the overall economy[1]. One of the main questions is whether there is a lead-lag relation between housing and the business cycles.

Figure 1.1 plots the growth rates of US real GDP and the growth rates of total building permits (BP). The low-frequency components of the two series share a striking resemblance. More noteworthy is when housing slumps, it is likely that there will be an economic contraction in the following quarters. The procycli-

[1]On the theoretical side, studies have investigated housing's role in the business cycles (e.g., Iacoviello (2005), Davis and Heathcote (2005) and Fisher (2007)). On the empirical side, researchers examine housing's leading effect on the economy (e.g., Green (1997), Coulson and Kim (2000), Leamer (2007), Ghent and Owyang (2010) and Strauss (2013))

cal feature of the housing series shows why housing is potentially an important candidate to understand the dynamics of the business cycles.

Figure 1.1: US Quarterly Real GDP (left) and Building Permit (BP; right) Growth Rates



Notes: Shaded areas correspond to the NBER recession dates.

However, empirical results of housing's leading role in the economy are mixed. Leamer (2007) points out that housing downturns are reliable signals of incoming national recessions. This evidence is echoed by the findings in Strauss (2013), who shows that building permits can be used to predict to a large extent the emergence of recessionary events at state level. On the contrary, Ghent and Owyang (2010), using linear VAR approach, find no consistent statistical relationship displaying housing's leading effect on regional business cycles. One explanation of the disagreement among these studies is that the relation between housing and economic activity is time-varying[2].

This is the first paper to study the US housing-output link by employing the Markov-Switching Vector Autoregressive (MS-VAR) approach. First, this approach enables us to examine whether the housing-output relation changes over time. If such asymmetry exists, the predictive contents of one variable on the other one cannot be fully studied in a linear model. Second, regime-dependent Granger causality analysis from the MS-VAR model is capable of revealing different lead-lag patterns between BP growth rate and GDP growth rate in the regimes[3].

The findings of the current research shed new light on the housing-output link. Our empirical results suggest that the bivariate system of BP growth rate and GDP growth rate is subject to shifts in regime. Notably, the timing of the identified high-volatility regime matches the timing of the NBER recessions. Results from the Granger causality tests show that BP growth rate Granger causes GDP growth rate only in the regime associated with the downturn phases in both the housing and business cycles. Our findings not only confirm the argument that housing leads the business cycles, but also show evidence of time-varying leading effect of housing on the overall economic activity.

The rest of the paper is organized as follows. In section 1.2, we introduce the data and provide a preliminary evidence of time-varying housing-output relation. Section 1.3 introduces the MS-VAR model and the regime-dependent Granger causality test. Section 1.4 presents the empirical results. Section 1.5 concludes.

[2]Recently there has been a growing literature on housing's asymmetric impact on macroeconomic aggregates (see, for instance, Chen, Chen, and Chou (2010), Márquez, Martínez-Cañete, and Pérez-Soba (2013), Case, Quigley, and Shiller (2013), Aye, Balcilar, Bosch, and Gupta (2014) and Guerrieri and Iacoviello (2015)).

[3]To account for the fact that the relation between BP growth rate and GDP growth rate may be due to the omission of monetary variables (see Smets (2007)), the MS-VAR model controls for interest rates or, in the robustness section, other variables.

1.2 Data and Preliminary Analysis

Our analysis is based on quarterly observations of US real GDP and total building permits over the period 1960Q1 to 2013Q4 (216 observations), covering a total of eight recessions. We use BP as the housing variable because Leamer (2007) suggests that it is the housing volume that matters for employment and GDP. Housing prices, on the contrary, are inflexible and can be unable to fully and timely depict fluctuations in the housing cycles. In addition, BP lead residential investment since resources are used in construction projects after the approval is obtained from local authority, and thus are better at disclosing first-hand housing market conditions[4]. All data are obtained from the Federal Reserve Bank of St. Louis. The study uses the log-differences of GDP and BP, which are suggested by the Augmented Dickey-Fuller (ADF) test to be stationary.

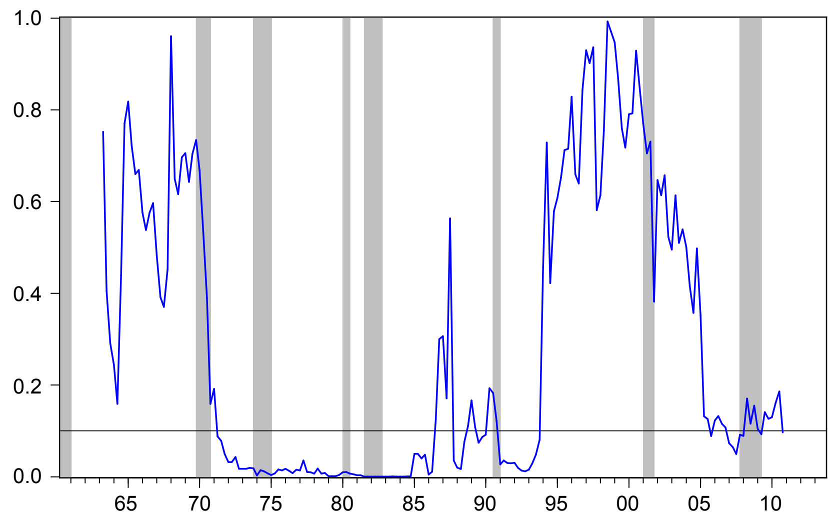
To provide a preliminary evidence of housing's time-varying leading effect on output, we use F-tests for Granger causality computed from 6-year (24 observations) fixed window rolling regressions. Based on single equation regressing GDP growth rate on two lagged terms of itself and two lagged terms of BP growth rate, we test the null hypothesis that there is no Granger causality from BP growth rate to GDP growth rate.

Figure 1.2 shows the p-values of the rolling test statistics. The leading pattern of the housing variable changes over the sample period. There are three sub-periods when the p-values are below the 0.1 line (10% significance level), and thus BP growth rate has predictive content for GDP growth rate. The first sub-period, 1971-1986, reflects the time when the US was plagued with recessions, while the latter two, 1991-1993 and 2007-2008, are in fairly close proximity to recession

[4]Our calculation suggests that BP growth rates lead the growth rates of residential investment by about 3 quarters.

dates, suggesting that housing's leading role is linked to the emergence of recessions. On the other hand, there are two sub-periods, 1963-1970 and 1994-2005, when housing did not have significant leading effects. These findings indicate that the housing-output link may vary over time and the asymmetry is associated with the state of the economy.

Figure 1.2: P-Values of Rolling Granger Non-Causality F-Tests from BP growth rate to GDP growth rate



Notes: Null hypothesis: BP growth rate does not Granger cause GDP growth rate. The horizontal line indicates 10% significance level. Shaded areas correspond to the NBER recession dates.

1.3 Econometric Methodology

1.3.1 Markov-Switching Vector Autoregressive Model

To model the asymmetric relation between housing and aggregate economic activity, we consider the following Markov-Switching Vector Autoregressive Model:

$$\Delta bp_t = a_{\Delta bp}^{(s_t)} + \sum_{k=1}^{p} a_{\Delta bp,\Delta bp,k}^{(s_t)} \Delta bp_{t-k} + \sum_{k=1}^{p} a_{\Delta bp,\Delta y,k}^{(s_t)} \Delta y_{t-k} + \sum_{k=0}^{p} \beta_{\Delta bp,r,k}^{(s_t)} r_{t-k} + u_{\Delta bp,t} \ ,$$
$$\Delta y_t = a_{\Delta y}^{(s_t)} + \sum_{k=1}^{p} a_{\Delta y,\Delta bp,k}^{(s_t)} \Delta bp_{t-k} + \sum_{k=1}^{p} a_{\Delta y,\Delta y,k}^{(s_t)} \Delta y_{t-k} + \sum_{k=0}^{p} \beta_{\Delta y,r,k}^{(s_t)} r_{t-k} + u_{\Delta y,t} \ , \tag{1.1}$$

where Δbp_t and Δy_t denote the growth rates of building permit and real GDP, respectively. Smets (2007) suggests the leading effect from housing to output might result from the omission of some important monetary variables that simultaneously affect both housing and output, therefore we consider federal funds rates, r_t, as an exogenous variable[5]. $[u_{\Delta bp,t}, u_{\Delta y,t}]'$ is the error term that follows normal distribution with regime-dependent covariance matrix, $\Sigma^{(s_t)}$. The latent variable, s_t, is assumed to follow a M-regime Markov chain with transition probabilities given by

$$p_{ij} = Pr(s_{t+1} = j | s_t = i), \ \ i, j \in \{1, ..., M\}, \tag{1.2}$$

with $\sum_{j=1}^{M} p_{ij} = 1$. p_{ij} is interpreted as the probability of being in regime j at time $t+1$ given that the system is in regime i at time t. Using the transition probabilities, the expected duration of each regime can be computed as:

$$E[D|s_t = m] = \frac{1}{1 - p_{mm}}, \tag{1.3}$$

where $m \in \{1, ..., M\}$.

The identification of regimes rests on smoothed probabilities, which provide an inference about the likelihood of the system being in certain regime at time t conditioned on the full sample period. If two regimes are assumed, the system would be considered as being in regime i at time t whenever $Pr(s_t = i | Y_T) > 0.5$, where $Y_T = \{y_1, ..., y_T\}$ and $i \in \{1, 2\}$.

[5]Note that the interest rate can have instantaneous effect on BP growth rate and GDP growth rate.

As suggested in Hamilton (1990) and Krolzig (1997), the maximum likelihood estimation of the model is based on the Expectation-Maximization (EM) algorithm. The first step (Expectation) makes optimal inference about hidden Markov chain conditional on a given set of parameters. The second step (Maximization) re-estimates the parameters given the inferred hidden Markov chain. These steps are repeated until convergence.

1.3.2 Regime-Dependent Granger Causality

Unlike the standard Granger causality analysis that reveals permanent causal patterns among the variables, the regime-dependent Granger causality analysis from the currently studied MS-VAR model is capable of capturing time-varying relationship between the variables, allowing us to fully explore the links between housing and output. This is done by testing the following null hypothesis:

$$H_0 : a^{(s_t=i)}_{\Delta y,\Delta bp,1} = a^{(s_t=i)}_{\Delta y,\Delta bp,2} = ... = a^{(s_t=i)}_{\Delta y,\Delta bp,p} = 0, \qquad (1.4)$$

which is equivalent to testing that BP growth rate does not Granger cause GDP growth rate in regime i. Imposing the above restrictions, we estimate a MS-VAR model with the coefficients of all lagged BP growth terms in the GDP growth equation in regime i equal to zero, and obtain the restricted log likelihood value (L_R). Together with the log likelihood value from the unrestricted model (L_U), we conduct a Likelihood Ratio (LR) test, $LR = 2(L_U - L_R)$, which follows a χ^2_k distribution with k equal to the number of restrictions. In a similar fashion, we can test the null hypothesis that GDP growth rate does not Granger cause BP growth rate in regime i.

1.4 Empirical Results on Housing-Output Relation

1.4.1 Model Specification

In the current study we assume that the latent variable, s_t, follows a two-regime Markov chain, in order to capture the downturns and upturns in the housing market and the overall economy. To determine the lag length of the MS-VAR model, we rely on the suggestion (2 lags) from the Schwarz information criterion (SIC) and the Hannan-Quinn Criterion (HQC) for the linear VAR model.

To see whether the data is supportive of the non-linear modeling, we test the null hypothesis of time-invariant VAR model against the alternative hypothesis of MS-VAR model. Due to the presence of nuisance parameters under the null, LR test statistic does not have standard asymptotic distribution. However, Davies (1977) proposes a method which derives an upper bound for the significance level of the LR test statistic. We therefore apply the bounded likelihood ratio test to test the null of no regime dependence. Panel A in Table 1.1 shows that the Davies' test (the largest p-value) is smaller than any significance level, suggesting that the non-linear modeling approach is preferred over the linear approach in depicting the joint dynamics of the growth rates of BP and GDP. By using the MS-VAR model, we are able to explore different dynamic interactions between the variables in each regime, which might be disguised under a linear VAR framework presuming parameter constancy.

Next we examine which parts, either the autoregressive parameters or the covariance matrix or both, of the MS-VAR model are conditional on the regime of the Markov chain. The hypothesis tests below are conducted using standard LR test. This is because when the number of regimes is unaltered under the null, LR test statistic derived from a MS-VAR model has the asymptotic properties similar to those of the LR test statistic derived from linear VAR model (see Krolzig

(1997)).

Table 1.1: Tests for the Specification of MS-VAR Model

(A)	H_0: No regime-switching in the model (linear-VAR) H_a: Regime-switching in the model (MS-VAR)	Davies=0.00***
(B)	H_0: Only the covariance matrix is regime-dependent H_a: All parameters are regime-dependent	LR=28.08**
(C)	H_0: Only the autoregressive parameters are regime-dependent H_a: All parameters are regime-dependent	LR=20.33***

Notes: Davies means Davies' test, which is an upper bound for the significance level of the LR test statistic under the null. LR denotes the likelihood ratio test. $*$, $**$ and $***$ denote statistical significance at the 10%, 5% and 1% level.

We first test the null hypothesis that only the covariance matrix is regime-dependent against the alternative hypothesis that the covariance matrix and the autoregressive parameters are regime-dependent. Panel B in Table 1.1 displays the result indicating rejection of the null at 5% significance level. Therefore, the MS-VAR model considered in our study encompasses time-varying autoregressive parameters. In a similar fashion, we test the null hypothesis that only the autoregressive parameters are regime-dependent against the alternative hypothesis that both parts are conditional on the regime. Panel C in Table 1.1 suggests rejection of the null at any significance level. Thus the data is in favor of a MS-VAR model with heteroskedastic error term rather than one with homoskedastic error term.

In sum, the empirical analysis and the following estimation results are based on a MS-VAR model with the number of regime as well as the autoregressive order equal to two. The model's autoregressive parameters and covariance matrix are all subject to shifts in the regime.

1.4.2 Is There an Asymmetric Impact of Housing on Output?

Table 1.2 summarizes the estimation results on the regime-dependent relation between BP growth rate and GDP growth rate[6]. In regime 1, the estimated coefficients for the first and second lags of BP growth rate in the GDP growth equation, $a^{(1)}_{\Delta y,\Delta bp,1} = 0.0028$ and $a^{(1)}_{\Delta y,\Delta bp,2} = 0.0096$, are small and statistically insignificant at any level. On the contrary, in regime 2, the estimated coefficients of BP growth rate at lag 1 and 2 ($a^{(2)}_{\Delta y,\Delta bp,1} = 0.0481$ and $a^{(2)}_{\Delta y,\Delta bp,2} = 0.0172$) are about 17 and 1.8 times larger than their respective counterparts in regime 1, with the first coefficient being significant at 5% level while the latter insignificant. This finding provides the first indication of the asymmetric leading effect of BP growth rate on GDP growth rate.

We identify regime 1 as low volatility regime and regime 2 as high volatility regime, because the standard deviation of both BP growth rate and GDP growth rate are higher in regime 2 ($\sigma^{(2)}_{\Delta bp} = 123.05$ and $\sigma^{(2)}_{\Delta y} = 0.7$) than in regime 1 ($\sigma^{(1)}_{\Delta bp} = 17.96$ and $\sigma^{(1)}_{\Delta y} = 0.29$). The estimated transition probabilities, $p_{11} = 0.95$ and $p_{22} = 0.88$, imply that the two regimes are very persistent. The expected duration of the low volatility regime (18.31 quarters or, equivalently, 4.58 years) is longer than that of the high volatility regime (8.57 quarters or, equivalently, 2.14 years).

[6]The complete results can be found in Table 1.5 in the appendix.

Table 1.2: Estimated Parameters from the MS-VAR Model

	Regime 1	low volatility	Regime 2	high volatility
$a_{\Delta y,\Delta bp,1}$	0.0028	(0.24)	0.0481^{**}	(2.56)
$a_{\Delta y,\Delta bp,2}$	0.0096	(1.01)	0.0172	(1.12)
$\sigma_{\Delta bp}$	17.96^{***}	(5.97)	123.05^{***}	(4.17)
$\sigma_{\Delta y}$	0.29^{***}	(7.44)	0.7^{***}	(4.03)
p_{11}	0.95			
p_{22}	0.88			

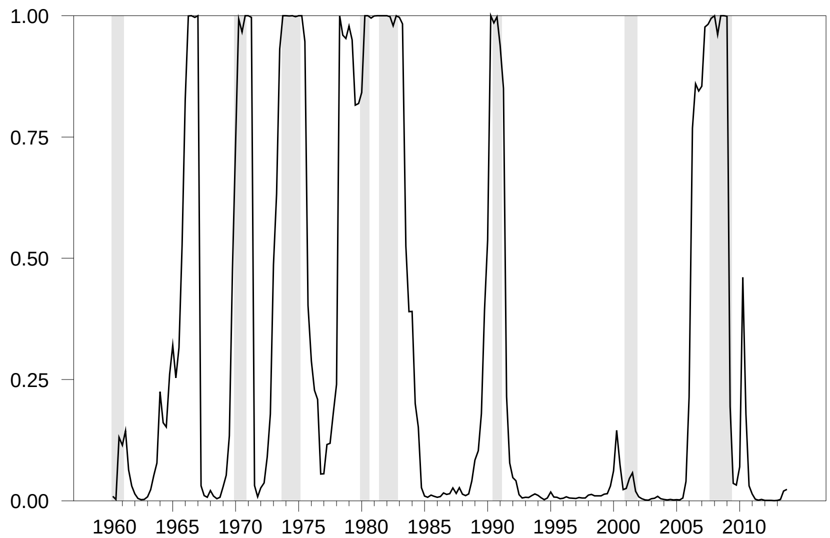
Notes: $a_{equation,variable,lag}$. t-statistics are reported in parentheses. $*$, $**$ and $***$ denote statistical significance at the 10%, 5% and 1% level.

The estimated smoothed probabilities of being in the high volatility regime (regime 2), shown in Figure 1.3, display patterns of ups and downs, revealing the fact that the system of BP growth rate and GDP growth rate switches between the two regimes repeatedly. Notably, the timing of the high volatility regime appears to overlap with the timing of six of the eight NBER-identified recessions over the past 50 years: recessions of 1969-70, 1973-75, 1980, 1981-1982, 1990-1991 and 2007-2009[7]. Over the same time period housing market also experienced declines in construction activity. In fact, 73% of the quarters with negative GDP growth are covered in the high volatility regime, and 77% of the quarters with positive GDP growth are covered in the low volatility regime. Analogously, 93% of the quarters with BP growth rate smaller than -10 percent are covered in the high volatility

[7] Recall that the main purpose of this study is to examine the links between housing and the aggregate economy under different regimes, rather than to provide a delineation of the dates at which the turning points in the business cycles take place (see Hamilton (1989) and Chauvet and Piger (2003)).

regime[8], and 80% of the quarters with positive BP growth rate are covered in the low volatility regime. As a result, it is reasonable to relate the model-identified high/low volatility regime to the downturn/upturn phase in both the housing and business cycles.

Figure 1.3: Smoothed Probabilities of High Volatility Regime



Notes: Shaded areas correspond to the NBER recession dates.

Table 1.3 provides new evidence on the asymmetric leading effect of housing on the economy. In panel A and B, the null hypothesis that BP growth rate does not Granger cause GDP growth rate in the low volatility regime cannot be rejected at any significance level, whereas the null hypothesis that BP growth rate does not Granger cause GDP growth rate in the high volatility regime can be rejected at 1% significance level. In panel C and D, the null hypothesis of no Granger causality from GDP growth rate to BP growth rate cannot be rejected in any of the

[8] Since it is not uncommon for BP growth rate to fluctuate around 0 percent, we choose -10 percent rather than 0 percent as a threshold so that any quarter with BP growth rate smaller than -10 percent is considered as one with housing market downturn.

two regimes. These findings, together with the association between the high/low volatility regime and the downturn/upturn phase of the housing and business cycles, indicate that BP growth rate Granger causes GDP growth rate only when the housing and economic activities are experiencing contractions.

Table 1.3: Regime-Dependent Granger Causality Tests

(A)	H_0: BP growth rate does not Granger cause GDP growth rate in low volatility regime H_a: BP growth rate Granger causes GDP growth rate in low volatility regime	LR=1.62
(B)	H_0: BP growth rate does not Granger cause GDP growth rate in high volatility regime H_a: BP growth rate Granger causes GDP growth rate in high volatility regime	LR=27.33***
(C)	H_0: GDP growth rate does not Granger cause BP growth rate in low volatility regime H_a: GDP growth rate Granger causes BP growth rate in low volatility regime	LR=0.3
(D)	H_0: GDP growth rate does not Granger cause BP growth rate in high volatility regime H_a: GDP growth rate Granger causes BP growth rate in high volatility regime	LR=0.8

Notes: LR denotes the likelihood ratio test. $*$, $**$ and $***$ denote statistical significance at the 10%, 5% and 1% level.

Regime-dependent causality analysis shows the importance of modeling housing-output link in a nonlinear fashion. Based on linear VAR approach, Ghent and

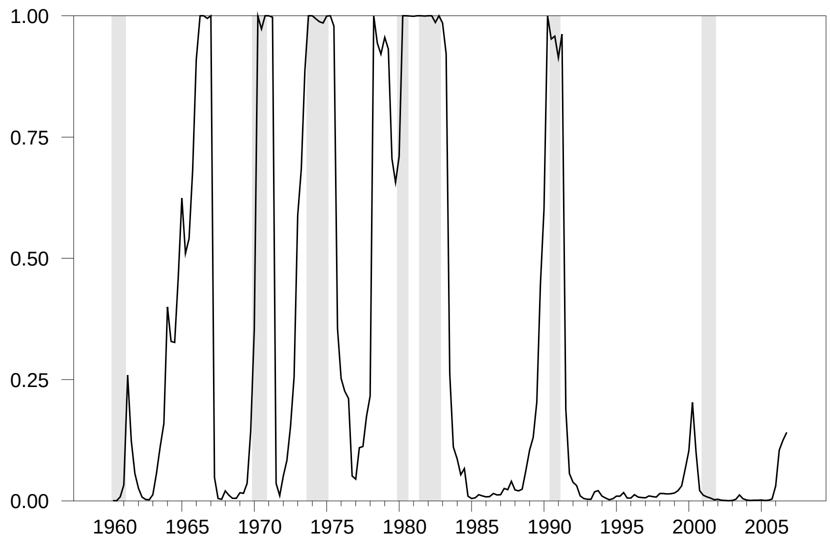
Owyang (2010) find no consistent statistical relationship showing that housing affects business cycles at city-level. We argue that the discrepancy between their findings and ours may be because the information content of BP growth rate cannot be fully exploited in a linear VAR model. Since the authors examine the variables' relationship over the entire sample period (1983Q1-2008Q4), they rule out the possibility of structural breaks in the relationship.

Our results from the Granger causality tests support the views of Leamer (2007), Case and Quigley (2008) and Strauss (2013) that housing downturns are closely linked to economic recessions. Moreover, the results are in line with the previous works on housing's asymmetric impact on macroeconomic aggregates (Case, Quigley, and Shiller (2013) and Guerrieri and Iacoviello (2015)). Finally, Smets (2007) raises the doubt that housing's leading effect may be due to the omission of several monetary variables. Our results verify that housing continues to be a strong leading factor after interest rates are taken into consideration. To ensure robustness, in the next section we also examine the housing-output link after several monetary variables, i.e. term spreads, 10-year interest rates, real interest rates and inflation, are controlled for.

1.4.3 Robustness Checks

In this section we conduct two robustness checks. First, many believe that the recession of 2007 was triggered by problems in the housing markets, therefore we consider a shorter sample period (1960Q1-2006Q4) in order to see whether the asymmetric leading effect of BP growth rate on GDP growth rate remains. Second, as Smets (2007) points out that housing's leading effect on the economy may disappear after several monetary factors are taken into consideration, we estimate several MS-VAR models using term spreads, 10-year interest rates, inflation and real interest rates separately as control variable.

Figure 1.4: Smoothed Probabilities of High Volatility Regime



Notes: Shaded areas correspond to the NBER recession dates.

Figure 1.4 shows the estimated smoothed probabilities using the shorter sample period. As with the full sample case, the high volatility regime (regime 2) is related to the downturn phases in both the housing and business cycles. Table 1.4 presents the results of model specification and regime-dependent Granger causality tests in panels (A) and (B), respectively. The first column corresponds to the short sample period, denoted as SHORT. For the model specification, we see that the null hypotheses of linear VAR model and of regime-switching only in parts of the model are rejected at 1%, 1%, and 10% significance levels, thus the data is in favor of a MS-VAR model with all parameters subject to regime change. For the Granger causality tests, the causal pattern is the same as that found in the full sample case: BP growth rate Granger causes GDP growth rate only in the high-volatility regime, and there is no reverse causality from GDP growth rate in both regimes.

Table 1.4: Results of Robustness Checks

	SHORT	TS	INT10	INF	RFFR
(A) VAR vs MS-VAR (Davies)	0.000***	0.000***	0.000***	0.000***	0.000***
A vs AC	43.02***	38.03***	51.59***	13.34***	49.24***
C vs AC	25.61*	26.43**	36.93***	18.47	24.71*
(B) BP does not GC GDP (1)	3.65	2.3	4.08	5.26*	3.66
BP does not GC GDP (2)	18.08***	11.62***	29.67***	19.74***	23.69***
GDP does not GC BP (1)	4.05	2.63	5.87*	3.71	0.79
GDP does not GC BP (2)	3.55	1.54	0.26	3.44	5.24*

Notes: SHORT indicates that a shorter sample period (1960Q1-2006Q4) is chosen. TS/INT10/INF/RFFR indicates using term spreads/10-year interest rates/inflation/real interest rates as control variable. The first row of panel A tests the null hypothesis of linear VAR against the alternative hypothesis of MS-VAR. The second row of panel A tests the null hypothesis of regime-switching only in the autoregressive part (A) of the MS-VAR model against the alternative of regime-switching in all parameters (AC) . The third row of panel A tests the null hypothesis of regime-switching only in the covariance matrix (C) of the MS-VAR model against the alternative of regime-switching in all parameters (AC). Panel B displays the results of Granger causality tests. (1) indicates low-volatility regime and (2) high-volatility regime. For instance, the first row in panel B tests the null hypothesis that BP growth rate does not Granger cause (GC) GDP growth rate in the low-volatility regime. All tests, except for the linearity test which is based on the Davies' test, are conducted using the standard LR test. $*$, $**$ and $***$ denote statistical significance at the 10%, 5% and 1% level.

The estimation results of the MS-VAR models controlling for other monetary variables are shown starting from the second column of Table 1.4, in this order: term spreads (TS), 10-year interest rates (INT10), inflation (INF) and real interest rates (RFFR). We see that a MS-VAR model with regime-dependence in the autoregressive parameters and the covariance matrix is preferable to models with other specifications in all cases except for INF, for which a model with regime-dependence only in the covariance matrix seems to be preferred. In regard to the causality patterns, the evidence of BP growth rate Granger causing GDP growth rate in the high-volatility regime (second row in panel B) remains the same as before in all cases. Note that all LR test statistics are relatively large and thus indicate strong rejection of the null hypothesis. The overall results suggest that BP growth rate strongly lead GDP growth rate when both the housing and aggregate activity are experiencing downturns.

1.5 Conclusions

This paper investigates housing's role in the overall economy by employing a regime-switching VAR framework. Previous works have provided mixed results of housing's leading effect on the business cycles. Leamer (2007) and Strauss (2013) claim housing to be strong leading indicator of the economy, while Ghent and Owyang (2010) find no consistent statistical relationship displaying housing's leading effect at city-level. We argue that the discrepancy may be due to the fact that housing has time-varying effect on the economy. We propose to model the housing-output relation using MS-VAR approach, allowing the system of variables of interest to follow a stochastic regime-switching Markov chain. Consequently, we are able to see how these variables affect each others in each regime.

Our empirical results show that the housing-output link is regime-dependent. The model-identified high-volatility regime corresponds to the downturn phase of the housing and business cycles, while the model-identified low-volatility regime is associated with the upturn phase. Regime-dependent Granger causality tests suggest that the causal link exists from the growth rate of building permit to the growth rate of GDP only in the high-volatility regime, and there is no reverse causation from GDP growth to building permit growth in both regimes. In other words, housing leads the aggregate economy only when both the housing and business cycles are experiencing contractions.

It remains an open question why BP growth rate leads GDP growth rate in an asymmetric fashion. However, it would be possible to attribute the leading effect of BP growth rate on GDP growth rate during recession to the housing variable's high correlation with consumer expectation (Strauss (2013)). Consumer sentiment has long been thought to contain predictive information for GDP around the recession periods (Batchelor and Dua (1998) and Christiansen, Eriksen, and Møller (2014)).

1.A Complete Estimation Results

Table 1.5: Estimated Parameters of the MS-VAR Model with FFR as the Control Variable

	Regime 1		Regime 2	(recessions)
$a_{\Delta bp}$	3.132***	(3.23)	-4.385	(-0.79)
$a_{\Delta bp,\Delta bp,1}$	0.216**	(2.37)	0.173	(0.66)
$a_{\Delta bp,\Delta bp,2}$	0.0151	(0.2)	0.349	(1.43)
$a_{\Delta bp,\Delta y,1}$	-0.78	(-1.07)	-1.018	(-0.42)
$a_{\Delta bp,\Delta y,2}$	1.003	(1.36)	0.019	(0.007)
$a_{\Delta bp,i}$	-2.505***	(-2.59)	-0.896	(-0.419)
$a_{\Delta bp,i,1}$	1.587	(0.9)	-3.665	(-0.98)
$a_{\Delta bp,i,2}$	0.444	(0.46)	4.938**	(2.23)
$a_{\Delta y}$	0.476***	(3.74)	1.111***	(2.85)
$a_{\Delta y,\Delta bp,1}$	0.0028	(0.24)	0.0481**	(2.56)
$a_{\Delta y,\Delta bp,2}$	0.0096	(1.01)	0.017	(1.12)
$a_{\Delta y,\Delta y,1}$	0.225**	(2.39)	-0.114	(-0.42)
$a_{\Delta y,\Delta y,2}$	0.204**	(2.56)	0.202	(1.02)
$a_{\Delta y,i}$	0.074	(1.06)	0.084	(0.42)
$a_{\Delta y,i,1}$	-0.224	(-1.48)	0.017	(0.07)
$a_{\Delta y,i,2}$	0.156	(1.42)	-0.153	(-0.94)
$\sigma_{\Delta bp}$	17.96***	(5.97)	123.05***	(4.17)
$\sigma_{\Delta y}$	0.29***	(7.44)	0.7***	(4.03)
p_{11}	0.95			
p_{22}	0.88			
Duration	18.31	(quarter)	8.57	

Notes: $a_{equation,variable,lag}$; t-statistics are reported in parentheses; $*$, $**$ and $***$ denote statistical significance at the 10%, 5% and 1% level.

Chapter 2

Housing Market Spillovers: Identifying Housing Demand Shocks Using Sales Variable

2.1 Introduction

The existing empirical studies on housing spillovers often define a housing demand shock as an unexplained change in housing prices (Musso, Neri, and Stracca (2011)), or as one that affects housing prices and residential investment simultaneously and in the same direction (Jarociński and Smets (2008)). However, unlike other asset values, housing prices may not reflect changes in market conditions in a timely manner. For instance, if, due to imperfect information, sellers' price-setting decisions depend on their gradual awareness of the bargaining power they possess, housing prices are likely to respond to changes in market demand with delay, see Berkovec and Goodman (1996) and Hort (2000). Failing to account for the timing of the housing demand shocks could explain why the existing literature has found small and questionable effects of housing spillovers.

In this paper we propose a new way to identify housing demand shocks. The first step is to show that housing sales react more quickly than housing prices to changes in demand factors, as suggested by the theory in Berkovec and Goodman (1996). We then propose a structural vector autoregression (SVAR) model in which the unexplained movements in housing sales are labeled as housing demand shocks, and seek to address the following two questions. First, how does an unanticipated expansion in housing demand affect housing variables and other macroeconomic variables? Second, through which channel is the housing sector linked to the broader economy?

Similar to the previous studies (Hort (2000), Andrew and Meen (2003), Oikarinen (2012) and de Wit, Englund, and Francke (2013)) that investigate the responses of the housing variables to changes in demand factors, we find that housing sales respond instantly to interest rate shocks, whereas housing prices exhibit delayed responses. The results confirm the implications of the search theory in Berkovec and Goodman (1996) that sales are superior to prices as demand measure. According to this theory, sellers' offer prices are adjusted with time delay as they do not immediately observe changes in market conditions. In contrast, buyers' decisions - whether to enter or withdraw from the market - are directly influenced by market fundamentals and reflected in the number of sales.

Our empirical findings show that the unexplained movements in housing sales have the interpretation of shifts in housing market-specific demand. For instance, an unanticipated increase in housing sales leads to a rise in residential investment and, in particular, causes a delayed increase in housing prices. The unanticipated rise in housing sales also causes delayed, but persistent, increases in private consumption. These results are in line with Iacoviello (2005) and Iacoviello and Neri

(2010), who show that housing demand shocks not only generate fluctuations in housing variables, but can also affect household expenditure[1]. Likewise, mortgage debt, short-term interest rate and the aggregate price level rise following an unexpected growth in housing sales. On the contrary, unexplained movements in housing prices generally have small and even counterintuitive effects on the macroeconomic variables.

Splitting the entire sample period into two subperiods shows that the housing demand shocks trigger greater housing spillovers to the consumption goods sector after the early 1980s, an era characterized by financial innovation and deregulation, than before. We argue that the strong response in spending in the second period is mainly due to housing collateral channel rather than wealth channel. In a more developed financial market, homeowners can borrow against higher housing equity in order to finance extra spending, therefore their consumption is likely to respond more to housing demand shocks.

The remainder of the paper is organized as follows. In section 2.2 we summarize the search model in Berkovec and Goodman (1996) which provides the motivation for our empirical strategy, present some stylized facts on the housing sales and prices, and study the reactions, especially the timing of the responses, of these housing variables to shocks to demand factors. Section 2.3 suggests a new way to identify housing demand shocks. Section 2.4 examines the impact of housing demand shocks on the housing dynamics and the broader economy before and after the financial innovation and deregulation, and identifies the channel through

[1]Using a dynamic stochastic general equilibrium (DSGE) model, Iacoviello (2005) thinks of housing price shocks as housing demand shocks because housing prices move instantly following shifts in housing demand. However, since the DSGE model is a stylized model of the economy, it is possible that it cannot depict the precise response of housing prices to shocks in the actual economic system (see Lütkepohl and Netšunajev (2012)). In other words, the DSGE model in Iacoviello (2005) may fail to capture the fact that housing prices are slow-moving.

which the housing sector is linked to the overall economy. Section 2.5 conducts robustness analysis. Section 2.6 concludes.

2.2 Sales As Measure of Housing Demand

2.2.1 The Search Model

To motivate the empirical strategy in the current work, we present the basic features of the search model in Berkovec and Goodman (1996), which explains why housing sales lead housing prices and act as a better indicator of housing demand[2].

There is a sequence of periods in the model. In each period sellers and buyers search for a potential trading partner. Buyers' bid prices are drawn from a uniform distribution between $\bar{P}_t$ and $\underline{P}_t$. The probability of a successful match (i.e. sale) for a particular seller is defined as:

$$M_t(P_{t,j}) = (\frac{B_t}{S_t})\,(\frac{\bar{P}_t - P_{t,j}}{\bar{P}_t - \underline{P}_t}), \tag{2.1}$$

where the first component is the ratio of the number of buyers to the number of sellers, indicating the likelihood that a seller is visited by a buyer and is irrelevant

[2]There are other explanations for the sale-price co-movement. Wheaton (1990) argues that a higher matching rate between buyers and sellers reduces the supply of for-sale units, pushing sellers' reservation prices upward. Stein (1995) and Ortalo-Magné and Rady (2006) emphasize on the down-payment requirement in the housing market. Most of the buyers use their proceeds from selling the existing houses to finance the down-payment for the new houses. When home values increase, it becomes easier for buyers to fulfill the down-payment requirement, thus sales increase. Genesove and Mayer (2001) find that when households experience housing price losses, they tend to offer higher asking prices due to loss aversion behavior, causing the housing sales to decline. In our empirical analysis we test the implications of these theories. Just as most of the works in the empirical literature, our results are in line with the implications of the search theory in Berkovec and Goodman (1996).

of the price[3]. The second component is the probability of a sale if the price set by the seller is $P_{t,j}$, given that the buyer and seller meet. The subscript j indicates the number of periods the seller has been holding the house without selling it. It is supposed that sellers have time pressure to sell and therefore will set the prices at $\underline{P}_t$ to ensure the disposal of their houses once j is equal to, say, J. As a result, all sellers adopt a price-setting policy that induces them to reduce the prices with the length of time their houses remain unsold in the market.

The amount of sales, T_t, depends on the number of different seller types and the probabilities with which they are able to dispose of their houses

$$T_t = \sum_{j=1}^{J} q_{t,j} \, M_t(P_{t,j}), \tag{2.2}$$

where $q_{t,j}$ is the number of sellers that have held the houses for j periods.

All market participants' common expected price, P_t^e, can jointly influence buyers' bid prices as well as sellers' offer prices at time t, and is assumed to have a backward-looking nature. That is, the formation of the common expected price depends primarily on previous period's average price for the completed sales

$$P_{t-1} = \frac{\sum_{j=1}^{J} P_{t-1,j} \, q_{t-1,j} \, M_{t-1}(P_{t-1,j})}{\sum_{j=1}^{J} q_{t-1,j} \, M_{t-1}(P_{t-1,j})}. \tag{2.3}$$

Suppose the economy receives an external negative housing demand shock, e.g. an increase in interest rate. Some buyers would choose to leave the market as the cost of obtaining loans has become higher, leading to a lower ratio of buyers to sellers, $\frac{B_t}{S_t}$[4]. The decrease in the matching probability, M_t, results in an immediate reduction in the number of sales, T_t. In the meanwhile, since the

[3]It is assumed that there are always more sellers than buyers in the market.

[4]In this model economy housing dynamics is mainly driven by market demand. We believe that this depiction of the housing market is to some extent true in reality, at least in the short run. First, housing stock is fixed and thus is unlikely to influence the number of houses for sale (number of

current common price expectation depends on last period's price level, buyers' bid prices and sellers' offer prices remain unchanged, therefore the average price for the completed sales in the current period does not alter[5]. In the next period, the remaining unsuccessful sellers have the pressure to sell their homes and tend to adjust the offer prices downward, thus lowering the transaction prices. Further reductions in prices occur as price expectation drops[6]. The model predicts that housing sales respond quickly to shifts in housing demand whereas housing prices exhibit lagged response. Similarly, based on a search-and-matching model, Carrillo, de Wit, and Larson (2015) also suggest that changes in housing demand quickly translate to movements in sales rather than prices[7]. Subsequent empirical works support the predictions of the search model, see Hort (2000), Andrew and Meen (2003), Oikarinen (2012) and de Wit, Englund, and Francke (2013).

2.2.2 Stylized Facts on Housing Series

To depict housing sales activity, we use new single-family housing sale variable rather than existing single-family housing sale variable. This is because, due to differences in the variables' definitions, the former variable leads the latter by one or two months and thus is better at reflecting promptly the changes in sales

home sellers) in the short run. Second, although some suggest that existing home sellers can react instantly to changes in fundamental factors such as interest rate, the findings in de Wit, Englund, and Francke (2013) do not support this argument.

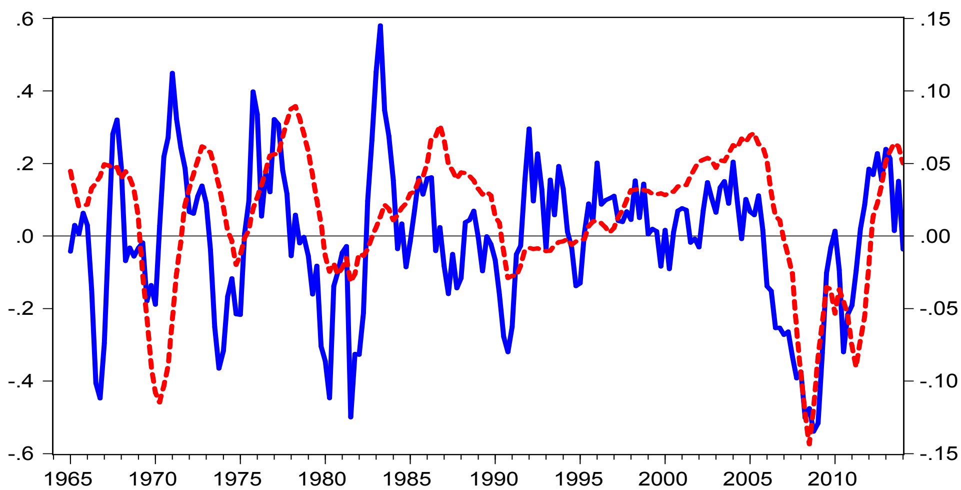
[5]Note that after plugging the sales probability into the average price equation, the average price is not dependent on the ratio of buyers to sellers.

[6]The dynamic behavior of the housing variables can be seen in the simulation exercise in Berkovec and Goodman (1996).

[7]We do not use the theoretical model in Carrillo, de Wit, and Larson (2015) to motivate our empirical strategy, because the model primarily emphasizes on the derivation of two measures, sellers' bargaining power and sale probabilities, and their predictive content for future home price appreciations.

activity. Following the definitions by the U.S. Census Bureau, a sale of new house takes place whenever a sales contract is signed or a deposit is received. On the other hand, according to the National Association of Realtors® and the Census Bureau, "the majority of existing home transactions are reported when the sales contract is closed and most transactions involve a mortgage which takes 30-60 day to close." In other words, an reported existing housing sale is likely to be a sale that has taken place one or two months before. In the robustness section, we see that the main results based on existing housing sales are nevertheless qualitatively similar to those based on new housing sales. Note that for brevity, housing sales correspond to new housing sales in this study.

Figure 2.1: Annual Growth Rates of Housing Sales and Housing Prices



Notes: Housing sales (blue solid line, left axis) and housing prices (red dotted line, right axis) are in annual growth rate terms. Housing sales are provided by the U.S. Census Bureau. Nominal house prices, constructed using interpolation and extrapolation methods (see Davis, Lehnert, and Martin (2008) for details), are provided by the Lincoln Institute of Land Policy. Nominal prices are converted to real prices using the consumer price index from the OECD economic outlook data.

Figure 2.1 displays the annual growth rates of both housing sales and housing prices. The sales cycles have the tendency to lead the price cycles. In particular, sales growth often drops before declines in price growth, and also picks up prior to price recoveries. These can be seen around 1970, 1975, 1980, 1990 and 2006. Cross correlations between the growth rates of sales and prices verify this perception and are summarized in Table 2.1. The correlations between lagged sales growth and price growth are high, ranging from 0.45 to 0.53. On the contrary, the correlations between price growth and sales growth one to four quarters ahead are generally small, ranging from 0.02 to 0.24 in absolute terms.

Table 2.1: Correlation Between Housing Sales Growth at Quarter t+k and Housing Prices Growth at Quarter t

k =	-4	-3	-2	-1	0	1	2	3	4
	0.52	0.53	0.50	0.45	0.36	0.24	0.11	-0.02	-0.14

Notes: Correlations are computed using annual growth rate series.

2.2.3 Do Sales Respond Before Prices to Changes in Demand Factors?

To see whether sales are a better indicator of shifts in housing demand than prices, we use a vector autoregression (VAR) model including the housing variables as well as a market demand factor. The impulse response analysis provides a way to examine the reaction speed of sales and prices following a shock to the demand factor. Previous studies on international data have adopted this multiple variable approach to answer similar question, see Hort (2000), Andrew and Meen (2003), Oikarinen (2012) and de Wit, Englund, and Francke (2013).

We think of a market shock as an unexpected change in short-term interest rate. The view that monetary policy acts as an important factor driving the housing dynamics is common in the literature. For instance, interest rate shocks have been shown to affect housing quantity such as housing starts and residential investment, see Erceg and Levin (2006) and Vargas-Silva (2008), and to explain a significant fraction of housing prices, see Jarociński and Smets (2008), Musso, Neri, and Stracca (2011), Calza, Monacelli, and Stracca (2013) and Bjørnland and Jacobsen (2013).

We estimate a three-variable VAR model including the federal funds rate, the log of housing sales and the log of real housing prices[8]. The sample period spans from 1964Q1 to 2014Q1. The model is as follows:

$$Y_t = c + A_1 Y_{t-1} + ... + A_p Y_{t-p} + B\varepsilon_t \tag{2.4}$$

where Y_t is the vector of endogenous variables, c is the constant term, A_j $(j = 1, ..., p)$ are the $(3\ x\ 3)$ coefficient matrices, B is the matrix of contemporaneous interactions and ε_t is the vector of serially and mutually uncorrelated shocks with identity covariance matrix. Schwarz information criterion and Hannan-Quinn information criterion both suggest including two lags of each endogenous variable in the model.

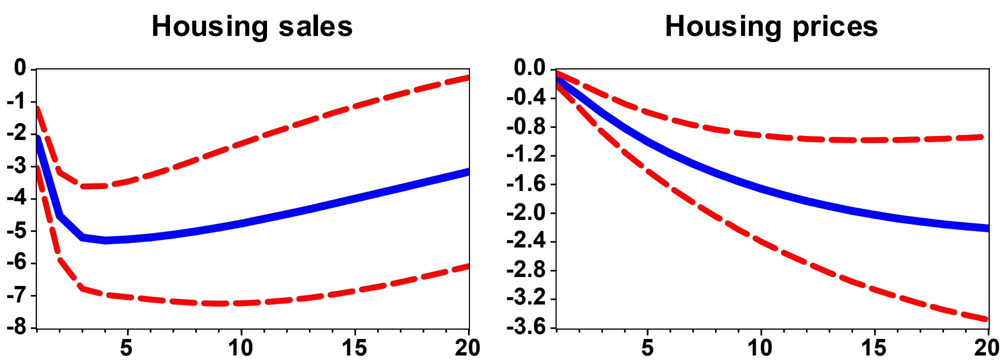
To identify the interest rate shocks, we use a recursive (i.e. Cholesky) identification scheme in which the ordering of the variables in the VAR model is: interest rate, housing sales and housing prices. This ordering assumes that the interest rate shocks have instantaneous impact on housing dynamics, whereas the short-term rate does not react to housing shocks within the same quarter[9]. One reason for the

[8]See Table 2.4 in the appendix for the definitions and sources of the variables.

[9]Similar assumption is made in Hort (2000), Iacoviello (2005), Oikarinen (2012) and de Wit, Englund, and Francke (2013)

ordering is that since our goal is to observe housing variables' reaction speed, we do not impose any restriction on the instantaneous reaction of these variables and instead let the data speak. Note that the overall results are not dependent on the ordering.

Figure 2.2: Responses of Housing Sales and Housing Prices to a One-Standard Deviation Interest Rate Shock



Notes: Responses are surrounded by 90% confidence intervals.

Figure 2.2 shows that a one-standard-deviation interest rate shock causes an immediate drop in housing sales. The largest (negative) response of sales occurs within a five-quarter period, followed by a gradual return to the pre-shock level. In contrast, housing prices dip only slightly on impact and decrease persistently over time[10]. The delayed response of housing prices is also documented in Bjørnland and Jacobsen (2013), who consider alternative schemes to identity the monetary policy shock. In sum, results from the VAR analysis indicate that a demand factor shock quickly translates into changes in housing sales rather than prices, which

[10]One criticism of this analysis can be that the model is too parsimonious. Based on a VAR model that incorporates more variables, we find that the time profiles of the housing variables' responses to the interest rate shock do not change substantially (See Figure 2.8 in appendix 2.B).

are not only in line with the previous empirical studies, but also confirm the predictions of the search theory[11].

2.3 Identifying Housing Demand Shocks

There is a considerable interest on the source and consequence of the movements in housing market. For instance, Iacoviello and Neri (2010) suggest that housing demand shocks not only explain large parts of variations in housing variables, but can also initiate spillovers to the broader economy. Given the previous findings that housing sales are a better summary measure of shifts in housing demand than housing prices, we propose a new way of identifying housing demand shocks to the existing literature.

We estimate a structural vector autoregression (SVAR) model similar to the one in Musso, Neri, and Stracca (2011), including several housing and conventional macroeconomic variables. The variables enter the SVAR model in this ordering: consumer price index, real private consumption, the federal funds rate, housing sales, real residential investment, real housing prices and real mortgage debt. All variables except for the short-term rate enter the model in logs [12].

The identification of the housing demand shocks is achieved through a recursive scheme. Consumption shocks may reflect changes in income expectation

[11] The financial reforms in the earlier 1980s may change the responses of the housing variables to fundamental shocks, see Dynan, Elmendorf, and Sichel (2006). Therefore we estimate the VAR model over two subsample periods, 1964Q1-1982Q4 and 1983Q1-2014Q1 (section 2.4 provides reasons for the choice of the splitting point), and investigate whether the financial reforms have altered the fact that housing sales react prior to housing prices to the interest rate shock. Although the results, provided upon request, show that the patterns of the housing variables' responses have slightly changed over time, sales have always reacted before prices to the shock.

[12] Table 2.4 in appendix 2.A reports the details of the variables.

or aggregate demand[13], while interest rate shocks may mirror monetary policy stance. The unpredictable movements in consumer price index can capture aggregate supply shocks. The SVAR model assumes that these fundamental shocks have instantaneous impact on the housing dynamics as well as mortgage debt. In contrast, shocks originating in housing and mortgage credit markets do not affect the three macro fundamental variables within the same quarter. The restrictions are motivated by the delayed reaction of the general public and monetary policy makers to the housing news[14], and by the sluggish behavior of the aggregate price level.

We refer to the innovations to housing sales that cannot be explained based on the fundamental shocks as housing-specific demand shocks. Housing prices, together with residential investment and mortgage credit, are allowed to move freely within the same quarter when the housing demand shocks occur. We can therefore see whether housing prices exhibit the sluggish responses as suggested by our previous findings and the search theory[15]. In Jarociński and Smets (2008)

[13]Cochrane (1994a,b) suggests that consumption conveys information about future income because economic agents use the news about future income when making consumption decisions.

[14]Since home sellers and buyers (the principal market participants) do not possess complete information about the current housing market conditions (see Berkovec and Goodman (1996)), it is natural to postulate that agents outside the housing markets are also not immediately informed of the market conditions. Empirical evidence from Bjørnland and Jacobsen (2013) shows that monetary policy does not respond strongly to housing price shocks in the short run.

[15]Admittedly, the ordering of the housing variables and mortgage is ambiguous. In particular, the search theory suggests that housing prices are a slow-moving variable, whereas housing sales are sensitive to demand-driven shocks. We have also considered the case when housing sales are placed after housing prices, residential investment and mortgage credit, so that sales are in the least favorable position in the sense that a shock to this variable does not immediately trigger movements in the other variables. We find that the results are both qualitatively and quantitatively similar to those based on the ordering we first propose.

and Musso, Neri, and Stracca (2011), the identification of housing demand shocks is related to an unexpected change in housing prices, implying that home values timely reflect shifts in the demand[16]. If this is not the case in practice, then the housing demand shocks in these paper may not be correctly identified.

Figure 2.3 plots the responses to a one-standard-deviation housing demand shock together with the 90% confidence intervals. Results suggest a structural economic interpretation of an expansion in housing demand: housing and non-housing variables all increase. The response of housing prices is small at the beginning, builds up slowly and reaches the peak about twelve quarters later. This time pattern is in line with our previous findings and the theory's predictions that housing prices respond to shifts in housing demand with delay[17]. Residential investment reacts quickly to an unanticipated expansion in housing demand and its response peaks within five quarters[18].

Next we examine the spillover effects caused by a housing demand shock. The response of consumption increases gradually before reaching the peak ten quarters later. Two potential channels can explain the co-movements between home values and household expenditure following the demand shock: the housing wealth channel and the collateral channel. In the next section we further discuss which channel is more likely to play a primary role for the housing spillovers. Analogous to consumption, mortgage debt also exhibits slowly building and persistent responses. Interest rate rises quickly and is significantly positive for about four

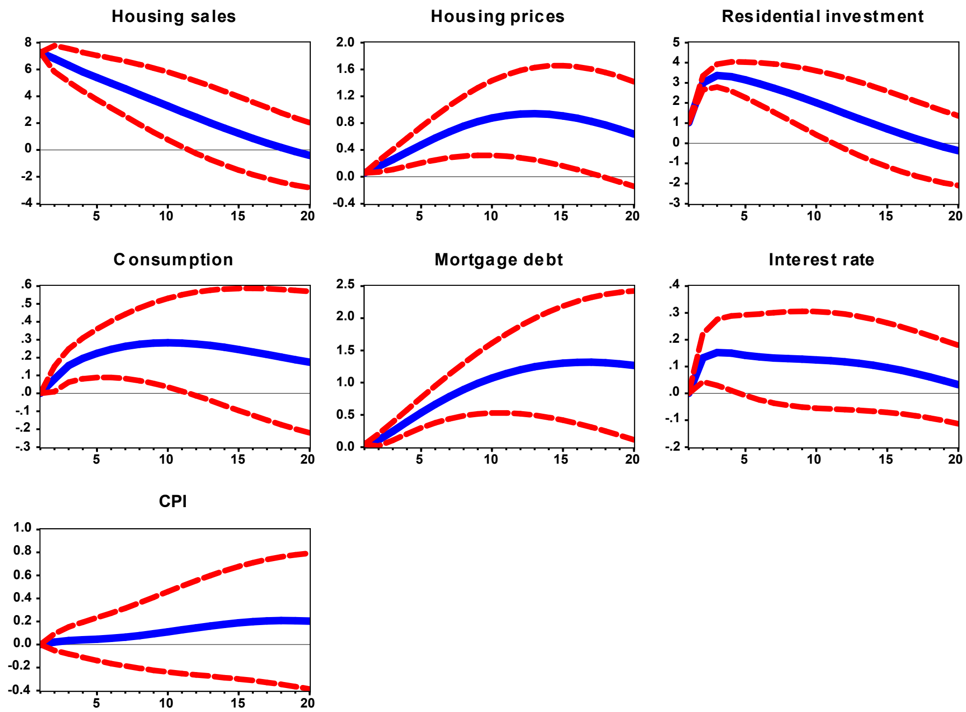
[16]Jarociński and Smets (2008) define a housing demand shock as one that leads to simultaneous increases in housing values and residential investment.

[17]Similar patterns are found when we consider alternative measures of housing prices (see Figure 2.9 in appendix C).

[18]Musso, Neri, and Stracca (2011) find that residential investment shocks have the structural interpretation of housing demand shocks in the US. We conjecture that this is because residential investment, just as housing sales, also reacts quickly to changes in housing demand.

quarters. The response of consumer price index is positive over time but insignificant.

Figure 2.3: Responses to a One-Standard Deviation Housing Demand Shock



Notes: Responses are surrounded by 90% confidence intervals.

The variance decomposition in Table 2.2 assesses the importance of housing demand shock for all variables. The shock accounts for 65%-80% of sales movements in the short run and about 35% twenty quarters later, suggesting that housing demand is a key driver of sales activity. At short horizons, only about 2% of the variation in housing prices, consumption and mortgage debt are explained by the shock. As the horizon increases, housing demand becomes an important contributor to the fluctuations in these variables. At twenty quarters, about 16%, 7% and 17% of the variation in housing prices, consumption and mortgage debt can be accounted for by the shock[19]. In line with Jarociński and Smets (2008), a large part of the variability in residential investment is explained by the demand shock across all horizons. The shock accounts for about 5% of the variation in interest rate at twenty quarters and less than 1.5% of the variation in CPI for all horizons.

Table 2.2: Shares of Housing Demand Shock in Variance Decomposition

Variables/ horizon	1	3	6	12	20
Housing sales	79.99	64.96	51.22	39.39	34.82
Housing prices	0.62	2.47	5.67	11.72	15.86
Residential investment	12.35	43.39	34.68	23.45	19.56
Consumption	0.00	2.42	5.50	7.36	6.76
Mortgage debt	0.29	2.33	8.59	15.10	16.95
Interest rate	0.00	2.07	3.12	4.68	5.47
CPI	0.00	0.08	0.13	0.45	1.14

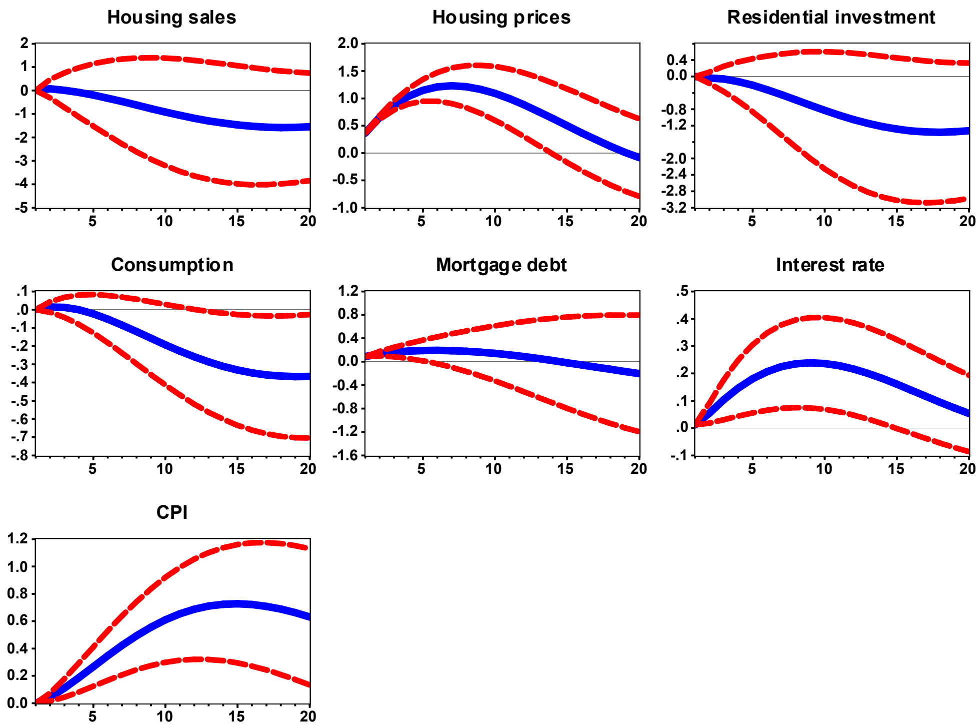
Notes: The variance decomposition is based on the recursive identification scheme according to which the ordering of the variables is consumer price index, real private consumption, interest rate, housing sales, real residential investment, real housing prices and real mortgage debt.

As in Musso, Neri, and Stracca (2011), a housing price shock does not drive the housing market and leads to questionable responses in housing sales and residential investment (see Figure 2.4). Moreover, the housing price shock has little

[19]When we consider a sample period that starts from the early 1980s onwards, the demand shock can account for about 25% and 47% of the fluctuations in consumption and mortgage debt at an horizon of twenty quarters after the shock. The increasingly important role of the demand shock is discussed in the next section.

impact on consumption and mortgage debt. The reason why this shock does not have the interpretation of housing demand shock is probably because housing values do not reflect market demand in a timely manner.

Figure 2.4: Responses to a One-Standard Deviation Shock to Housing Prices



Notes: Responses are surrounded by 90% confidence intervals.

2.4 Collateral Channel: Evidence from Financial Deregulation and Innovation

We have seen that an expansion in housing demand triggers housing appreciation and increases in private consumption. What remains unclear is which channel links the housing sector and the wider economy. The housing wealth channel indicates that changes in net wealth that permanently alter homeowners' resources should move consumption in the same direction. Several studies support this view, see Case, Quigley, and Shiller (2005), Carroll, Otsuka, and Slacalek (2011) and Case, Quigley, and Shiller (2013). The other explanation for the co-movements between housing prices and consumption is the collateral channel. Rising housing prices allow homeowners to borrow against higher collateral values in order to finance extra consumption, hence previously credit-constrained households are likely to increase their spending, see Iacoviello (2005) and Iacoviello and Neri (2010).

According to Buiter (2010), the wealth channel is likely to play a minor role since home generally serves as an asset and a consumption good. Rising housing prices can relax current homeowners' lifetime budget constraints and raise their consumption. On the other hand, higher housing prices can make those planning to purchase home worse off by inducing them to reduce their expenditure on non-housing goods. As a result, the offsetting effects of housing appreciations render the wealth channel ambiguous.

The collateral channel is a more plausible candidate for explaining the rise in consumption following the demand shock. As Cooper and Dynan (2014) point out, a precondition for this channel is that the financial market must provide access for households to achieve housing capital gains through home equity loans, suggesting that the degree of financial deregulation and development is a key factor for the functioning of this channel.

To test the hypothesis that the collateral channel links the housing market and the consumption good market, we make use of the financial liberalization period that occurred in the 1980s[20]. Specifically, we estimate the SVAR model from

[20] Studies that have also taken financial reforms into consideration include Ludwig and Sløk

the previous section over two subsamples, 1964Q1-1982Q4 and 1983Q1-2014Q1, and compare the impact of the housing demand shock in this two periods[21].

If the collateral effect dominates the wealth effect, we should see larger increases in consumption in the second period than in the first one. This is because in a deregulated and developed financial market, higher collateral values, due to housing appreciations, facilitate households' borrowing and thus raise their spending (Muellbauer (2007)), whereas in a less developed financial market households may not have the access to realize the housing capital gains. Residential investment, housing sales and mortgage debt are also expected to have larger responses in the more recent period, as it has become easier for previously credit-constrained home buyers to borrow and participate in the housing market.

If the wealth channel plays a dominant role, we should see increases in consumption in both periods, because household expenditure would respond the same way to rises in housing wealth regardless of the financial development.

Figure 2.5 plots the responses, surrounded by the 90% confidence intervals, to a one-unit shock to housing demand from the second period (solid lines) as well as the responses to a one-unit shock to housing demand from the first period (dotted lines). The response of consumption over the more recent period is larger than that over the earlier one, even when the uncertainty surrounding the responses is taken into account. These findings suggest the collateral channel to be the primary link between the housing sector and the broader economy[22]. Interestingly,

(2004), Goodhart and Hofmann (2008), Oikarinen (2009) and Iacoviello and Neri (2010)

[21]Following Iacoviello and Neri (2010), we choose 1982Q4 to be the splitting point as the time point is in accordance with the enactment of the Garn-St Germain Depository Institutions Act of 1982, which deregulates savings and loan associations. Note that the results are robust when we use 1980Q1 or 1985Q1 as the splitting point.

[22]Cooper (2013) and Abdallah and Lastrapes (2013) also suggest housing affects household spending through the collateral channel and not the wealth channel.

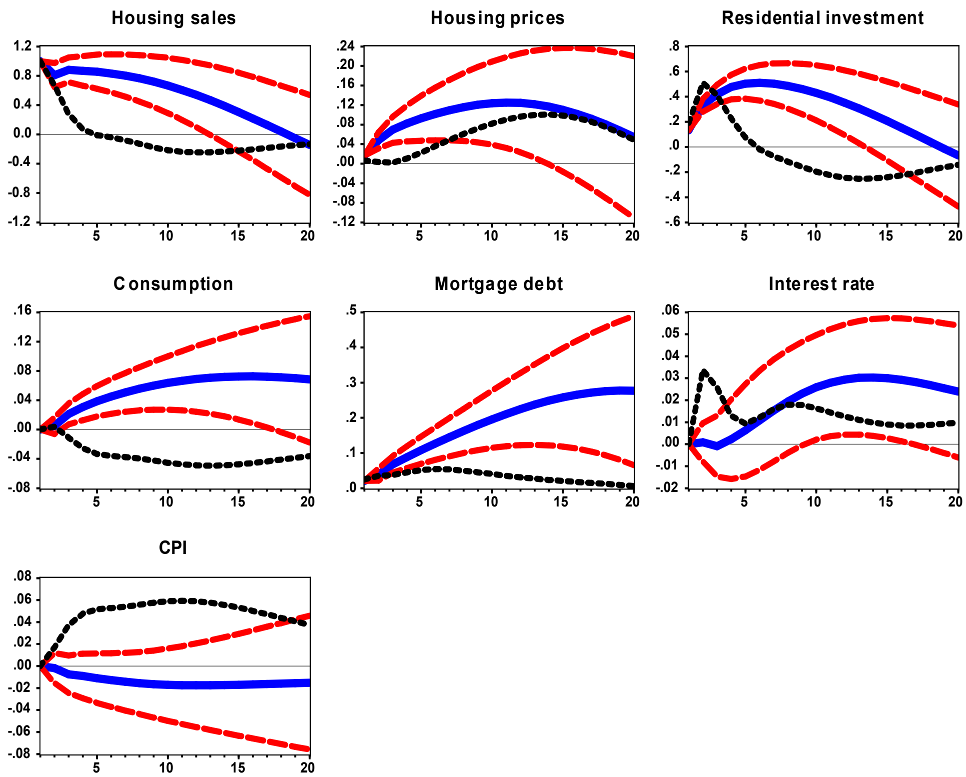
consumption shows negative reactions in the former sample. Two explanations can be given for this finding: (1) when credit market liberalization is absent, home buyers may have to save more in the face of down-payment, thus reducing their spending on non-housing goods (Aron, Duca, Muellbauer, Murata, and Murphy (2012)); and (2) when credit is scarce, a housing demand shock tends to cause the interest rate to rise quickly, which in turn can suppress household consumption.

Housing variables and housing debt also have larger responses over the more recent period. The response of residential investment peaks about five quarters later and slowly returns to the pre-shock level in the second sample, whereas in the first sample it peaks within three quarters, reverses quickly and declines six quarters later. The increase in housing sales is immediate and persistent in the latter sample, as opposed to the quick rise in sales which turns into decline five quarters later in the earlier sample. The response of housing prices rises with time delay and peaks more than ten quarters later in both cases, suggesting that the sluggishness in the adjustment process of housing prices remains over time. Mortgage debt's response in the second period is significantly larger than that in the first period.

Interest rate's response is quick in the first period, whereas in the second period its response is small at first and reaches the peak about thirteen quarters later. The demand shock has large and persistent positive effects on the overall price level before the financial reforms, which is line with the view that consumer prices are sensitive to macroeconomic shocks before the 1980s (see Goodhart and Hofmann (2008)). On the contrary, the reaction of the overall price level is small and insignificant, though negative, in the second sample[23].

[23]When excluding the crisis period, the response of the CPI is positive, yet small and insignificant, in the latter sample. The asymmetry in the CPI's responses reminds us of the missing deflation puzzle during the Great Recession. Thus, it should be noted that the linear modeling

Figure 2.5: Responses to a One-Unit Housing Demand Shocks in Two Periods: 1964Q1-1982Q4 (Black Dotted Line) and 1983Q1-2014Q1 (Blue Solid Line)



Notes: Responses are surrounded by 90% confidence intervals. Note that for housing sales, residential investment, consumption, mortgage debt and CPI, the confidence intervals of the responses in the first period, when plotted, generally do not overlap with their counterparts in the second period.

approach adopted in this study cannot capture the non-linear relationships between the variables.

Table 2.3 shows the quantitative importance of the housing demand shock over time. The shock can explain much more fraction of the twelve- and twenty-quarter-ahead forecast-error variance of all variables, except for CPI, in the recent period (1983Q1-2014Q1) than in the earlier one (1964Q1-1982Q4). The general price level in the latter period seems to be insulated against disturbances from the housing market. This can be due to the fact that the central bankers pursue a price-stability-oriented monetary policy after the early 1980s.

Table 2.3: Shares of Housing Demand Shock in Variance Decomposition across Two Periods: 1964Q1-1982Q4 (Period 1) and 1983Q1-2014Q1 (Period 2)

	Period 1		Period 2	
Variables/ horizon	12	20	12	20
Housing sales	18.55	16.54	63.82	49.39
Housing prices	6.83	12.01	18.74	19.37
Residential investment	13.82	14.23	51.71	39.62
Consumption	10.61	14.79	22.15	25.15
Mortgage debt	6.38	5.78	38.01	47.21
Interest rate	4.91	4.73	7.40	15.65
CPI	24.25	15.78	2.31	3.49

Notes: The variance decomposition is based on the recursive identification scheme according to which the ordering of the variables is consumer price index, real private consumption, interest rate, housing sales, real residential investment, real housing prices and real mortgage debt.

2.5 Robustness Checks

2.5.1 Housing and Business Investment

So far we have only studied housing's role in the household sector. Yet, spillovers from the housing market to the business sector have also been documented in recent literature (see, for instance, Chaney, Sraer, and Thesmar (2012) and Liu, Wang, and Zha (2013)). In particular, Liu, Wang, and Zha (2013) find that a housing demand shock originating from the household sector can trigger co-movements between business investment and land prices[24].

To empirically examine the impact of the housing demand shock on business investment, we extend the baseline VAR model to include business investment and replace housing prices by land prices[25]. A housing demand shock, identified via a recursive scheme, is defined as an unexpected change in housing sales that cannot be explained by shocks to the fundamental variables and business investment[26]. We assume that the housing dynamics react instantaneous to business

[24]Using a dynamic stochastic general equilibrium (DSGE) model, the authors show that a housing demand shock triggers competition for land between households and entrepreneurs. The resulting higher land prices increase firms' net worth and expand their borrowing capacity, allowing them to raise business investment. Expansion in production increases households' wealth which in turn leads to more demand for land and even higher land prices. This financial spiral generates large fluctuations in land prices and business investment.

[25]Following Liu, Wang, and Zha (2013), we use land prices because the movements in housing prices are mainly driven by land values rather than by the values of structures (see Davis and Heathcote (2007)). The land price index is constructed by Davis and Heathcote (2007) and is available on the website of Lincoln Institute of Land Policy. Nominal land price index is converted to real land price index using the consumer price index from the OECD economic outlook data. Definition and sources of the variables can be found in 2.A. Note that the results do not change much if we use housing prices.

[26]The ordering of the variables in the extended model is: consumer price index, real private

shocks, while the business sector reacts to unexpected changes in the housing market with delay.

Figure 2.6 shows that a housing demand shock generates significant positive responses in business investment, supporting the theory that housing demand shocks in the household sector can spill over to the business sector[27]. Interestingly, the demand shock generates the stylized facts in the housing and business cycle literature: residential investment leads both the business investment and the business cycles (see Green (1997), Coulson and Kim (2000) and Leamer (2007)). Specifically, the response of residential investment is sensitive to the housing demand shock on impact and peaks about five quarters later, whereas business investment's response increases more gradually and peaks ten quarters later[28]. Our findings, together with the theories, could provide a new structural explanation for the observed lead-lag relations between these two GDP components[29].

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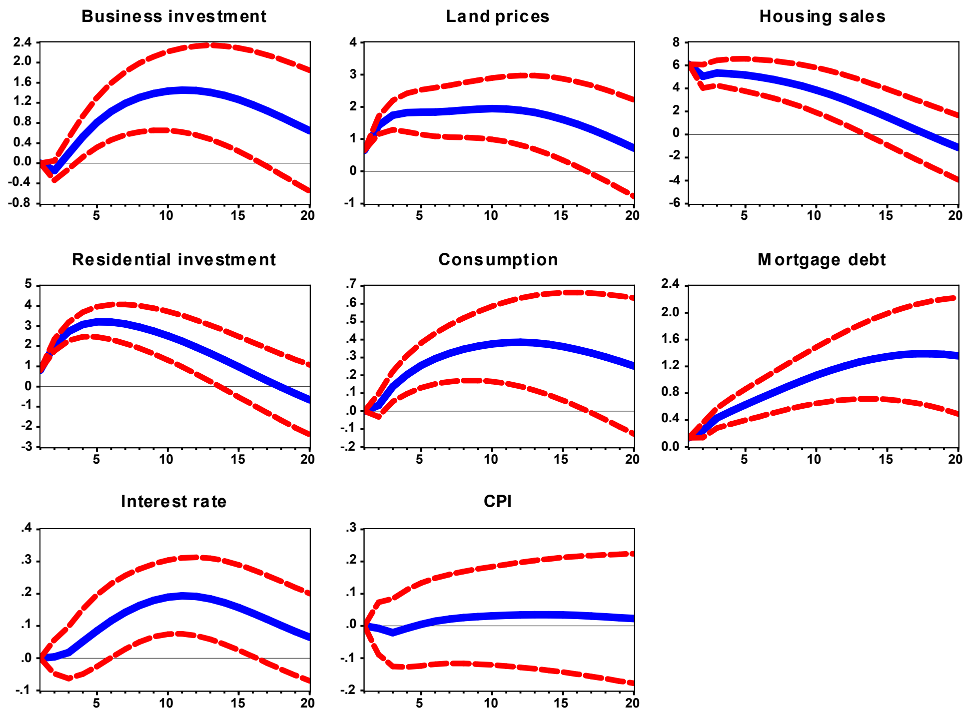
consumption, real business investment, the federal funds rate, housing sales, real residential investment, real land prices and real mortgage debt. All variables, except the short-term interest rate, are in logs. We estimate the model using the sample period from 1983Q1 onwards, as the collateral effect is likely to be stronger during this period.

[27]Unlike the strong response in land prices, we find that the values of structures have small and insignificant response to the demand shock (results are provided upon request). These findings are in line with Davis and Heathcote (2007), who argue that changes in demand for housing can have large impact on land values as land is non-reproducible. In contrast, since structures can be easily reproduced, shifts in housing demand should have small effect on the values of structures.

[28]An explanation for the quick adjustment of residential investment is that more resources will be used in construction works or in renovation of newly traded houses after a rise in housing demand. On the other hand, the reallocation channel (competition for land) and the collateral channel require time to transmit a housing demand shock from the household sector to the business sector, thus leading to a delayed response in corporate investment. Note that the shape of the response does not change much even when we allow the business investment to react instantaneously to the housing demand shock.

[29]By incorporating housing sector in the model, Fisher (2007) reconciles the real business cycle

Figure 2.6: Responses to a One-Standard Deviation Housing Demand Shock



Notes: Responses are surrounded by 90% confidence intervals.

2.5.2 Existing Housing Sales

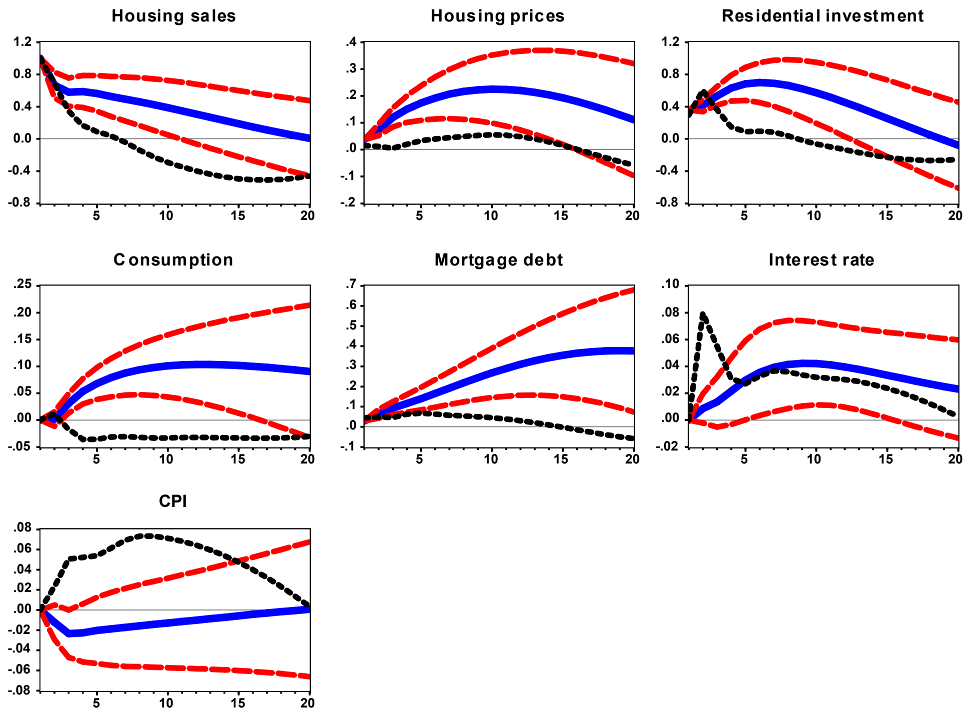
In this study we use new housing sales to depict sales activity, because existing housing sales, due to the definitions of this variable, are likely to be reported with time delay. Some authors might argue that the existing housing sales account for the majority of the total number of transactions in the housing market, and therefore are a better measure of the sales activity[30]. In the following we show the

theory with the lead-lag relation between residential and business investments.

[30] According to our calculation, existing housing sales are about five times as large as new housing sales before 2008Q1 and about ten times as large as new housing sales afterwards. Note

robustness of the results to the use of existing housing sales.

Figure 2.7: Responses to a One-Unit Shock to Existing Housing Sales in Two Periods: 1968Q1-1982Q4 (Black Dotted Line) and 1983Q1-2014Q1 (Blue Solid Line)



Notes: Responses are surrounded by 90% confidence intervals.

Figure 2.7 displays the impulse responses to a one-unit shock to existing housing sales in the post-financial reform subsample (solid lines), as well as the responses to a one-unit shock to existing housing sales in the pre-financial reform subsample (dotted lines). The overall results are as before. That is, an unanticipated increase in existing sales leads to hump-shaped response in most of the variables in the second subsample, while most of the variables' response in the

that the existing housing sales series is available from 1968Q1 onwards.

first subsample is weak. The response of consumption is negative in the first subsample, and the response of the CPI is larger in the earlier period than that in the more recent period.

2.6 Conclusions

Topics on housing dynamics and housing spillovers have been of considerable interest to academics and policy makers. However, the approaches taken in the literature to investigate these issues are not without problems. Based on VAR techniques, when unexpected movements in housing prices are regarded as changes in housing demand, the responses of the economy to housing demand shocks are generally inconclusive.

The problem of using housing prices as a housing demand indicator may arise from the fact that housing prices are not capturing the timing of shifts in housing demand. For instance, the price-setting decisions of home sellers may show delay as they only observe changes in market conditions at a later time.

This paper proposes another housing variable that can better reflect changes in housing demand, and investigates the impacts of shifts in housing demand on the wider economy. Our findings can be summarized as follows. First, in line with the search theory in Berkovec and Goodman (1996), we find that housing sales respond more quickly to fundamental shocks than housing prices. Thus this housing quantity is a better summary measure of market demand. Second, we show that an unexpected increase in housing sales has the interpretation of a housing demand shock, raising the housing variables as well as the conventional macroeconomic variables. Third, a housing demand shock triggers stronger spillovers to the consumption good sector in the post-financial reform period than in the pre-financial reform period. This finding provides evidence that the collateral channel, rather than the wealth channel, serves as the primary link between housing market and the broader economy.

An implication of our analysis is that one should be cautious when using housing prices as housing demand measure. Cesa-Bianchi (2013) investigates international housing spillovers by studying the responses of real economic activity in different countries to housing price shocks originating in the US, the advanced economies or the emerging economies. Fratzscher, Juvenal, and Sarno (2010) examine the role of asset prices, i.e. housing prices and equity prices, as a driver of the US trade balance. It is for future research to find out whether the identification scheme proposed in the current study is more appropriate when tackling issues in these papers.

2.A Macroeconomic Variables

Table 2.4: Definitions and sources

Name	**Definition**	**Source**
Housing sales	New One Family Houses Sold (seasonally adjusted annual rate, thousands)	Census Bureau
Existing housing sales	Sales of existing single-family homes (seasonally adjusted annual rate)	National Association of Realtors
Housing prices	Housing prices extrapolated using the Federal Housing Finance Agency (FHFA) "purchase-only" price index from the year 2000 onwards, deflated with the CPI	Lincoln Institute of Land Policy
Land prices	Aggregate U.S. Land Prices (Index numbers 2000 Q2 = 1.0)	Lincoln Institute of Land Policy
Consumer prices	Consumer price index	OECD economic outlook data
Interest rate	Effective Federal Fund Rate (quarterly units)	Federal Reserve Bank of St. Louis

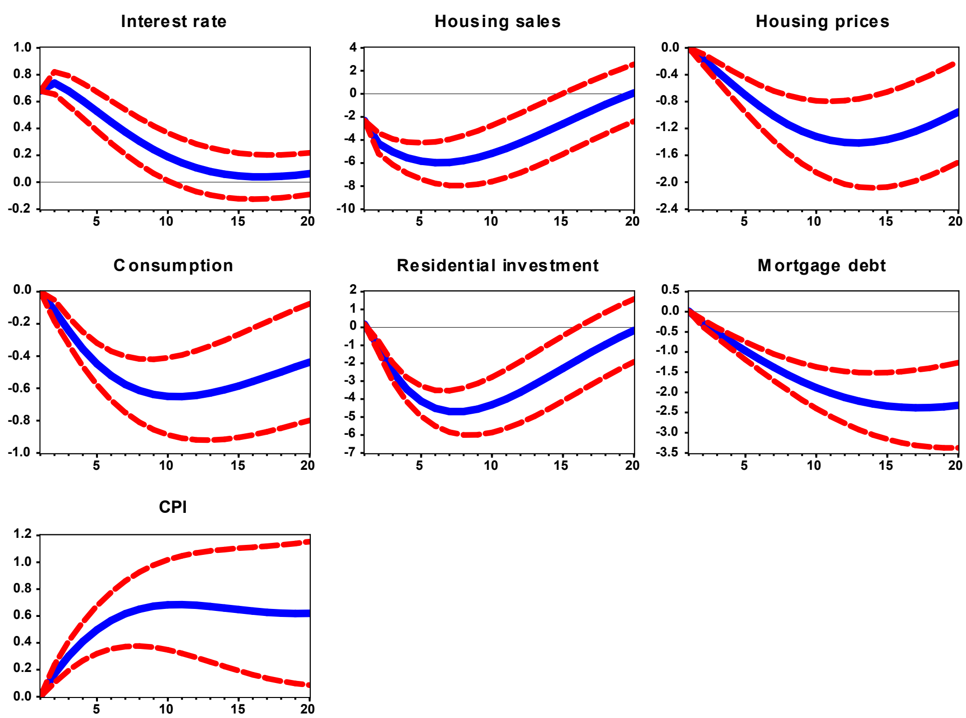
Mortgage debt	Households and nonprofit organizations home mortgages liability (seasonally adjusted, billions of dollars)	Board of Governors of the Federal Reserve System
Private consumption	Real personal consumption expenditures (seasonally adjusted annual rate, billions of chained 2009 dollars)	Bureau of Economic Analysis
Residential investment	Real private residential fixed investment (seasonally adjusted, quantity indexes)	Bureau of Economic Analysis
Business investment	Real private nonresidential fixed investment: Equipment and intellectual property products (seasonally adjusted, quantity indexes)	Bureau of Economic Analysis
FHFA	Repeat-sales housing price index (not seasonally adjusted)	Federal Housing Finance Agency
Case-Shiller	Composite of single-family home price indexes for the nine U.S. Census divisions (seasonally adjusted)	S&P Dow Jones Indices LLC

Freddy Mac	Repeat-transactions housing price index (not seasonally adjusted)	Freddie Mac
Census Bureau	Median sales prices of new homes sold (not seasonally adjusted)	Census Bureau

2.B Interest Rate Shock in a Seven-Variable System

Figure 2.8 presents the responses to a one-standard-deviation shock to interest rate. We see that an unanticipated increase in interest rate leads to decreases in all housing variables, consumption and mortgage debt. In particular, housing sales drop faster than housing prices do. The rise of the aggregate price level suggests the presence of the price puzzle.

Figure 2.8: Responses to a One-Standard Deviation Shock to Interest Rate

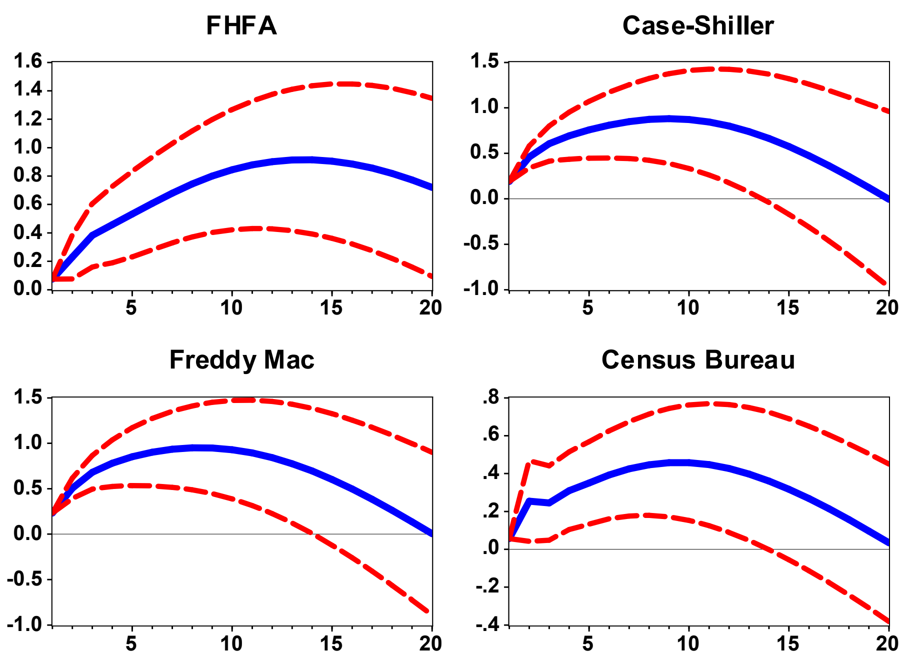


Notes: The interest rate shock is identified via a recursive scheme according to which the ordering of the variables is: consumer price index, real private consumption, interest rate, housing sales, real residential investment, real housing prices and real mortgage debt. Responses are surrounded by 90% confidence intervals.

2.C Alternative Measures of Housing Prices

Figure 2.9 shows the responses of alternative measures of housing prices to a housing demand shock. Note that since several housing price indexes have different starting dates, we choose the sample period 1983Q1-2014Q1, a period characterized by financial reforms (see Section 2.4), for all indexes when estimating the models. We see that a housing demand shock leads to hump-shaped responses in all housing price indexes.

Figure 2.9: Alternative Measures of Housing Prices. Responses to a One-Standard Deviation Housing Demand shock



Notes: FHFA denotes the housing price index from the Federal Housing Finance Agency; Case-Shiller indicates the Case-Shiller housing price index; Freddy Mac is the Freddie Mac house price index; Census Bureau indicates the median sales prices of new homes sold provided by the Census Bureau.

Chapter 3

Can We Predict Housing Price Downturns?

3.1 Introduction

Housing price fluctuations have drawn the attention of both academics and policy-makers, as they turned out to exert substantial impact on the real economy and financial markets. Numerous studies have devoted to forecasting housing price developments. Some have proposed incorporating large information sets in the forecasting exercises (see, for instance, Rapach and Strauss (2009) and Gupta and Das (2010)), while others have identified the forecasting power of specific predictors motivated by economic theories (see, for instance, Chen, Cheng, and Mao (2014) and Carrillo, de Wit, and Larson (2015)).

This paper differentiates itself from the earlier works by focusing on the prediction of the downturn phases in housing price cycles, i.e. the period of time when housing prices are experiencing declines. There are several reasons why this forecasting exercise is important and useful in practice. First, policy-makers and market participants are concerned about whether a correction is likely to occur after observing a period of housing price expansion. Second, Case, Quigley, and Shiller (2013) and Guerrieri and Iacoviello (2015) report that declines in home values have larger impact on household consumption than increases in home values[1]. Similarly, as seen in the last financial crisis, housing price busts have substantial implications for financial stability worldwide. Third, binary models, in which the dependent variable is a dichotomous index, tend to produce more stable forecasting results than continuous models, whose dependent variable is continous, do (Estrella, Rodrigues, and Schich (2003)).

Cyclical fluctuations in housing prices have been widely documented in the literature (see Girouard, Kennedy, Van Den Noord, and Andre (2006), Agnello and Schuknecht (2011), Claessens, Kose, and Terrones (2011) and Bracke (2013)). We follow the previous works by using the nonparametric approach popularized by Harding and Pagan (2002) to identify housing price cycles. This approach first pinpoints local peaks and troughs in housing price series, then divides the series into upturn and downturn phases based on certain rules.

The forecasting variables of housing price downturns are motivated by economic theories. First, the search theory in Berkovec and Goodman (1996) suggests that housing sales (or number of homes sold) are a good summary measure of shifts in housing demand, and a leading indicator of movements in home values. The idea behind this theory is that housing sales can immediately reflect changes in market demand, whereas the price-setting decision is lagged behind due to informational asymmetry. Second, a general equilibrium model, proposed

[1]Guerrieri and Iacoviello (2015) attribute the asymmetric relationship between housing prices and consumption to the presence of collateral constraint, which serves as a principal mechanism to explain the Great Recession.

by Iacoviello (2005) and further simplified by Chen, Cheng, and Mao (2014), suggests that several conventional macroeconomic variables are related to housing price determination, and thus may have predictive content for housing price fluctuations.

The empirical strategy in this paper follows the one adopted by Estrella and Mishkin (1998) and Chen (2009). We estimate probit models including the selected forecasting variables in turn, so that we can see whether there are good individual predictors for housing price downturns. The performance of each predictor is compared with that of the others in the forecasting exercise.

Our results can be summarized as follows. Housing sales growth outperforms the other predictors in both in-sample and out-of-sample tests. Moreover, the addition of other predictors in the sales model generally does not improve the forecasting results. We also find that an augmented sales model, which incorporates further lags of sales growth, improves the forecasting performance, particularly one through five quarters ahead. The model shows the capability of accurately and consistently predicting future housing price downturns. Our findings not only confirm the search theory's prediction that movements in housing sales precede movements in home values, but also suggest sales growth as a simple and reliable indicator of future housing price corrections.

The study proceeds as follows. Section 3.2 presents the approach employed to identify the housing price cycles and introduces the forecasting model. Section 3.3 describes the data and discusses why several macroeconomic variables are related to housing price movements. Section 3.4 presents the results of the in-sample and out-of-sample forecasting tests. In section 3.5, several robustness checks are performed. Section 3.6 concludes.

3.2 Methodology

3.2.1 Dating the Housing Price Downturns

To characterize the distinct phases in the housing price cycles, we follow the procedure proposed by Harding and Pagan (2002). The first step is to apply the dating algorithm of Bry and Boschan (1971) to find local peaks and troughs in the price series. Together with an alternation rule and a censoring rule, the turning points are then used to segment the series into upturn and downturn phases[2].

Specifically, the procedure performs the following three tasks:

1. y_t^P is defined as a local peak in the (log) housing price series if $(y_{t-j},...,y_{t-1}) < y_t^P > (y_{t+1},...,y_{t+j})$. Similarly, y_t^T is defined as a local trough in the housing price series if $(y_{t-j},...,y_{t-1}) > y_t^T < (y_{t+1},...,y_{t+j})$.
2. Peaks and troughs must alternate. That is, a local peak must be followed by a trough, and vice versa [3]. The phase that starts with peak and ends with trough is defined as a downturn. Similarly, the phase that starts with trough and ends with peak is defined as an upturn.
3. The censoring rule ensures that the length of each phase must be at least q quarters.

Because the housing price cycles are found to be longer in duration than the business cycles (see Ceron and Suarez (2006) and Strohsal, Proaño, and Wolters (2015)), we follow Bracke (2013) by choosing a larger size window: $j = 6$. In addition, Strohsal, Proaño, and Wolters (2015) show that the average length of

[2]Agnello and Schuknecht (2011) and Bracke (2013) adopt a similar approach to identify housing price cycles in several industrialized countries. Candelon, Piplack, and Straetmans (2008) and Chen (2009) use a similar way to date the bullish and bearish periods in stock markets. Proaño and Theobald (2014) apply a modified version of the Bry and Boschan (1971) algorithm for the identification of business cycles.

[3]If there are two consecutive peaks (troughs), the highest (lowest) one is selected.

the housing price cycles is shorter before 1985. We thus set the minimum phase length, q, to be four, in order to avoid ignoring cycles due to the choice of a relatively long minimum phase length.

The housing price series is transformed into a binary series, with one indicating that the housing price is in downturn phase and zero indicating that the housing price is in upturn phase. In the robustness section we apply a Markov-switching model as well as a naïve moving average method as alternative ways to characterize housing price fluctuations[4].

3.2.2 The Forecasting Model

With the binary series on hand ($D_t = 1$ corresponds to price downturn and $D_t = 0$ corresponds to price upturn), we use a probit model to examine several variables' predictability for the occurrence of housing price corrections. The model hypothesizes the following linear relationship

$$y^*_{t+k} = c + \beta' x_t + \varepsilon_t \tag{3.1}$$

where y^*_{t+k} is a latent variable that determines the presence of price corrections, c is a constant term, x_t is a vector of potential predictors and ε_t is a standard normally distributed error term. The latent variable is linked to the downturn indicator by the assumption

[4]We prefer the Harding and Pagan (2002) procedure over these two dating approaches for the following two reasons. First, the procedure is highly robust to changes in sample period, whereas the Markov-switching approach is often not robust to either sample period or the choice of model (see Harding and Pagan (2003)). Second, unlike the moving average method, the timing of the turning points identified by the Harding and Pagan (2002) procedure is not influenced by the amplitude of a series' actual path.

$$D_{t+k} = \begin{cases} 1, & \text{if} \quad y^*_{t+k} \geq 0 \\ 0, & \text{if} \quad y^*_{t+k} < 0. \end{cases}$$

The conditional probability of a housing price correction episode can thus be written as

$$P(D_{t+k} = 1|x_t) = \Phi(c + \beta' x_t) \tag{3.2}$$

where Φ is the standard normal cumulative distribution function[5]. The model is estimated using maximum likelihood estimation.

One of the aims in this study is to assess the predictive content of individual predictors based on their in-sample and out-of-sample forecasting performance. In the in-sample case the single predictor models are estimated using the entire sample period. In order to conduct out-of-sample test, we extrapolate these models repeatedly beyond the estimation period and collect the forecasts, which are subsequently compared with the actual values of price downturn indicator. For instance, we initially estimate a single predictor model using observations up to, say, 1988Q4 and compute the two-quarter-ahead forecast at 1989Q2. Next, we include one more observation from 1989Q1 in the estimation period and compute the forecast at 1989Q3. The procedure is repeated until the last forecast is obtained.

Alternatively, one can use a single-equation linear model to forecast housing returns, see Rapach and Strauss (2009), Chen, Cheng, and Mao (2014) and Carrillo, de Wit, and Larson (2015). However, as pointed out by Rossi (2013), there is widespread evidence that this approach can lead to instability in the prediction

[5] The derivations of the conditional probability:

$D_{t+k} = 1 \Leftrightarrow y^*_{t+k} \geq 0 \Leftrightarrow c + \beta' x_t + \varepsilon_t \geq 0 \Leftrightarrow c + \beta' x_t \geq -\varepsilon_t \Leftrightarrow P(D_{t+k} = 1|x_t) = \Phi(c + \beta' x_t)$.
Since the distribution of ε_t is symmetric around 0, we can drop the minus sign in front of it.

model, that is, the variables of interest and their predictors have unstable relationship over time. Using an autoregressive model that further includes the predictors in turn, we indeed find that the model's forecastability for housing returns varies across different time periods. In contrast, we find stable forecasting relationship between the binary price downturn indicator and the predictors when using probit model.

3.2.3 Evaluation Measures

To evaluate the in-sample fit of a forecasting model, we use the pseudo R^2 developed by Estrella (1998). We denote the maximum value of the unconstrained likelihood function by L_U, and the maximum value of the constrained likelihood function, where all coefficients are equal to zero except for the constant, by L_R[6]. The measure of the fit is defined as

$$\text{Pseudo } R^2 = 1 - (\frac{\log L_U}{\log L_R})^{-(\frac{2}{T})\log L_R}, \tag{3.3}$$

where T is the number of observations. The pseudo R^2 ranges from zero to one, which correspond to "no fit" and "perfect fit", respectively.

As in Estrella and Mishkin (1998), we also compute the Newey-West t-statistics for statistical hypothesis testing. The t-statistics allow us to examine the significance of a predictor's effect on future housing price corrections, and to check whether the sign of the estimated coefficient is consistent with economic intuition. Because the in-sample predictive content does not necessarily translate into out-of-sample forecasting ability (Rossi (2013)), we complement the in-sample forecasting exercise with an investigation on the predictors' out-of-sample forecasting power.

[6] Recall that $L_U(c,\beta) = \prod_t [\Phi(c+\beta' x_t)]^{D_{t+k}} [1-\Phi(c+\beta' x_t)]^{1-D_{t+k}}$

The first evaluation measure in the out-of-sample forecasting exercise is again the pseudo R^2. Note that in this case it is possible that this measure takes negative value, which we interpret as a very poor out-of-sample fit[7]. The second evaluation measure is the quadratic probability score (QPS) applied in Diebold and Rudebusch (1989):

$$\text{QPS} = \frac{1}{T'}\sum_t 2[D_{t+k} - P(D_{t+k} = 1|x_t)]^2 \tag{3.4}$$

where T' is the number of out-of-sample forecasts. The QPS ranges from zero to two, which correspond to *"perfect fit"* and *"no fit"*, respectively.

3.3 Data

3.3.1 Potential Predictors of Housing Price Downturns

Housing sales. - Numerous studies have provided explanations as to why housing prices and housing sales co-move, see, for instance, Wheaton (1990), Stein (1995), Berkovec and Goodman (1996), Genesove and Mayer (2001), Ortalo-Magné and Rady (2006) and Carrillo, de Wit, and Larson (2015)[8]. The search

[7]As Estrella and Mishkin (1998) suggest, it can be thought of that the selected predictors perform worse than a constant term.

[8]Wheaton (1990) argues that a higher matching rate between buyers and sellers reduces the supply of for-sale units, pushing sellers' reservation prices upward. Stein (1995) and Ortalo-Magné and Rady (2006) put emphasis on the down-payment requirement in the housing market. Most of the buyers use their proceeds from selling the existing houses to finance the down-payment for the new houses. When home values increase, it becomes easier for buyers to fulfill the down-payment requirement, thus sales increase. Genesove and Mayer (2001) stress on the loss aversion behavior of the sellers. The authors find that households tend to offer higher asking prices when experiencing housing price losses, which causes the housing sales to decline.

theory in Berkovec and Goodman (1996), in particular, suggests that these two housing variables not only co-move but also that sales tend to lead prices.

According to the search theory, a housing demand shock immediately affects the number of buyers on the market as they can freely enter or leave the market. The changes in the ratios of buyers to sellers, i.e. market tightness, determine the probability of a successful match and thus the number of sales. In the following periods, sellers adjust the prices according to the length of time a property remains unsold on the market[9]. For instance, suppose there are fewer buyers in the market due to a negative demand shock. Realizing that the difficulty of finding a match has increased, sellers tend to lower the prices in order to dispose of their houses. In sum, the search theory predicts that shifts in housing demand will be quickly translated to changes in sales, and then prices[10]. Subsequent empirical works support the theory's predictions, see Hort (2000), Andrew and Meen (2003), Oikarinen (2012) and de Wit, Englund, and Francke (2013).

Note that since the U.S. existing single-family housing sales are frequently reported with a delay of one to two months, we use new single-family housing sales, which are not prone to delayed record, as a proxy for the overall sales activity[11]. In the robustness section we also examine the predictive power of existing

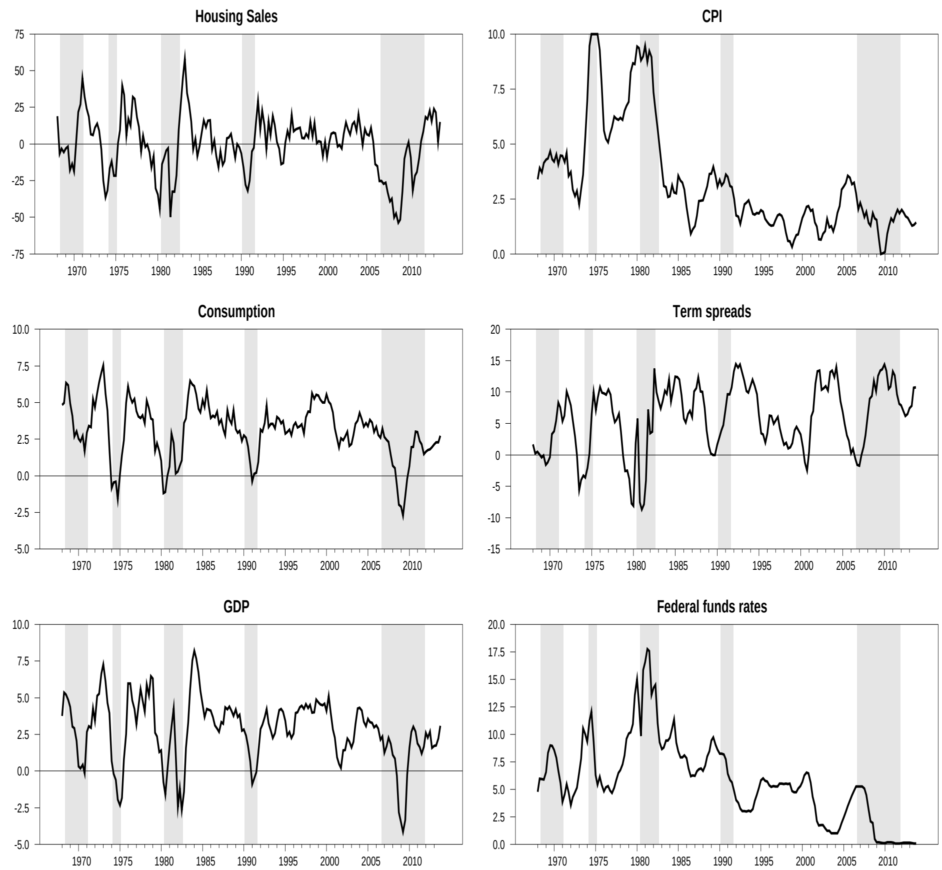
[9]In the model two crucial assumptions are made. First, home sellers have time pressure to dispose of their home and will offer a lower price if failing to sell the property in the previous period. Second, the price expectations of both buyers and sellers are backward-looking, meaning that an economic shock does not immediately alter their expectation of housing prices. Therefore, buyers' bid prices as well as sellers' offer prices remained unchanged when the shock hits the market.

[10]Based on a search-and-matching model that incorporates several features of the model in Berkovec and Goodman (1996), Carrillo, de Wit, and Larson (2015) also find that sales move prior to prices in response to housing demand shocks.

[11]According to the National Association of Realtors® and the Census Bureau, "the majority of existing home transactions are reported when the sales contract is closed and most transactions

housing sales.

Figure 3.1: Macroeconomic Series



Notes: Besides term spreads and federal funds rates, which are in level, all other variables are in four-quarter growth rates (percent change from a year ago). Shaded areas are the housing price downturn periods identified following the procedure of Harding and Pagan (2002).

Other macroeconomic aggregates. - We also consider the following variables

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involve a mortgage which takes 30-60 day to close." In contrast, the definitions by the U.S. Census Bureau indicate that a new home sale takes place and is recorded whenever a sales contract is signed or a deposit is received.

that can affect housing price developments: real GDP, real private consumption, CPI, term spreads (the difference between the 10-year treasury constant maturity rate and the 3-month treasury bill rate) and federal funds rates. Table 3.11 in the appendix reports the sources of the variables. A general equilibrium model, first developed by Iacoviello (2005) and later simplified by Chen, Cheng, and Mao (2014), shows the link between housing prices and these macroeconomic variables[12].

To obtain the predictors for housing price downturns, we take the four-quarter growth rates of housing sales, CPI, real consumption and real GDP, and use term spreads and federal funds rates in level (see Figure 3.1). Standard unit root tests show that, with the exception of the short term rates, the predictor series are stationary.

3.3.2 Housing Prices

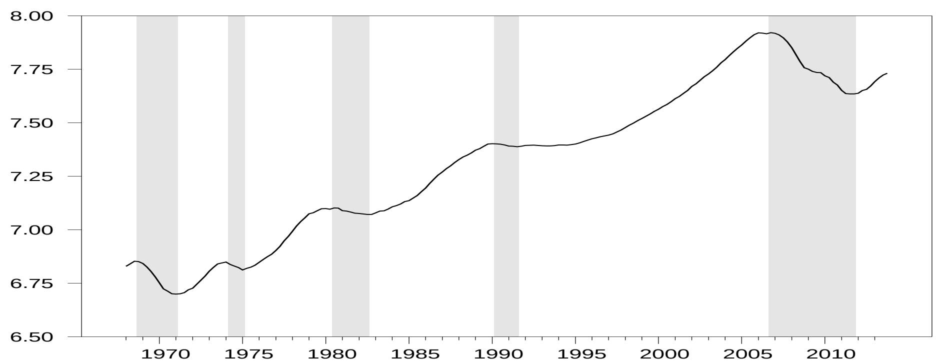
In this study we make use of a long housing price series, constructed by Davis, Lehnert, and Martin (2008), that spans from 1968Q1 to 2013Q4. First, the authors use micro data from the Decennial Census of Housing (DCH) surveys to develop benchmark estimates of average home values. Then they use the Federal Housing Finance Agency (FHFA) "purchase-only" price index to interpolate average housing prices quarterly between the DCH benchmarks and to extrapolate after 2000. Since the FHFA price index is only available from 1975 onwards, the authors interpolate before 1975 using the median price of new homes sold from the U.S. Bureau of the Census[13]. The data is available on the website of the Lincoln

[12]See appendix A in Chen, Cheng, and Mao (2014) for the derivations.

[13]It is true that the interpolation and extrapolation methods can affect the turning point identification. However, we do not see this as a major problem. First, the turning points identified in the long housing price series closely match those identified in the FHFA price series. Second, the

Institute of Land Policy. We convert nominal housing prices to real housing prices using the consumer price index.

Figure 3.2: Real Housing Prices and the Downturn Episodes



Notes: The housing price index is from the Lincoln Institute of Land Policy. We convert the nominal housing prices to real housing prices using the consumer price index. Shaded areas are the housing price downturn periods identified following the procedure of Harding and Pagan (2002).

Figure 3.2 displays the real housing price series as well as the housing price downturn dates in gray shading. The use of this long series allows us to identify two downturn episodes, beginning in 1968Q3 and 1974Q1, respectively, that are unidentifiable when using conventional housing price indexes which generally start from 1975. Moreover, we identify three downturn episodes which began in 1980Q3, 1990Q1 and 2006Q4, respectively. The four most recent downturn events are also identified in Bracke (2013). To ensure that the results do not depend on the choice of housing price index, in the robustness section we use other housing prices indexes, e.g. the FHFA index, the Case-Shiller index and the Freddy Mac index, to identify housing price cycles.

robustness checks show that the overall results do not change substantially when turning points are identified using alternative housing price series.

3.4 Can We Predict Housing Price Downturns?

3.4.1 In-Sample Results

Table 3.1 reports the forecasting results of the single predictor models for the in-sample period from 1968Q1 to 2013Q4. We choose forecasting horizons of one to eight quarters. Pseudo R^2 indicates that housing sales growth exhibits strong predictive power for price correction episodes, in particular between one and five quarters ahead. Consumption and GDP growths are also good predictors, but the predictability is limited to short horizons. Term spreads produce good fit over quarters three through five. In contrast, the fit of the inflation and federal funds rates models is generally poor across all horizons.

Turning to the hypothesis testing, we see that housing sales growth is significantly and negatively associated with housing price downturns in all forecasting horizons. This result is in line with the prediction of the search theory in Berkovec and Goodman (1996) that housing sales are a leading indicator of changes in housing prices. Suppose there is a negative housing demand shock, the withdrawal of buyers from the market results instantly in fewer successful matches or sales. In later periods, as the remaining sellers realize the difficulty to sell their houses, they incline to adjust the prices downward in order to dispose of them, leading to a higher probability of price correction.

To continue, the results are significant at the 5% level up to six and five quarters for consumption and GDP growths, respectively. The negative t-statistics indicate that slowdowns in aggregate economic activity may dampen housing activity and increase the chance of housing price downturn. Term spreads have significant negative t-statistics in all horizons. The expectations contained in term spreads can be a possible explanation for the variable's predictive power. When agents foresee a price correction in housing market, term spreads (the difference between long term interest rates and short term interest rates) become smaller as they expect easing monetary policy in the future[14]. Thus there is a negative predictive relationship between term spreads and future housing price downturns. Inflation and federal funds rates have significant positive predictive power over short horizons. The former predictor suggests the role of supply shock while the latter predictor shows the impact of monetary policy on home values.

Table 3.1: In-Sample Results for Predicting Housing Price Downturns

Predictors/ k		1	2	3	4	5	6	7	8
Housing sales$_4$	R^2	0.43	0.48	0.43	0.30	0.18	0.12	0.10	0.11
	t-stat	-5.97	-6.45	-5.66	-5.77	-5.10	-4.57	-4.36	-4.45
Consumption$_4$	R^2	0.32	0.22	0.16	0.10	0.06	0.04	0.02	0.01
	t-stat	-5.61	-5.32	-4.79	-3.73	-2.90	-2.40	-1.94	-1.29
GDP$_4$	R^2	0.25	0.15	0.08	0.04	0.02	0.01	0.01	0.00
	t-stat	-5.59	-5.01	-3.89	-2.75	-2.12	-1.59	-1.00	-0.53
CPI$_4$	R^2	0.04	0.03	0.02	0.01	0.01	0.01	0.00	0.00
	t-stat	2.57	2.26	1.89	1.47	1.21	0.99	0.79	0.74
Term spreads	R^2	0.07	0.12	0.17	0.20	0.18	0.14	0.10	0.07
	t-stat	-3.24	-4.11	-4.75	-5.07	-4.94	-4.56	-4.01	-3.45
Federal funds rates	R^2	0.02	0.03	0.03	0.02	0.01	0.00	0.00	0.00
	t-stat	1.87	2.19	2.19	1.96	1.44	0.81	0.10	-0.66

Notes: The critical values are 1.64 (10%), 1.96 (5%) and 2.58 (1%). The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

[14]Recall that the long term rate is equal to the average of expected future short term rates plus a risk premium. Chen (2009) also uses the expectation theory to explain the predictability of term spreads for future bearish stock market.

Table 3.2: In-Sample Results for Predicting Housing Price Downturns (Housing Sale Growth Included)

Predictors/k		1	2	3	4	5	6	7	8
Housing sales$_4$	R^2	**0.43**	**0.48**	**0.43**	**0.30**	**0.18**	**0.12**	**0.10**	**0.11**
	t-stat	**-5.97**	**-6.45**	**-5.66**	**-5.77**	**-5.10**	**-4.57**	**-4.36**	**-4.45**
Consumption$_4$	R^2	0.50	0.49	0.44	0.30	0.18	0.12	0.11	0.12
	t-stat	-3.08	-1.53	-0.46	-0.03	-0.07	-0.09	0.28	1.24
	t-stat$_{HS}$	-4.59	-5.46	-4.75	-4.65	-4.04	-3.66	-3.66	-4.10
GDP$_4$	R^2	0.52	0.50	0.44	0.30	0.18	0.12	0.11	0.12
	t-stat	-3.53	-1.84	-0.19	0.42	0.15	0.19	0.64	1.24
	t-stat$_{HS}$	-5.63	-5.95	-5.16	-5.19	-4.57	-4.17	-4.12	-4.31
CPI$_4$	R^2	0.43	0.48	0.43	0.30	0.18	0.12	0.11	0.11
	t-stat	0.66	0.14	-0.14	-0.10	0.13	0.16	0.04	-0.06
	t-stat$_{HS}$	-5.78	-6.24	-5.46	-5.64	-5.05	-4.52	-4.34	-4.45
Term spreads	R^2	0.43	0.50	0.50	0.41	0.28	0.21	0.16	0.14
	t-stat	-0.80	-2.01	-3.30	-3.98	-3.95	-3.63	-3.04	-2.33
	t-stat$_{HS}$	-5.72	-6.04	-5.38	-5.15	-3.75	-3.13	-3.10	-3.52
Federal funds rates	R^2	0.43	0.48	0.44	0.30	0.18	0.12	0.11	0.12
	t-stat	-0.07	0.24	0.34	0.55	0.38	-0.04	-0.73	-1.62
	t-stat$_{HS}$	-5.79	-6.24	-5.57	-5.68	-5.05	-4.58	-4.54	-4.82

Notes: The critical values are 1.64 (10%), 1.96 (5%) and 2.58 (1%). The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor. t-stat$_{HS}$ indicates t-statistic for housing sales predictor. Bold entries indicate that the results are based on single-predictor model.

We also estimate probit models containing sales growth and each of the other variables in turn, in order to examine the forecasting ability of sales growth after controlling for other variables[15]. Table 3.2 presents the results based on the two-

[15]Estrella and Mishkin (1998) adopt the same strategy to show that the forecasting power of

predictor models. There are two points worth noting. First, the goodness-of-fit of the multiple models is generally not much better than the goodness-of-fit of the sales growth model. Exceptions are the pseudo R^2 of the augmented model combining sales growth with consumption or GDP growths for the forecasting horizon of one, and the pseudo R^2 of the model combining sales growth and term spreads over quarters three through seven. Second, while the significance of sales growth remains undiminished, the predictive power of other variables is reduced substantially.

3.4.2 Out-of-Sample Results

We choose the initial estimation period to be 1968Q1-1988Q4 and the out-of-sample period to be 1989Q1-2013Q4, the latter includes two housing price downturn episodes. Table 3.3 displays the pseudo R^2 and quadratic probability score (QPS). We present only the nonnegative pseudo R^2 as the negative ones suggest very poor fit. Recall that the QPS ranges from zero to two, with zero indicating perfect fit.

In line with the in-sample results, the pseudo R^2 show that housing sales growth has strong out-of-sample predictive power across all forecasting horizons. Consumption and GDP growths also have good forecasting performance over short horizons. But their out-of-sample fit declines quickly as the horizon increases and eventually becomes poor. For inflation rate, term spreads and federal funds rates, the out-of-sample fit is very poor in nearly all horizons. Analogously, the QPS measures for the sales growth model are small, whereas the measures for other predictors are relatively large. The results for the non-housing predictors are reminiscent of the facts that in-sample predictive content does not necessarily

term spread for economic recessions is undiminished even after controlling for other variables.

translate into out-of-sample predictability (Rossi (2013)).

Table 3.3: Out-of-Sample Results for Predicting Housing Price Downturns

Predictors/k		1	2	3	4	5	6	7	8
Housing sales$_4$	R^2	0.57	0.62	0.58	0.44	0.28	0.20	0.17	0.18
	QPS	0.17	0.16	0.18	0.24	0.32	0.35	0.36	0.36
Consumption $_4$	R^2	0.34	0.26	0.19	0.13	0.06	0.02	—	—
	QPS	0.27	0.30	0.34	0.37	0.41	0.42	0.44	0.45
GDP$_4$	R^2	0.29	0.19	0.11	0.04	0.00	—	—	—
	QPS	0.29	0.33	0.37	0.40	0.43	0.44	0.45	0.46
CPI$_4$	R^2	—	—	—	—	—	—	—	—
	QPS	0.42	0.43	0.44	0.44	0.45	0.44	0.44	0.44
Term spreads	R^2	—	—	—	—	—	—	—	0.05
	QPS	0.45	0.45	0.44	0.42	0.42	0.41	0.40	0.40
Federal funds rates	R^2	—	—	—	—	—	—	—	—
	QPS	0.44	0.45	0.45	0.45	0.46	0.45	0.46	0.46

Notes: The QPS ranges from zero to two, which correspond to *"perfect fit"* and *"no fit"*, respectively. — indicates negative value. The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

It is worthwhile to provide an explanation as to why housing sales growth outperforms the other macroeconomic variables, some of which are typically considered as housing demand shifters, in predicting housing price downturns. As housing sales serve as a summary measure of changes in housing demand (Berkovec and Goodman (1996)), this variable can possibly incorporate the information content contained in all housing demand determinants and reflect which of these demand determinants plays a dominant role at a certain time. As a result, there is a stable predictive relation between the sales growth and housing price slumps, whereas there is instability in the forecasting performance of the other predictors.

Table 3.4 reports the results from the models combining sales growth and other predictors in turn. Besides the first horizon and a few exceptions, the multiple models' performance (based on pseudo R^2 and QPS) does not improve in comparison to that of the sales model. Thus, unlike previous works that rely on large forecasting models, we are able to identify a single variable that has strong predictive content for housing price slumps.

Table 3.4: Out-of-Sample Results for Predicting Housing Price Downturns (Housing Sale Growth Included)

Predictors/k		1	2	3	4	5	6	7	8
Housing sales$_4$	R^2	**0.57**	**0.62**	**0.58**	**0.44**	**0.28**	**0.20**	**0.17**	**0.18**
	QPS	**0.17**	**0.16**	**0.18**	**0.24**	**0.32**	**0.35**	**0.36**	**0.36**
Consumption$_4$	R^2	0.62	0.62	0.56	0.41	0.25	0.16	0.12	0.12
	QPS	0.14	0.15	0.18	0.25	0.33	0.37	0.39	0.39
GDP$_4$	R^2	0.64	0.63	0.57	0.42	0.26	0.16	0.11	0.11
	QPS	0.14	0.15	0.18	0.25	0.33	0.37	0.39	0.39
CPI$_4$	R^2	0.54	0.60	0.56	0.40	0.23	0.14	0.10	0.10
	QPS	0.19	0.17	0.19	0.26	0.34	0.38	0.40	0.40
Term spreads	R^2	0.47	0.44	0.31	—	—	—	—	0.12
	QPS	0.21	0.22	0.25	0.37	0.44	0.44	0.42	0.39
Federal funds rates	R^2	0.53	0.56	0.52	0.36	0.17	0.10	0.06	0.01
	QPS	0.20	0.19	0.21	0.29	0.37	0.40	0.41	0.43

Notes: The QPS ranges from zero to two, which correspond to *"perfect fit"* and *"no fit"*, respectively. — indicates negative value. The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor. Bold entries indicate that the results are based on single-predictor model.

3.4.3 Exploiting the Lag Structure of Sales Growth

So far we have seen that the sales growth model is the best single predictor model. In this section we investigate whether including further lags of sales growth in the model can improve its forecasting performance[16]. A simple way of model selection is proposed as follows. First, besides the lagged sales growth that corresponds to the forecasting horizon, k, we allow at most two more lagged sales growths in the model

$$P(D_t = 1|X) = \Phi(c + \beta_1 x_{t-k} + \beta_2 x_{t-m} + \beta_3 x_{t-n}) \tag{3.5}$$

where x_t is the sales growth and $k < m \leq n \leq 10$. When m is equal to n, the model has only two lagged sales growths as the explanatory variables[17]. Second, the model is estimated using the entire sample period and the selection of lagged sales growths is determined by the Bayesian information criterion (BIC). Table 3.5 presents the results of model selection. For forecasting horizons of one and two, models with three lagged sales growths are suggested by the criterion. For forecasting horizons between three to seven, models with two lagged sales growths are preferred, whereas for forecasting horizon of eight a single predictor model is recommended.

Table 3.6 displays the in-sample forecasting results for single predictor and augmented sales models. The pseudo R^2 shows that the augmented model's gains in in-sample fit are substantial for forecasting horizons between one and five quarters. Similarly, the pseudo R^2 and QPS in Table 3.7 show that, in the out-of-sample forecast, the augmented model performs better than the single predictor model for most of the forecasting horizons.

[16]We consider models including only lagged sales growths, as we are interested in the predictive content for the housing price correction solely contained in sales growth, i.e. whether the sales variable itself serves as a strong leading indicator of future price movements.

[17]Models with four or more lagged sales growths are not recommended by model selection criterion for all forecasting horizons.

Table 3.5: Model Selection Based on Bayesian Information Criterion

k	1	2	3	4	5	6	7	8
$M_{1,k}$	$148.62_{(1)}$	$139.04_{(2)}$	$147.32_{(3)}$	$174.17_{(4)}$	$195.22_{(5)}$	$203.67_{(6)}$	$208.83_{(7)}$	$\mathbf{208.98}_{(8)}$
$M_{2,k}$	$126.83_{(1,9)}$	$124.52_{(2,9)}$	$\mathbf{136.22}_{(3,9)}$	$\mathbf{162.14}_{(4,9)}$	$\mathbf{185.98}_{(5,9)}$	$\mathbf{199.29}_{(6,10)}$	$\mathbf{208.33}_{(7,10)}$	$212.28_{(8,10)}$
$M_{3,k}$	$\mathbf{110.41}_{(1,3,9)}$	$\mathbf{121.63}_{(2,6,10)}$	$139.52_{(3,7,9)}$	$164.69_{(4,5,8)}$	$189.55_{(5,7,9)}$	$203.92_{(6,9,10)}$	$213.29_{(7,9,10)}$	$217.29_{(8,9,10)}$
$M_{4,k}$	$113.02_{(1,3,5,9)}$	$125.69_{(2,5,6,10)}$	$142.39_{(3,5,7,10)}$	$167.40_{(4,5,8,10)}$	$193.25_{(5,7,9,10)}$	$208.45_{(6,7,9,10)}$	$218.48_{(7,8,9,10)}$	—

Notes: This table presents the results of model selection based on the BIC. $M_{1,k}$ denotes single predictor model, where k is the forecasting horizon and also indicates the (smallest) lag of sales growth in the models. $M_{2,k}$ denotes two-predictor model including two lagged sales growths. Similar definitions can be made for $M_{3,k}$ and $M_{4,k}$. The subscript shows the chosen lags of sales growth in the model that has the lowest BIC value among the models with the same number of predictors (for a particular forecasting horizon). Bold entries indicate the selected models for different forecasting horizons.

Table 3.6: In-Sample Results for Sales and Augmented Sales Models

k	1	2	3	4	5	6	7	8
R^2_{single}	0.43	0.48	0.43	0.30	0.18	0.12	0.10	0.11
$R^2_{augmented}$	0.66	0.61	0.52	0.38	0.27	0.19	0.15	0.11

Notes: *single* indicates that the measure is computed based on single predictor sales model: $P(D_t = 1|x_{t-k}) = \Phi(c + \beta x_{t-k})$. *augmented* indicates that the measure is computed based on augmented model including further lags of sales growth: $P(D_t = 1|X) = \Phi(c + \beta_1 x_{t-k} + \beta_2 x_{t-m} + \beta_3 x_{t-n})$, where $k < m \leq n \leq 10$. The lags included, (k, m, n), in the eight forecasting models are the following: (1,3,9), (2,6,10), (3,9), (4,9), (5,9), (6,10), (7,10) and (8).

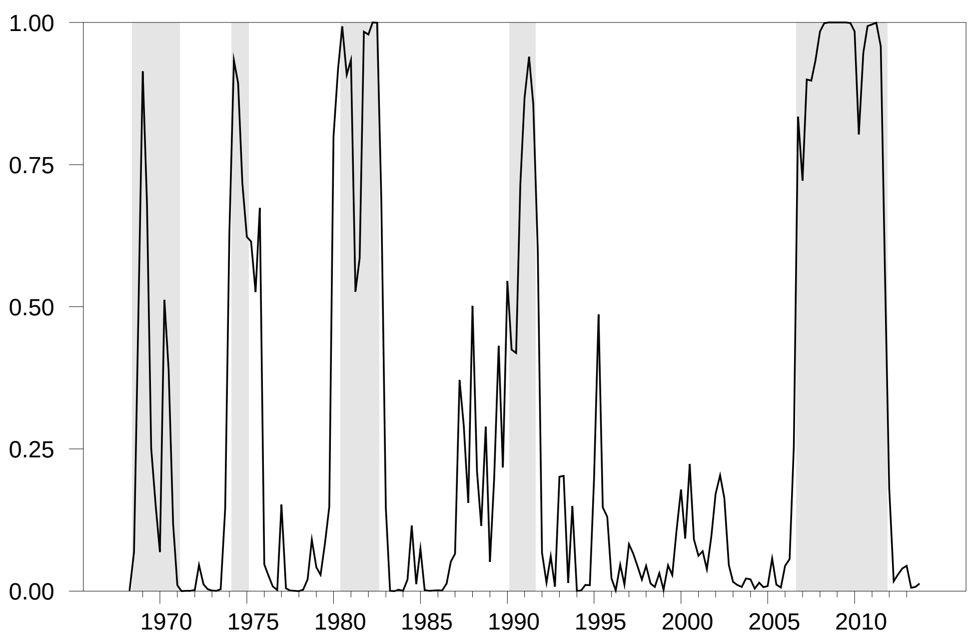
Table 3.7: Out-of-Sample Results for Sales and Augmented Sales Models

k	1	2	3	4	5	6	7	8
R^2_{single}	0.57	0.62	0.58	0.44	0.28	0.20	0.17	0.18
$R^2_{augmented}$	0.79	0.74	0.66	0.53	0.40	0.30	0.22	0.18
QPS_{single}	0.17	0.16	0.18	0.24	0.32	0.35	0.36	0.36
$QPS_{augmented}$	0.07	0.10	0.14	0.20	0.26	0.31	0.34	0.36

Notes: The out-of-sample period spans from 1989Q1 to 2013Q4. The QPS ranges from zero to two, which correspond to *"perfect fit"* and *"no fit"*, respectively. *single* indicates that the measure is computed based on single predictor sales model: $P(D_t = 1|x_{t-k}) = \Phi(c + \beta x_{t-k})$. *augmented* indicates that the measure is computed based on augmented model including further lags of sales growth: $P(D_t = 1|X) = \Phi(c + \beta_1 x_{t-k} + \beta_2 x_{t-m} + \beta_3 x_{t-n})$, where $k < m \leq n \leq 10$. The lags included, (k, m, n), in the eight forecasting models are the following: (1,3,9), (2,6,10), (3,9), (4,9), (5,9), (6,10), (7,10) and (8).

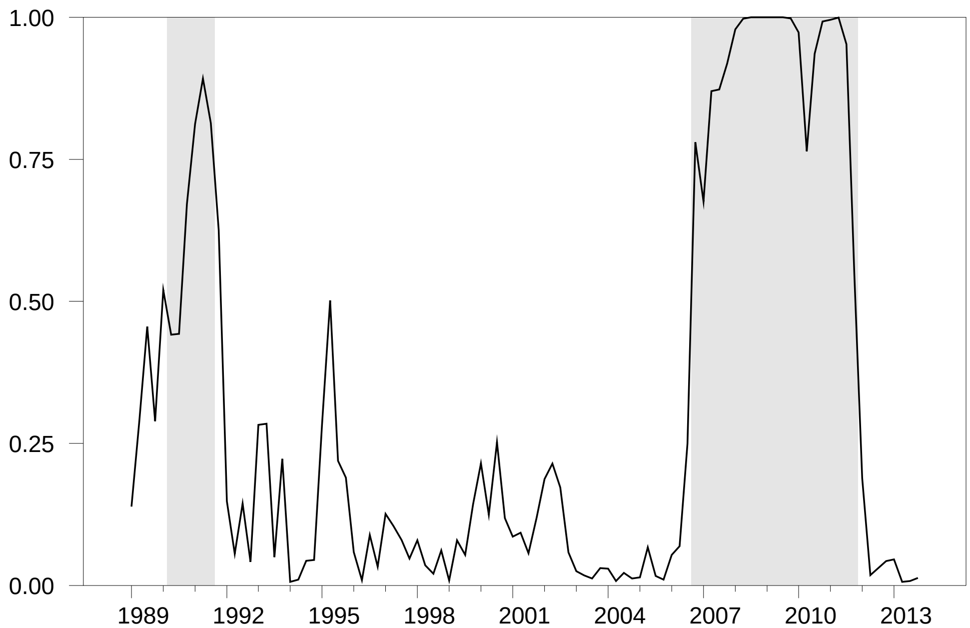
Figure 3.3 displays the in-sample housing price downturn probabilities one quarter ahead. The forecasting model provides very accurate signals of price slumps, as the fitted values closely match the dates when price corrections take place. In terms of the out-of-sample forecasting performance, Figure 3.4 shows that the augmented model has strong ability to forecast the 1989-1991 and 2006-2011 housing price slumps one quarter ahead. In sum, this forecasting exercise provides evidence that housing sales growth is a reliable and consistent predictor of future housing price downturns.

Figure 3.3: In-Sample Housing Price Downturn Probabilities. One Quarter Ahead



Notes: The forecasting model includes the first, third and ninth lags of four-quarter sales growth. Shaded areas are the housing price downturn periods identified following the procedure of Harding and Pagan (2002).

Figure 3.4: Out-of-Sample Housing Price Downturn Probabilities. One Quarter Ahead



Notes: The forecasting model includes the first, third and ninth lags of four-quarter sales growth. Shaded areas are the housing price downturn periods identified following the procedure of Harding and Pagan (2002).

3.5 Robustness Checks

3.5.1 Alternative Approaches to Identify Housing Price Cycles

Markov switching model. - We now use a parametric method to model the growth rates of housing prices, because the housing price upturns and downturns are associated with prolonged periods of positive and negative housing returns, respectively. Similar econometric approach has been used in stock market literature to examine cyclical fluctuations in stock returns (see, for instance, Chen (2009) and Nyberg (2013)).

We denote r_t as the log-difference of the real housing prices. To characterize the booms and busts in housing price cycles, we impose a two-regime Markov switching model which can be written as

$$\begin{aligned} r_t &= \mu_{s_t} + \varepsilon_t, \\ \varepsilon_t &\sim NID(0, \sigma_{s_t}^2) \end{aligned} \tag{3.6}$$

where μ_{s_t} and $\sigma_{s_t}^2$ are the regime-dependent mean and variance of r_t. s_t is an unobservable state variable that follows a two-regime Markov process with transition probabilities given by

$$p_{ij} = Pr(s_t = j | s_{t-1} = i), \;\; i, j \in \{1, 2\}, \tag{3.7}$$

with $\sum_{j=1}^{2} p_{ij} = 1$. Table 3.8 reports the estimation results for the Markov switching and linear models. First, the log-likelihood value of the non-linear model is larger than that of the linear one, suggesting that the former model performs better than latter one in terms of depicting the dynamics of housing returns. Second, in regime 1, $\mu_1 = 1.29$ and $\sigma_1 = 0.27$, while in regime 2, $\mu_2 = -0.59$ and $\sigma_2 = 1.01$. As a result, we can identify regime 1 as upturn phase when housing returns are positive and stable and regime 2 as downturn phase when housing returns are negative and volatile.

Naïve moving average approach. - Following Chen (2009), we further consider a moving average approach to identify the periods of housing price upturns and downturns. We define $\bar{r}_t$ as the average of the present and past housing returns, $\frac{r_t + r_{t-1} + r_{t-2} + r_{t-3}}{4}$. The housing price downturn indicator is defined as

$$D_t^* = \begin{cases} 1 \text{ (downturn)}, & \text{if } \; \bar{r}_t < 0 \\ 0 \text{ (upturn)}, & \text{if } \; \bar{r}_t \geq 0. \end{cases}$$

Figure 3.5 presents the identified downturn periods implied by the Markov switching model and the naïve moving average method. The dashed line is the smoothed probabilities of the regime with negative and volatile housing returns, which coincides with most of the housing price bust periods, the shaded areas, identified by the procedure of Harding and Pagan (2002)[18]. An exception occurs in the first half of the 1990s when the non-linear parametric approach seems to suggest longer period of price downturn. Similarly, the price bust time suggested by the moving average method (solid line) closely matches the shaded areas, except for the boom-bust cycle that occurred from 1992 to 1994.

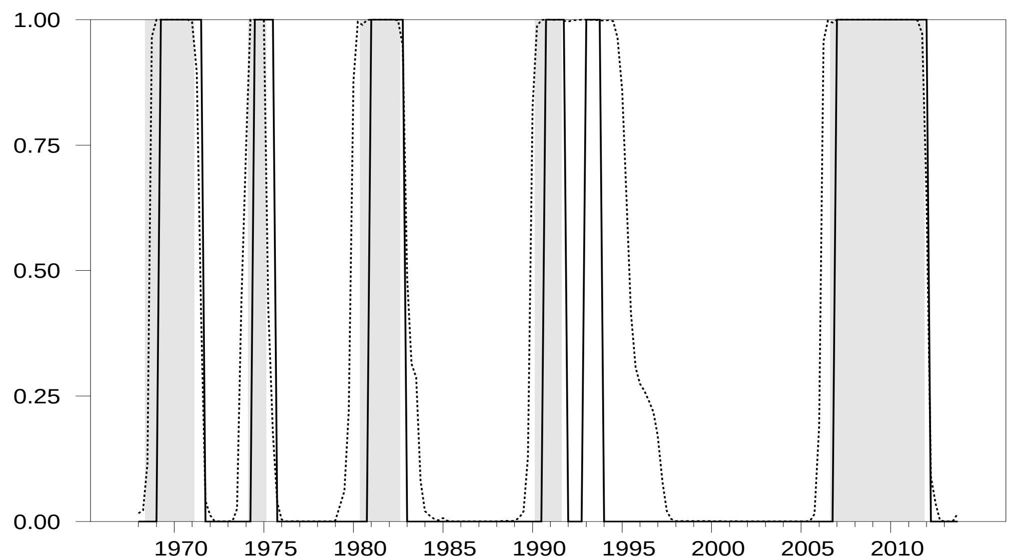
Table 3.8: Markov-Switching and Linear Models of Housing Returns

	Regime 1	Regime 2		Linear
μ_{s_t}	1.29	-0.59	μ	0.53
	(0.05)	(0.15)		(0.08)
σ_{s_t}	0.27	1.01	σ	1.18
	(0.04)	(0.21)		
p_{11}	0.95			
p_{22}	0.93			
log-L	-218.81			-308.03

Notes: Standard errors are reported in parentheses.

[18]We consider a quarter as belonging to housing price bust (boom) period when the smoothed probability of the downturn regime in that quarter is larger (smaller than or equal to) than 0.5. Therefore we obtain a binary indicator series for price bust episodes as before.

Figure 3.5: Alternative Approaches to Date Housing Price Downturns: Markov-Switching Model and Naïve Moving Average Method



Notes: The dash-dot line is the smoothed probabilities of the downturn regime. A quarter is considered to be in housing price bust (boom) periods if the smoothed probability in that quarter is larger (smaller than or equal to) than 0.5. The solid line corresponds to the downturn periods identified by the naïve moving average method. Shaded areas are the downturn periods identified following the procedure of Harding and Pagan (2002).

Table 3.9 reports the in-sample forecasting results. For the sake of brevity, we only show the forecasting performance of housing sales growth and leave the full results in the appendix. According to the pseudo R^2, sales growth maintains its strong predictive power for housing price bust events based on the two alternative dating approaches. Likewise, the t-statistics suggest significant forecastability across all horizons in both cases. The out-of-sample results, reported in Table 3.10, are in line with the in-sample results and show that housing sales growth remains a strong predictor.

Table 3.9: Summary of Sales Model's In-Sample Forecasting Performance

Predictors/k		1	2	3	4	5	6	7	8
MS									
Housing sales_4	R^2	0.29	0.35	0.34	0.26	0.16	0.09	0.08	0.08
	t-stat	-5.59	-6.56	-6.71	-6.13	-5.13	-4.03	-3.74	-3.86
MA									
Housing sales_4	R^2	0.19	0.27	0.37	0.34	0.27	0.18	0.12	0.10
	t-stat	-4.62	-4.9	-6.01	-5.96	-5.85	-5.05	-4.34	-4.25
FHFA									
Housing sales_4	R^2	0.54	0.60	0.56	0.45	0.33	0.28	0.26	0.21
	t-stat	-6.32	-7.28	-6.49	-6.67	-5.79	-5.86	-5.79	-5.46
CS									
Housing sales_4	R^2	0.41	0.44	0.42	0.38	0.32	0.27	0.28	0.25
	t-stat	-5.7	-5.5	-5.62	-5.89	-5.89	-5.52	-5.52	-5.31
FRMA									
Housing sales_4	R^2	0.40	0.40	0.37	0.31	0.24	0.23	0.23	0.23
	t-stat	-5.8	-5.72	-5.68	-5.73	-5.08	-5.13	-5.09	-5.22
EHS									
Housing sales_4	R^2	0.29	0.33	0.30	0.23	0.15	0.12	0.10	0.09
	t-stat	-6.07	-5.62	-5.48	-4.98	-4.56	-4.2	-4.04	-3.84

Notes: MS / MA indicates that the downturn phase is identified by a MS model / naïve moving average approach. FHFA / CS / FRMA indicates that the downturn phase is identified using FHFA / Case-Shiller / Freddie Mac index. EHS indicates that existing housing sales growth is used as the predictor for housing price downturns. The critical values are 1.64 (10%), 1.96 (5%) and 2.58 (1%). The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

Table 3.10: Summary of Sales Model's Out-of-Sample Forecasting Performance

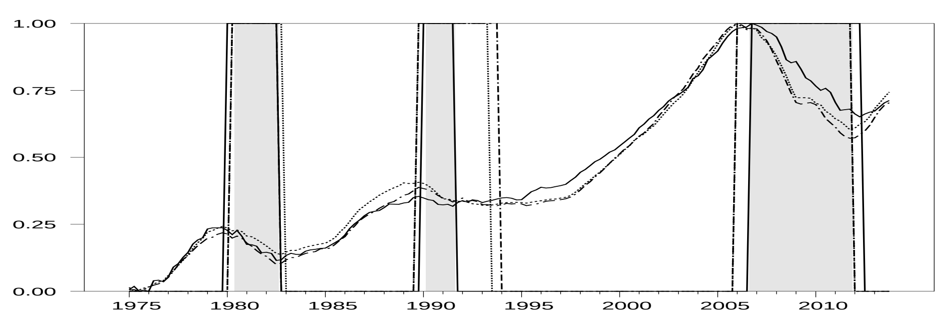
Predictors/k		1	2	3	4	5	6	7	8
MS model									
Housing $sales_4$	R^2	0.32	0.31	0.27	0.26	0.21	0.15	0.13	0.14
	QPS	0.35	0.36	0.38	0.42	0.46	0.49	0.50	0.50
Naïve method									
Housing $sales_4$	R^2	0.30	0.38	0.47	0.38	0.30	0.25	0.18	0.18
	QPS	0.29	0.26	0.23	0.26	0.31	0.35	0.39	0.40
FHFA index									
Housing $sales_4$	R^2	0.50	0.62	0.62	0.54	0.42	0.35	0.31	0.25
	QPS	0.21	0.18	0.20	0.23	0.27	0.30	0.31	0.34
CS index									
Housing $sales_4$	R^2	0.37	0.21	0.27	0.37	0.36	0.35	0.34	0.30
	QPS	0.30	0.32	0.33	0.33	0.34	0.36	0.36	0.37
FRMA index									
Housing $sales_4$	R^2	0.28	0.24	0.29	0.29	0.29	0.29	0.30	0.29
	QPS	0.33	0.35	0.36	0.38	0.41	0.42	0.42	0.41
Existing house sales									
EHS_4	R^2	0.24	0.32	0.31	0.26	0.17	0.13	0.13	0.11
	QPS	0.28	0.25	0.27	0.30	0.35	0.37	0.38	0.38

Notes: MS / MA indicates that the downturn phase is identified by a MS model / naïve moving average approach. FHFA / CS / FRMA indicates that the downturn phase is identified using FHFA / Case-Shiller / Freddie Mac index. EHS indicates that existing housing sales growth is used as the predictor for housing price downturns. The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor. The QPS ranges from zero to two, which correspond to *"perfect fit"* and *"no fit"* respectively. — indicates negative value. The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

3.5.2 Other Housing Price Indexes

To ensure that the main results in this study are not dependent on the selection of housing price series, in this robustness exercise we identity price downturns based on the use of different housing price measures, i.e. the Federal Housing Finance Agency (FHFA) index, the Case-Shiller (CS) index and the Freddie Mac (FRMA) index. Note that these housing price series are shorter than the housing price index from the Lincoln Institute of Land Policy (LILP) and are available from 1975Q1 onwards. Figure 3.6 presents the real housing price series and their corresponding price bust periods, identified using the procedure of Harding and Pagan (2002). The FHFA, CS and FRMA price series (solid, dotted and dashed lines, respectively) have their busts episodes fairly matching the ones based on the LILP price series (shaded areas). Exceptions are the downturns in the CS and FRMA price series in 1990s which lasted for about two years longer than the shaded areas.

Figure 3.6: Other Housing Price Index Series and the Corresponding Identified Housing Price Downturns



Notes: The solid lines correspond to the Federal Housing Finance Agency index and its identified downturn periods (based on the procedure of Harding and Pagan (2002)). The dash-dot lines correspond to the Freddy Mac index and its identified downturn periods. The dotted lines correspond to the Case-Shiller index and its identified downturn periods. Shaded areas are the downturn periods identified using the Lincoln Institute of Land Policy index.

Table 3.9 and 3.10 show that sales growth have strong predictive content in both in-sample and out-of-sample forecasting exercises, regardless of the choice of housing price index. We can therefore confirm the role of sales growth as a robust leading indicator of housing price busts.

3.5.3 Alternative Measure of Sales Activity

In this study we use new housing sales to depict overall sales activity, because existing housing sales, due to its definitions, are likely to be reported with delay. Some might argue that the existing housing sales account for the majority of the total number of transactions in the housing market, and therefore are a better measure of the sales activity[19]. Here we examine the robustness of the forecasting results to the use of existing housing sales.

In table 3.9 and 3.10 we see that the existing sales predict well the price downturns in both in-sample and out-of-sample cases, although their predictive power is not as strong as that of new housing sales.

3.6 Conclusions

In this paper we examine several macroeconomic variables' ability in predicting future housing price downturns. We first identify the housing price cycles using a nonparametric approach. Then, we select the potential predictors based on economic theories. A search theory suggests housing sales to be a leading indicator of housing prices, while a simple general equilibrium model shows the role of several conventional macroeconomic variables in determining housing prices.

[19]According to our calculation, existing housing sales are about five times as large as new housing sales before 2008Q1 and about ten times as large as new housing sales afterwards.

The empirical results from our analysis are as follows. First, sales growth outperforms the other macroeconomic variables in both in-sample and out-of-sample forecasting tests. Second, when the macroeconomic variables are included in turn in the model with sales growth, the forecasting performance does not improve in general, suggesting sales growth as a strong single predictor of housing price corrections. Third, a model that incorporates further lags of sales growth improves its forecasting performance. This analysis proposes housing sales growth as a simple and reliable indicator of strong movements in home values, and suggests that our findings can be used to double-check more elaborate predictions.

3.A Macroeconomic Variables

Table 3.11: Definitions and Sources

Name	Definition	Source
Housing sales	New One Family Houses Sold (seasonally adjusted annual rate, thousands)	Census Bureau
Existing housing sales	Sales of existing single-family homes (seasonally adjusted annual rate)	National Association of Realtors
Housing prices	Housing prices extrapolated using the Federal Housing Finance Agency (FHFA) "purchase-only" price index from the year 2000 onwards, deflated with the CPI	Lincoln Institute of Land Policy
Consumer prices	Consumer price index	OECD economic outlook data
3-month interest rate	3-Month treasury bill: secondary market rate (quarterly units)	Federal Reserve Bank of St. Louis
10-year interest rate	Market yield on U.S. Treasury securities at 10-year constant maturity (quarterly units)	Board of Governors of the Federal Reserve System

Federal funds rates	Effective Federal Funds Rate (quarterly units)	Federal Reserve Bank of St. Louis
GDP	Real Gross Domestic Product (seasonally adjusted, quantity indexes, Index numbers 2009=100)	Bureau of Economic Analysis
Private consumption	Real personal consumption expenditures (seasonally adjusted annual rate, billions of chained 2009 dollars)	Bureau of Economic Analysis
FHFA	Repeat-sales housing price index (not seasonally adjusted)	Federal Housing Finance Agency
Case-Shiller	Composite of single-family home price indexes for the nine U.S. Census divisions (seasonally adjusted)	S&P Dow Jones Indices LLC
Freddy Mac	Repeat-transactions housing price index (not seasonally adjusted)	Freddie Mac

3.B Complete Estimation Results of Robustness Checks

Table 3.12: In-Sample Results (Markov-Switching Model)

Predictors/k		1	2	3	4	5	6	7	8
Housing sales$_4$	R^2	0.29	0.35	0.34	0.26	0.16	0.09	0.08	0.08
	t-stat	-5.59	-6.56	-6.71	-6.13	-5.13	-4.03	-3.74	-3.86
Consumption$_4$	R^2	0.35	0.26	0.20	0.13	0.08	0.06	0.05	0.04
	t-stat	-6.28	-5.69	-5.34	-4.43	-3.58	-3.14	-2.92	-2.71
GDP$_4$	R^2	0.27	0.18	0.12	0.06	0.03	0.02	0.01	0.01
	t-stat	-5.76	-5.04	-4.39	-3.15	-2.25	-1.97	-1.65	-1.5
CPI$_4$	R^2	0.02	0.02	0.01	0.01	0.00	0.00	0.00	0.00
	t-stat	2.03	1.82	1.56	1.21	0.94	0.69	0.52	0.37
Term spreads	R^2	0.01	0.04	0.06	0.07	0.08	0.06	0.03	0.01
	t-stat	-1.46	-2.57	-3.15	-3.51	-3.76	-3.23	-2.34	-1.6
Federal funds rates	R^2	0.01	0.02	0.01	0.01	0.01	0.00	0.00	0.00
	t-stat	1.32	1.7	1.59	1.38	1.08	0.48	-0.23	-0.87

Notes: The critical values are 1.64 (10%), 1.96 (5%) and 2.58 (1%). The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

Table 3.13: Out-of-Sample Results (Markov-Switching Model)

Predictors/k		1	2	3	4	5	6	7	8
Housing sales$_4$	R^2	0.32	0.31	0.27	0.26	0.21	0.15	0.13	0.14
	QPS	0.35	0.36	0.38	0.42	0.46	0.49	0.50	0.50
Consumption$_4$	R^2	0.29	0.25	0.22	0.17	0.11	0.07	0.04	0.02
	QPS	0.39	0.41	0.43	0.46	0.49	0.52	0.53	0.54
GDP$_4$	R^2	0.22	0.18	0.14	0.08	0.02	—	—	—
	QPS	0.42	0.44	0.47	0.50	0.54	0.56	0.57	0.58
CPI$_4$	R^2	—	—	—	—	—	—	—	—
	QPS	0.57	0.58	0.58	0.59	0.59	0.59	0.59	0.59
Term spreads	R^2	—	—	—	—	—	—	—	—
	QPS	0.63	0.69	0.70	0.70	0.71	0.67	0.64	0.60
Federal funds rates	R^2	—	—	—	—	—	—	—	—
	QPS	0.62	0.65	0.65	0.64	0.63	0.61	0.59	0.59

Notes: The QPS ranges from zero to two, which correspond to *"perfect fit"* and *"no fit"*, respectively. — indicates negative value. The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

Table 3.14: In-Sample Results (Naïve Moving Average Method)

Predictors/k		1	2	3	4	5	6	7	8
Housing $sales_4$	R^2	0.19	0.27	0.37	0.34	0.27	0.18	0.12	0.10
	t-stat	-4.62	-4.9	-6.01	-5.96	-5.85	-5.05	-4.34	-4.25
$Consumption_4$	R^2	0.33	0.31	0.27	0.18	0.14	0.11	0.09	0.06
	t-stat	-6.12	-6	-5.73	-5.11	-4.64	-3.94	-3.47	-3.02
GDP_4	R^2	0.36	0.29	0.20	0.11	0.07	0.06	0.04	0.04
	t-stat	-6.72	-6.06	-5.55	-4.45	-3.75	-3.2	-2.78	-2.48
CPI_4	R^2	0.03	0.03	0.02	0.02	0.01	0.00	0.00	0.00
	t-stat	2.45	2.35	2.02	1.63	1.23	0.93	0.82	0.69
Term spreads	R^2	0.00	0.01	0.03	0.07	0.11	0.12	0.11	0.09
	t-stat	-0.27	-1.33	-2.17	-3.11	-3.91	-4.13	-4.05	-3.84
Federal funds rates	R^2	0.00	0.00	0.01	0.02	0.01	0.01	0.00	0.00
	t-stat	0.31	0.73	1.16	1.51	1.52	1.18	0.72	0.17

Notes: The critical values are 1.64 (10%), 1.96 (5%) and 2.58 (1%). The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

Table 3.15: Out-of-Sample Results (Naïve Moving Average Method)

Predictors/k		1	2	3	4	5	6	7	8
Housing $sales_4$	R^2	0.30	0.38	0.47	0.38	0.30	0.25	0.18	0.18
	QPS	0.29	0.26	0.23	0.26	0.31	0.35	0.39	0.40
$Consumption_4$	R^2	0.34	0.29	0.24	0.19	0.18	0.15	0.12	0.06
	QPS	0.28	0.31	0.33	0.36	0.37	0.38	0.40	0.43
GDP_4	R^2	0.35	0.27	0.20	0.13	0.09	0.07	0.04	0.02
	QPS	0.28	0.32	0.36	0.39	0.41	0.42	0.44	0.46
CPI_4	R^2	—	—	—	—	—	—	—	—
	QPS	0.46	0.47	0.48	0.48	0.48	0.48	0.48	0.48
Term spreads	R^2	—	—	—	—	—	—	—	—
	QPS	0.46	0.49	0.51	0.51	0.50	0.49	0.48	0.48
Federal funds rates	R^2	—	—	—	—	—	—	—	—
	QPS	0.46	0.49	0.50	0.52	0.51	0.50	0.49	0.49

Notes: The QPS ranges from zero to two, which correspond to *"perfect fit"* and *"no fit"*, respectively. — indicates negative value. The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

Table 3.16: In-Sample Results (FHFA Index)

Predictors/k		1	2	3	4	5	6	7	8
Housing sales$_4$	R^2	0.54	0.60	0.56	0.45	0.33	0.28	0.26	0.21
	t-stat	-6.32	-7.28	-6.49	-6.67	-5.79	-5.86	-5.79	-5.46
Consumption$_4$	R^2	0.53	0.45	0.34	0.26	0.21	0.18	0.14	0.11
	t-stat	-6.59	-6.78	-6.66	-6.35	-5.98	-5.39	-4.95	-4.37
GDP growth$_4$	R^2	0.34	0.27	0.16	0.11	0.08	0.06	0.05	0.03
	t-stat	-5.08	-5.31	-4.45	-3.79	-3.46	-2.93	-2.6	-2.09
Inflation$_4$	R^2	0.06	0.07	0.07	0.07	0.06	0.06	0.05	0.04
	t-stat	3.02	3.33	3.39	3.24	3.08	2.94	2.68	2.51
Term spreads	R^2	0.06	0.09	0.13	0.16	0.15	0.13	0.09	0.06
	t-stat	-3	-3.61	-4.07	-4.37	-4.34	-3.97	-3.45	-2.82
Federal funds rates	R^2	0.02	0.02	0.02	0.02	0.02	0.01	0.00	0.00
	t-stat	1.49	1.63	1.73	1.73	1.47	1.09	0.67	0.2

Notes: The critical values are 1.64 (10%), 1.96 (5%) and 2.58 (1%). The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

Table 3.17: Out-of-Sample Results (FHFA Index)

Predictors/k		1	2	3	4	5	6	7	8
Housing sales$_4$	R^2	0.50	0.62	0.62	0.54	0.42	0.35	0.31	0.25
	QPS	0.21	0.18	0.20	0.23	0.27	0.30	0.31	0.34
Consumption$_4$	R^2	0.41	0.29	0.20	0.18	0.15	0.12	0.10	0.05
	QPS	0.26	0.31	0.36	0.38	0.39	0.39	0.40	0.41
GDP$_4$	R^2	0.32	0.25	0.16	0.11	0.07	0.03	-0.01	-0.06
	QPS	0.30	0.34	0.38	0.41	0.42	0.43	0.44	0.46
CPI$_4$	R^2	—	—	—	—	—	—	—	—
	QPS	0.49	0.52	0.53	0.53	0.51	0.50	0.48	0.47
Term spreads	R^2	—	—	—	—	—	—	—	—
	QPS	0.47	0.48	0.48	0.50	0.45	0.44	0.43	0.43
Federal funds rates	R^2	—	—	—	—	—	—	—	—
	QPS	0.52	0.53	0.53	0.52	0.50	0.49	0.48	0.47

Notes: The QPS ranges from zero to two, which correspond to *"perfect fit"* and *"no fit"*, respectively. — indicates negative value. The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

Table 3.18: In-Sample Results (Case-Shiller Index)

Predictors/k		1	2	3	4	5	6	7	8
Housing sales_4	R^2	0.41	0.44	0.42	0.38	0.32	0.27	0.28	0.25
	t-stat	-5.7	-5.5	-5.62	-5.89	-5.89	-5.52	-5.52	-5.31
Consumption_4	R^2	0.48	0.46	0.43	0.37	0.31	0.26	0.21	0.15
	t-stat	-6.96	-7.05	-7.84	-7.08	-6.67	-6.32	-6.02	-5.17
GDP_4	R^2	0.35	0.28	0.21	0.15	0.12	0.11	0.09	0.05
	t-stat	-5.89	-5.11	-4.8	-4.18	-3.95	-3.7	-3.42	-2.75
CPI_4	R^2	0.05	0.07	0.08	0.09	0.09	0.09	0.08	0.07
	t-stat	3.03	3.51	3.78	3.99	3.82	3.57	3.37	3.1
Term spreads	R^2	0.03	0.06	0.10	0.14	0.16	0.14	0.12	0.09
	t-stat	-1.89	-2.93	-3.73	-4.35	-4.76	-4.52	-3.97	-3.49
Federal funds rates	R^2	0.02	0.03	0.03	0.03	0.03	0.03	0.02	0.01
	t-stat	1.69	2.03	2.18	2.25	2.23	1.91	1.5	1.11

Notes: The critical values are 1.64 (10%), 1.96 (5%) and 2.58 (1%). The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

Table 3.19: Out-of-Sample Results (Case-Shiller Index)

Predictors/k		1	2	3	4	5	6	7	8
Housing sales_4	R^2	0.37	0.21	0.27	0.37	0.36	0.35	0.34	0.30
	QPS	0.30	0.32	0.33	0.33	0.34	0.36	0.36	0.37
Consumption_4	R^2	0.27	0.26	0.32	0.33	0.31	0.27	0.21	0.13
	QPS	0.36	0.39	0.39	0.37	0.38	0.39	0.42	0.45
GDP_4	R^2	0.27	0.24	0.21	0.18	0.15	0.13	0.09	0.03
	QPS	0.38	0.40	0.42	0.43	0.45	0.46	0.47	0.50
CPI_4	R^2	—	—	—	—	—	—	—	—
	QPS	0.57	0.60	0.62	0.61	0.60	0.58	0.57	0.55
Term spreads	R^2	—	—	—	—	—	—	—	0.03
	QPS	0.55	0.57	0.57	0.57	0.57	0.56	0.53	0.50
Federal funds rates	R^2	—	—	—	—	—	—	—	—
	QPS	0.62	0.64	0.64	0.62	0.60	0.57	0.55	0.55

Notes: The QPS ranges from zero to two, which correspond to *"perfect fit"* and *"no fit"*, respectively. — indicates negative value. The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

Table 3.20: In-Sample Results (FRMA Index)

Predictors/k		1	2	3	4	5	6	7	8
Housing sales$_4$	R^2	0.40	0.40	0.37	0.31	0.24	0.23	0.23	0.23
	t-stat	-5.8	-5.72	-5.68	-5.73	-5.08	-5.13	-5.09	-5.22
Consumption$_4$	R^2	0.44	0.42	0.36	0.31	0.29	0.26	0.21	0.16
	t-stat	-7.3	-7.15	-6.97	-6.59	-6.7	-6.32	-5.97	-5.27
GDP$_4$	R^2	0.30	0.25	0.17	0.13	0.12	0.11	0.09	0.06
	t-stat	-4.98	-5.09	-4.45	-4.04	-3.96	-3.69	-3.44	-2.86
CPI$_4$	R^2	0.04	0.06	0.06	0.06	0.06	0.06	0.05	0.05
	t-stat	2.73	3.11	3.26	3.2	3.07	2.97	2.77	2.66
Term spreads	R^2	0.02	0.04	0.07	0.11	0.11	0.09	0.07	0.06
	t-stat	-1.86	-2.49	-3.18	-3.83	-3.89	-3.49	-3.15	-2.89
Federal funds rates	R^2	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.00
	t-stat	1.27	1.46	1.62	1.72	1.55	1.26	0.95	0.64

Notes: The critical values are 1.64 (10%), 1.96 (5%) and 2.58 (1%). The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

Table 3.21: Out-of-Sample Results (FRMA Index)

Predictors/k		1	2	3	4	5	6	7	8
Housing sales$_4$	R^2	0.28	0.24	0.29	0.29	0.29	0.29	0.30	0.29
	QPS	0.33	0.35	0.36	0.38	0.41	0.42	0.42	0.41
Consumption$_4$	R^2	0.28	0.27	0.28	0.29	0.31	0.28	0.23	0.17
	QPS	0.39	0.41	0.41	0.40	0.40	0.41	0.43	0.45
GDP$_4$	R^2	0.28	0.23	0.19	0.16	0.16	0.13	0.10	0.04
	QPS	0.39	0.42	0.45	0.46	0.47	0.48	0.49	0.52
CPI$_4$	R^2	—	—	—	—	—	—	—	—
	QPS	0.59	0.62	0.64	0.63	0.62	0.60	0.59	0.58
Term spreads	R^2	—	—	—	—	—	—	—	0.03
	QPS	0.58	0.60	0.61	0.59	0.60	0.58	0.55	0.53
Federal funds rates	R^2	—	—	—	—	—	—	—	—
	QPS	0.63	0.65	0.66	0.65	0.62	0.59	0.58	0.58

Notes: The QPS ranges from zero to two, which correspond to *"perfect fit"* and *"no fit"*, respectively. — indicates negative value. The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

Table 3.22: In-Sample Results (Existing Housing Sales)

Predictors/k		1	2	3	4	5	6	7	8
EHS_4	R^2	0.29	0.33	0.30	0.23	0.15	0.12	0.10	0.09
	t-stat	-6.07	-5.62	-5.48	-4.98	-4.56	-4.2	-4.04	-3.84
$Consumption_4$	R^2	0.32	0.22	0.16	0.10	0.06	0.04	0.02	0.01
	t-stat	-5.61	-5.32	-4.79	-3.73	-2.90	-2.40	-1.94	-1.29
GDP_4	R^2	0.25	0.15	0.08	0.04	0.02	0.01	0.01	0.00
	t-stat	-5.59	-5.01	-3.89	-2.75	-2.12	-1.59	-1.00	-0.53
CPI_4	R^2	0.04	0.03	0.02	0.01	0.01	0.01	0.00	0.00
	t-stat	2.57	2.26	1.89	1.47	1.21	0.99	0.79	0.74
Term spreads	R^2	0.07	0.12	0.17	0.20	0.18	0.14	0.10	0.07
	t-stat	-3.24	-4.11	-4.75	-5.07	-4.94	-4.56	-4.01	-3.45
Federal funds rates	R^2	0.02	0.03	0.03	0.02	0.01	0.00	0.00	0.00
	t-stat	1.87	2.19	2.19	1.96	1.44	0.81	0.10	-0.66

Notes: The critical values are 1.64 (10%), 1.96 (5%) and 2.58 (1%). The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

Table 3.23: Out-of-Sample Results (Existing Housing Sales)

Predictors/k		1	2	3	4	5	6	7	8
EHS_4	R^2	0.24	0.32	0.31	0.26	0.17	0.13	0.13	0.11
	QPS	0.28	0.25	0.27	0.30	0.35	0.37	0.38	0.38
$Consumption_4$	R^2	0.34	0.26	0.19	0.13	0.06	0.02	—	—
	QPS	0.27	0.30	0.34	0.37	0.41	0.42	0.44	0.45
GDP_4	R^2	0.29	0.19	0.11	0.04	0.00	—	—	—
	QPS	0.29	0.33	0.37	0.40	0.43	0.44	0.45	0.46
CPI_4	R^2	—	—	—	—	—	—	—	—
	QPS	0.42	0.43	0.44	0.44	0.45	0.44	0.44	0.44
Term spreads	R^2	—	—	—	—	—	—	—	0.05
	QPS	0.45	0.45	0.44	0.42	0.42	0.41	0.40	0.40
Federal funds rates	R^2	—	—	—	—	—	—	—	—
	QPS	0.44	0.45	0.45	0.45	0.46	0.45	0.46	0.46

Notes: The QPS ranges from zero to two, which correspond to *"perfect fit"* and *"no fit"*, respectively. — indicates negative value. The subscript indicates that the variable enters the forecasting model in four-quarter growth rates as predictor.

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Ehrenwörtliche Erklärung

Ich habe die vorgelegte Dissertation selbst verfasst und dabei nur die von mir angegebenen Quellen und Hilfsmittel benutzt. Alle Textstellen, die wörtlich oder sinngemäß aus veröffentlichten oder nicht veröffentlichten Schriften entnommen sind, sowie alle Angaben, die auf mündlichen Auskünften beruhen, sind als solche kenntlich gemacht.

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