Research Methodology 04
-Analyzing Data-

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0. Outline of Today's Lecture

- 1. Research Question and Data,
- 2. Overview of multivariable analysis,
- 3. The aims and methodology of Econometrics.
- 4. Methodology for Analyzing Data

- Review of Statistics: Describing Data, Numerical.
- Simple Regression.

- Case: Housing Bubbles in Japan and the United States.

1. Research Question and Data

- Stock and Watson (2015), Chap1.
- Ask a half dozen econometricians what econometrics is, and you could get a half dozen different answers.

- One might tell you that econometrics is the science of **testing economic theories.**
- A second might tell you that econometrics is the set of tools used for **forecasting future values of economic variables, such as a firm's sales, the overall growth of the economy, or stock prices.**
- Another might say that econometrics is the process of **fitting mathematical economic models to real-world data**.
- A fourth might tell you that it is **the science and art of using historical data to make numerical, or quantitative, policy recommendations in government and business**.

Main purpose of today's class.

- Econometric methods are used in many branches of economics, including finance, labor economics, macroeconomics, microeconomics, marketing, and economic policy. Econometric methods are also commonly used in other social sciences, including political science and sociology.

- **Today's class concludes with a survey of the main types of data available to econometricians for answering these and other quantitative economic questions.**

Research Question

- We Examine many decisions in economics, business, and government hinge on understanding relationships among variables in the world around us.
- →These decisions require quantitative answers to quantitative questions.(Research topic in Class 2.)

- This class examines several quantitative questions taken from current issues in economics.

Question #1: Does Reducing Class Size Improve Elementary School Education?

- Proposals for reform of the public education system generate heated debate. Many of the proposals concern the youngest students, those in elementary schools. Elementary school education has various objectives, such as developing social skills, but for many parents and educators, the most important objective is basic academic learning: reading, writing, and basic mathematics.
- One prominent proposal for improving basic learning is to reduce class sizes at elementary schools. With fewer students in the classroom, the argument goes, each student gets more of the teacher's attention, there are fewer class disruptions, learning is enhanced, and grades improve.

- But what, precisely, is the effect on elementary school education of reducing class size? **Reducing class size costs money**: It requires hiring more teachers and, if the school is already at capacity, building more classrooms. A decision maker contemplating hiring more teachers must weigh **these costs against the benefits**.
- To weigh costs and benefits, however, the decision maker must **have a precise quantitative understanding of the likely benefits**. Is the beneficial effect on basic learning of smaller classes large or small? Is it possible that smaller class size actually has no effect on basic learning?
- Although common sense and everyday experience may suggest that more learning occurs when there are fewer students, common sense cannot provide a quantitative answer to the question of what exactly is the effect on basic learning of reducing class size.

Data:

TABLE 1.1 Selected Observations on Test Scores and Other Variables for California School Districts in 1999

Observation (District) Number	District Average Test Score (fifth grade)	Student–Teacher Ratio	Expenditure per Pupil ($)	Percentage of Students Learning English
1	690.8	17.89	$6385	0.0%
2	661.2	21.52	5099	4.6
3	643.6	18.70	5502	30.0
4	647.7	17.36	7102	0.0
5	640.8	18.67	5236	13.9
⋮	⋮	⋮	⋮	⋮
418	645.0	21.89	4403	24.3
419	672.2	20.20	4776	3.0
420	655.8	19.04	5993	5.0

Note: The California test score data set is described in Appendix 4.1.

- To provide such an answer, we must examine empirical evidence—**that is, evidence based on data—relating class size to basic learning in elementary schools.**
- Research examines the relationship between class size and basic learning, using data gathered from 420 school districts .
- In the data, ***students in districts with small class sizes tend to perform better on standardized tests than students in districts with larger classes.*** While this fact is consistent with the idea that smaller classes produce better test scores, it might simply reflect many other advantages that students in districts with small classes have over their counterparts in districts with large classes.
- **Method:**
- →Regression

Similar research question in Real Estate Studies

- ***Greenhouse gas emissions*** of transport and buildings >66% of total GHG.
- Existing urban models identify ***multiple feedback loops*** between ***transport costs*** and ***location behaviour*** and ***real estate prices***.
- Most existing urban models do ***not*** yet take account of energy efficiency.
- Urban models need to understand and predict the magnitude of these ***interactions*** between ***transport*** and ***energy efficiency*** of buildings.
- **BUT: does energy efficiency have a spatial dimension, i.e. is it linked to location?**
- Preliminary empirical evidence suggests that the ***environmental cost of sprawl*** may be even higher when ***energy efficiency of buildings*** is taken into account.
- **However,** there may be ***offsetting factors***. New buildings built to high energy-efficiency standards are more likely to be located at the urban periphery with poor public transport and so may generate more and longer car trips.
- We investigate how retrofitting existing buildings and energy-efficient new buildings may influence residential location and travel behaviour in an urban model

Data & method

Tokyo condominium transaction database with property and buyer characteristics 2001-2011:

- Data source: Japanese Real Estate Economic Institute's database combined with large-scale questionnaire survey of prices and characteristics (Recruit Housing Institute).
- Variables:

  Asking price, transaction price, name of development company, development scale, size and age of property, location characteristics (coordinates, address, nearest station, distance to nearest station), building characteristics (building area, land area, building structure).

Data & method

Variables (continued):

- Buyer characteristics (annual income, size of family, etc.) gathered by the Recruit Housing Institute.
- Tenure type (leasehold types etc.)
- Property management type (24-hour etc.)
- First-month contract rate (i.e. time on market). Higher the first month contract rate, the more affordable prices are in relation to the condominium's features.
- **Method:**

  Hedonic method or Regression.

  (Quasi) cross-sectional hedonic model with robust S.E., time fixed effects and buyer characteristics.

Tokyo Green Building Label

- Tokyo Metropolitan Government's Green Labeling System for Condominiums.

- Green Labeling System for Condominiums (2002, revised in 2005 & 2010), mandatory for new construction and major refurbishment to organize and publish information based on a) building insulation, b) energy efficiency & performance, c) lifespan extension (durability) and d) greening (plants etc.) of the building. The evaluation results for the respective items are expressed as a number of star symbols, max: ★ ★ ★ .

Estimation results

	Model 1 log (price)		Model 2 log(price)		
Regressor	***Coefficient***	***t stat***	***Regressor***	***Coefficient***	***t stat***
cost	0.005	10.59	green2005	0.045	2.40
green	0.064	19.45	green2006	0.0487	5.72
trgreen	-0.009	-2.37	green2007	0.0596	7.40
			green2008	0.0844	10.42
			green2009	0.096	14.14
			green2010	0.0438	8.68
			tgreen2005	-0.0486	-2.14
			tgreen2006	-0.003	-0.27
			tgreen2007	0.010	1.05
			tgreen2008	-0.034	-2.80
			tgreen2009	-0.029	-3.79
			tgreen2010	0.008	1.65
Property & condo attributes	Yes			Yes	
Developer fixed effects	Yes			Yes	
Location controls	Yes			Yes	
Management fixed effects	Yes			Yes	
Buyer characteristics	No			Yes	
Time fixed effects	*Yes*			*Yes*	*Yes*
N	**48,740**			**48,740**	
R^2	**0.805**			**0.814**	

Question #2: Is There Racial Discrimination in the Market for Home Loans?

- Most people buy their homes with the help of a mortgage, a large loan secured by the value of the home. By law, U.S. lending institutions cannot take race into account when deciding to grant or deny a request for a mortgage: Applicants who are identical in all ways except their race should be equally likely to have their mortgage applications approved.

- In theory, then, **there should be no racial bias in mortgage lending**. In contrast to this theoretical conclusion, researchers at the Federal Reserve Bank of Boston found (using data from the early 1990s) that **28% of black applicants are denied mortgages, while only 9% of white applicants are denied.**

- Do these data indicate that, in practice, there is ***racial bias*** in mortgage lending? If so, how large is it? The fact that more black than white applicants are denied in the Boston Fed data does not by itself provide evidence of discrimination by mortgage lenders because the black and white applicants differ in many ways other than their race.
- Before concluding that there is bias in the mortgage market, **these data must be examined more closely to see if there is a difference in the probability of being denied for otherwise identical applicants and, if so, whether this difference is large or small.**

- **Method:**
- **Regression with a Binary dependent variable.**

Question #3: How Much Do Cigarette Taxes Reduce Smoking?

- Cigarette smoking is a major public health concern worldwide. Many of the costs of smoking, such as the medical expenses of caring for those made sick by smoking and the less quantifiable costs to nonsmokers who prefer not to breathe secondhand cigarette smoke, are borne by other members of society. Because these costs are borne by people other than the smoker, there is a role for government intervention in reducing cigarette consumption.
- One of the most flexible tools for cutting consumption is to increase taxes on cigarettes. Basic economics says that if cigarette prices go up, consumption will go down.
- **But by how much?**

- If we want to reduce smoking by a certain amount, say 20%, by raising taxes, then we need to know **the price elasticity of demand** to calculate the price increase necessary to achieve this reduction in consumption.
- But what is the price elasticity of demand for cigarettes?
- Although economic theory provides us with the concepts that help us answer this question, it does not tell us the numerical value of the price elasticity of demand.
- To learn the elasticity, we must examine **empirical evidence about the behavior of smokers and potential smokers**; in other words, we need to analyze data on cigarette consumption and prices.

Data:

TABLE 1.3 Selected Observations on Cigarette Sales, Prices, and Taxes, by State and Year for U.S. States, 1985–1995

Observation Number	State	Year	Cigarette Sales (packs per capita)	Average Price per Pack (including taxes)	Total Taxes (cigarette excise tax + sales tax)
1	Alabama	1985	116.5	$1.022	$0.333
2	Arkansas	1985	128.5	1.015	0.370
3	Arizona	1985	104.5	1.086	0.362
⋮	⋮	⋮	⋮	⋮	⋮
47	West Virginia	1985	112.8	1.089	0.382
48	Wyoming	1985	129.4	0.935	0.240
49	Alabama	1986	117.2	1.080	0.334
⋮	⋮	⋮	⋮	⋮	⋮
96	Wyoming	1986	127.8	1.007	0.240
97	Alabama	1987	115.8	1.135	0.335
⋮	⋮	⋮	⋮	⋮	⋮
528	Wyoming	1995	112.2	1.585	0.360

Note: The cigarette consumption data set is described in Appendix 12.1.

- **Data:**
- The data they examine are **cigarette sales, prices, taxes, and personal income** for U.S. states in the 1980s and 1990s.
- In these data, states with low taxes, and thus low cigarette prices, have high smoking rates, and states with high prices have low smoking rates.
- However, the analysis of these data is complicated because **causality runs both ways**: ***Low taxes lead to high demand, but if there are many smokers in the state, then local politicians might try to keep cigarette taxes low to satisfy their smoking constituents.***

- **Method:**

  Instrumental Variable Regression.

#4: By How Much Will U.S. GDP Grow Next Year?

- It seems that people always want a sneak preview of the future. What will sales be next year at a firm that is considering investing in new equipment? Will the stock market go up next month, and, if it does, by how much? Will city tax receipts next year cover planned expenditures on city services? Will your microeconomics exam next week focus on externalities or monopolies? Will Saturday be a nice day to go to the beach?
- One aspect of the future in which macroeconomists are particularly interested is the growth of real economic activity, as measured by real gross domestic product (GDP), during the next year. A management consulting firm might advise a manufacturing client to expand its capacity based on an upbeat forecast of economic growth.

Data:

TABLE 1.2 Selected Observations on the Growth Rate of GDP and the Term Spread in the United States: Quarterly Data, 1960:Q1–2013:Q1

Observation Number	Date (year:quarter)	GDP Growth Rate (% at an annual rate)	Term Spread (% per year)
1	1960:Q1	8.8%	0.6%
2	1960:Q2	−1.5	1.3
3	1960:Q3	1.0	1.5
4	1960:Q4	−4.9	1.6
5	1961:Q1	2.7	1.4
⋮	⋮	⋮	⋮
211	2012:Q3	2.7	1.5
212	2012:Q4	0.1	1.6
213	2013:Q1	1.1	1.9

Note: The United States GDP and term spread data set is described in Appendix 14.1.

- **<u>Data:</u>**
- Professional economists who rely on precise numerical forecasts use econometric models to make those forecasts. A forecaster's job is to predict the future by **<u>using the past</u>**, and **<u>econometricians do this by using economic theory and statistical techniques to quantify relationships in historical data.</u>**
- The data we use to forecast the growth rate of GDP are past values of GDP and the "term spread" in the United States. The term spread is the difference between long-term and short-term interest rates. It measures, among other things, whether investors expect short-term interest rates to rise or fall in the future.
- **<u>Method:</u>**
- **<u>Time Series Regression and Forecasting.</u>**

2. Overview of multivariable analysis

- Hair, Black, Babin, and Anderson (2010),Chap1.
- Multivariate analysis methods will increasingly influence not only the analytical aspects of research but also the design and approach to data collection for decision making and problem solving.
- Although multivariate techniques share many characteristics with their univariate and bivariate counterparts, several key differences arise in the transition to a multivariate analysis.
- You should be able to do the following:
- a) Explain what multivariate analysis is and when its application is appropriate.
- b) Discuss the nature of measurement scales and their relationship to multivariate techniques.

- c) Understand the nature of measurement error and its impact on multivariate analysis.
- d) Determine which multivariate technique is appropriate for a specific research problem.
- e) Define the specific techniques included in multivariate analysis.
- f) Discuss the guidelines for application and interpretation of multivariate analyses.
- g) Understand the six-step approach to multivariate model building.

1) What is Multivariate Analysis?

- Many multivariate techniques are extensions of univariate analysis (analysis of single-variable distributions) and bivariate analysis (***cross-classification, correlation, analysis of variance, and simple regression*** used to analyze two variables).
- For example, ***simple regression*** (with one predictor variable) is extended in the multivariate case to include several predictor variables.
- Likewise, the single dependent variable found in analysis of variance is extended to include multiple dependent variables in multivariate analysis of variance.

- Some multivariate techniques (e.g., ***multiple regression and multivariate analysis of variance***) provide a means of performing in a single analysis what once took multiple univariate analyses to accomplish.

- Other multivariate techniques, however, are uniquely designed to deal with multivariate issues, such as factor analysis, which identifies the structure underlying a set of variables, or discriminant analysis, which differentiates among groups based on a set of variables.

- Confusion sometimes arises about what multivariate analysis is because the term is not used consistently in the literature. Some researchers use multivariate simply to mean examining relationships between or among more than two variables. Others use the term only for problems in which all the multiple variables are assumed to have a multivariate normal distribution.
- To be considered truly multivariate, however, all the variables must be random and interrelated in such ways that their different effects cannot meaningfully be interpreted separately.
- Some authors state that the purpose of multivariate analysis is to measure, explain, and predict the degree of relationship among variates (weighted combinations of variables).

2) A Classification of Multivariate Techniques

- The classification of multivariate techniques is based on three judgments the researcher must make about the research objective and nature of the data:

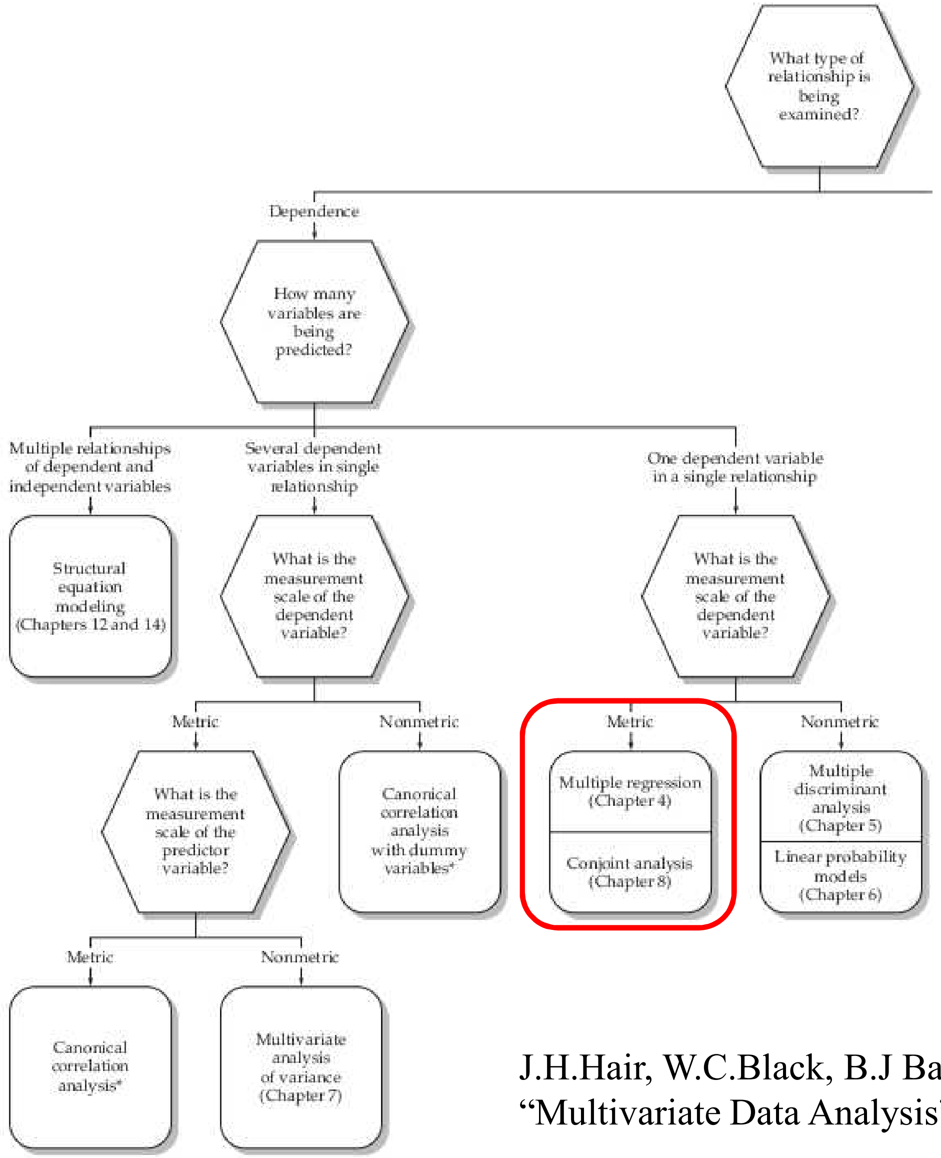
- 1. Can the variables be divided into independent and dependent classifications based on some theory?
- 2. If they can, how many variables are treated as dependent in a single analysis?
- 3. How are the variables, both dependent and independent, measured?

- See. 160128Lec03_Stat.pdf

- Selection of the appropriate multivariate technique depends on the answers to these three questions.

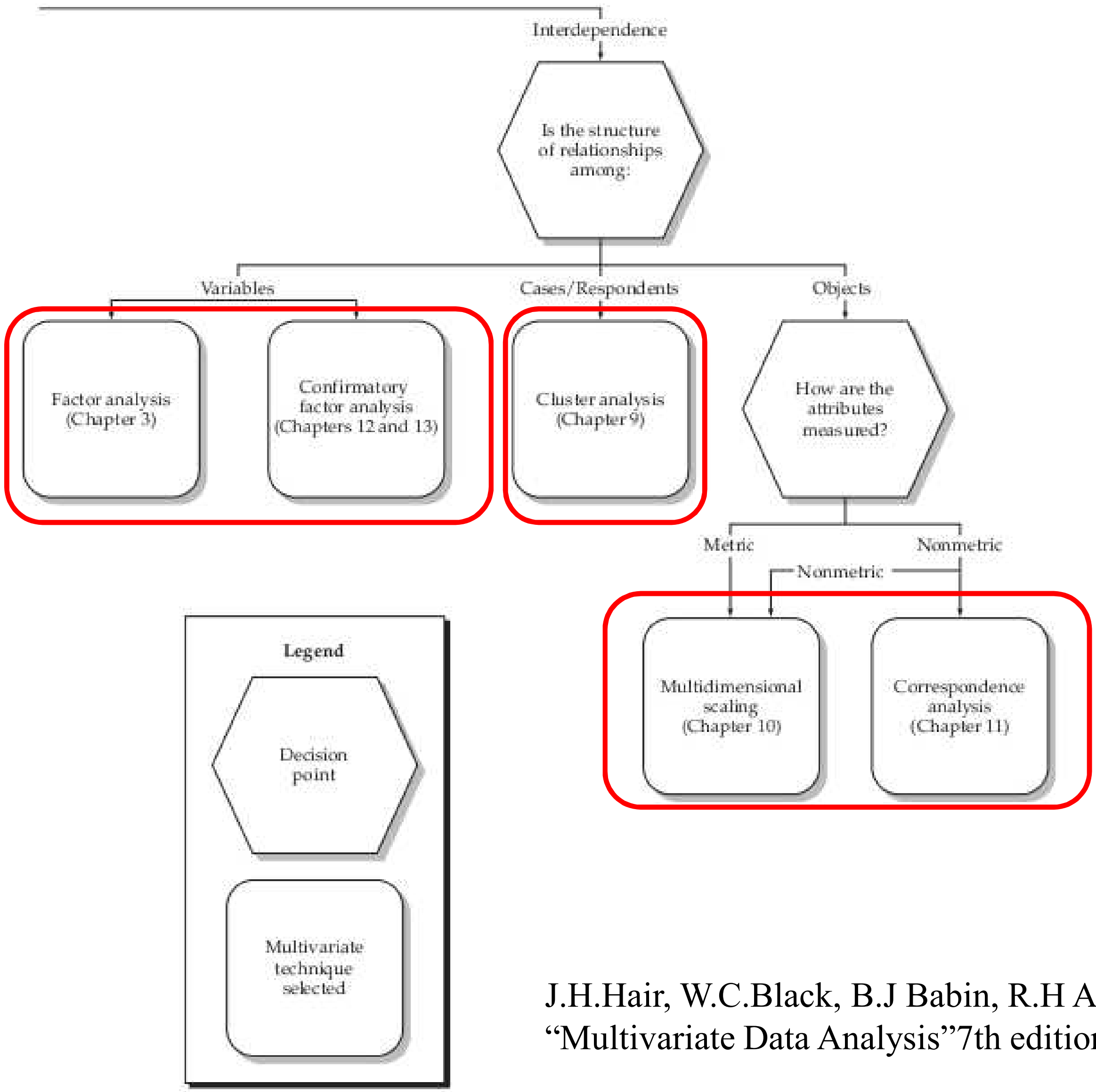
- When considering the application of multivariate statistical techniques, the answer to the first **question—Can the data variables be divided into independent and dependent classifications?**—indicates whether a dependence or interdependence technique should be utilized.

Selecting a Multivariate Technique



J.H.Hair, W.C.Black, B.J Babin, R.H Anderson (2010), “Multivariate Data Analysis”7th edition.

Selecting a Multivariate Technique



J.H.Hair, W.C.Black, B.J Babin, R.H Anderson (2010), "Multivariate Data Analysis"7th edition.

3) Dependence Techniques

- The different dependence techniques can be categorized by two characteristics:
- (1) the number of dependent variables and
- (2) the type of measurement scale employed by the variables.
- metric (quantitative/numerical) or nonmetric (qualitative/categorical) dependent variables.

The Relationship Between Multivariate Dependence Method

Canonical Correlation

$$\underset{\text{(metric, nonmetric)}}{Y_1 + Y_2 + Y_3 + \cdots + Y_n} = \underset{\text{(metric, nonmetric)}}{X_1 + X_2 + X_3 + \cdots + X_n}$$

Multivariate Analysis of Variance

$$\underset{\text{(metric)}}{Y_1 + Y_2 + Y_3 + \cdots + Y_n} = \underset{\text{(nonmetric)}}{X_1 + X_2 + X_3 + \cdots + X_n}$$

Analysis of Variance

$$\underset{\text{(metric)}}{Y_1} = \underset{\text{(nonmetric)}}{X_1 + X_2 + X_3 + \cdots + X_n}$$

Multiple Discriminant Analysis

$$\underset{\text{(nonmetric)}}{Y_1} = \underset{\text{(metric)}}{X_1 + X_2 + X_3 + \cdots + X_n}$$

Multiple Regression Analysis

$$\underset{\text{(metric)}}{Y_1} = \underset{\text{(metric, nonmetric)}}{X_1 + X_2 + X_3 + \cdots + X_n}$$

Conjoint Analysis

$$\underset{\text{(nonmetric, metric)}}{Y_1} = \underset{\text{(nonmetric)}}{X_1 + X_2 + X_3 + \cdots + X_n}$$

Structural Equation Modeling

$$\begin{aligned} Y_1 &= X_{11} + X_{12} + X_{13} + \cdots + X_{1n} \\ Y_2 &= X_{21} + X_{22} + X_{23} + \cdots + X_{2n} \\ \underset{\text{(metric)}}{Y_m} &= \underset{\text{(metric, nonmetric)}}{X_{m1} + X_{m2} + X_{m3} + \cdots + X_{mn}} \end{aligned}$$

J.H.Hair, W.C.Black, B.J Babin, R.H Anderson (2010), “Multivariate Data Analysis”7th edition.

4) Types of Multivariate Techniques

- 1. Principal components and common factor analysis
- 2. Multiple regression and multiple correlation
- 3. Multiple discriminant analysis and logistic regression
- 4. Canonical correlation analysis
- 5. Multivariate analysis of variance and covariance
- 6. Conjoint analysis
- 7. Cluster analysis
- 8. Perceptual mapping, also known as multidimensional scaling
- 9. Correspondence analysis
- 10. Structural equation modeling and confirmatory factor analysis

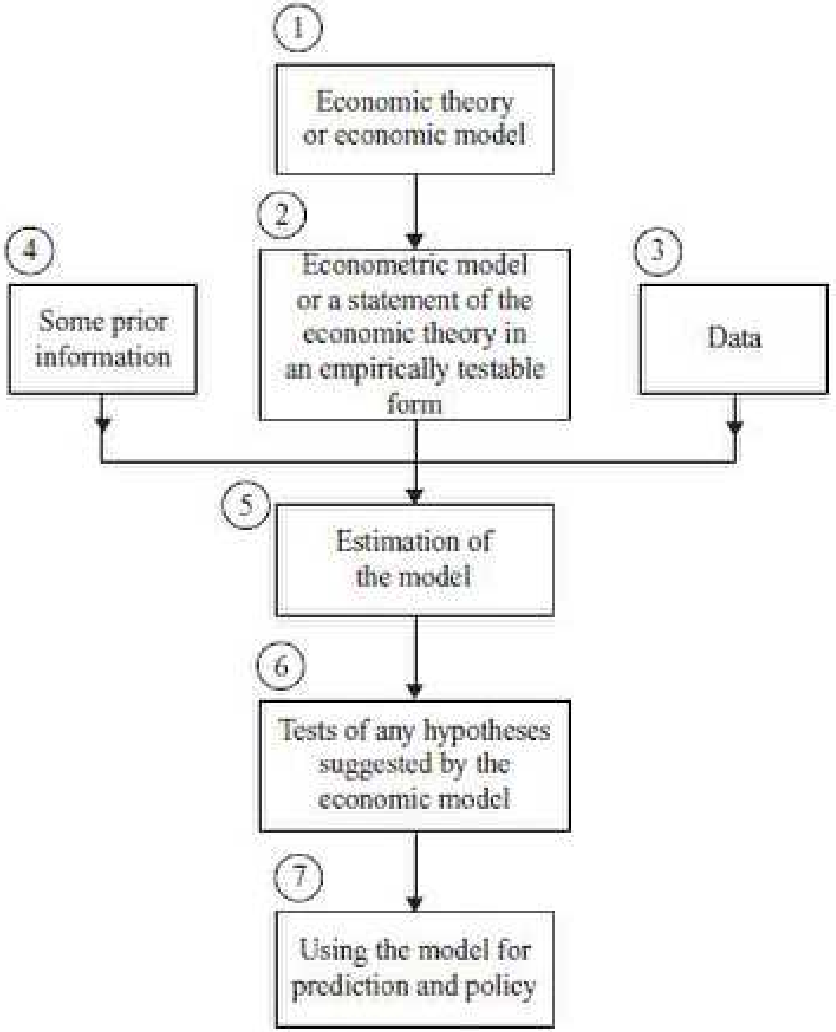
5) A Structured Approach to Multivariate Model Building

- Stage 1: Define the Research Problem, Objectives, and Multivariate Technique to Be Used.
- Stage 2: Develop the Analysis Plan.
- Stage 3: Evaluate the Assumptions Underlying the Multivariate Technique
- Stage 4: Estimate the Multivariate Model and Assess Overall Model Fit.
- Stage 5: Interpret the Variate(s) .
- Stage 6: Validate the Multivariate Model.

3. The aims and methodology of Econometrics

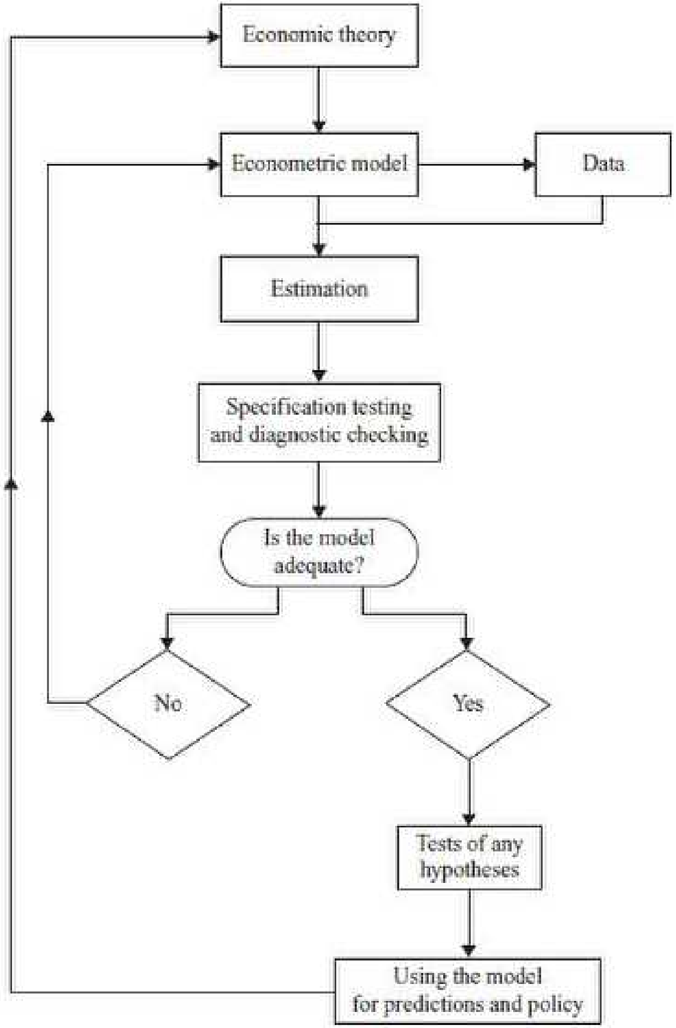
- G.S.Maddara and K. Lahiri (2009), “Introduction to Econometrics” 4th edition.
- The aims of econometrics are:
- 1. Formulation of econometric models, that is, formulation of economic models in an empirically testable form. Usually, there are several ways of formulating the econometric model from an economic model, because we have to choose the functional form, the specification of the stochastic structure of the variables, and so on. This part constitutes the specification aspect of the econometric work.
- 2. Estimation and testing of these models with observed data. This part constitutes the inference aspect of the econometric work.
- 3. Use of these models for prediction and policy purposes.

A schematic description of the steps involved in an econometric analysis of economic models.



G.S.Maddara and K. Lahiri (2009), "Introduction to Econometrics" 4th edition.

A revised schematic description of the steps involved in an econometric analysis of economic models.



G.S.Maddara and K. Lahiri (2009), "Introduction to Econometrics" 4th edition.

- 1. From econometric results to economic theory.
- 2. From specification testing and diagnostic checking to revised specification of the economic model.
- 3. From the econometric model to data.

- In the foregoing scheme we have talked of only one theory, but often there are many competing theories, and one of the main purposes of econometrics is to help in the choice among competing theories. This is the problem of **model selection**.

What Constitutes a Test of an Economic Theory?

- One of the aims of econometrics was that of testing economic theories.
- An important question that arises is: What constitutes a test?
- As evidence of a successful test of economic theory, it is customary to report that the signs of the estimated coefficients in an econometric model are correct. This approach may be term
- In many areas of economics, different econometric studies reach conflicting conclusions and, given the **available data**, there are frequently **no effective methods** for deciding which conclusion is corrected the approach of confirming economic theories.

Econometric and Statistical Software.

- Advantage and disadvantage in Software or program
- Statistical Software
- Advantage and disadvantage in Software or program

SPSS	EViews	Stata	SAS	R
Social Science	Econ & Finance	Economics	Finance & Bio Stat	Bio Stat
Simple	Time Series	Regression & Clean Data	Big Data	Programing (Loop)
Basic	Basic	Professional	Professional	Professional

Introduction to Statistics02

- Describing Data: Numerical
- Single Regression

P. Newbold, W.L. Carlson, B. M. Thorne (2010), "Statistics for Business and Economics"7th edition.

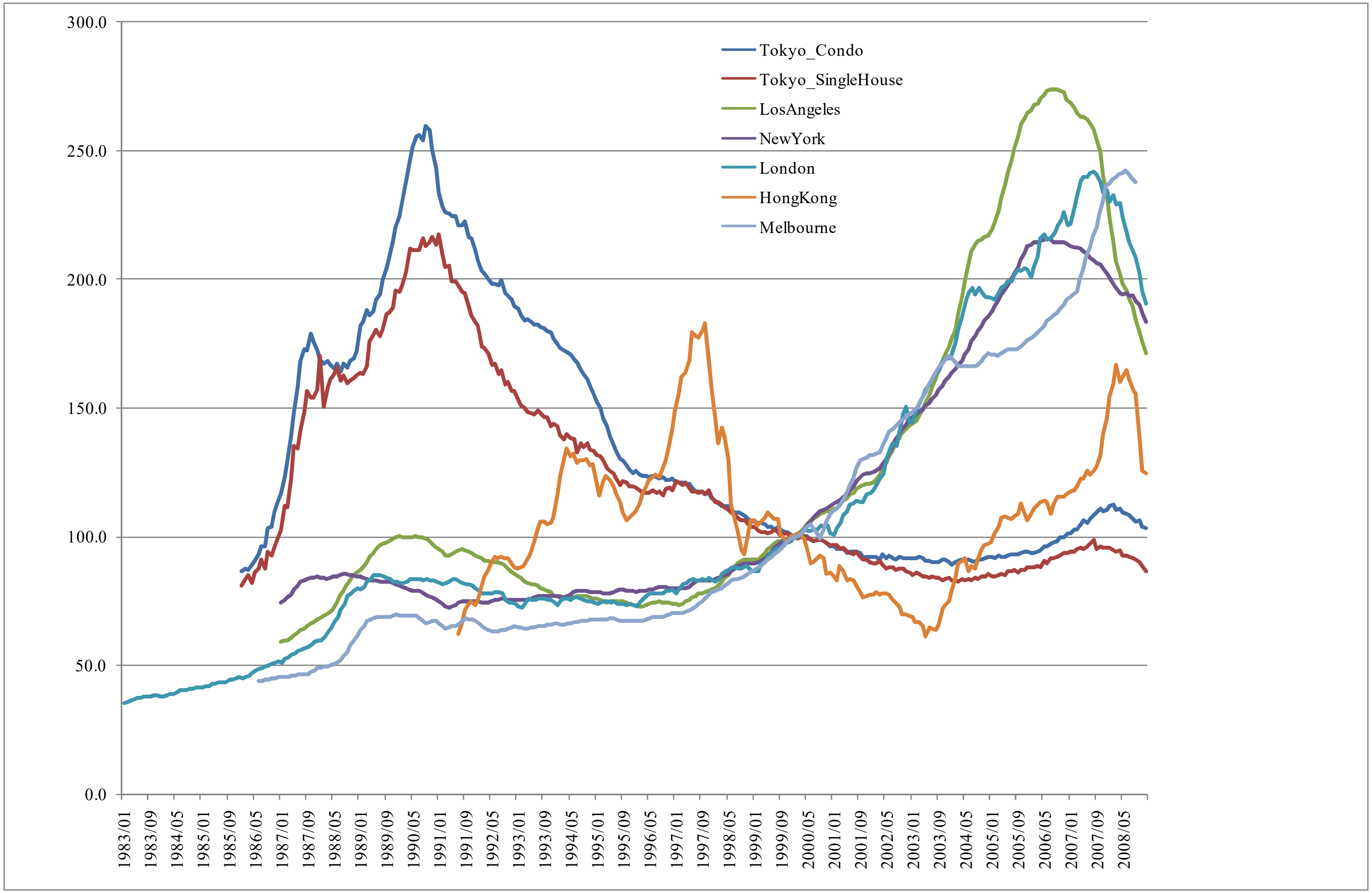
Chapter 2: Describing Data: Numerical

Chapter11: Simple Regression

Today’s Case:

- Shimizu,C and T.Watanabe(2010), “Housing Bubble in Japan and the United States,” Public Policy Review Vol.6, No.3, 431-472.

Macro Dynamic Trend of House Price Indices



Granger Causality

Pairwise Granger Causality Tests

Null Hypothesis:	Obs	F-Statistic	Prob.	
D(TOKYO_SINGLEHOUSE) does not Granger Cause D(TOKYO_CONDO)	264	5.00054	0.00000	*
D(TOKYO_CONDO) does not Granger Cause D(TOKYO_SINGLEHOUSE)		6.82566	0.00000	*
D(LOSANGELES) does not Granger Cause D(TOKYO_CONDO)	252	0.79408	0.64590	
D(TOKYO_CONDO) does not Granger Cause D(LOSANGELES)		0.86687	0.57360	
D(NEWYORK) does not Granger Cause D(TOKYO_CONDO)	252	0.39261	0.95810	
D(TOKYO_CONDO) does not Granger Cause D(NEWYORK)		0.70586	0.73250	
D(LONDON) does not Granger Cause D(TOKYO_CONDO)	264	0.45663	0.92800	
D(TOKYO_CONDO) does not Granger Cause D(LONDON)		0.15499	0.99920	
D(HONGKONG) does not Granger Cause D(TOKYO_CONDO)	198	1.49256	0.13780	
D(TOKYO_CONDO) does not Granger Cause D(HONGKONG)		0.82749	0.61270	
D(MELBOURNE) does not Granger Cause D(TOKYO_CONDO)	256	0.55889	0.86080	
D(TOKYO_CONDO) does not Granger Cause D(MELBOURNE)		0.45035	0.93140	
D(LOSANGELES) does not Granger Cause D(TOKYO_SINGLEHOUSE)	252	0.87579	0.56480	
D(TOKYO_SINGLEHOUSE) does not Granger Cause D(LOSANGELES)		0.79469	0.64530	
D(NEWYORK) does not Granger Cause D(TOKYO_SINGLEHOUSE)	252	0.84724	0.59300	
D(TOKYO_SINGLEHOUSE) does not Granger Cause D(NEWYORK)		0.96253	0.48150	
D(LONDON) does not Granger Cause D(TOKYO_SINGLEHOUSE)	264	0.35852	0.97040	
D(TOKYO_SINGLEHOUSE) does not Granger Cause D(LONDON)		0.17325	0.99870	
D(HONGKONG) does not Granger Cause D(TOKYO_SINGLEHOUSE)	198	1.39645	0.17810	
D(TOKYO_SINGLEHOUSE) does not Granger Cause D(HONGKONG)		1.7357	0.06910	**
D(MELBOURNE) does not Granger Cause D(TOKYO_SINGLEHOUSE)	256	0.57265	0.85010	
D(TOKYO_SINGLEHOUSE) does not Granger Cause D(MELBOURNE)		0.46809	0.92160	
D(NEWYORK) does not Granger Cause D(LOSANGELES)	252	1.24507	0.25830	
D(LOSANGELES) does not Granger Cause D(NEWYORK)		5.08511	0.00000	*
D(LONDON) does not Granger Cause D(LOSANGELES)	252	3.88808	0.00004	
D(LOSANGELES) does not Granger Cause D(LONDON)		2.40775	0.00760	
D(HONGKONG) does not Granger Cause D(LOSANGELES)	198	0.41059	0.95010	
D(LOSANGELES) does not Granger Cause D(HONGKONG)		1.69785	0.07720	
D(MELBOURNE) does not Granger Cause D(LOSANGELES)	249	1.75829	0.06250	
D(LOSANGELES) does not Granger Cause D(MELBOURNE)		2.46411	0.00630	
D(LONDON) does not Granger Cause D(NEWYORK)	252	3.22273	0.00040	*
D(NEWYORK) does not Granger Cause D(LONDON)		1.6578	0.08420	
D(HONGKONG) does not Granger Cause D(NEWYORK)	198	0.75721	0.68220	
D(NEWYORK) does not Granger Cause D(HONGKONG)		1.14808	0.32700	
D(MELBOURNE) does not Granger Cause D(NEWYORK)	249	1.8336	0.04960	
D(NEWYORK) does not Granger Cause D(MELBOURNE)		1.46852	0.14450	
D(HONGKONG) does not Granger Cause D(LONDON)	198	1.4457	0.15630	
D(LONDON) does not Granger Cause D(HONGKONG)		1.60956	0.09950	
D(MELBOURNE) does not Granger Cause D(LONDON)	256	2.15627	0.01760	
D(LONDON) does not Granger Cause D(MELBOURNE)		2.5127	0.00520	*
D(MELBOURNE) does not Granger Cause D(HONGKONG)	195	1.0478	0.40680	
D(HONGKONG) does not Granger Cause D(MELBOURNE)		0.45614	0.92750	

Peason's Correlation coefficient

Tokyo_Single → Tokyo_Condo
Tokyo_Condo → Tokyo_Single
London → Los Angels
London → New York
London → Melbourne
Los Angels → New York
Los Angels → London
Los Angels → Melbourne

Granger Causality

Peason's Correlation

	TOKYO_CONDO	TOKYO_SINGLEHOUSE	LOSANGELES	NEWYORK	LONDON	HONGKONG	MELBOURNE
TOKYO_CONDO	1						
TOKYO_SINGLEHOUSE	0.463	1					
LOSANGELES	0.119	0.120	1				
NEWYORK	0.163	0.126	0.833	1			
LONDON	0.262	0.156	0.472	0.295	1		
HONGKONG	0.096	0.008	-0.174	-0.152	-0.017	1	
MELBOURNE	0.360	0.194	-0.166	-0.061	0.085	-0.024	1

Motivations:

- 1. What extent did house prices increase and decrease during the so-called “bubble” periods in Japan and the U.S?
- → A notable problem in Japan is the fact that no index exists that enables us to capture fluctuations in house prices

- 2. Why do housing bubbles occur?
- →We will compare the relationship between changes in house price and changes in demand based on population characteristics in Japan and the U.S.

- 3.Is there a relationship between house price and house rent?

Contents of Our Paper:

- 1.Introduction

- 2.Comparison of House Price Fluctuation with advanced countries
- 2.1.House Price Index
- 2.2.Causality of house price in major cities
- 2.3.Differencies house price fluctuation by region in Japan and US.

- **3.Fluctuation Factor of House Price**
- 3.1.Market Efficiency and Housing Supply
- 3.2.Housing Demand and House Price

- 4.House Price and House Rent

- 5.Conclusions

2.3.Pattern of House Price Appreciation by Regions.

- Assuming that the fluctuations in the housing market should vary by region.

- Our hypothesis is that in both Japan and the U.S., during the respective bubble periods fluctuations in housing prices varied by region.

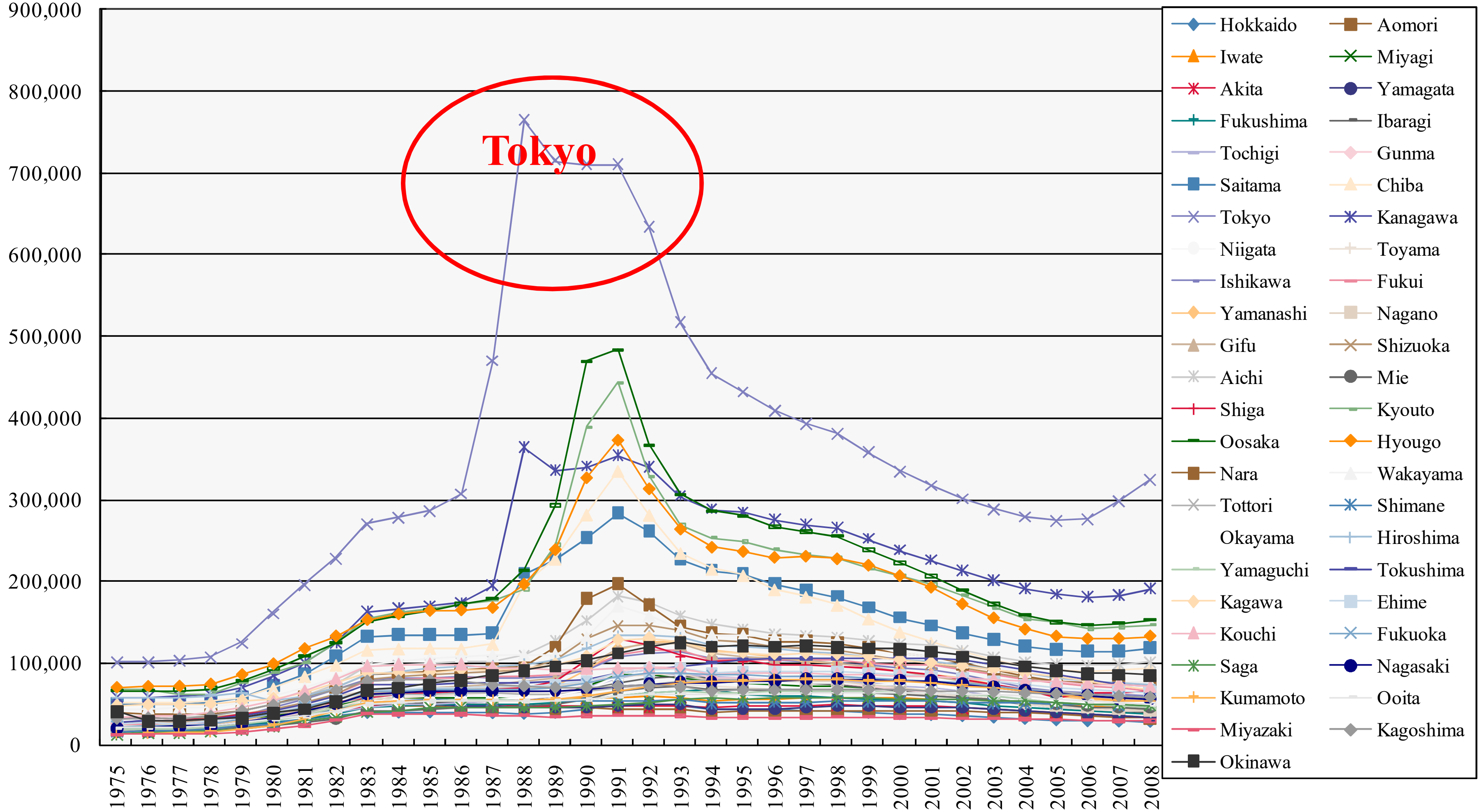
- US: The house price index by state published by OFHEO
- →Traditional Repeat Sales Method.
- Japan: The Residential Land Price by Public Land Price
- →Hedonic Method.

Estimation Results of Hedonic Function

Regression

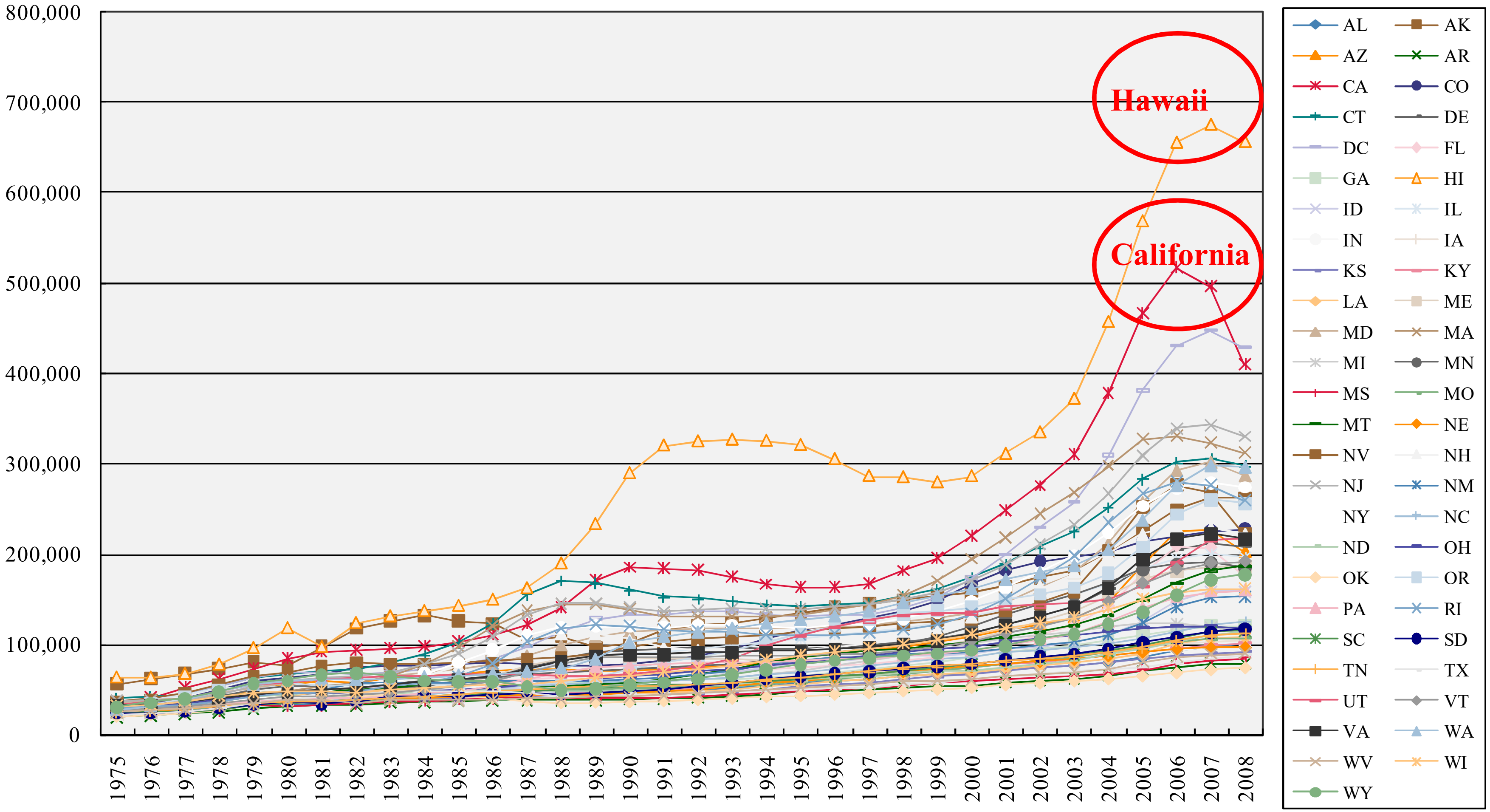
No	Prefecture	area	rw	ts	tt	gesui	sui	gas	UX	UY	UXX	UYY	cp1	cp3	cp6	cp7	tm	Number of Samples	adjusted R^2
1	Hokkaido	-1.180	0.179	-0.051	-0.409	0.288	0.004	0.415	-6.221	-24.091	0.022	0.276	-0.108	-0.275	0.878	-0.951	Yes	24,565	0.814
2	Aomori	-1.245	0.418	-0.038	-0.236	0.187	0.325	0.441	0.360	-0.919	-	-	-0.216	-0.034	[illegible]	-0.732	Yes	4,965	0.835
3	Iwate	-1.149	0.016	0.035	-0.321	0.217	0.086	0.256	0.530	-63.865	-	0.805	-0.117	-0.010	-	[illegible]	Yes	3,153	0.827
4	Miyagi	-1.108	0.237	-0.112	-0.365	0.143	0.232	0.180	0.284	0.040	-	-	-0.079	-0.037	-	[illegible]	Yes	[illegible]	[illegible]
5	Akita	-1.157	0.150	-0.074	-0.396	0.230	0.199	0.196	0.574	-151.022	-	1.896	-0.054	0.506	-	-0.776	Yes	3,300	0.867
6	Yamagata	-1.259	0.234	-0.054	-0.342	0.220	-	0.303	-0.177	-42.895	-	0.560	-0.056	-	-	-0.691	Yes	3,126	0.867
7	Fukushima	-1.135	0.135	-0.028	-0.193	0.165	0.398	0.257	0.050	-80.239	-	1.076	-0.001	0.139	-0.387	-0.839	Yes	8,462	0.851
8	Ibaragi	-1.216	0.181	-0.111	-0.140	0.206	0.148	0.330	-0.428	-0.274	-	-	-0.091	-	0.325	-0.710	Yes	14,836	0.877
9	Tochigi	-1.257	0.221	-0.050	-0.244	0.151	0.312	0.235	-0.204	-0.651	-	-	-0.021	-	-	-0.369	Yes	8,752	0.879
10	Gunma	-1.142	0.279	-0.062	-0.063	0.271	0.258	0.179	-0.264	-0.168	-	-	0.008	-	-	-0.455	Yes	7,188	0.839
11	Saitama	-1.039	0.145	-0.148	-0.173	0.109	-0.100	0.110	0.231	-2.411	-	-	-0.026	0.244	0.301	-0.599	Yes	28,425	0.943
12	Chiba	-1.096	0.120	-0.168	-0.283	0.077	0.307	0.261	-1.646	1.430	-	-	-0.055	-0.042	-	0.074	Yes	27,654	0.864
13	Tokyo	-0.871	0.144	-0.125	-0.724	0.086	0.089	0.186	-0.578	-0.560	-	-0.001	0.012	0.135	-0.349	-3.136	Yes	50,333	0.923
14	Kanagawa	-0.919	0.096	-0.107	-0.038	0.040	0.024	0.122	0.782	0.947	-	-	-0.008	-0.054	-0.195	-0.589	Yes	41,470	0.931
15	Niigata	-1.309	0.369	-0.131	-0.331	0.112	-0.082	0.316	-0.418	-11.409	-	0.150	-0.108	-	-	-0.797	Yes	7,386	0.851
16	Toyama	-1.080	0.242	-0.062	-0.179	0.294	0.103	0.231	-0.583	1.121	-	-	-0.110	-	-	-0.325	Yes	3,941	0.839
17	Ishikawa	-1.170	0.175	-0.057	-0.414	0.157	0.212	0.146	-0.604	-165.220	-	2.257	0.026	-	-0.044	-0.407	Yes	3,903	0.849
18	Fukui	-1.057	0.168	-0.129	-0.318	0.070	-0.106	0.124	-0.335	-0.935	-	-	-0.020	-	-	-1.107	Yes	2,090	0.858
19	Yamanashi	-1.143	0.215	-0.039	-0.155	0.028	0.335	0.158	1.087	0.627	-	-	-0.017	-	-0.078	-0.349	Yes	2,774	0.936
20	Nagano	-1.370	0.113	-0.062	-0.281	0.330	0.812	0.142	-0.122	90.043	-	-1.247	-0.085	0.460	0.202	-0.424	Yes	5,125	0.844
21	Gifu	-1.062	0.204	-0.047	-0.213	0.193	0.010	0.154	-0.323	0.771	-	-	-0.052	0.066	0.129	-0.559	Yes	6,207	0.893
22	Shizuoka	-1.154	0.116	-0.070	-0.125	0.131	-0.082	0.258	0.080	0.118	-	-	-0.058	0.159	-	-0.455	Yes	13,103	0.882
23	Aichi	-1.013	0.267	-0.066	-0.417	0.146	-0.051	0.131	0.623	-0.449	-	-	-0.033	-0.141	-0.314	-0.383	Yes	33,687	0.931
24	Mie	-1.116	0.329	-0.071	-0.040	0.060	0.155	0.318	0.212	-59.555	-	0.853	-0.032	-0.016	-	-0.635	Yes	8,298	0.885
25	Shiga	-1.310	0.395	-0.074	-0.158	0.111	0.092	0.268	-1.340	0.532	-	-	-0.085	-0.198	-0.490	-0.669	Yes	5,431	0.910
26	Kyouto	-0.994	0.270	-0.080	-0.318	0.134	0.830	0.241	1.174	1.080	-	-	0.004	-0.165	-0.188	-1.101	Yes	12,672	0.932
27	Oosaka	-0.965	0.221	-0.129	-0.342	0.083	-0.003	0.186	0.009	0.691	-	-	-0.031	0.040	-	-0.847	Yes	34,854	0.944
28	Hyougo	-0.983	0.201	-0.123	-0.062	0.077	0.106	0.380	0.911	-70.375	-	1.000	-0.110	-0.020	-	-0.930	Yes	25,911	0.875
29	Nara	-1.060	0.255	-0.133	-0.049	0.054	0.387	0.247	-1.254	2.115	-	-	-0.100	-	-0.572	-0.342	Yes	8,399	0.899
30	Wakayama	-1.094	0.168	0.014	-0.158	0.151	0.205	0.156	0.032	-0.225	-	-	-0.022	-0.171	-	-0.413	Yes	3,049	0.878
31	Tottori	-1.199	0.561	-0.182	-0.177	0.103	-0.670	0.158	-0.298	-0.233	-	-	-0.063	-0.102	-	-0.941	Yes	1,946	0.859
32	Shimane	-1.054	0.133	-0.094	-0.290	0.089	-	0.228	-0.680	-50.651	-	0.724	-0.038	-	-	-0.656	Yes	2,215	0.790
33	Okayama	-1.232	0.156	-0.086	-0.266	0.110	0.079	0.236	-0.444	-0.258	-	-	-0.110	-	-	-0.616	Yes	7,396	0.880
34	Hiroshima	-1.083	0.197	-0.103	-0.329	0.114	0.237	0.279	0.265	-0.905	-	-	0.002	0.097	-	-0.729	Yes	12,160	0.855
35	Yamaguchi	-1.143	0.146	-0.048	-0.010	0.022	0.366	0.402	0.330	0.399	-	-	-0.058	-	-	-1.079	Yes	5,714	0.817
36	Tokushima	-1.018	0.117	-0.037	-0.303	0.062	0.065	0.237	-0.573	-0.327	-	-	0.090	-	-	-0.063	Yes	2,518	0.929
37	Kagawa	-1.142	0.247	-0.163	-0.264	0.011	0.254	0.256	-0.626	0.088	-	-	-0.097	-	-	-0.462	Yes	2,866	0.913
38	Ehime	-1.240	0.306	-0.077	-0.208	0.180	-0.125	0.251	0.307	34.366	-	-0.518	-0.108	-0.263	-	-0.498	Yes	4,405	0.861
39	Kouchi	-1.232	0.284	-0.038	-0.272	0.218	0.176	0.195	0.304	34.104	-	-0.527	0.051	-	-	-0.292	Yes	2,644	0.890
40	Fukuoka	-0.992	0.157	-0.072	-0.434	0.280	0.182	0.232	0.611	-55.140	-	0.821	-0.035	0.635	0.039	-0.954	Yes	17,948	0.870
41	Saga	-1.294	0.153	-0.062	-0.186	0.094	0.096	0.200	0.243	1.040	-	-	-0.120	-	-0.181	-0.774	Yes	2,001	0.887
42	Nagasaki	-0.919	0.685	-0.006	-0.211	0.101	0.143	0.374	-0.298	-9.789	-	0.148	-0.012	-	-0.384	-0.831	Yes	4,922	0.815
43	Kumamoto	-1.222	0.311	-0.033	-0.265	0.116	0.199	0.315	-0.147	-0.607	-	-	-0.009	-	-	-0.349	Yes	5,186	0.901
44	Ooita	-1.139	0.418	-0.097	-0.232	0.106	0.695	0.254	-0.640	-0.765	-	-	-0.085	-	-	-0.040	Yes	4,496	0.856
45	Miyazaki	-1.168	0.125	-0.057	-0.273	0.259	0.140	0.244	0.634	-52.347	-	0.816	-0.038	-	-	-0.520	Yes	4,397	0.896
46	Kagoshima	-1.122	0.108	-0.092	-0.384	0.095	-	0.330	-0.264	1.593	-	-0.028	-0.064	-	-	-0.590	Yes	4,799	0.885
47	Okinawa	-1.225	0.318	0.015	-0.367	0.112	-0.067	0.006	-2.586	48.458	-	-0.873	-0.043	0.070	-	-1.261	Yes	3,348	0.929

(a). Real House prices by prefectures (JPN)



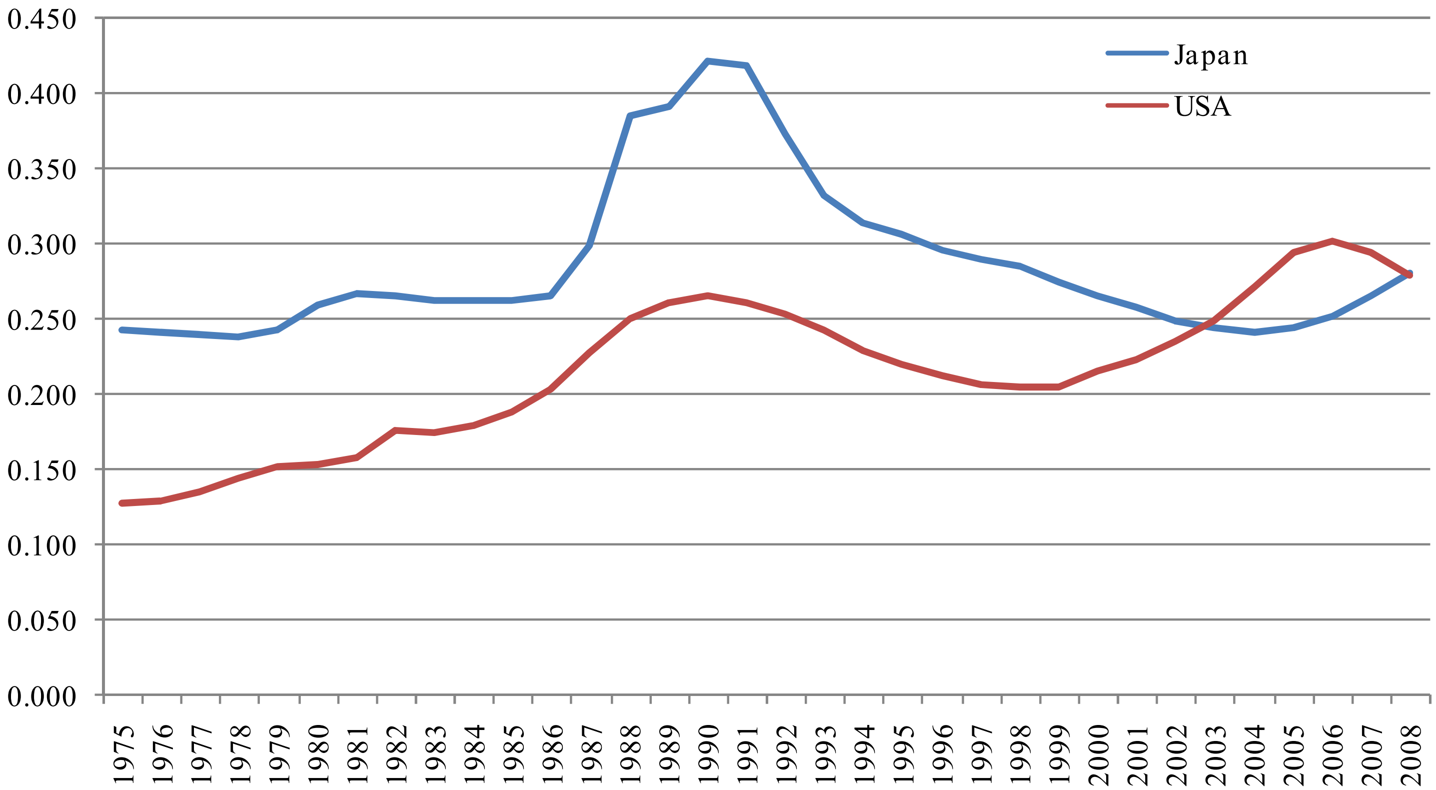
Source: Ministry of Land, Infrastructure, Transport and Tourism “Published Land Prices”

(b). Real House prices by states (U.S.)



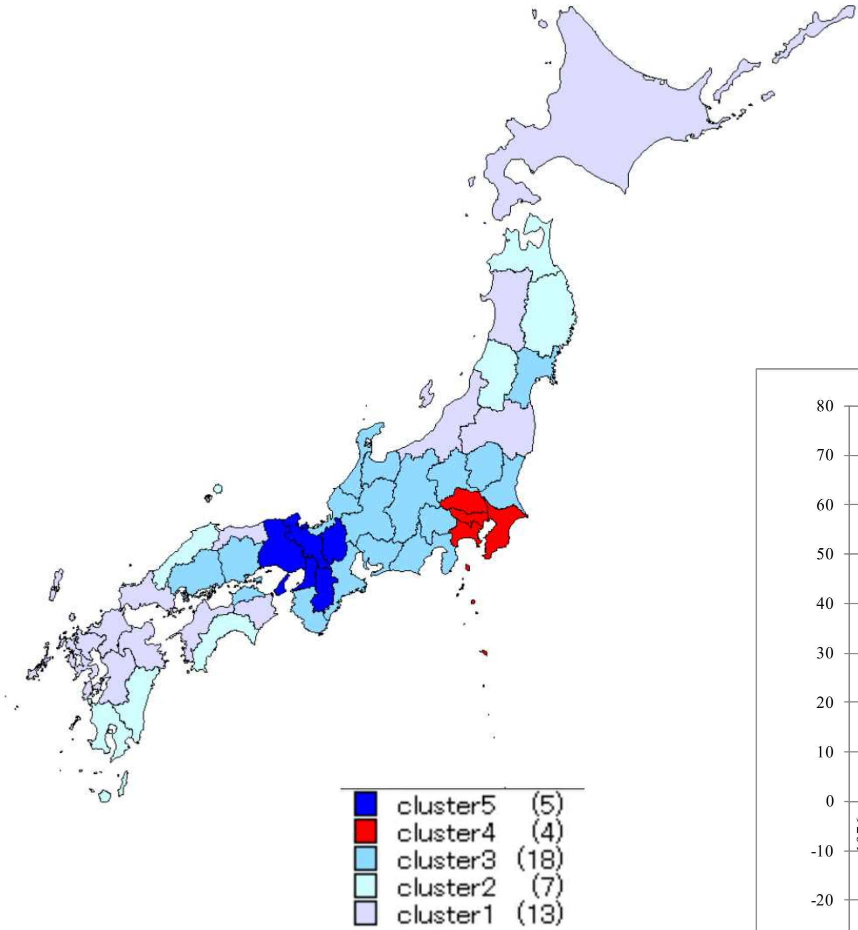
Source: Office of Federal Housing Enterprise Oversight, "House Price Index",
U.S. Census of Bureau, "Census of Housing: Median home value."

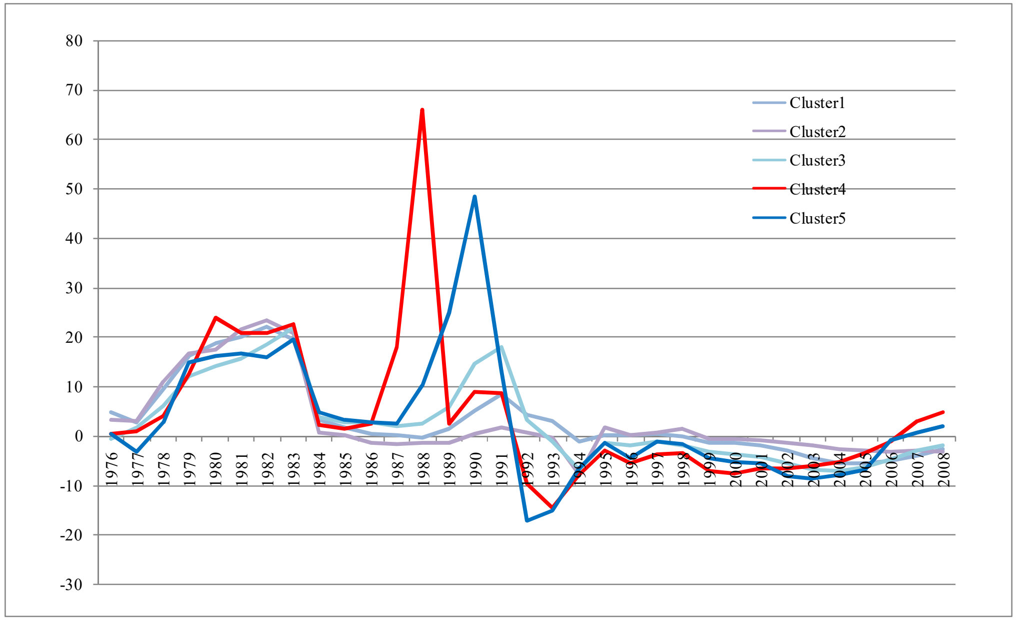
Gini's coefficient : Comparison between Japan and US



Cluster Classification in Japan by Appreciation Rate of Land Price

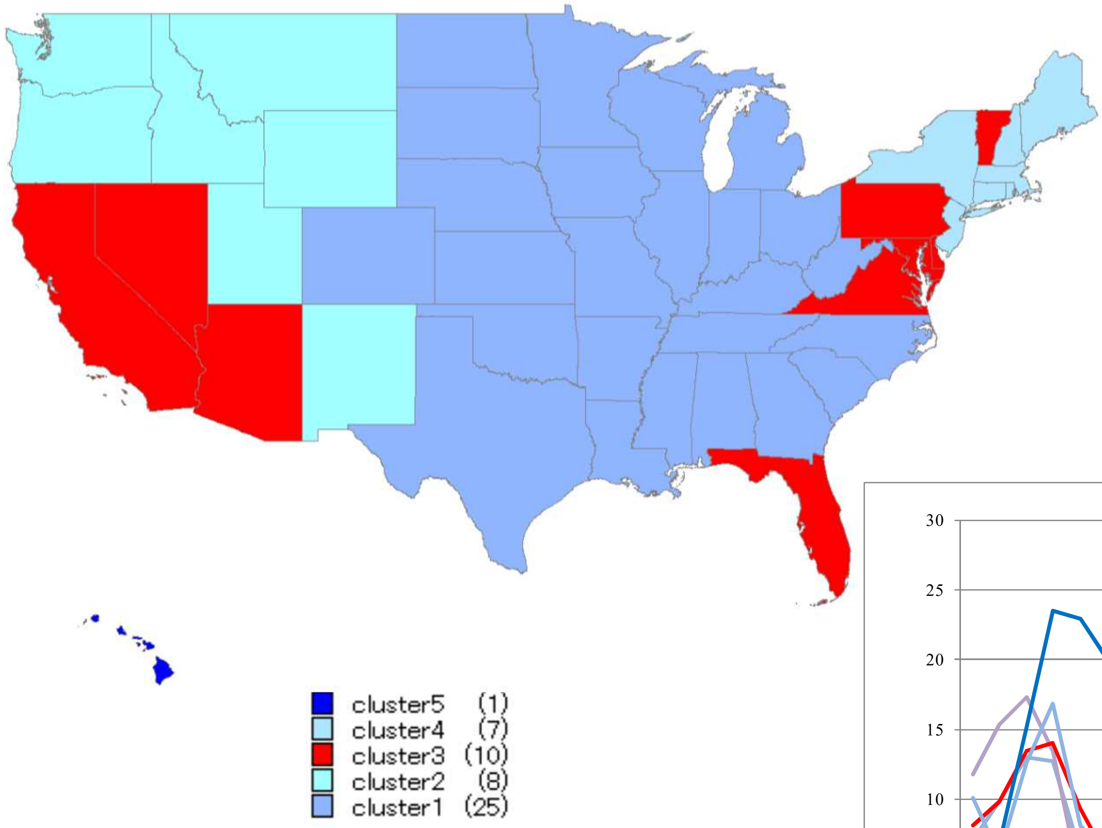
Cluster Analysis

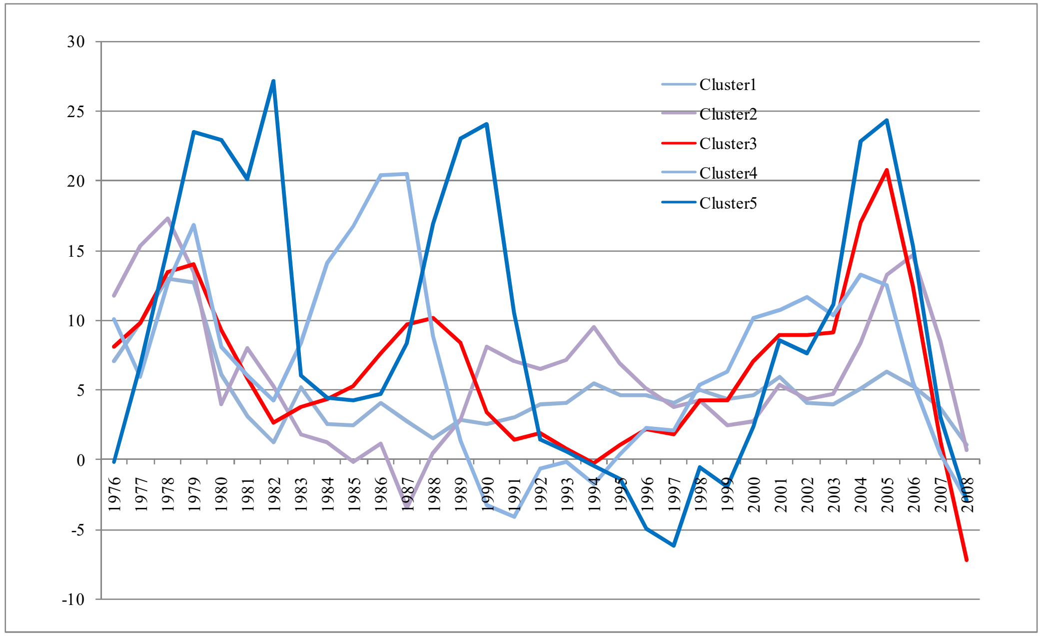




Cluster Classification in US by Appreciation Rate of House Price

Cluster Analysis





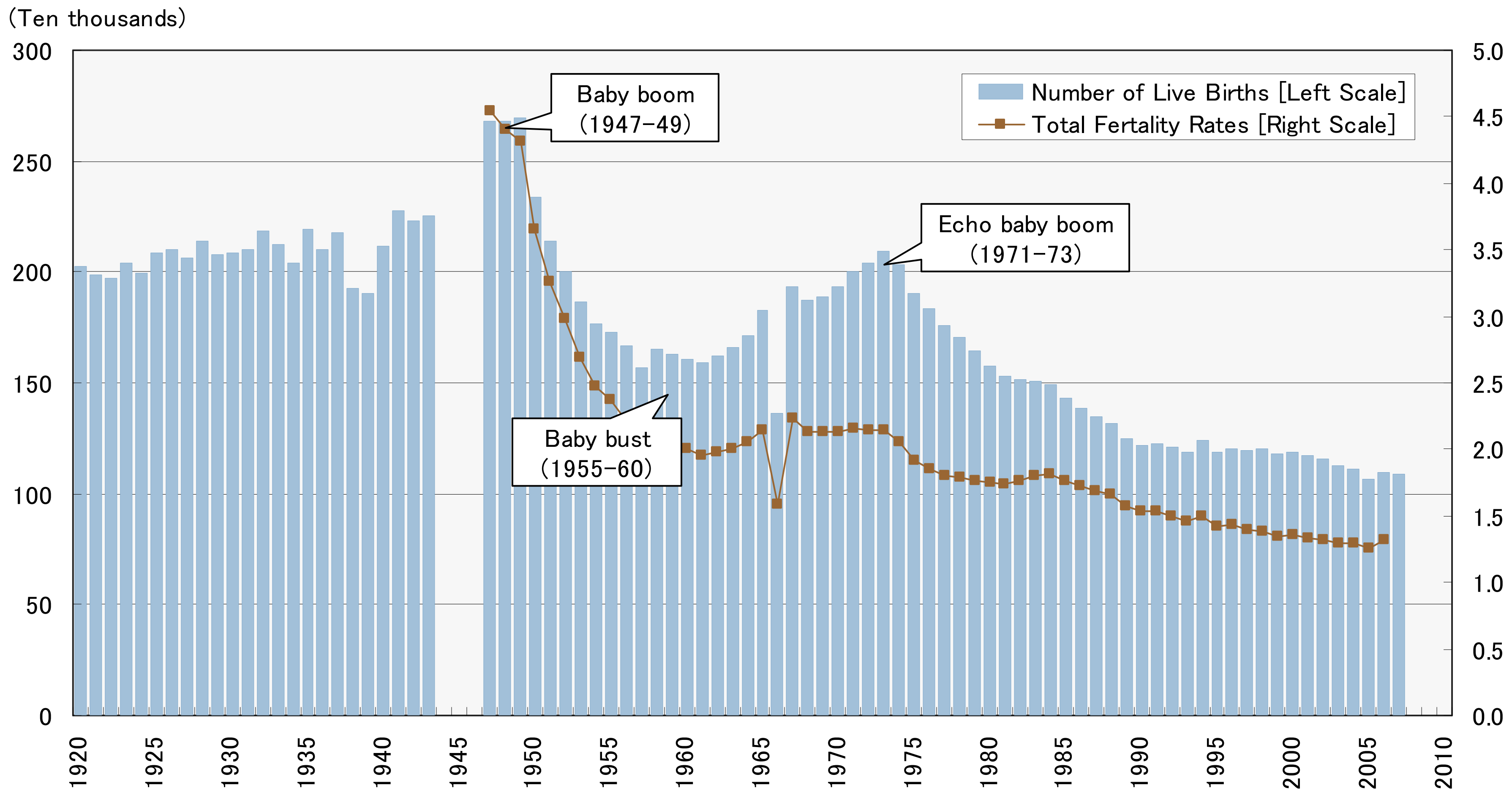
3.Fluctuation Factors of House Price.

- Housing demand has an impact on the housing market, then fluctuations in the housing market should vary by region.

- US: Mankiw, N. G., and D. N. Weil(1988)(1989)
- Japan: Ootake and Shintani(1994)(1996)

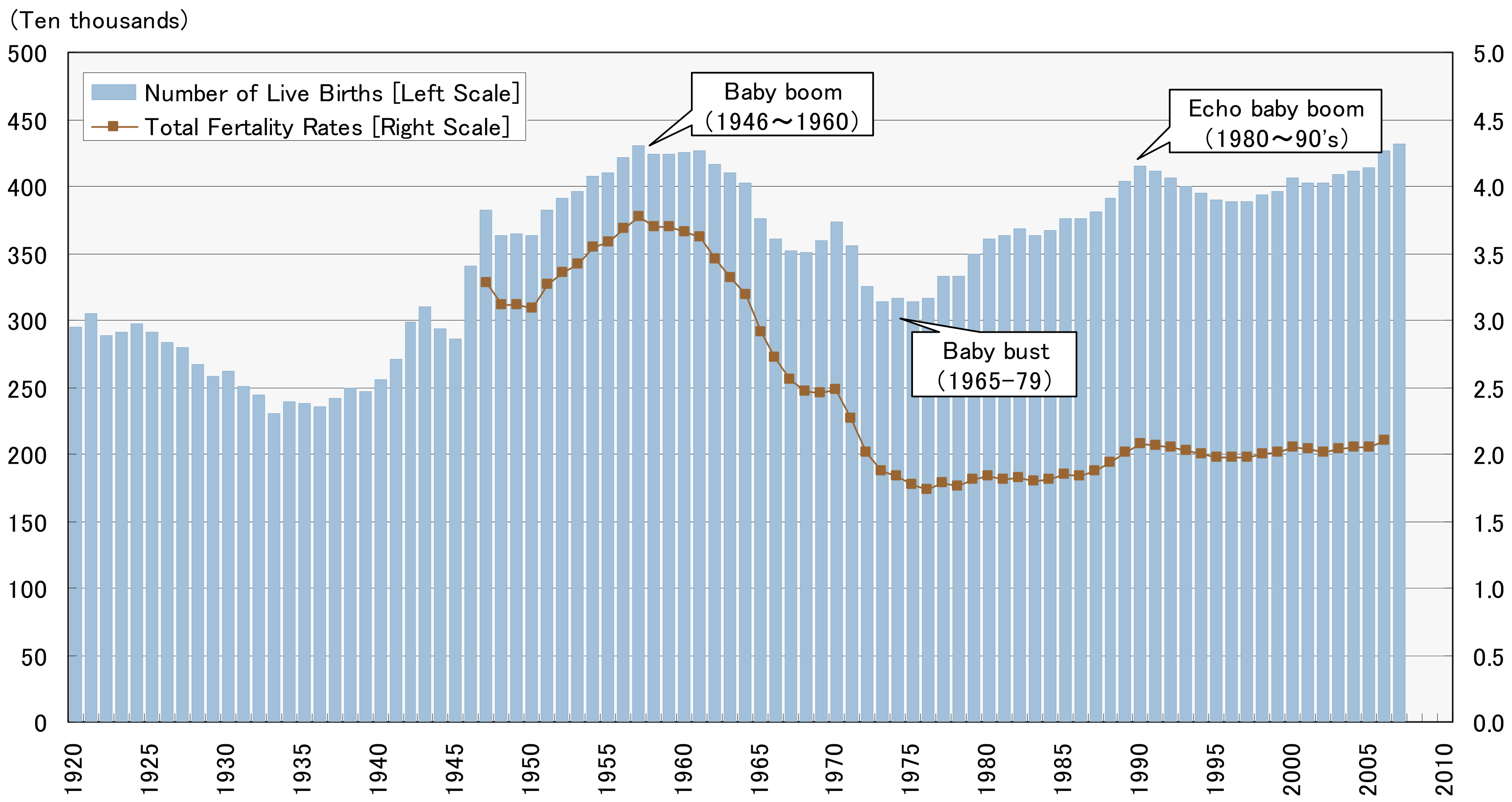
- Our hypothesis is that in both Japan and the U.S., during the respective bubble periods fluctuations in housing prices varied by region.

3-2(a). Demand: Number of live births (JPN)



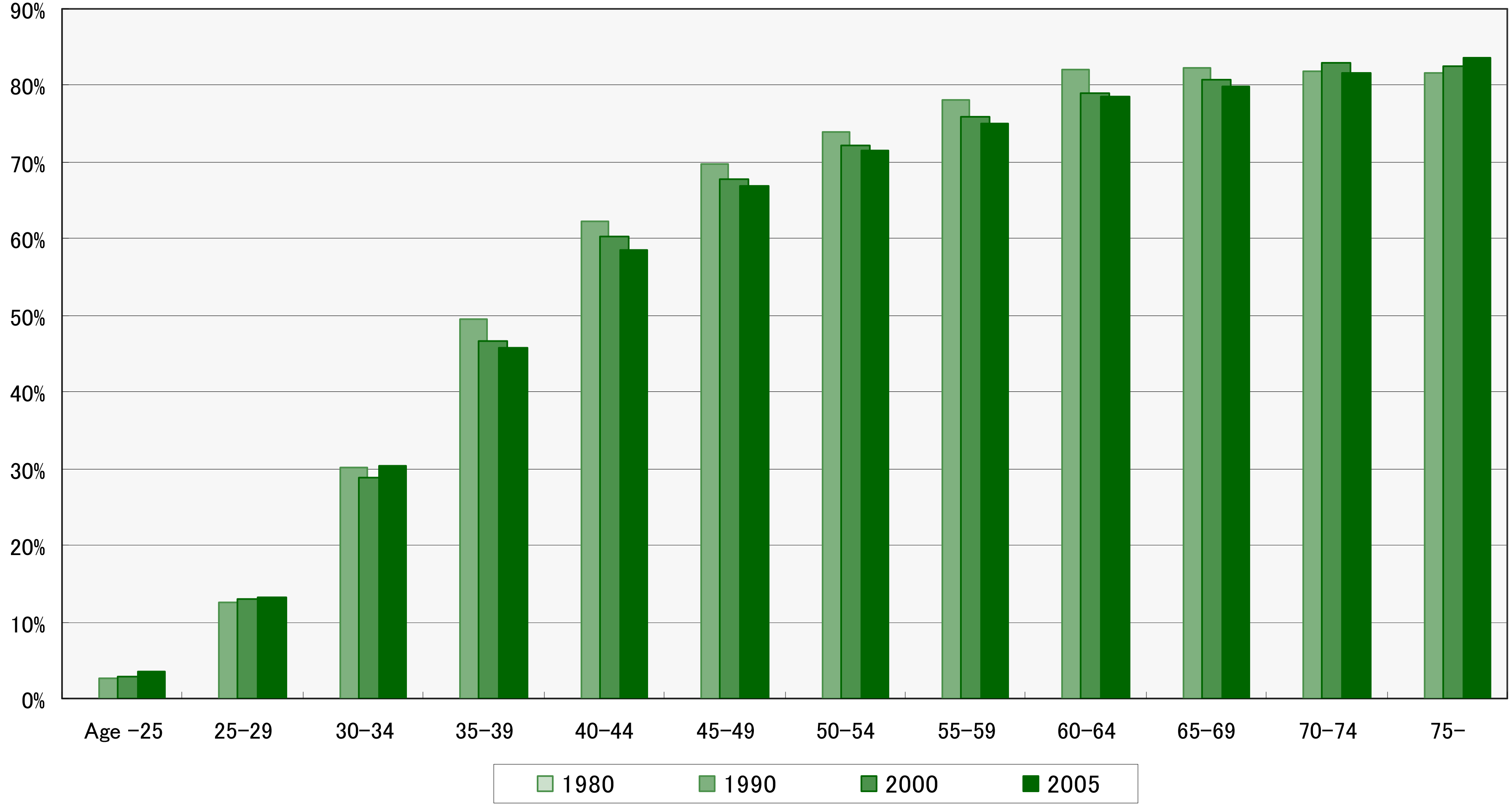
Source: Ministry of Health, Labor and Welfare

3-2(b). Demand: Number of live births (U.S.)



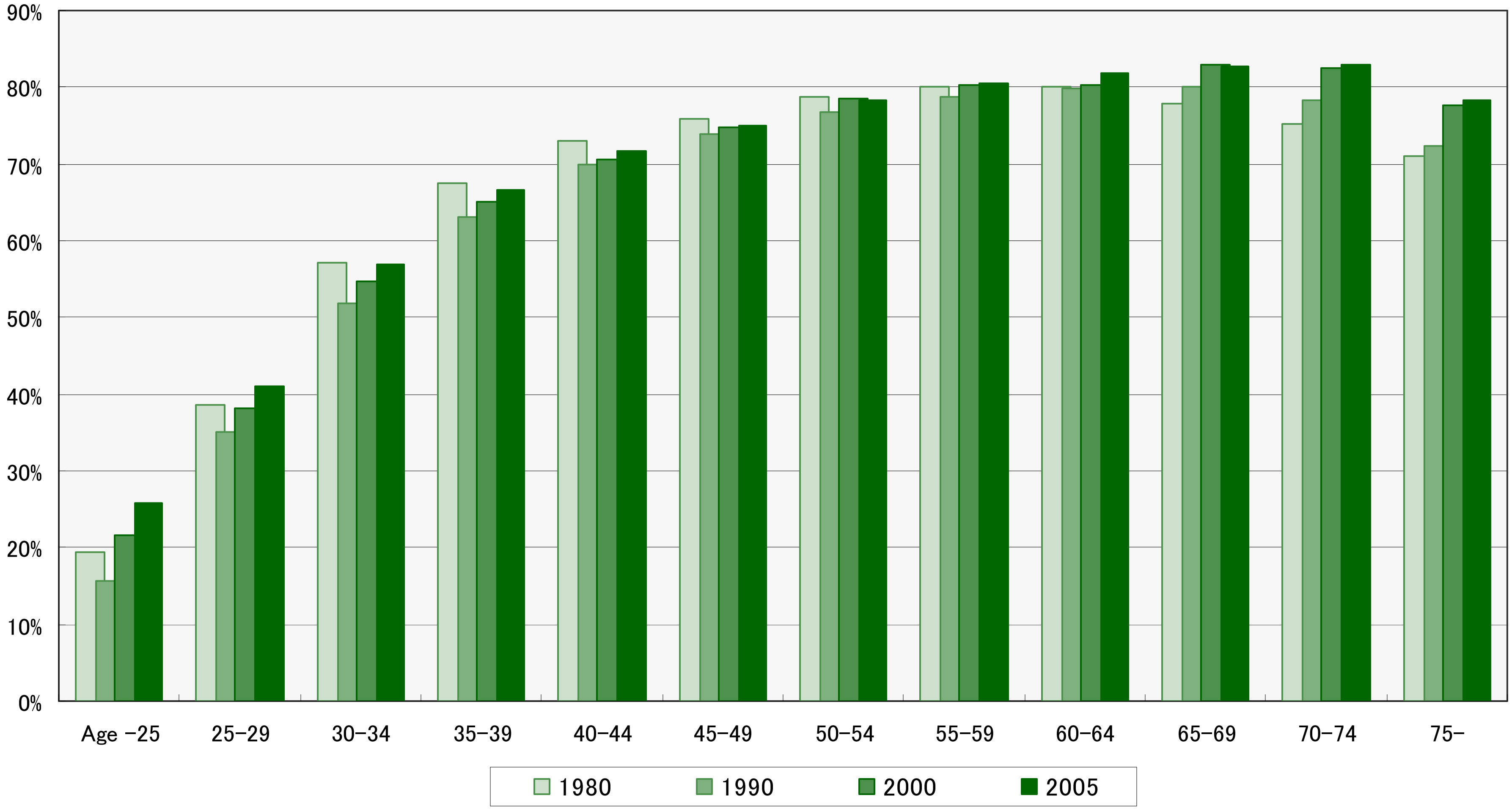
Source: National Center for Health Statistics, "National Vital Statistics Reports."

3-3(a). Home ownership rates (JPN)



Source: Ministry of Internal Affairs and Communications Statistics Bureau, “Census"

3-3(b). Home ownership rates (U.S.)



Source: U.S. Bureau of Census, "Housing Vacancies and Homeownership."

Housing Demand Indices

- 2 Housing Demand Indices;
- a) Mankiw and Weil's Index
- b) Population- Home ownership rates Based Index

Estimation Method of House Demand by Mankiw=Weil (1989)

- 1^{st}:the aggregate amount of housing demand for the specific age of each household member using the housing demand by household, and they created ;

$$D = \sum_{j=1}^{N} D_j \qquad (1)$$

Dj is the amount of housing demand for the *j*th member in the household, and *N* is the number of household members.

$$D_j = \alpha_0 Dummy0 + \alpha_1 Dummy1 + \cdots + \alpha_i Dummy_i \qquad (2)$$

- Dummy 0 is the dummy variable, and when age = 0, it becomes 1.

Combining formulas (1) and (2) above results in formula (3).

- $$D = \alpha_0 \sum Dummy0_j + \alpha_1 \sum Dummy1_j + \cdots + \alpha_i \sum Dummy_{ij} \qquad (3)$$

- the amount of housing demand αi for each age (age i) was estimated

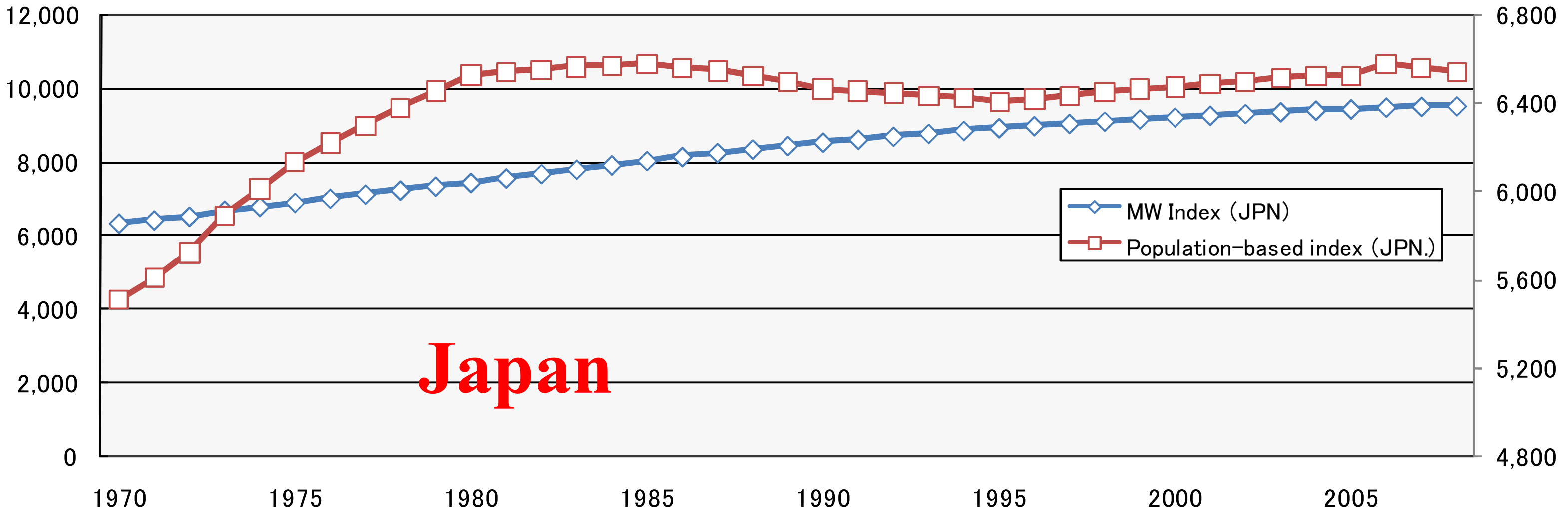
Estimation Method of House Demand by Home ownership rates

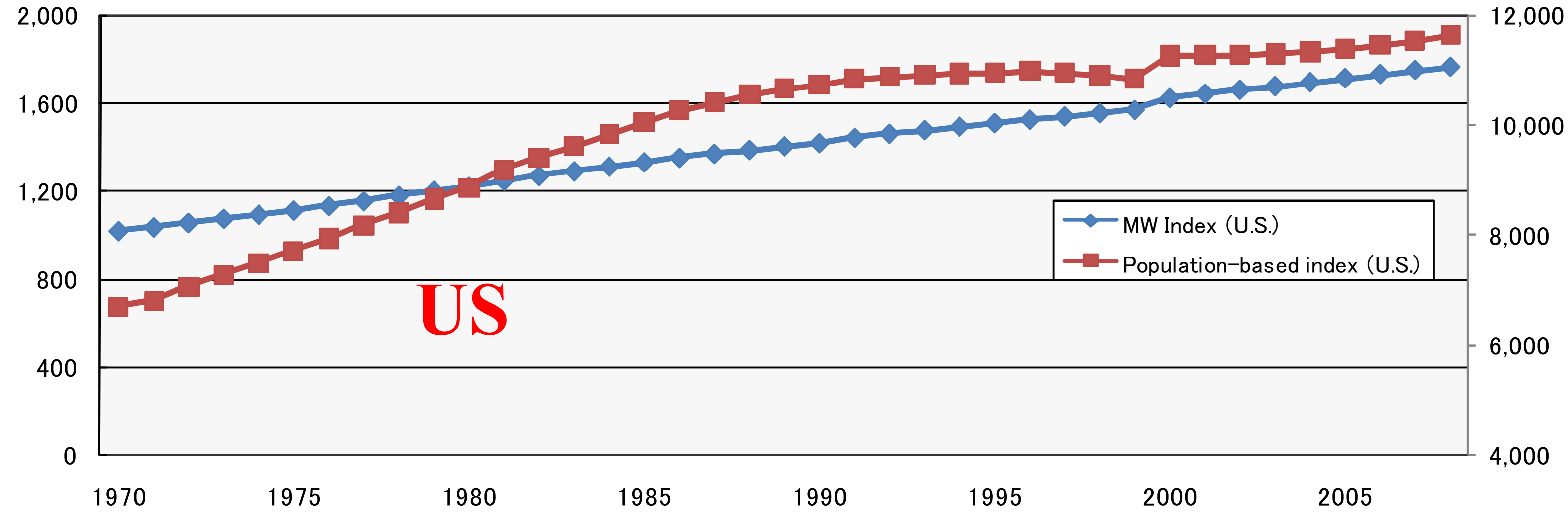
- Home ownership demand:
- we hypothesize that the increase in this rate is equivalent to the ownership demand occurring in that age group
- $$D_{j,t} = \left(O_{j,t} - O_{j,t-1}\right)N_{j,t}$$

Dj,t : home ownership demand for *j* cohort over *t* period
Oj,t : ownership rate for *j* cohort over *t* period
Nj,t : population of *j* cohort over *t* period

- Mankiw and Weil (1989) pointed out that there were no significant differences in the final housing prediction model estimates whether using adult population data or an estimated housing demand index based on individual data.

3-5. Estimated housing demand (JPN & U.S.)





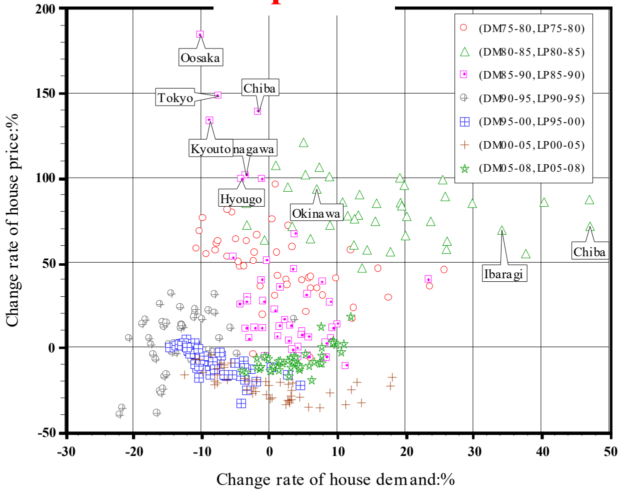
Source: Mankiw and Weil (1989), Ootake and Shintani(1994)

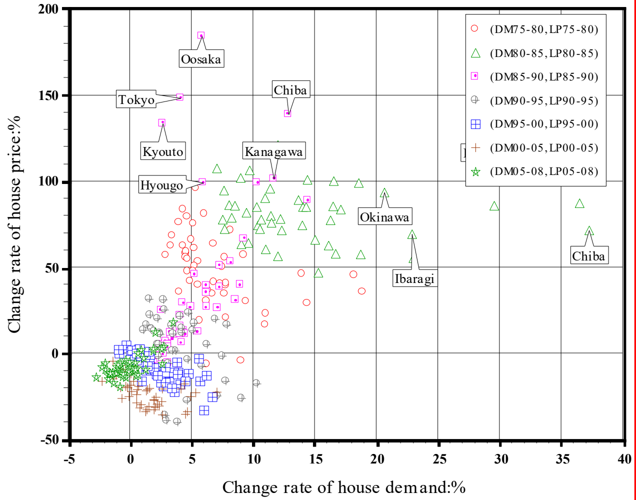
House Demand vs. House Price

Japan: 35- to 44-year-old population;
U.S.: 30- to 44-year-old population

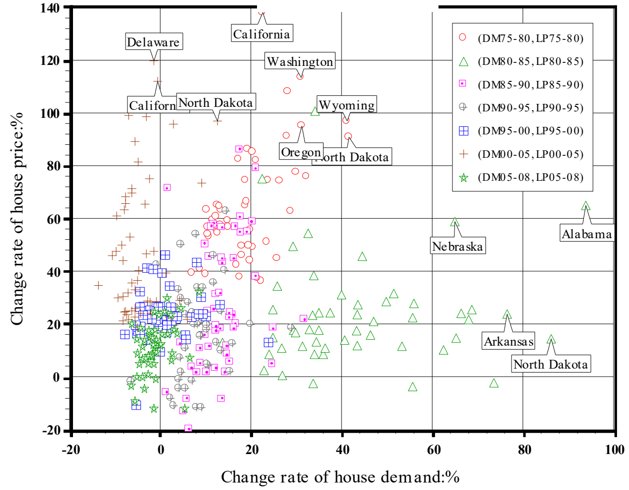
Mankiw House Demand Index

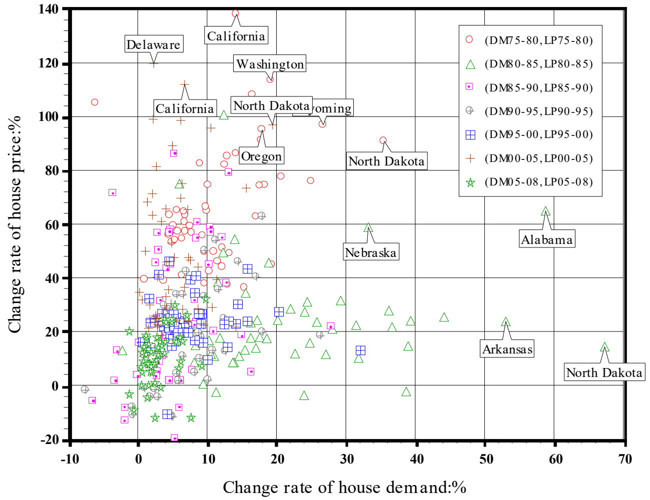
Japan





US





3-10. Result of Empirical Analysis

- Empirical Analysis: Model

- Granger-type VAR with Panel Data

$$P_{i,t} = \alpha_0 + \sum_k \alpha_k P_{i,t-k} + \sum_k \beta_k D_{i,t-k} + \phi_1 X_{i,t} + e_{1i,t}$$

$$D_{i,t} = \gamma_0 + \sum_k \gamma_k P_{i,t-k} + \sum_k \lambda_k D_{i,t-k} + \phi_2 X_{i,t} + e_{2i,t}$$

$P_{i,t}$: Housing Price

$D_{i,t}$: Demand Variable

$X_{i,t}$: Change in fundamentals (Conditioning Variable)

Table 3 VAR Model Estimation Results

Vector AR: Time Series

	VAR Estimate : Japan		VAR Estimate : USA	
	grHousePriceIndex	grHouseDemand	grHousePriceIndex	grHouseDemand
Constant	0.000	0.000	-0.001652	0.001226
	(0.0020)	(0.0001)	(0.0013)	(0.0004)
grHPI(Lag1)	0.611	0.000	0.03407	-0.009078
	(0.0259)	(0.0012)	(0.0237)	(0.0085)
grHPI(Lag2)	-0.130	-0.005	0.066647	0.391596
	(0.0247)	(0.0012)	(0.0631)	(0.0228)
grHD(Lag1)	-2.994	0.850	0.066647	0.391596
	(0.6973)	(0.0344)	(0.0631)	(0.0228)
grHD(Lag2)	4.274	0.048	-0.237661	0.269695
	(0.6712)	(0.0331)	(0.0620)	(0.0224)
dRate	0.014	0.000	-0.011743	0.004687
	(0.0022)	(0.0001)	(0.0010)	(0.0003)
grGDP	0.418	-0.001	0.353377	0.092434
	(0.0615)	(0.0030)	(0.0277)	(0.0100)
F-statistic	196.877	1240.132	240.292	241.092
Log likelihood	1882.096	5983.415	2822.327	4375.800
Akaike AIC	-2.751	-8.770	-3.680	-5.711

Figure 16 Relationship between Housing Prices and Demand 1: Japan

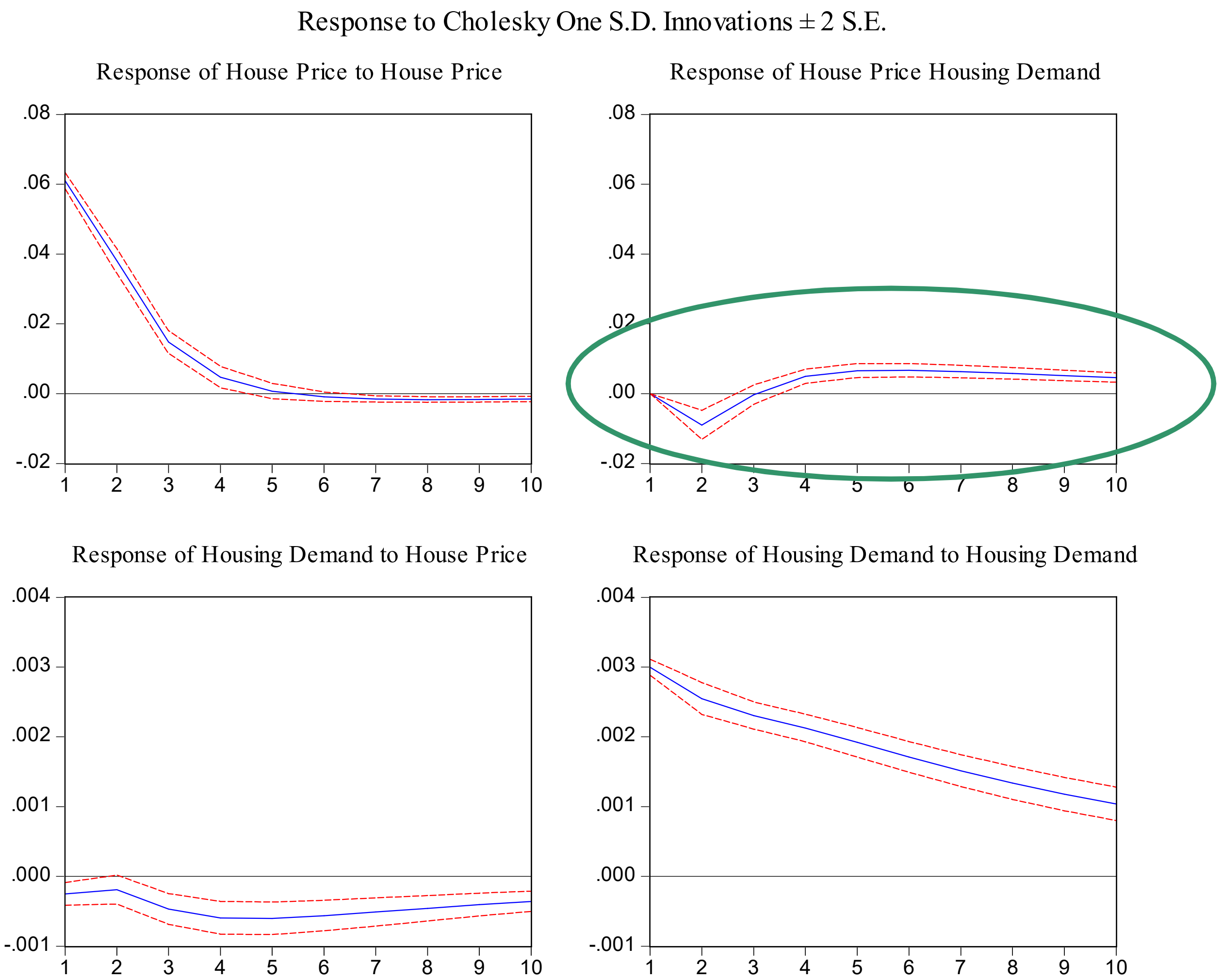


Figure 17 Relationship between Housing Prices and Demand 2: U.S.

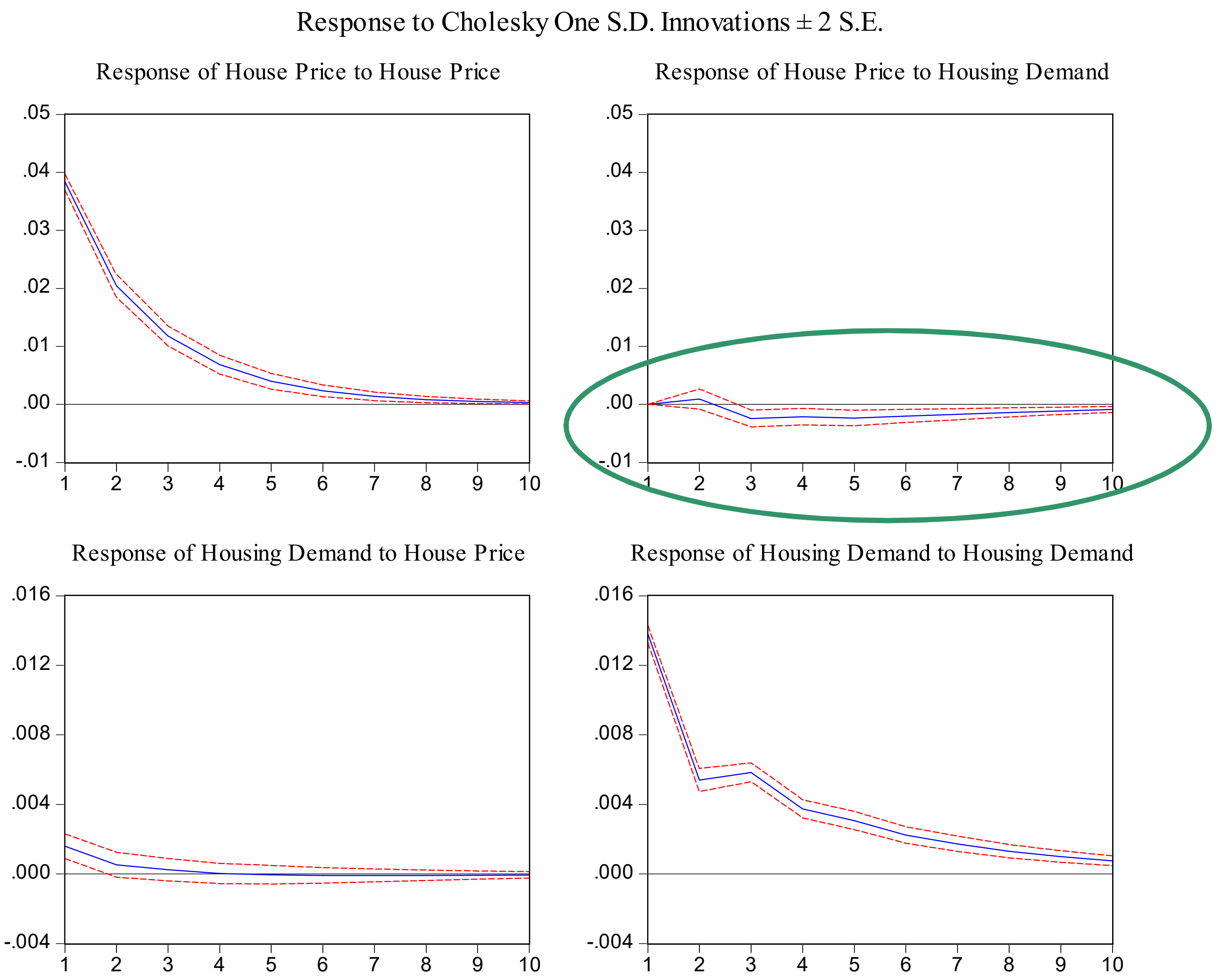


Figure 18 Relationship between Housing Prices and Demand 3: Japan

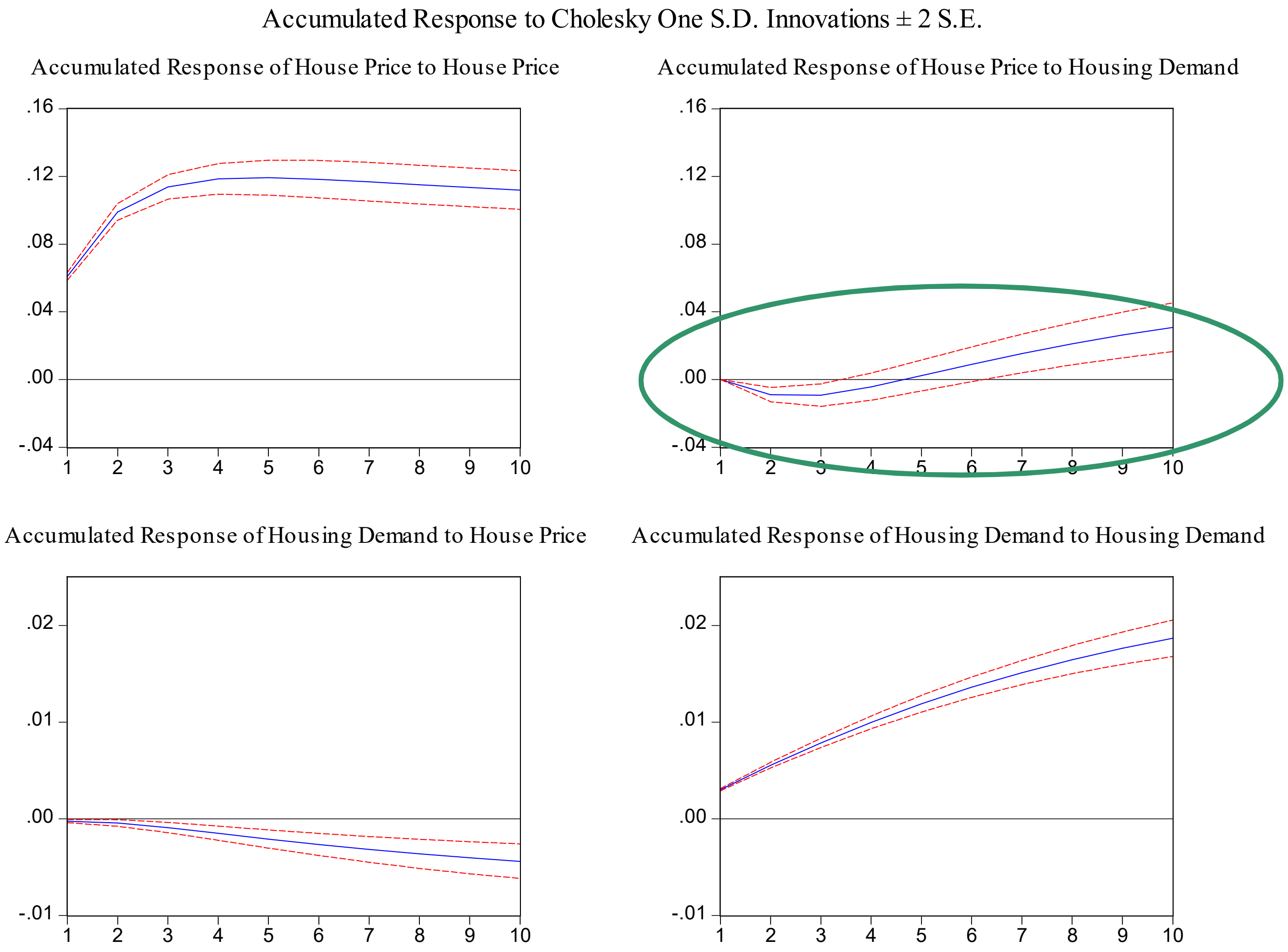
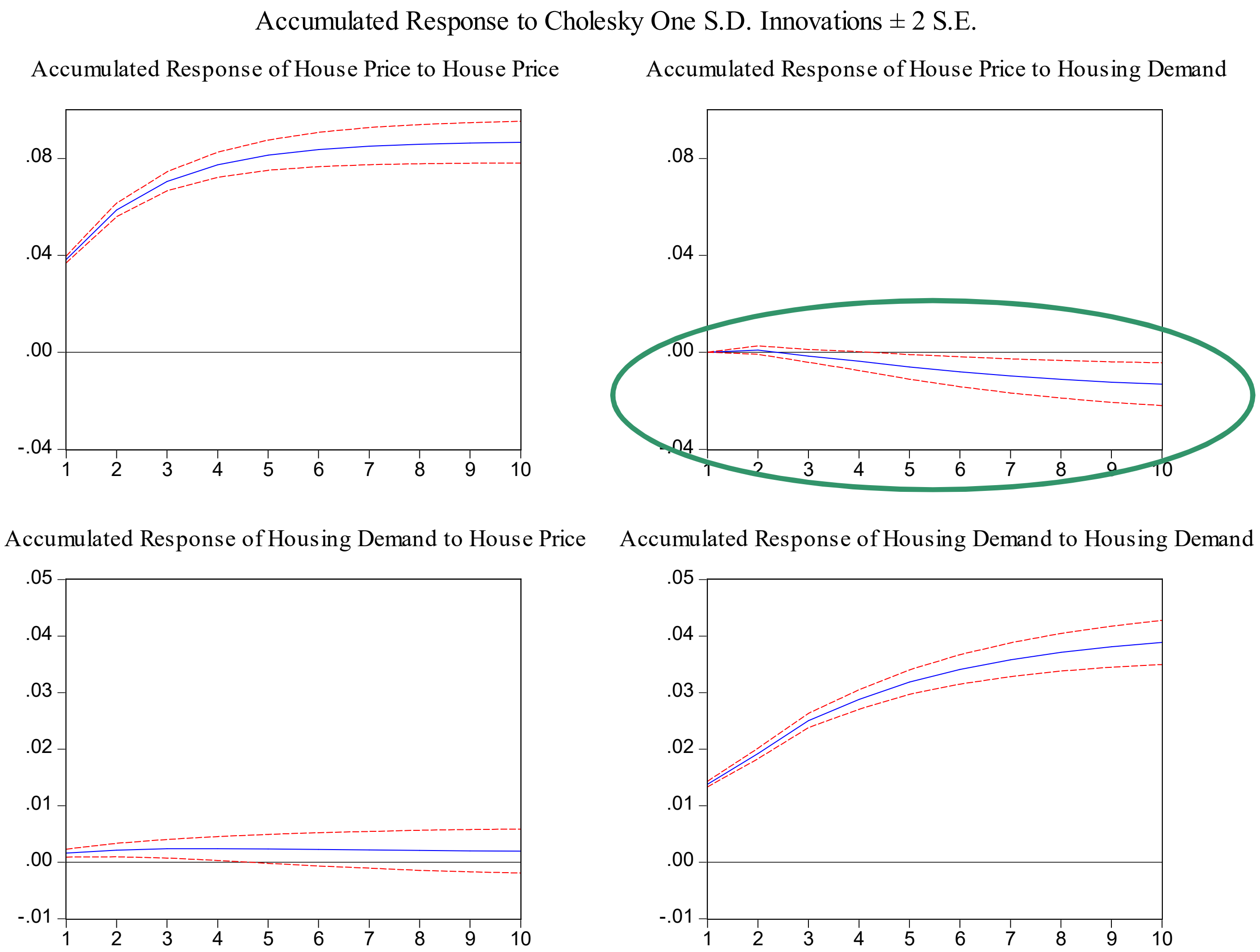


Figure 19 Relationship between Housing Prices and Demand 4: U.S



5.Conclusions:

- **1. What extent did house prices increase and decrease during the so-called "bubble" periods in Japan and the U.S?**
- →Condominium: Hedonic:May.2004(0.33)/ Repeat Sales :June.2005.6(0.26)
- Single House: Hedonic:August.2004(0.37)/ Repeat Sales :November.2005(0.31)
- **2. Does housing demand influence the house price?**
- **→There is no relationship between housing demand and house price during the bubble period.**
- **3.Is there a relationship between house price and house rent?**
- →The CPI inflation rate would have been higher by one percentage point during the bubble period, and lower by more than one percentage point during the period of bubble bursting.

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