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Cointegration Analysis of Regional House Prices in U.S.

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Abstract

Using quarterly U.S. census division data for time period 1975-2006, this paper investigates the dynamic relationships among the house prices of nine divisions (regions): Pacific, Mountain, South Atlantic, Middle Atlantic, New England, East South Central, West South Central, West North Central, and East North Central. Johansen's ML procedure is applied to shed light on the short-run and long-run components on the error correction model. Furthermore, a symmetric error-correction model is estimated followed by the contemporaneous causality structure that is provided by the directed acyclic graphs. The latter is used as an "input" for estimating the impulse response functions along with the forecast error variance decompositions.

The results provide evidence of the presence of large number of cointegration relations between the regional house prices in the US. Moreover, in most cases, West North Central and New England appear to strongly and positively lead the house price changes in most other regions. The statement holds for Middle Atlantic which actually generates negative responses. On the other hand, house prices in East North Central and Mountain are highly influenced by changes in house prices of other regions. These results mostly hold for the dynamic period or from time horizon 0 (contemporaneous) to 35 (8.5 years). Furthermore, the real estate market in the US appears to be mainly led by regions that are influential in many other ways, such as financial, economic, etc.

1. Induction

Real GDP is one of the many economic and financial indicators the Federal Reserve Bank (FED) considers in devising the nation's monetary policy. Combined with the trends of unemployment and inflation rates, the trend of the overall growth rate of the economy is constantly monitored to assess the consistency of the undertaken monetary policy which is the primary goal of the Fed (Federal Reserve

Bank of New York, Education Section). Provided that GDP is an important economic indicator, its individual components also must be important indicators for assessing the well being of the economy. The largest component, comprising about 70% of the GDP, is personal consumption and real estate is an important part of the personal consumption. Real estate is probably the most interest-rate sensitive sector of the economy. Although residential investments may not represent a large share of GDP (about 5% of GDP) over the short period of time they often account for a large share of GDP changes which is mainly due to its high volatility (about 12% of GDP).[16]

Analysis of the housing market is important. Noticeable changes in house prices will have an important impact on the U.S. economy because home ownership is the primary asset held by many households. Changes in house prices will result in changes in household wealth. Changes in mortgage interest rates, also will affect the financial cost of home ownership. Moreover, the high cost of home ownership might put the labor mobility at a disadvantage, thus negatively affecting the economy's efficient functioning (Alexander and Barrow, 1994). Consequently, there is growing attention centered on real estate from policy-makers, investors, researchers, and individual households. Thorough investigation of real estate markets can provide clues about the short-term performance of the economy and possible changes in the financial conditions.

Like most macroeconomic variables, real estate price pattern exhibits cycles, however, the cycles are relatively longer. For example, house price cycles for UK regions are found to be between 5-10 years (Rosenthal, 1986; Alexander and Barrow, 1994; Holmes and Grimes, 2005).[17] Hence, abrupt price

16 Various sources provide various numbers especially for different time periods, but the average is about what is presented above. For more details, see McCarthy and Steindel (2007), McConnell, M. M., Mosser, P.C., and Quiros, G.P. (1999) and the article in Business Week (2005). For education purposes, Federal Reserve Bank of New York provided brief description of the economic indicators and how each of them affects the general economy and the Fed's monetary policy.

17 Rosenthal (1986) suggested output and price cycles of 6-8 years which was later confirmed Holmes and Grimes (2005) who showed that rippling out process or the adjustment process towards long-run equilibrium takes long enough, about 6-8 years. On the other hand, Alexander and Barrow (1994), using spectral analysis, found that 5-10 year house price cycles are common to all the UK regions.

changes in real estate market last longer until they get back to equilibrium. Understanding of real estate cycles is important for analyzing the house price dynamics.

The importance of real estate for the economy is unquestionable. Meen and Andrew (1998) argued that for completely understanding the housing market, regional rather than aggregate or national data is required. This paper focuses on the regional house price data in US in order to study the linkages among the regional housing markets and the reasons for this study include the ripple effect, wealth distribution, labor mobility, house price prediction, and migration. The transmission of the shock in house prices of one region to another with possible time lags is referred as ripple effect. It has been found to be significant for UK as well as US regional housing market. Consequently, the ripple effect will have significant wealth distribution given the fact that housing comprises a large share of assets for many households (Alexander and Barrow, 1994; Holmes and Grimes, 2005). Furthermore, the regional house price analysis has an impact on the labor mobility as well as the migration, although it is weak because most households move from one region to another not only for house price differences but also for other factors (job opportunities, etc). Finally, the ability to correctly predict house prices in one region may be improved if the significant impact of house prices in other regions are considered.

Although the importance of the regional house price relationship is evident, most studies in this area are mainly concerned with the UK regional housing market. Only the study by Pollakowski and Ray (1997) focuses on the interrelationship among the house price of the US census divisions while the rest use metropolitan or other sub-market data. Recent methodological advances, extended data sets, as well as the thorough analysis of the regional housing market call for a complete study on the interdependence of the regional house prices in US. Consequently, this paper attempts to uncover the dynamic interaction among the US regional house prices by using innovative causality structure and identification of long-run structure. The application of the directed acyclic graphs (DAG) for analyzing the causality pattern in the US housing market is one of the major contributions of this paper to the existing literature. In addition, DAG is proposed to be used for identification of the long-run structure of the cointegrated Vector Autoregression (VAR). The data-implied causal ordering rather than Choleski or Bernanke orderings is used to obtain impulse responses and the forecast error variance decompositions. Furthermore, house price dynamics and the price discovery implications, not been thoroughly addressed before, are studied in this paper. The detailed examination of the extended data set, including such important events as the housing market boom and busts, stock market crash, major monetary policy changes, terrorist attack in 2001, US recession, oil crisis, and so on is another important addition to the existing literature. Therefore, to fill the gap this paper attempts to analyze the dynamic interrelationships among the house prices of nine U.S. census regions from a new prospective.[18]

This paper proceeds as follows: Section 2 provides a brief review of the previous research and the conceptual framework followed by Section 3 that analyzes the time series data and its pattern. Major methodological considerations and misspecification tests are covered in Section 4. Section 5 presents the empirical results and summary and the conclusions are provided in Section 6.

2. Review of the Previous Research

The relationship between the house prices and their determinants has been studied by many. Numerous research projects have been done focusing on the house price fundamentals, their roles and linkages with house prices in US. However, little attention has been paid on investigating the interrelationship between regional or census division house prices in US. On the other hand, many studies have been completed for the UK on this area of research which can be separated into various strands. One of the strands contains groups of studies attempting to empirically test the “ripple effect” hypothesis in the UK

18 Note that division and region in this study will be used interchangeably.

housing market. It is commonly defined as the propensity of house prices to first rise in South East of England during the upswings then filter out to other regions of UK over time (Holmans, 1990; MacDonald and Taylor, 1993; Alexander and Barrow, 1994; Drake, 1995; Ashworth and Parker, 1997; Meen, 1999; Peterson et al., 2002, Cook, 2003; Cook and Thomas, 2003; Cook, 2005; Holmes and Grimes, 2005). Results of studies on the presence of ripple effect in UK housing market have been mixed. Although the ripple effect is not well understood (Meen. 1996a), some studies strongly support its existence, some studies only provide very weak and limited evidence, while other studies argue against the existence of the ripple effect.[19]

The second strand of literature tackles the issues of long-run relationships or equilibrium and convergence of house prices. Although numerous methodologies have been utilized, the findings commonly suggest that short-run regional house prices might diverge from one another, but long-run regional house prices tend to some equilibrium and relative constancy (Holmans, 1990; MacDonald and Taylor, 1993; Alexander and Barrow, 1994; Drake, 1995; Ashworth and Parker, 1997; Meen, 1999; Peterson et al., 2002, Cook, 2003; Cook and Thomas, 2003; Cook, 2005; Holmes and Grimes, 2005, Cook, 2006). Causality between the house prices of different UK regions has been another important avenue for investigation. Similar to ripple effect, commonly suggested causal pattern runs from the South East to North via the Midlands. However, mixed results still exist.[20]

Lastly, the reasons and sources for such causal pattern, possible ripple effect, and the existence of long-run equilibrium are studied by some researchers. The most commonly suggested reasons are the

19 Meen (1999), Cook (2005), Cook and Thomas (2003), Drake (1995) Holmans (1990) strongly support the existence of the ripple effect emanating from the South East of England. Conversely, Ashworth and Parker (1997) argue against the ripple effect hypothesis and were able to empirically support their argument. Finally, MacDonald and Taylor (1993), Alexander and Barrow (1994), etc found only limited and weak evidence of ripple effect.

20 Except for Rosenthal (1986), all the studies found evidence of clear causal pattern running from the South East to the North through the Midlands (Hamnett, 1988; Bover et al., 1989; Holmans, 1990; Guissani and Hadjimatheou, 1991; MacDonald and Taylor, 1993; Alexander and Barrow, 1994).

demand factors such as income, taxes advantages, equity transfer, migration for job and non-job reasons, etc (Alexander and Barrow, 1994, Giussani and Hadjimathrou, 1991, Gordon, 1990, Holmans, 1991, Meen, 1999, Thomas, 1993, Bover et al., 1989, MacDonald and Taylor, 1993, Minford, et al. 1987). There are multiple reasons, however, there is no definite, universally accepted cause.

Interrelationships between the house prices of US census divisions are uncovered in this paper. Therefore, studies that concentrate on similar issues are of great interest. The best known studies that attempt to address similar issues to this paper are by MacDonald and Taylor (1993) and Alexander and Barrow (1994) for the UK housing sector, and Pollakowski and Ray (1997) for the US housing market. The former two investigate cointegrating relationships between the UK regional house prices. In other words, they examine whether or not the UK regional house prices are tied together in long-run over time. Both the Engle-Granger and Johansen's maximum likelihood methods for bivariate and multivariate analysis, respectively, are utilized to shed light on the cointegrating relations. Quarterly regional house price indices for UK regions are used to further test for the long-run and short-run house price properties, as well as the causal pattern. Significant number of cointegrating relations is detected that evidences the interrelated housing market in the UK. The South East region of England is found to be a price determining region. Moreover, East Midlands and/or East Anglia play vital roles in transmitting the information from south to the north. While Alexander and Barrow (1994) suggest that causality flows from the South to the North passing through the Midlands, MacDonald and Taylor (1993) claim the presence of weak segmentation in UK housing market, particularly, between the North and the South. The differences of regional house prices led to the notion of "two-nation" owner occupied housing market which in a way shares some similarities with the notion of "weak segmentation" (Hamnett, 1988).

With the emergence of new and more improved econometric and time series methods, more studies return to the question of whether or not cointegration in the UK housing market prevails. The existence of the long-run equilibrium among the UK regional house prices, even with new methods, is still strongly supported (Giussani and Hadjimatheou, 1990; Drake, 1995; Ashworth and Parker, 1997; Meen, 1999; Cook, 2003; Cook and Thomas, 2003; Cook, 2005; Holmes and Grimes, 2005). Most of these studies claim unidirectional causal flows emanating from the South (particularly South East or Greater London) to the rest of the country (mainly into North through Midlands). The most recent development in the housing literature is the use of non-parametric, asymmetric adjustment, principal component, and business cycle dating procedures.[21] In the economic literature, the cointegration analyses with the assumption of asymmetric adjustment mechanism are growing in their importance. Cook (2005) is the first to apply the methodology to analyze the housing market in the UK. Adopting the threshold autoregressive methods of Enders and Siklos (2001), Cook (2005) investigates the UK regional house price linkages from an aspect of asymmetric adjustment process. His findings show that allowing asymmetric reversion (adjustment) significantly increases the number of long-run relationships and dramatically changes the overall results of long-run relationship in UK regional house prices. On the other hand, Holmes and Grimes (2005) employed a new test that combines principal components analysis with unit root testing to examine long-run relationship of the UK regional house prices. UK regional house prices are driven by a single common stochastic trend which is regarded as strong convergence in the long-run.

Little research has been conducted to address the issues of possible long-run relationship between the house prices in US. Housing price diffusion at the local level, concentrating on the submarkets in Hartford, CT, was studied by Tirtiroglu (1992) and Clapp and Tirtiroglu (1994). The spatial

21 Cook (2003), Cook and Thomas (2003), Cook (2005), Holmes and Grimes (2005), Cook (2006) all use one or more of the mentioned methods.

aspect of the efficiency tests was applied to examine whether the house prices in a particular town are affected by the lagged own and neighboring towns' prices. They confirmed the existence of the spatial diffusion pattern where the coefficients of only the neighboring towns appear to be significant. Consequently, results consistently imply that individuals tend to overemphasize present evidence at the expense of historical evidence which is what is known as positive feedback hypothesis.[22] Subnational analysis has received large attention, although very limited for the US housing market. Only Pollakowski and Ray (1997) examine the spatial and temporal house price interrelationships between the nine U.S. census divisions as well as the metropolitan areas. Moreover, informational efficiency of the US housing market is tested in addition to the analysis of whether the house prices in any one location are predicted by only their own history or by the house price changes in other locations as well. Using VAR, block exogenity, and Granger-causality like tests for the period of 1975-1994, the authors discovered that house price in US are interrelated. Furthermore, census division analysis provide evidence of inefficient US housing market implying that shock in one location do cause any subsequent-period reactions in other locations. A survey of literature on housing market efficiency also showed considerable evidence of market inefficiency (Cho, 2004). Hence, information transfer is relevant, affecting other regions' house price movements. On the contrary to the previous studies (Tirtiroglu, 1992; Clapp and Tirtiroglu, 1994), Pollakowski and Ray (1997) fail to show price diffusion between the contiguous regions or divisions, but rather find that price diffusion patterns for neighboring and non-neighboring divisions are not significantly different. The presumed cause for such results is the interrelated regional economies ultimately reflected in the regional housing markets. Analysis of metropolitan areas, on the other hand, has a clear contiguous region effect. That is, house price changes in a particular region (area) have much

22 Positive-feedback hypothesis has been considered by Cutler, Poterba, Summers (1990), DeLong et al. (1990), Shiller (1990a, 1990b), Tirtiroglu (1992), Clapp and Tirtiroglu (1994), and Pollakowski and Ray (1997).

bigger effect on the house price changes of the contiguous regions (areas) than those of the non-neighboring areas.

Geographical proximity was also considered by other studies and was suggested to be important factor for house price transmission from region to region (MacDonald and Taylor, 1993; Alexander and Barrow, 1994; Giussani and Hadjimateou, 1990; Drake, 1995). Testing this hypothesis for US housing market with the extended dataset and improved methodologies will provide interesting insights about the nature of the possible long-run relationship.

3. Data

Following Meen and Andrew's (1998) suggestion to use regional rather than national data, this paper uses house price indexes for the nine US census divisions on a quarterly basis from 1975:1 to 2006:1. The house price indices for the nine US census divisions are retrieved from Office of Federal Housing Enterprise Oversight (OFHEO). The House Price Index (HPI hereafter) for each US census division is calculated using the repeated observations of housing values for individual single-family residential properties on which at least two mortgages were originated and afterwards purchased by either the Federal Home Loan Mortgage Corporation (Freddie Mac) or Federal National Mortgage Association (Fannie Mae). The HPI is commonly referred as "constant quality" house price index as the differences in quality of houses are controlled via the use repeat transactions. Moreover, it is based on the modified version of the weighted-repeat sales methodology proposed by Case and Shiller (1989) and is available since January 1975.[23]

23 Detailed technical description of the HPI and its construction is provided by Calhoun (1996).

In real estate literature, it is common to use house price indices as the data for analysis. Some studies utilize the HPI by the OFHED while others tend to construct house price indices using hedonic pricing method or others methods. For example, Pollakowski and Ray (1997) construct weighted repeat-sales index using the method of Case and Shiller (1987). Although house price indexes as a source for empirical analysis have been criticized due to the index construction (McCarthy and Peach, 2004; Himmelberg, Mayer, and Sinai, 2005, Bourassa, Hoesli, and Sun, 2006; Can and Megbolugbe, 2006), it still remains one of the best and readily available dataset for researchers which controls the house quality (Harter-Dreiman, 2003; Wheelock, 2006). However, there are some limitations of using this index such as the fact that it accounts for only single-family detached properties and excludes condominiums, multi-family residential properties, etc. Moreover, HPI does not account for government insured loans, more than two mortgages, etc. It is important to note that regardless of the construction method, the house price indices will always have some limitations, which implies limitations in the results. Podlodowski and Ray (1997) suggest that their results cannot be applied to predict the behavior of all single-family residences. Furthermore, additional limitations arise from the fact that data source is partially truncated. MacDonald and Taylor (1993) have also noted that results might be data dependent (the way the house price indices are constructed might fail to account for the quality of the housing. Moreover, limitations might arise also from the fact that the results do not distinguish between the ripple down effect caused by the arbitrage or some regional element such as the business cycle. It has also been suggested that using sub-regional or even arbitrarily defined regional boundaries might be more appropriate in analyzing the relationships of house price than using the regional house price data (Alexander and Barrow, 1994; Bourassa, Hamelink, Hoesli, and MacGregor, 1999; Bourassa, Hoesli, and Peng, 2003; Bourassa, Cantoni, and Hoesli, 2005). Similarly, our conclusion can be made regarding to the house price indices only for single-family residential properties, even though the analyses of other type of residential properties will most likely closely resemble that of the single-family residential property.[24]

The nine US census divisions used in this paper are the Pacific (PC), the Mountain (MT), the West North Central (WNC), the West South Central (WSC), the East North Central (ENC), the East South Central (ESC), the South Atlantic (SA), the Middle Atlantic (MA), and the New England (NE). The one year change in house prices of those nine divisions are given in Figure 1. The main purpose of the figure is to provide information about house prices appreciation in each division which may have further implications on the causal structure among the nine divisions. Results of the paper in the later section will elaborate whether or not the regions with high observed house price appreciation actually play important role in the overall housing market. According to the figure, consistent with the expectations, house prices in Pacific went up by 14.1%, which is one of the highest percentage increases observed among the nine regions. Equivalently, the house prices in Mountain increased by the same percentage (14.1%). The second highest percentage increase in house prices is observed in South Atlantic (13.7%) followed by the Middle Atlantic (11%). The percentage change in house prices of other regions are less than 10% with the lowest being in East North Central (4.0%).

Moreover, the figure will enable readers to visualize the locations and the included states of each of the nine divisions even though the detailed information regarding to this is included in Appendix A. Unfortunately, the figure does not provide additional information about the house price appreciation rates in each states which would clarify each state's contribution to the overall regional house price changes.

24 Note that this is just hypothesis.

US Economy and Housing Market

Complete understanding of the economic, financial, as well as political situations and events is necessary for modeling the interactions of the US regional housing market correctly. On top of this, the graphical analysis will enhance the knowledge of the US housing market trend as well as the problems that have to be addressed to obtain reliable implications. Historical HPIs for nine US census divisions are presented in Figure 2. Natural logarithmic transformation of the HPIs is used due to the assumed multiplicative effect (Johansen, 1995). The house prices in all the nine divisions have been increasing at a relatively constant rate starting from early or mid 90's, while more volatile growth rates are observed for time periods before 90s. There have been many booms and busts in the U.S. economy and housing sector from around 1970's to 1990's which perhaps is the reason for observed high volatility. The graphical examination is extremely valuable in assessing the nature of house price change, i.e. whether it is permanent or temporary shift in house prices. The distinction between the permanent and the temporary shift might vary from author to author, but, in general, at least if the change to a certain direction remains for more than several quarters (or periods), it is usually considered permanent, otherwise, temporary. In addition, permanent change is oftentimes regarded as one that shifts the mean of the series for several periods (Juselius, 2006). Similar definition is extended to the booms and busts. For example, Wheelock (2006) defines the housing boom as an increase in the ratio of HPI to state per capita income of at least 7 percent for three or more consecutive quarters. The resulting evidence suggests that between the 1980 and 1999 U.S. states experienced about twenty house price booms. Some of those booms were followed by housing busts, while others were not. However, most states experienced housing booms at different time periods or at different extent, hence it is hard to define any peaks or troughs for the regional house prices as booms or busts. Moreover, notice that all regions experience similar shocks at different time frames with different magnitudes which brings up the question this study focuses on - which region the shock in house prices originates in? Is that shock transmitted to other regions? Does the transmission process happen immediately or with some time lags? Does it move the house prices of other regions in the same direction or the opposite? These and many other questions are intended to be answered in this paper.

Juselius (2006) suggested using the plots on both level and differenced data to get an idea of the possible misspecification problems in the data and model. The assumption of the constant mean does not seem to hold based on the level plots (see Figure 2), while it appears to be more appropriate for the differenced series (see Figure 3). Inferences about the variance constancy is harder to make from the levels of variables, hence the differenced data is of great help. From Figure 3, it can be seen that high variability in series is especially pronounced in the beginning of the sample period. Moreover, most series, except for the HPI changes in SA which are fairly stable over the entire sample period, appear to have relatively constant variance after the mid 1980's. However, a few exceptions are observed. Relatively high variability is noticed for the period of 1987-1989 in changes of PC and WSC. In addition, from 2003 and on there is slight variability observed in changes of almost all the series, except for WSC and ESC.

The plot of the differenced series can also be an important tool for inspecting the normality of the marginal processes (Juselius, 2006). If the observations lie symmetrically on both sides of the mean, then marginal processes are normal. Most of the series do not seem to have symmetric observations, but rather appear to have some outlier observations emphasized mostly in the first part of the sample. Further, the detailed examination of the possible causes for such outlier observations follows which is highly important for the house price modeling.

The evolution of the various events from 1970's to 1980's put the US economy and its various sectors into unstable and severe situation. The first recession for the period of 1970-2006 was due to the first oil crisis which occurred in 1973 (Mishkin, 1987). The first signs of recovery was noticed in the first quarter of 1976, which then was followed by the slow growth rates, unemployment and price rise. Moreover, the trade balance dramatically fell, which then was followed by a slight recovery in the fourth quarter of the same year (Supel, 1979). Although the US economy commenced expanding with lower unemployment rate and increasing GDP, the inflation rate continued to increase reaching to double digits. Moreover, the second oil crisis in 1979-1980 seemed to aggravate the economy leading it to the path of another economic recession. The recession affected the nominal and real interest rates, which in turn directly influenced the current as well as the future level of investment. Consequently, Fed announced tight or contractionary monetary policy to ease the economic situation by undertaking the anti-inflationary and dollar strengthening programs. As a result, investment purchases decreased until the third quarter of 1980. The recession continued becoming severe when Reagan came to power in 1980. Also as a result of the Volker's policies, recession lasted about two years, in 1980 and 1981, termed as "twin recessions". Both the real interest rate and the US dollar exchange rate increased sharply (Mishkin, 1987; Kim, Leatham, Bessler, 2007). Until about 1981, the inflation rate still remained at double-digits. The international oil price rises, monetary policies and the governmental spending were commonly considered to be the main sources for high inflation in the country.

The two-year severe recession was shortly followed by the two-year robust recovery in 1982. However, it should be mentioned that until 1983, the economy followed an erratic pattern. For example, the slowdown of the GDP growth in 1979 was followed by an actual fall in GDP after the second quarter of 1980. Starting from about 1982, the economy continued growing, inflation and unemployment rates dropped, level of investment increased, pushing the nation into the economic boom. In addition, the law of the largest tax cut in US was signed by Reagan in 1981. Consequently, tax cuts, the increased government purchases and the anti-inflation program put the US economy on the prosperous path from about 1983, which were later termed as the "Reagan Boom". The economic boom of the early and mid-eighties, however, coincided with a number of alarming developments. Among those, perhaps the most outstanding are the federal tax reform in 1986 and the stock market crash in 1987 (Kim, Leatham, and Bessler, 2007).

Most of the above mentioned economic events and distresses were reflected in the housing market. Years later a couple of more recessions occurred, however, they did not seem to have any significant impact on the real estate market.[25]Other factors that are worth mentioning due to their direct effect on the housing sector are the emergence of the new institutions, financial system, products, etc. In the evolution of the US housing system, the era of securitization from 1970s to 1980s is very important and coincided with the above mentioned economic events. Due to the increase of interest rates, there was duration mismatch of the assets and the liabilities. This was more crucial for the Savings and Loans institutions in 1980s. Consequently, many banking institutions (predominantly S&Ls) defaulted, which then initiated the need for new reforms and laws (Integrated Financial Engineering, Inc., 2006).

All the above discussed events that took place in US from 1970's to 2000's will be incorporated with the appropriate methodological procedures. In addition, the knowledge of the possible outlier observations will be used in the following section which deals with the modeling of the regional house prices.

4. Methodology

The methodological section is the heart of this and any other paper as it allows us employ the best method to obtain reliable and robust results. A list of methodologies is used in this section which is presented here, which starts with the background information about the common methodologies that

25 The recession in 1991 and the 2000 recession which was due to the burst of the dot-com-bubble did not have significant influence on the log HPIs.

similar studies have used. Then, the cointegration test is described followed by the misspecification tests that are used to ensure the best model is of use. Following subsection details the identification issue and the proposed method of obtaining identification of long-run structure.

The list of the methodologies used to study the housing market has been expanding over time. It already has been two decades since more powerful statistical and/or econometric tools have emerged and been in use by economists in various fields. Cointegration analysis, pioneered by Engle and Granger (1987) and Johansen (1988), has been extensively used for modeling house price determination. Observed spatial pattern in regional house prices directed researchers to consider time-series properties of regional price data. Numerous studies that attempted to include explanatory variables for housing market investigation, had to tolerate the variable selection issue which has been an important empirical issue. The data limitation and the peculiar house price pattern certainly impose restrictions in terms of number of variables in the model. To approach this issue, researchers have sought various ways. For instance, some used reduced-form approach to identify and estimate appropriate supply and demand variables. This approach however, presumes that housing market is in the steady-state equilibrium (Meese and Wallace, 1993). Another group of researchers specify that equilibrium house prices are implied by fundamental variables (Abraham and Hendershott, 1996). Furthermore, the cointegration approach used by Giussani and Hadjimatheou (1991), MacDonald and Taylor (1993), Alexander and Barrow (1994), Pollakowski and Ray (1997), Meen (1999) enables them to explain the spatial differences in regional house prices. The notion of cointegration is concerned with the long-run relationships among variables or sets of variables. This typically tests if the long-run movement in house price in one region is related to the long-run price changes in another region(s). This study, similar to the above mentioned ones, utilizes the cointegration approach in addition to more recently developed procedures, to examine the long-run relationships of US regional house prices.

Cointegration Tests

Similar to most studies conducting multivariate cointegration tests, this study uses Johansen (1988) procedure. The initial step of statistical analysis starts with the unrestricted vector autoregressive model (VAR). The p-dimensional VAR model of order k with Gaussian errors is expressed by the following equation:

$$Y_t = \alpha + \sum_{i=1}^{k} A_i Y_{t-i} + \varepsilon_t \qquad t = 1, \ldots, 125 \qquad (1)$$

where Y_t is a $px1$ vector of p series with $p = 9$ representing the HPIs for each nine divisions used in this paper. A_i is a (9 x 9) coefficient matrix, α is a 9 x 1 drift vector, ε_t is a (9 x 1) innovation vector which are normal independent identically distributed ($N_p(0, \Omega)$), and the k is the maximum lag length. Fitting the unrestricted VAR model with the k lags does not involve complications; they arise when the necessary assumptions of the underlying model need to be checked. In particular, the lag lengths k needs to be determined, the serial correlation and the conditional heteroskedasticity, as well as the distribution of the errors should be checked (Johansen, 1988, 1991, 1996; Juselius, 2006). More detail discussion of the misspecification tests is given in the following section.

Since there is no prior information about the cointegration rank, it is determined using the likelihood ratio test or trace test proposed by Johansen (1988, 1991) (Bruggemann, Lutkepohl, Saikkonen, 2006). The null hypothesis of the trace test statistics of Johansen (1991) is that there are at most r cointegrating vectors, which in our case is 8, i.e. $r = 0, \ldots, 8$. Furthermore, three cases are possible. First, if the rank of Π is full ($r = p$), then the Y_t is stationary and VAR at levels is appropriate. Second, if the rank is zero ($r = 0$), all series are nonstationary and there is no combination of two or more nonstationary series that is stationary at levels. Hence, VAR at first differences should be used for analyzing dynamic relationships of the series. Finally, if the rank is between zero and full rank, i.e. $0 < r < p$, then the existence of r cointegrating vectors indicates the presence of the r linear combinations of series that make the process stationary. In this case, error-correction model is used (Johansen, 1996, Juselius, 2006). To determine the cointegrating vector r, the trace tests results are compared with only two models: the first model includes constant (intercept) in the cointegration relations, and the second model includes the first model in addition to the deterministic trend in levels (outside the cointegration relations). These two models are the best to use for such data. Because there are deterministic variables included in the model, the critical values of Johansen (1996) are no longer valid. For this purpose, the critical values are simulated specifically for our model.[26]

Results of the trace test indicate that the VAR in error-correction form is appropriate to use, thus further analysis are conducted using the vector error correction model (VECM). Juselius (2006) provides several advantages of the ECM formulation. Among those, the multicollinearity effects are significantly reduced in ECM formulation and the distinction between the short-run and the long-run effects is very clear and their interpretations are more intuitive. Error correction model (ECM) can be presented based on VAR component in first differences with the order of k-1:

$$\Delta Y_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \Pi Y_{t-1} + \varepsilon_t \qquad (2)$$

$\Pi = \alpha\beta'$ has a reduced rank where α and β are pxr matrices, $r \leq p$. Here Δ represents the first differences, Γ_i and Π are short-run and long-run coefficient matrices, respectively; μ is a vector of constants or drift, and k is the appropriate number of lags. In addition, ΠY_{t-1} term is the error

26 Note that all the time series analysis are conducted using CATS in RATS software grounded on Dennis, Hansen, Johansen, and Juselius (2006).

correction component at levels for $t = 1,\ldots,125$ of total observations in this study. Furthermore, under the hypothesis of nonstationary $I(1)$ processes, cointegrated VAR model is given by:

$$\Delta Y_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \alpha\beta' Y_{t-1} + \varepsilon_t \qquad (3)$$

where $\beta' Y_{t-1}$ is an $rx1$ vector of stationary cointegration relations, where α is the loadings. The importance of Π comes from the fact that its rank determines the number of cointegrating vectors. Hence, alternative formulation of the trace test includes the rank of Π. The null hypothesis of the rank Π is $r = 0$ at 5% significance level which implies that no cointegrating vector exits between the two series. The alternative hypothesis of the rank Π is that $r \geq 1$, indicating that at least one cointegrating vector exists. Depending on the decision, null goes up to $r = 8$.

Misspecification Tests

The model presented above is the basic one, assuming that the model is well specified. However, real world examples oftentimes have one or more specification problems. The importance of misspecification analysis of the model comes from the fact that a study might fail to convey reliable implications, thus the results can not be fully trusted. Hence, a thorough examination of the data and the model is critical.

The descriptive statistics on HPI for each division are presented in Table 1. New England appears to have the highest mean HPI, followed by the Middle Atlantic and Pacific. It is interesting to note also that these three divisions have the most volatile HPIs. On the contrary, West South Central has the lowest mean HPI as well as standard deviation. Furthermore, to avoid spurious results, all the nine series were tested to be sure they satisfied the stationarity condition. Series are stationary if their mean and the variance are stable over time. According to Figures 2 and 3, all the nine series exhibit unit root or nonstationary pattern. Several techniques are known in the literature to overcome the nonstationarity problem in levels and one of the most commonly used and easy method is differencing the series until they are stationary (Engle and Granger, 1987; Johansen, 1988; Juselius, 2006). In this paper, we conduct Dickey-Fuller test of stationarity, the results of which are reported in Table 2.[27] Series are nonstationary at levels and stationary at the first difference, thus to sustain stationarity, all of the nine series are first differenced. In other words, all the series are integrated of order one, i.e. $I(1)$. Hence, cointegration analysis can be conducted.

As suggested by Juselius (2006), every assumption is based on the presumption that others are satisfied. For example, to check for normality of the series, it is assumed that every other assumption of the underlying model is satisfied. Hence, specification tests have to be performed after each assumption is checked for to confirm that the rest is unchanged (Juselius, 2006). The maximum number of lags (k) is estimated using the Schwartz Loss (SIC) and Hannan and Quinn (HQ) loss matrices. Given the small sample size of 125 and VAR of 9 (p) dimension, the maximum lag length is restricted to be 4. The results, which are reported in Table 3, are somewhat odd. VAR with one lag is suggested by the SIC, while H-Q metrics results in optimal lag length of 4.[28] Sometimes when the results of the information criteria do not match and large lag length is found to be optimal by one of the measures, there is a possibility that

27 However, since Dickey-Fuller test of stationarity is proven to have low power, other tests such as Phillips and Perron, KPSS, and ADF have conducted for robustness purposes (DeJong et al., 1989; Diebold and Rudebusch, 1990; Kwiatkowski, Phillips, Schmidt, and Shin, 1992; MacDonald and Taylor, 1993; Hansen, 1995; Johansen, 1988; so on). The results of these tests are not reported but are available upon the request from authors. Note that the conclusions of the stationarity tests are the same regardless of the test used.

28 Different lag lengths with a variety of deterministic components, such as seasonal dummy variables, constant, drift, and dummy variables for outliers, have been used. However, the results of the lag length have remained unchanged except for the case when we used maximum lag length of 5 and more. In those cases, the largest lag is found to be optimal by H-Q loss metrics. These results are not reported, but available upon request from authors.

it is not correctly determined due to some specification problems such as outlier observations and mean shifts (Juselius, 2006). Hence, we initially start with a VAR of order two.

Generally, for time series data a list of misspecification tests are of importance and need to be checked. Univariate misspecification tests include the normality test for each series using Jarque-Bera test and the ARCH effect of each series for autoregressive conditional heteroskedasticity. In addition, the first four moments are also highly important to find the source of the problem, if any. Multivariate tests, on the other hand, include the LM test for residual autocorrelation, Ljung-Box test for correlation, and Doornik and Hansen (1994) test for normality of all the series.

Table 4 provides the results of the misspecification tests for an unrestricted VAR(2). The multivariate tests for normality and residual autocorrelation are rejected at even 10% significance level. On the other hand, univariate test for normality is not rejected for the MT, SA, and NE regions at 5% significance level. This might be due to the moderate skewness and kurtosis for these series. Most series, except for the MT and ESC, pass the ARCH test at least at 10 % significance level. The R^2 for each equation (i.e. $\Delta PC, \Delta MT, \ldots, \Delta ENC$) is not high. However, the R^2 values are misleading and should not be subject to much emphasize when it is calculated for the unrestricted VAR in levels. Similarly, the overall measure of goodness of fit in the VAR model is given by the trace correlation statistic which is not significantly high. It can be approximately considered as an average R^2 in the p VAR equations (Juselius, 2006). Overall, the model is not well specified and from the skewness and kurtosis it can be concluded that there are large residuals. In addition, graphical inspection of both the level and the differenced data reveals that series have seasonal and trending patterns.[29] This may also create some specification problems. Hence, detrending and seasonal adjustment procedures are performed on all

29 Juslieus (2006) suggests that graphical analysis for the specification checking is highly recommended and even might reveal specification problems that tests fail to find.

the series (Harvey and Trimbur, 2003). It is known that each series are composed of seasonal factor, trend-cycle, and the irregular component. Multiplicative model with the seasonal span of four and linear trend is calculated and extracted leaving only the irregular component in the series.[30]

To illustrate the pattern of the new series (detrended and seasonally adjusted), the plot of the differenced data of the original and the new series is presented by Figure 4. The new series is well-behaved without rough spikes. Consequently, VAR is re-estimated using the new dataset. The misspecification tests using the new, corrected series show huge improvement in terms of the problems that were present before. However, the problem with the residual autocorrelation and normality still exist. Further analyses provide evidence of large residuals which need to be carefully considered given their importance to the econometric results.

Usually, residuals larger than $|3.3\sigma_{\varepsilon}|-|3.5\sigma_{\varepsilon}|$ should be treated with care since they indicate possible outlier observations (Juselius and MacDonald, 2004; Juselius, 2006). The residuals of most series are relatively large at the beginning of the sample period. Given the US economy at the time, the high residuals are quite intuitive indicating that some sort of intervention took place. For example, the rising inflation rates perhaps accounts for the pre-recession shock in the WNC at 1977:01 that caused the residuals to exceed $|3.5\sigma_{\varepsilon}|$. Other series, except for PC, MT, SA, and NE also appear to fluctuate greatly perhaps as a result of the inflation rate changes. The announcement of the tight monetary policy by the Fed appears to have had its effect on the housing market. Furthermore, the lagged effect of the monetary policy and the twin recessions influenced housing market as well, with more pronounced effect on MA in 1980:1 and WNC in 1980:04. Furthermore, a large residual is

30 The classical decomposition of the series, say PC, into a trend-cycle (TC), seasonal (S) and irregular (I) components can be modeled either as additive ($PC = TC + S + I$) or multiplicative ($PC = TC \times S \times I$). The later model is used in this paper because the seasonality of the series seems to increase with the trend. @classicalDecomp procedure in RATS does this type of decompositions.

observed in the ENC series for the date of 1985:03. Unlike most other shocks, this shock does not appear to be intuitive since it does not coincide with any major events either in US economy as a whole or the housing sector. The large residual in the MT series in 1986:04 and 1987:01 is explained by the federal tax reforms (Kim, Leatham, and Bessler, 2007) and perhaps the conditions that later caused the stock market crash. The final observation of abnormal residuals is for PC in 2004:1. Although the analysis of the US economic history does not seem to offer any logical explanation, volatile residuals for most of the series were observed during the period of 2004-2006. In fact, late 2005 and the beginning of 2006 was actually the start of the housing market downturn. Very large residuals are detected for most series at this time, therefore these two observations (i.e. 2006:01 and 2005:04) are not used. Certainly, these dates are highly informative of the housing sector, however, the loss (arising specification problems) from including the observations for those dates outweighs the gain. Hence, the further analysis proceed with 123 observation rather than 125.

It is common to consider the observations with large residuals as outlying observations. Outliers can seriously distort the autocorrelation structure of the time series (see Chernick et al., 1982). If the outliers are ignored and left in the time series they may seriously bias the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the series (Mills and Prasad, 1992). In practice, it is common to treat outlying observations to be the results of intervention, structural break, etc. Thus, to overcome the outlier problems, the addition of the dummy variables to the model is very common. However, one needs to be careful about the type of outliers since each type of outlier should be treated differently. For example the additive outliers should be corrected for before proceeding with any analysis. On the other hand, the transitory and the permanent outliers need to be included in the model due to the important information they convey.[31]

Outlier observations are corrected with the addition of the seven dummy variables in the VAR model. Permanent blip dummies, which take a value of 1 on the date of shock and 0 otherwise, are added for the following observations: 1980:04, 1985:03, and 2004:01. In the case of +/- effect of the residuals which has a dynamic effect on the later observations, transitory dummy variable is used. Hence, transitory dummy variables, that take a value of 1 on the shock date, -1 for the next observation, and 0 otherwise, are set for 1977:01 and 1980:01 observations. Further, a dummy variable that takes a value of 1 on two consecutive dates is included for 1986:04. The difference of the last dummy variable is also included due to its importance for the shock and the model. All of them are included as restricted deterministic components in the VECM.

Although the misspecification tests may improve with the inclusion of the dummy variables and suggest the goodness of the model, the parameters of the model can still suffer from non-constancy. Various methods (tests) are used in this paper to tackle the parameter constancy problem thoroughly. Both backward and forward recursive tests are conducted, each of which is useful for testing different time periods of the entire sample. The main purpose of these tests is to find out if the sample period of 1975-2006 is appropriate for analysis or if there is any structural change that suggests the model needs to be re-specified for the sample period, perhaps partitioning it into several sub-periods. All the following tests performed here are recursive meaning that the models are first estimated for sub-sample of 1 to T1, then increasing the unit period until it covers the full sample, whereas in case of backward recursion, the models are estimated first for the subsample of T to T1, then increasing the unit

31 More detailed information about the outliers, their detection, type, and the ways of fixing them see Tsay (1988), Frances and Lucas (1998), Nielsen (2004, 2007), Johansen (2006).

period until it covers the beginning of the sample (full sample). These procedures are fully covered in Hansen and Johansen (1999) and Juselius (2006).

There is some evidence of parameter instability, however, the time range the parameters are the most volatile is the beginning of the sample which coincides with the high inflation rates, tight monetary policy, twin recessions, oil shocks, etc. In other words, it is somewhat expected even looking at the plot of the differenced series. The significance and the importance of these shift dummies are further tested to get the best and the most parsimonious model. It is common practice to partition the sample into two (if there is one structural break) sub-samples and estimated each subsample separately (Hansen and Johansen, 1999). However, the small sample size puts restrictions on the estimation methods. Therefore, it is not optimal to partition the sample into various parts to account for the structural breaks. The next popular method of dealing with the parameter non-constancy is by using dummy variables, particularly shift dummies (Juselius, 2006). Consequently, shift dummies are included in the model. Interestingly, the goodness of the model and the parameters did not change much with the shift dummies either each separately or combined.[32] Hence, insignificance of the shift dummies leads to considering the model with no shift dummy variables.

Reconciling all the above changes, the VAR(k) model in ECM form is now given by:

$$\Delta Y_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \alpha\beta' Y_{t-1} + \Phi D_t + \varepsilon_t \qquad t = 1,\ldots,123 \qquad (4)$$

The model has the same specification as Equation (3) with the only addition of the vector of dummy variables (D_t); Φ is the vector of coefficients for the dummy variables. The estimated model is then checked for the validity of the underlying assumptions. A clear improvement in terms of univariate

32 The results with shift dummies are not reported in this paper.

normality, the trace correlation (goodness of fit of the model), and standard deviations is revealed. Although the multivariate normality statistics, ARCH statistics, and LM(1) and LM(k) values are greatly reduced, the null hypothesis for these tests is still rejected. Hence, there are a few specification issues remaining in the model.

It is well evidenced that small sample size will likely cause the series to deviate from normality assumption, which further will cause some additional problems with respect to residual autocorrelation, ARCH, etc. Hence, some misspecification in the model is not considered to be unusual given the limited sample size and large dimension (Franses and Haldrup, 1994; Bruggemann, Lutkepohl, Saikkeonen, 2006; Juselius, 2006). Consequently, model in equation (4) does seem to be acceptable given the limited sample size and the number of parameters to be estimated.

Cointegration analysis is conducted to shed light on the long-run relations that may exist among the nine series. Some authors suggest that the unrestricted VAR has to be well specified before estimating the restricted VECM, while others claim that the model will be well specified after the estimation of the reduced form. The proponent of the first approach is Juselius (2006), who proposes to test for cointegration once the model is well specified. On the other hand, it has been suggested that some of the misspecification problems that prevail should be checked again after the determination of the correct cointegration rank. In other words, reduced form model has to be checked again for specification issues (Juselius, 2006; Bruggemann, Lutkepohl, Saikkonen, 2006). However, one needs to be cautious regarding the model check due to the small sample size distortions.

Johansen's trace test is used to determine the number of common cointegrating relations in the model. Although the trace test has been criticized for not accounting for the small sample size and deterministic components, the corrected version of trace test is "Bartlett corrected" for small samples and accounts for deterministic components added to the model.[33] To calculate the corrected version of the trace test, we simulated the critical values for 2000 replications and length of the random walks of 123 (i.e. number of observations used after accounting for seasonal and trend adjustments). The importance of simulation comes from the fact that small samples usually tend to deviate from the normality assumption and asymptotic distribution does not seem to hold for small samples. Hence, the corrections are vital for correct results. The results of trace test are reported in Table 5. It can be seen that the difference between the corrected and not corrected tests is enormous. Without Bartlett correction for small samples and the deterministic components, the rank of 8 would have been accepted at 4.5% significance level, while with Bartlett correction the rank of 4 is accepted at even 1% significance level. Thus, the small sample size distortion and the inclusion of the deterministic component could mask the true long-run relations among the series.

After the determination of the cointegration rank, the tests of long-run exclusion of a variable (i.e. a zero row restriction on β), unit vector of alpha for a variable, and the weak exogenity of a variable (i.e. a zero row restriction on α) are conducted which later will have bearings on the identification of the model. The results indicate that none of the variables are weakly exogenous which implies that in short-run all of them respond to the perturbations in long-run relations. Unit vector test is rejected for all the variables as well. On the other hand, the result of the long-run exclusion test suggests that MT is not included in the cointegration space. Therefore, it should be omitted from the cointegration space and from the long-run relations at 5% and higher significance levels. This information is further used to test various restrictions. The test of restriction given the hypothesis that MT should be omitted from the cointegration relations for

$$Y_t' = [PC_t \quad MT_t \quad SA_t \quad MA_t \quad NE_t \quad ESC_t \quad WSC_t \quad WNC_t \quad ENC_t]$$

33 See Johansen (2000, 2002) and Juselius (2006) for more details about Bartlett correction and the trace test for more sophisticated models.

is given by: $H_1 : \beta^r = H\varphi \quad or \quad R'\beta = 0$. Although the hypothesis of four zero restrictions on the MT is accepted with the p-value of 0.24, the model is not identified. Thus, as mentioned in Juselius (2006), completely omitting the MT series will affect the long-run identification negatively.

Various restrictions that are either suggested by the data (using the DAG), model (significance levels), or by the tests such as long-run exclusion are investigated. The following section will shed light on the identification problem and the proposed methods using DAG which is discussed next.

Identification

The issue of identification is central for the complete understanding of economic models. Unique identification is necessary for estimation and interpretation of the parameters of the dynamics of the system of the vector autoregressive model. Alternatively stated, the reduced form model with correlated innovations has to be transformed into a structural form with uncorrelated, economically interpretable shocks. This problem is especially pronounced in the case of non-stationary data (variables) that allows us to formulate two separate identification problems: identification of the long-run (cointegration relations) and short-run (equations of systems) structures. The identification of the long-run structure imposes long-run economic structure on the unrestricted cointegration relations, whereas the identification of the short-run structure imposes short-run dynamic adjustment structure on the equations for the differenced process (Johansen, 1991, 1995; Juselius, 2006).

Cointegrated VAR model both in reduced-form and the structural form can be used for analyzing the long-run structure. The reduced form cointegrated VAR is used in this paper, which eliminates the worries about the identification of the short-run structure as its parameters are uniquely defined in this case. Although the long-run parameters are also uniquely defined based on the normalization of the eigenvalue problem, just-identifying restrictions on the long-run structure are necessary.

Three different aspects of identification is acknowledged which are the generic identification (statistical model), empirical identification (parameter significance), and the economic identification (Johansen and Juselius, 1994). The first two conditions are satisfied if one follows the correct steps of model estimation, while the last condition is much more complicated. For example, if one examines a micro or macroeconomic problem, theory and the existing literature is almost always used for identification of the long-run and short-run structures. The problem arises when research involves either something absolutely new for which there is no set theory or dynamic relationships (linkages) among certain variables for which no formal theory exists.[34] Hence, the achieved identification is not based on solid economic or econometric arguments (Lack and Lenz, 2005). In this paper we offer a new method for long-run identification by utilizing the causal structure which is a direct result of the DAG.

The DAG, discussed in the next section, is used to obtain the causal structure among the variables. The covariance/correlation matrix from the innovations of the reduced form cointegrated VAR is used to obtain the DAG. The graph along with the results of the test for exclusion is used to get just-identifying restrictions on the long-run structure. The DAG without MT (excluded) confirms the above findings of four cointegrating vectors. Moreover, it provides important information as to what are the cointegrating relations and which variables are included in it. The four major divisions (Figure 5) which have arrowheads directed to them are the four cointegrating relations where only the regions that cause these four regions are included in the model and the others are restricted in the long-run structure. As a result, the long-run system has the following form[35]

34 Brief history of the identification problem is well introduced by Lack and Lenz (1999).

35 Note that in the third relation which corresponds to the ESC equation on the graph, the effect of MA is not accounted for because its innovation is transferred to ESC via NE. Hence, NE is included but not the MA.

$$\beta' X_{t-1} = \begin{bmatrix} \beta_{11} & 0 & \beta_{13} & 0 & \beta_{15} & 0 & 0 & 0 & \beta_{19} & \beta_{01} \\ \beta_{21} & 0 & 0 & 0 & 0 & 0 & \beta_{17} & 0 & \beta_{19} & \beta_{02} \\ 0 & 0 & 0 & \beta_{34} & \beta_{35} & 0 & 0 & \beta_{38} & 0 & \beta_{03} \\ 0 & 0 & 0 & 0 & \beta_{45} & \beta_{46} & \beta_{47} & \beta_{48} & \beta_{49} & \beta_{04} \end{bmatrix} \begin{bmatrix} PC_{t-1} \\ MT_{t-1} \\ SA_{t-1} \\ MA_{t-1} \\ NE_{t-1} \\ ESC_{t-1} \\ WSC_{t-1} \\ WNC_{t-1} \\ ENC_{t-1} \\ 1 \end{bmatrix}$$

The restriction is just-identifying and model is accepted with $\mathrm{X}^2(9) = 16.389$ and $p - value = 0.059$. The first three relations are invariant to MT inclusion, and only the fourth relation is altered due to MT. Therefore, the confidence of the first three relations to achieve long-run identification is very high due to its robustness. Conversely, the last relation is dependent upon the test of exclusion (i.e. MT exclusion) which is why confidence of the last relation as identifying is limited. However, even in this case the contribution of the DAG to the identification issue is enormous. Unlike the automated identification available from CATS in RATS which is not based on data inferences or economic theory, the identification procedure proposed in this paper bases completely on the observed innovations among the variables, data, and model inferences using the causal structure. This is especially useful when the supporting economic theory is incomplete or non-existent. The description and application of DAG in impulse response functions is presented next.

Directed Acyclic Graphs (DAG)

In real estate literature that focuses primarily on the dynamic interrelations of regional house prices, no study has ever used the Directed Acyclic Graphs (DAG). This paper employs DAG to investigate the contemporaneous causal relationships among innovations of the nine series. In addition, its importance for price discovery implications which is later discussed and the above mentioned identification issues is inevitable. Besides its importance in model identification, DAG is also highly important in VAR-type innovation accounting as it enables us to assign the contemporaneous causal ordering of the variables based on the data. Hence, instead of randomly choosing the causal pattern, data-inferred pattern can be used and justified through DAG when studying the dynamics of the system.

The orthogonality among the innovations is very important for VAR. Furthermore, modeling the contemporaneous causal relationship among innovations is vital for the accuracy and consistency of the innovation accounting. Early papers tend to use Choleski factorization of contemporaneous covariance to find the orthogonalized innovations (Sims, 1980). Another approach, which relaxes the Cholesky ordering, is used by Bernanke (1986). The Bernanke factorization puts “over-identified” restrictions based on the existing theoretical information related to the variables. Recently, a more sophisticated DAG approach is being used which is based on the observed innovations among the variables. This approach has been used for innovation accounting from VAR which provides data-based ordering of the innovations (Bessler and Akleman, 1998; Hoover, 2005; Kim, Leatham, and Bessler, 2007).

A directed graph is a graphical representation of the causal relationship among a set of vertices (for this paper - among innovations from the VAR).[36] There are three possibilities that the lines and the arrowheads between the variables can be arranged. First, it is the unidirectional causal flow such as A→B, which indicates that variable A causes variable B. Second, it is the undetermined causal direction, A − B, which means that there is some relationship between A and B, however, the direction of the causation is undetermined. Finally the third, in which case there is bidirectional causation presented as

36 This paper will introduce the DAG in a simple and concise way, but for readers who are motivated to read about the DAG more detailed, we refer them to Spirtes et al. (1993), Pearl (2000), Bessler and Yang (2003) and Kim, Leatham, and Bessler (2007). The latter articles explore the DAG in economics field and motivate its applications in applied economics due to its importance.

$A \leftrightarrow B$ implying that A causes B and B causes A. If this happens, most likely there is an omitted variable between A and B.

The direction of the causal flows among the variables is assigned using D-separation which formally represents the screening-off phenomenon (Pearl, 2000). Among three variables A, B, and C the following causal patterns can be formed. “Causal fork” is formed as $A \leftarrow B \rightarrow C$, where B is the common cause of A and C, thus the measure of unconditional association between A and C is non-zero. However, the association between A and C will be zero if B is conditioned on. Another causal pattern, which is observationally equivalent to the causal fork, is the “causal chain”: $A \rightarrow B \rightarrow C$. Similar to the case of causal fork, the unconditional association between A and C is non-zero, while it becomes zero as one conditions on B. In both cases, variable B screens-off the association between the two end variables. Finally, the last causal pattern called “causal inverted fork” is given by $A \rightarrow B \leftarrow C$ and is observationally different from the above two cases. In this case, the unconditional association between the two end variables is zero, while if we condition on the common effect B, the association becomes non-zero. The common effect B does not screen-off the association between its common causes.

Spirtes et al. (1993) have incorporated d-separation into an algorithm (PC algorithm) to assign casual flows among a set of variables using the covariances of innovations. Alternatively stated, the algorithm builds directed graph. Notice that directed graph, or more precisely the directed acyclic graph does not allow the causal flows among the variables such that the variable that causes another one will eventually be caused indirectly by its own cause (i.e. acyclic graph can contain only one of each variable). The notion of sepset, a variable that is conditioned on to remove the edges between the two variables, is essential to the construction of the directed graph. The process of building directed acyclic graphs starts with the undirected graph, then the PC algorithm, which is an ordered set of commands, removes edges in that undirected graph based on the tests of independence and conditional independence. After checking for any relationship between pairs of variables the edges connecting them are removed if no correlation between them is found. The checking process continues until all the possible relations among the variables are tested. After the completion of the zero order conditional correlation, the process continues for first and second order correlations, and then it continues up to N-2 order conditional correlation. Furthermore, the direction of the causality is assigned based on differences in the covariance structure of causal fork or chain and inverted causal fork. The choice of the appropriate significance level is one of the drawbacks of the PC algorithm. PC is not used in this study due to the more advanced algorithms such as the GES.

The GES algorithm starts with the DAG with no edges. Furthermore, the addition of edges one-by-one with all possible directions is evaluated using the Bayesian scoring function. As a result, causal structure that obtains the maximum Bayesian score is chosen. It is important to note that only the acyclic causal structures are considered.[37] The advantage of this algorithm is the independence of the final causal structure from the significance level, while the drawback is exponentially increasing models to consider when there are many variables. However, the modern technology makes it easy. The GES algorithm is estimated via the TETRAD IV software.[38]

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37 For more information about the GES algorithm, see Chickering (2002).

38 The web site of Carnegie-Melon University, Philosophy department provides free TETRAD IV software (http://www.phil.cmu.edu/projects/tetrad/).

38 The mobility among the regions was suggested to be on of the reasons of house price changes in other regions due to shocks in others (Bover et al, 1988; Meen, 1999; Gordon, 1990; Holmans, 1990, etc).

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Appendix A

The distribution of 50 U.S. States among the 9 census divisions

Pacific	– Alaska, California, Hawaii, Oregon, Washington
Mountain	– Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming
West North Central	– Iowa, Kansas, Minnesota, Missouri, Nebraska, South Dakota, North Dakota
West South Central	– Arkansas, Louisiana, New Mexico, Oklahoma, Texas
East South Central	– Alabama, Kentucky, Mississippi, Tennessee
East North Central	– Illinois, Indiana, Michigan, Ohio, Wisconsin
South Atlantic	– Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia
Middle Atlantic	– New Jersey, New York, Pennsylvania
New England	– Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont

Table I. Descriptive statistics on house price indexes for nine US census regions, 1975-2006 quarterly data.

Census Regions (House Price Index)	Mean (Price Index)	Mean Rank	Min. (Price Index)	Max. (Price Index)	SD (Price Index)	SD Rank	CV	CV Rank	Skewness	Kurtosis
House Price Indexes in Logarithm										
PC	5.1365	3	3.7675	6.3542	0.5897	2	0.1148	1	-0.2970	-0.2668
MT	4.9615	6	3.9845	5.8923	0.4428	4	0.0892	4	-0.1368	-0.3109
SA	5.0555	4	4.2138	6.0113	0.4384	5	0.0867	6	-0.1017	-0.5272
MA	5.2429	2	4.2299	6.2524	0.5434	3	0.1036	3	-0.3768	-0.8368
NE	5.3778	1	4.2103	6.4424	0.6062	1	0.1127	2	-0.3930	-0.8081
ESC	4.9486	7	4.2101	5.6074	0.3717	8	0.0751	8	-0.1743	-0.8599
WSC	4.8144	9	4.0635	5.3625	0.2966	9	0.0616	9	-0.6463	0.4705
WNC	4.9344	8	4.1551	5.6951	0.3901	7	0.0790	7	0.0707	-0.6229
ENC	4.9960	5	4.1537	5.7569	0.4379	6	0.0877	5	-0.0558	-1.0165

Note: Observed data are quarterly house prices indexes for each US census division. The data is house price indexes expressed in natural logarithm. The “Mean” labeled column is the simple mean price index for census divisions listed on the far left-hand-most column of each row over the observation period 1975:1 – 2006:1. The columns labeled “Min” and “Max” refer to the minimum and maximum numbers for the far left-hand-most column over the period mentioned above. The column headed “SD” shows the standard deviation of each divisions’ house price index over the observed time period. Entries in the column labeled “CV” refer to the coefficient of variation, which is SD/Mean for each division. The table also provides the ranks on mean, standard deviation, and coefficient of variation respectively for the far left-hand-most column. In the rankings, the order is from 1 to 9, “1” being the highest value and “9” being the least one.

Table 2. Dickey-Fuller test results of house price indexes of each nine US census division, 1975-2006

Series	Number of Differences	DF test
PC	1	-4.163
MT	1	-6.426
SA	1	-5.307
MA	1	-7.907
NE	1	-5.343
ESC	1	-14.443
WSC	1	-5.329
WNC	1	-7.371
ENC	1	-6.120

Table 3. Lag length selection tests

Model	k	T	Regr	Log-Lik	SC	H-Q	LM(1)	LM(k)
VAR(5)	5	120	46	5750.242	-79.321	-85.032	0.000	0.060
VAR(4)	4	120	37	5565.389	-79.471	-84.065	0.000	0.006
VAR(3)	3	120	28	5378.156	-79.582	-83.059	0.000	0.000
VAR(2)	2	120	19	5263.055	-80.895	-83.254	0.000	0.000
VAR(1)	1	120	10	5121.032	-81.760	-83.002	0.000	0.000

Table 4. Misspecification tests based on the unrestricted VAR (2).

Trace Correlation	0.53								
Log(|Ω|)	-86.79								
Multivariate Tests									
Residual Autocorrelation									
	LM(1):	$X^2(81)$		218.3		p-val.		0.00	
	LM(4):	$X^2(81)$		169.7		p-val.		0.00	
Normality									
	LM:	$X^2(81)$		197.9		p-val.		0.00	
Univariate Tests									
	ΔPC	ΔMT	ΔSA	ΔMA	ΔNE	ΔESC	ΔWSC	ΔWNC	ΔENC
ARCH(2)	0.89	17.86	8.25	1.67	5.72	14.67	4.04	2.72	1.67
p-value	0.64	0.00	0.02	0.43	0.06	0.00	0.13	0.26	0.44
Normality	15.91	4.02	1.28	31.29	4.98	15.43	15.90	31.22	14.29
p-value	0.00	0.13	0.53	0.00	0.08	0.00	0.00	0.00	0.00
Skewness	0.95	-0.21	-0.15	1.35	-0.43	-0.56	0.41	-0.52	0.74
Kurtosis	5.33	3.65	3.21	8.87	3.70	5.07	4.94	6.25	5.15
Std. Deviation	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
R^2	0.76	0.47	0.68	0.56	0.71	0.38	0.63	0.55	0.58

Table 5. Trace test results

Decision	p-r	R	Eig. Value	Trace	Frac95	P-value	Tarce*	P-value*
F/F*	9	0	0.781	536.974	189.418	0.000	271.730	0.000
F/F*	8	1	0.560	356.492	155.041	0.000	188.928	0.000
F/F*	7	2	0.499	258.926	124.951	0.000	128.037	0.032
F/F*	6	3	0.413	176.577	96.621	0.000	101.808	0.020
F/R*	5	4	0.248	113.117	72.605	0.000	54.439	0.524
F/R*	4	5	0.242	79.132	50.450	0.000	38.527	0.412
F/R*	3	6	0.161	46.172	33.022	0.001	18.571	0.715
F/R*	2	7	0.129	25.348	18.588	0.004	11.758	0.402
R/R*	1	8	0.073	8.961	8.730	0.045	5.891	0.180

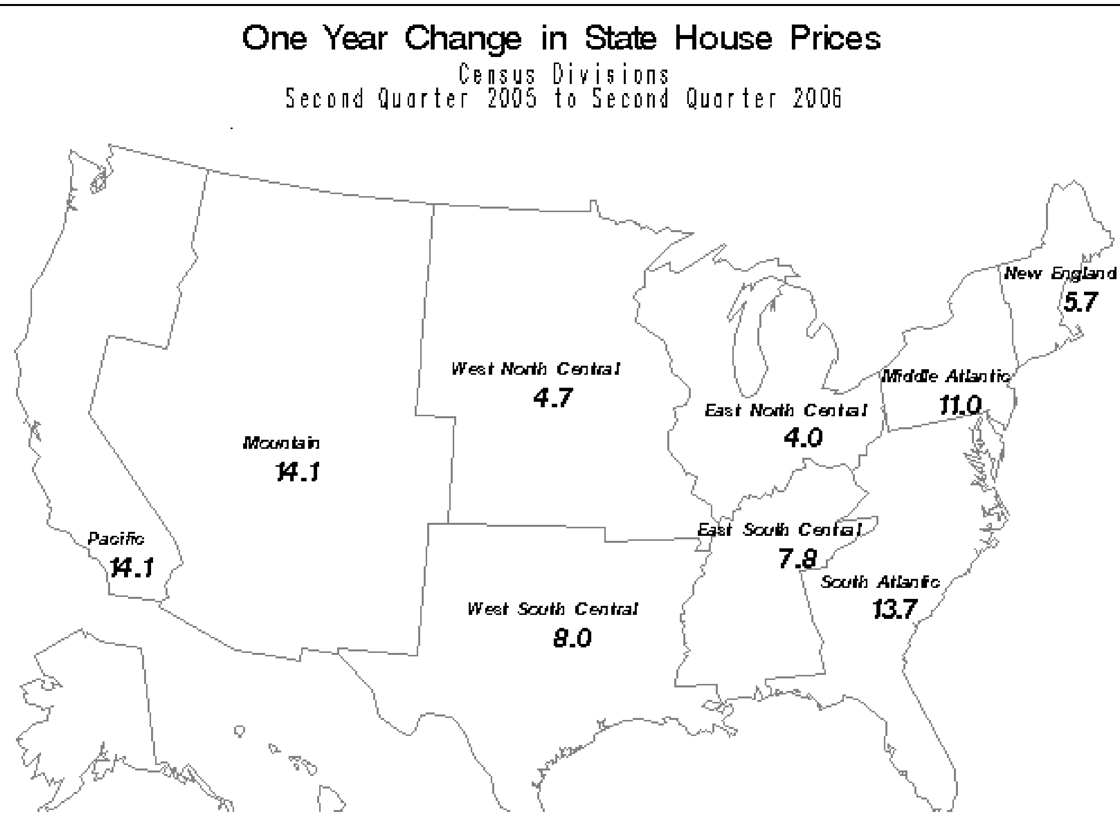
Note: * represents the Barlett corrected trace test which accounts for the small sample size and the inclusion of the dummy (deterministic) component. The trace test is accepted at >5% significance level for the Barlett-corrected trace test, while it is only boarder line accepted (4.5%) for the traditional, not-corrected trace test.

Table 6. Variance Decomposition of House Price Indexes from Nine Census Regions Based on Bernanke Decomposition

Horizon	PC	MT	SA	MA	NE	ESC	WSC	WNC	ENC
					PC				
0	84.199	0.000	0.000	5.556	6.613	0.418	0.000	3.213	0.000
1	83.297	0.196	0.003	2.995	9.370	0.507	0.187	3.435	0.010
8	59.132	6.214	12.281	5.161	14.622	0.487	0.244	0.807	1.053
16	16.268	10.416	17.745	6.661	25.115	3.016	0.052	19.024	1.702
28	5.190	7.463	15.428	3.529	30.136	1.987	0.007	32.398	3.864
					MT				
0	11.564	80.138	0.000	0.064	0.164	7.992	0.000	0.079	0.000
1	15.474	62.819	2.229	0.141	0.371	17.257	0.087	0.467	1.154

8	11.372	36.556	2.800	1.213	12.008	12.217	2.856	14.485	6.492
16	6.897	25.855	5.037	0.610	17.392	6.754	3.316	27.915	6.225
28	2.795	14.529	9.835	0.176	23.472	3.171	1.915	39.027	5.080
					SA				
0	1.298	0.000	75.762	3.939	8.734	1.938	4.974	2.523	0.830
1	4.542	0.545	60.347	8.480	15.370	0.869	4.233	4.414	1.200
8	5.721	13.987	40.734	2.544	18.153	2.113	0.355	14.734	1.659
16	2.887	15.186	27.481	0.316	22.767	1.805	0.423	25.880	3.255
28	2.320	11.487	22.598	0.471	28.256	0.619	0.168	30.581	3.501
					MA				
0	0	0	0	100	0	0	0	0	0
1	0.384	0.030	0.188	94.068	1.207	0.000	0.181	3.688	0.253
8	5.354	0.924	6.291	17.299	10.473	5.296	3.212	48.869	2.282
16	0.930	0.654	3.670	3.110	16.766	9.359	1.279	59.376	4.855
28	1.372	0.202	1.599	6.123	17.979	11.591	0.305	55.653	5.176
					NE				
0	0	0	0	35.162	41.855	2.646	0	20.337	0
1	0.271	0.013	0.219	22.152	41.137	4.379	0.046	31.476	0.307
8	0.252	0.007	0.822	1.776	19.677	13.878	0.762	58.782	4.045
16	1.002	0.023	0.301	5.795	17.936	15.406	0.145	53.811	5.582
28	2.209	0.764	0.720	11.408	12.913	18.681	0.033	48.022	5.250
					ESC				
0	0	0	0	4.326	0	95.674	0	0	0
1	0.394	0.177	1.095	4.771	1.193	88.145	0.629	3.414	0.181
8	0.389	3.618	3.870	0.289	6.544	42.659	1.760	35.221	5.651
16	0.249	3.715	3.066	0.055	11.538	25.981	1.601	45.842	7.952

28	0.067	1.508	1.854	0.561	13.053	18.407	1.430	55.523	7.597
					WSC				
0	15.451	0	0	0.005	6.997	8.435	59.183	0.047	9.882
1	20.096	0.081	0.574	3.161	13.601	8.034	40.859	2.037	11.558
8	33.011	3.662	0.409	13.587	21.655	11.315	5.301	5.323	5.739
16	33.367	3.470	0.130	22.197	15.044	12.635	1.517	9.048	2.592
28	18.009	1.419	0.442	23.145	16.289	13.602	0.450	24.069	2.577
					WNC				
0	0	0	0	0.518	0	11.454	0	88.028	0
1	0.623	0.019	0.000	0.720	0.020	13.921	1.026	83.651	0.017
8	2.704	0.188	1.369	10.093	5.333	21.696	1.702	56.319	0.597
16	2.291	0.380	2.144	9.456	11.794	16.326	0.501	54.433	2.673
28	1.188	0.300	2.811	6.847	15.263	12.123	0.337	57.348	3.782
					ENC				
0	0	0	0	0.121	0	2.672	0	20.534	76.674
1	0.062	0.225	1.108	0.023	0.328	9.811	1.624	32.228	54.592
8	0.050	0.855	1.884	2.139	3.795	29.480	5.291	55.062	1.443
16	0.078	0.578	2.003	1.824	9.727	20.805	2.100	59.629	3.258
28	0.244	0.153	1.100	1.252	10.782	16.172	1.441	63.885	4.971



Source: Office of Federal Housing Enterprise Oversight (OFHEO), 2006

Figure 1. One Year Change in House Prices of Nine Census Division

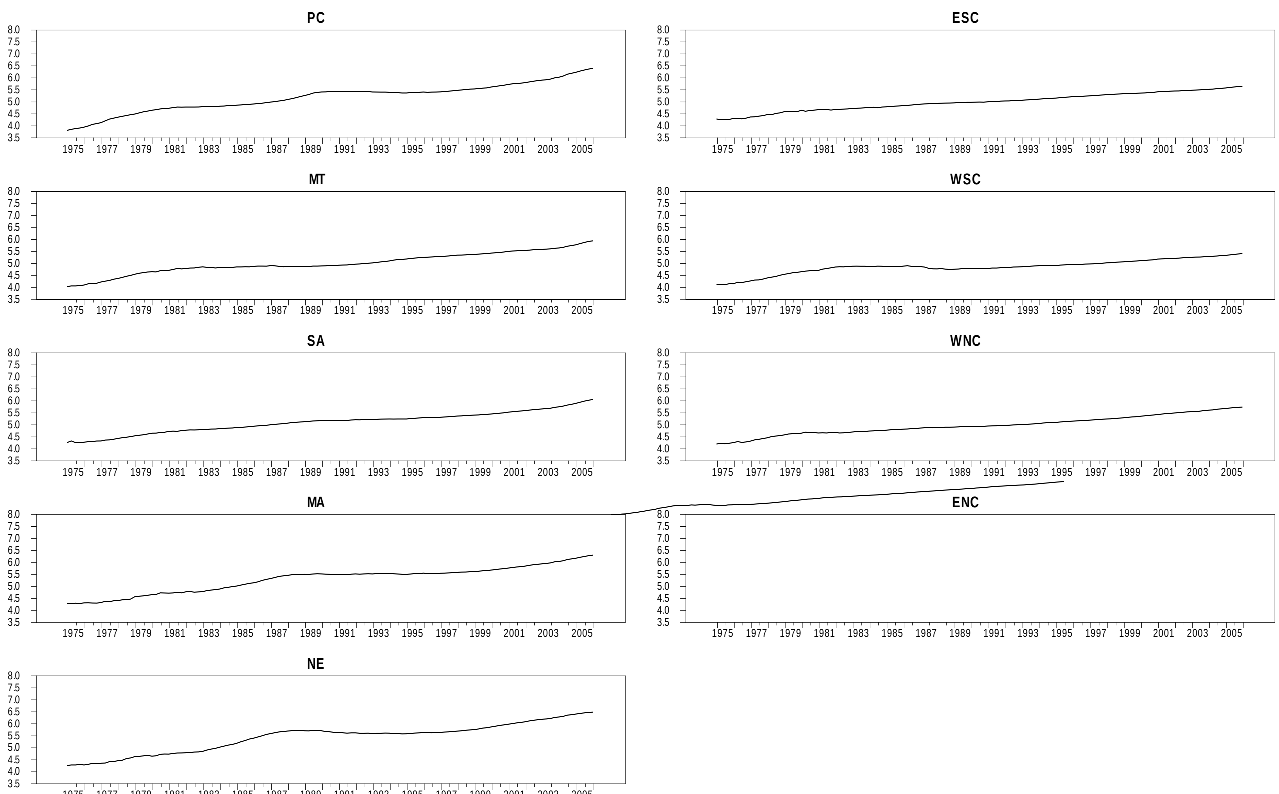


Figure 2. Plots of Historical Data on House Price Indexes, 1975-2006

Note that the y-axis is house price index in natural logarithm and the x-axis is time in quarters and years, 1975-2006.

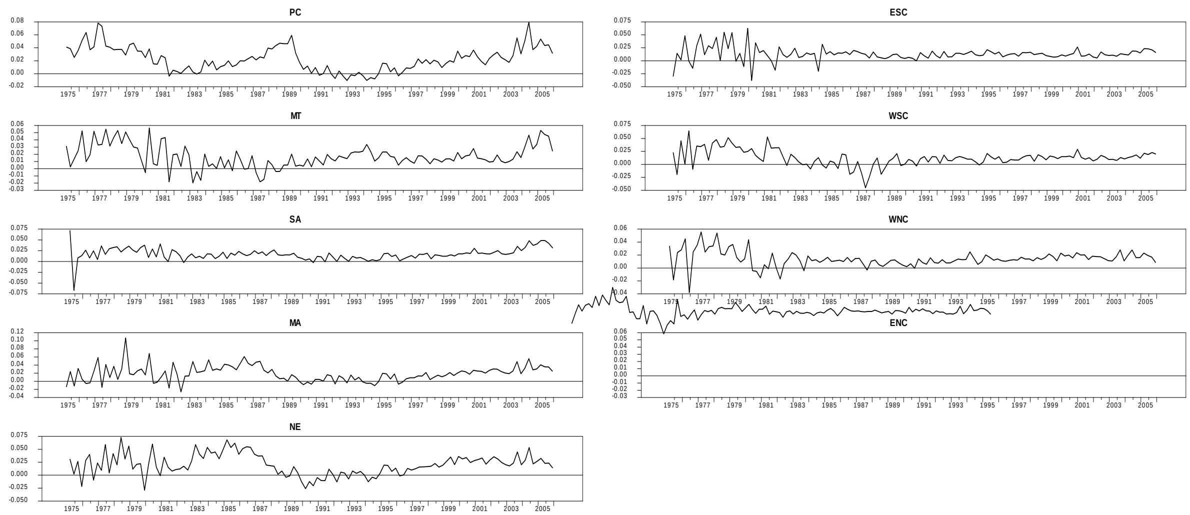


Figure 3. Plots of the Differenced House Price Indexes, 1975-2006

Note that the y-axis is differenced house price index in natural logarithm and the x-axis is time in quarters and years, 1975-2006.

Comparison of the original and new data sereis

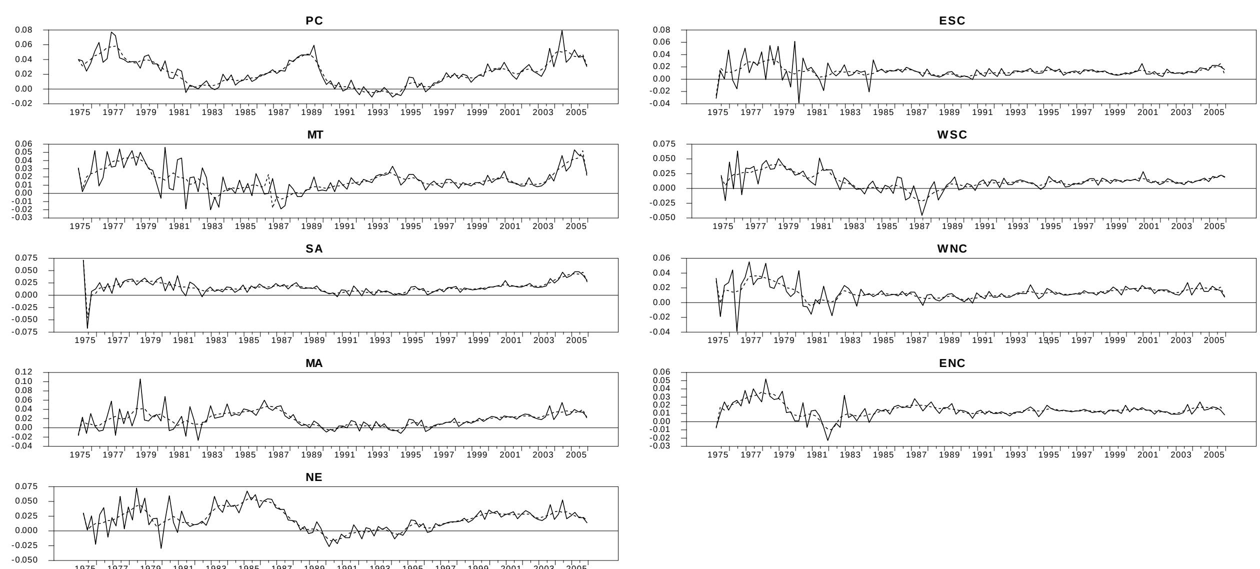


Figure 4. Plots of the Original and Smoothed House Price Indexes, 1975-2006

Note that the y-axis is differenced price index in natural logarithm and the x-axis is time in quarters and years, 1975-2006.

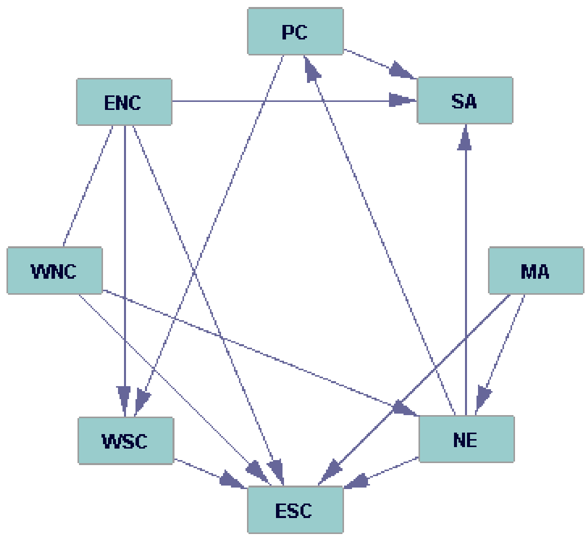
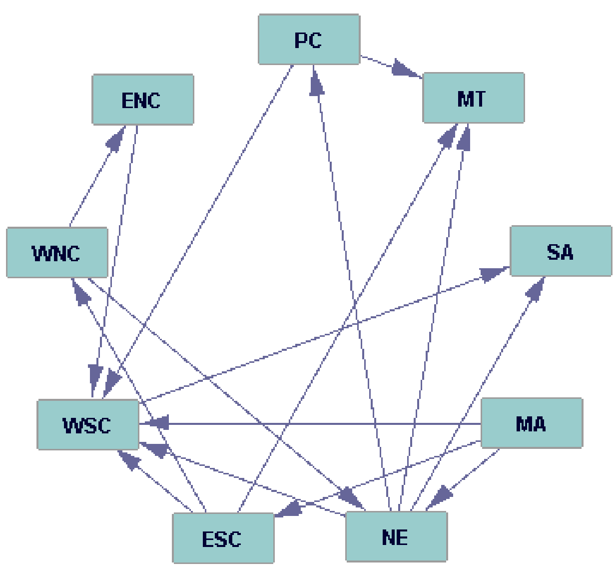


Figure 5. Directed Acyclic Graph with MT excluded for identification purposes



The complete correlation matrix resulting from the just-identifying model is fed into TETRAD to obtain the contemporaneous causal structure among the nine US census divisions. Given the results of the exclusion test and the negligible role of MT in the US housing market, a tier (knowledge) is added which restricts the MT to cause any other region contemporaneously. The resulting graph in DAG pattern illustrates how the US regions interact with each other instantaneously. Further, the results of it have bearing on the dynamic structure of the overall system. Afterwards, due to the relative limitation

Figure 6. Directed Acyclic Graph with the knowledge tier for the causality purposes.

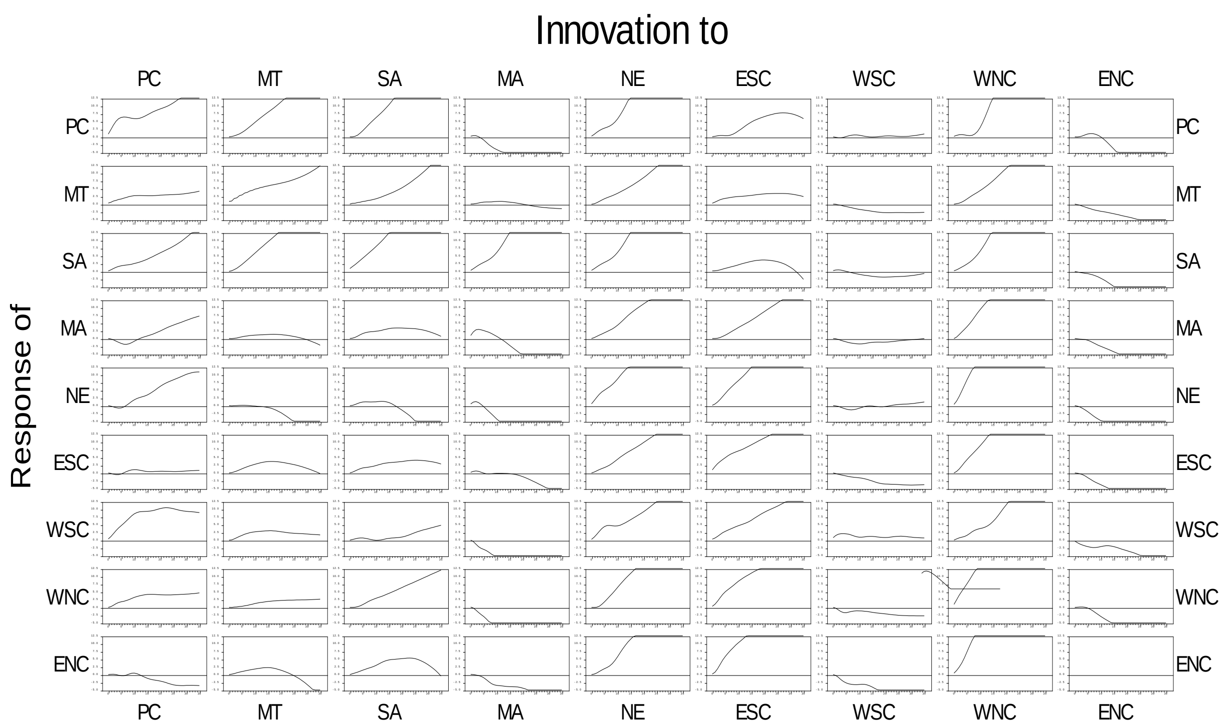


Figure 7. Impulse Response Functions for the US regional house prices

of coefficient interpretation from the reduced form just-identified model, the innovation accounting is utilized (Bessler and Yang, 2003). It facilitates the interpretation and summary of the dynamic relationship between regional house prices using the findings of the above mentioned procedures (i.e. just-identified model and DAG).

5. Results

The above estimated just-identified model and the DAG facilitate the calculation of the innovation accounting. Particularly, the impulse response function and the forecast error variance decomposition are used to shed light on the dynamics of the US housing market. The role of the DAG in directing the causal flows among the series contemporaneously and the further use in the innovation accounting is fully elaborated.

The results from the DAG with MT and tiers which is provided in Figure 6 and DAG without MT (Figure 5) differ slightly boosting the confidence in the resulting causal structure. The robust orderings of causal flows show how the house price innovations of certain census divisions cause house price changes in others. Among the robust causal structures is the contemporaneous causal effect of NE on PC, MA and WNC on NE, NE on SA, MA on ESC, PC and ENC on WSC. Hereafter, the DAG with MT and tier will be used for interpreting the instantaneous causal ordering. The MA appears to be the only exogenous region at contemporaneous time. Hence, shocks arising in this region are transmitted into other regions affecting their housing markets through the house price changes. The exogenity of the MA is expected due to its importance in both economic and financial sectors in the nation. All the states included in MA, New York, New Jersey, and Pennsylvania, have very important roles and do affect the dynamics of the national economy. Consequently, the finding of MA being the source of the changes in the house prices in the US is consistent with its role in the overall economy. While the exogenity of MA is expected due to the high house prices and the leading role of the region in the overall economy, it is very surprising to find that NE and PC are not exogenous in the short run. This is perhaps due to the fact, that in the short run a region affecting house prices in other regions is not as intuitive given the housing market cycle of more than 6-8 years (Rosenthal, 1986, Alexander and Barrow, 1994, Pollakowski and Ray, 1997).

The housing prices in SA, WSC, and MT are completely influenced by other regions' house price shocks. In other words, they are information "sinks" in the US regional housing market. The insignificant role of MT can be explained by the fact that it has very negligible influence in the overall economy, although some of the states included in the region are somewhat important in agricultural sector. The explanation of the WSC which includes several important oil and crop-rich states, is somewhat logical as house prices in those states (thus in the region overall) are lower relative to the national average and the growth has not been outstanding. Conversely, it would be more logical to see SA, which includes states that have very high house prices (such as Washington D.C., Virginia, Florida, North Carolina, etc) and high growth, as an important player in the housing marker rather than as information "sink". Other regions that extensively take part in transmitting the received shocks to the other regions include PC, NE, ESC, WNC, and ENC. While the results might be somewhat debatable regarding to the importance of PC and NE, they are quite intuitive with respect to the WNC, ENC, and ESC as house price shock transmitters.

Overall, the results based on the DAG are generally intuitive and are used in ordering of causal flows for the VAR-type innovation accounting. It provides the user imputed causal ordering among the variables in Bernanke decomposition which further provides impulse response function and the forecast error variance decompositions. The later two help to summarize the structural form of the model. The impulse response function describes the in-sample effect of a typical shock to the system and can be used to economically interpret the behavior of the system (Lack and Lenz, 1999). Figure 7 presents the impulse response functions for one-time-only positive shocks in information from house prices in each US region. In each graph, the vertical axis represents the standardized responses with the range of -3 to +3. The horizontal axis, on the other hand, represents time periods (in quarters) following the information shock. In each graph we use maximum of 35 quarters (eight years and 3 quarters). Note that Figure 7 does not intend to explicitly show the numbers of each axis, instead, the purpose for reporting the figures is to show the pattern of the curves.

Large negative responses are generated by most regions due to the innovations in the ENC house price series. The responses become more negative with the time horizon and the adjustment process back to equilibrium appears to be very slow. On the contrary, innovations in house price of WNC and NE generate large positive responses which adjust very slowly as well. Similarly, innovations in ESC house prices generate large positive responses in house prices of all other regions except for the MT and SA which tend to respond by small positive changes with shorter adjustment periods. It is interesting to note that the responses to shocks in MA series are mostly positive at the shorter horizons (in short-run), becoming negative at intermediate and longer time periods, with exception of MT that does not respond and the SA which responds positively for the whole period of analysis. With some exceptions, moderate positive responses are originated in house prices series of all the regions due to the shocks in PC, MT, and SA. However, in some cases insignificant responses outweigh the significant ones (i.e. innovations in SA). Lastly, the insignificance of the WSC is confirmed by observing the impulse response functions where shocks in WSC generate nearly no response in the US housing market.

Overall, it can be seen that innovations in most house price series generate quite volatile responses from other regions. The adjustment back to equilibrium for most cases is slow. It can be concluded from the impulse response function that the house prices in WSC appear to be the least influential generating the least responses from other series followed by the SA and MT series. On the other hand, the series WNC and NE generate the largest positive responses in other series with slow adjustment periods. Opposite observation applies to ENC and MA which have similar rate of adjustment but negative responses.

Although the impulse response function gives good intuition about the pattern created by the shocks, decomposition of the error variance numerically will be more informative. The variance decomposition assesses the importance of different shocks by determining relative share of variance that each structural shock contributes to the total variance of each variable (Lack and Lenz, 2005). More detailed information about the uncertainty in each region's price series at different time horizons in future is reported in Table 6. Forecast error variance decomposition is given for every series at horizons of 0, 1, 8, 16, and 28 quarters ahead. It shows how the innovations in each region affects the house prices of the same and other regions at the specified time horizons. The maximum time horizon of 28 quarters is chosen due to the suggested notion of Pollakowski and Ray (1997) about the real estate cycle being 6-8 years.

In the short-run, uncertainty in PC is mainly explained by the innovations in its own series (84%). However, 8 periods ahead (2 years), the innovations in NE and SA comprise large portion of uncertainty in PC (14% and 12%). At the longer horizons the role of shocks in its own series fades away becoming less significant in explaining the uncertainty in PC house prices. Instead, the SA which is only influences PC, NE, and WNC become more significant (about 17%, 30%, and 32%). The percentage of uncertainty in PC explained by other series is smaller than 10%. Furthermore, PC itself along with the ESC explains about 15% uncertainty in MT in short-run becoming less important with time and reaches to about 3% 7 years ahead. On the other hand, NE and WNC become more significant in explaining the MT variance in long time horizons reaching to 23% and 39%, respectively. Similar to the PC case, the self-explanatory power of MT drops dramatically from about 80% to 14% as the time horizon increases. The MT, on the other hand, becomes significant after about 2 years accounting for up to 15% of the SA variance.

Interestingly, MA which was found to be the only exogenous series by DAG explaining all the uncertainty in itself, is about 86% explained by other series in the long-term being mainly influenced by NE (17%) and WNC (59%). However, its role in leading the NE in short-run and WSC in long-run cannot be left unnoticed. Up to 35% of the uncertainty in NE is attributed to the innovations arising in MA in short-run, leaving about 58% and 18% of uncertainty to be explained by WNC and ESC in longer horizons. NE itself appears to be one of the main leaders in the housing market affecting all regions significantly. However, its effect on house prices in ESC and ENC is relatively small. The findings regarding to the NE are consistent with those of Pollakowski and Ray (1997) that showed the lagged NE price changes are quite significant in 6-9 census divisions. However, our findings do not support the notion that NE is a “leading indicator” which was suggested in the previous studies, but it certainly confirms the finding of Pollakowski and Ray (1997) regarding to the NE’s explanatory power.

WNC appears to have the major influence on the house prices in ESC reaching to about 55%. Surprisingly, ESC itself explains large portion of its uncertainty and dies off slowly relative to the others. The exact opposite is observed in WSC series which accounts for only 59% of its uncertainty in short-run exponentially dropping to 0.5%. In addition, this is perhaps the only region where the house price dynamics are greatly influenced by innovations of more than five regional house price series: PC (up to 33%), MA (23%), NE (21%), ESC (13%), WNC (24%), and ENC (11%). It is the only region that has nearly no influence on other regions’ house prices. The exact opposite is observed for the WNC house price series, which are the main leaders in the US housing market and remain relatively exogenous over time accounting for 88%-54% of its uncertainty over time. However, three other regions explain relatively significant portion in the WNC house price uncertainty: NE (15%), MA (10%), and ESC (21%). It is the main contributor of the house price dynamics in ENC explaining up to 63% of the uncertainty. Similar to the WSC series, uncertainty in ENC house prices explained by innovations arising in the own series comprises only very small percentage (2%) in long-run. The other regions that have significantly large affect on the ENC house prices include the NE (10%) and ESC (29%).

The overall results suggest that most regions are being influenced by innovations in other regions more in longer time horizons than in short-run. The most influential series WNC, followed by NE, ESC, and MA appear to always have vital roles for price discovery in the US housing market. On the contrary, WSC, SA, and ENC do not seem to be part of the long-run house price determination, and are rather greatly influenced by the other regional house price dynamics. These results appear to be consistent with the restricted model and the DAG results. Overall, the interrelated US regional house prices is found regardless the method applied.

6. Conclusion

Real estate market has proven to be important in many aspects. This fact has attracted many researchers to do various analysis involving house prices and other variables. Mostly UK studies explored the long-run relationships between the UK regional house prices. Only Pollakowski and Ray (1997) use the US regional house price data to explore their long-run relationship. However, the techniques and methodology used in their study are very simplistic and do not allow more thorough analysis of housing market.

The data used in this study is deseasoned and detrended to allow only the irregularities in the series. Model specification and identification is extensively analyzed leading to a highly significant and just-identifiable model. We use a method which facilitates identification of the long-run structure using the Directed Acyclic Graphs and the results of exclusion tests. Four cointegrating relations among the nine variables are found. Furthermore, using the proposed identification procedure, we find that the four cointegrating relations are those of ESC, WSC, SA, and NE. All the house price series are found to facilitate the adjustment back to equilibrium, but not all are part of the cointegration space (e.g. MT). Furthermore, DAG results suggest that MA appears to be the most exogenous, leading house prices in other regions. Somewhat different results are found based on the impulse response functions and the forecast error variance decomposition suggesting the central role of WNC followed by NE. The importance of the NE in the overall US housing market is also suggested by Pollakowski and Ray (1997), who claim that it is significant for six-nine census divisions.

In addition, our findings provide evidence that PC, MA, ESC, and ENC have moderate impact on house price determination. On the other hand, WSC, followed by the SA and MT, appears to be the least exogenous region not being part of any price discovery process followed. The house prices of these regions are considerably influenced by the rest of the market. Moreover, all the regions appear to explain less of their own price uncertainty as the time horizon increase. Put another way, at longer time horizons, such as 16 (4 years) and 28 (7 years), the uncertainty in house prices is mostly explained by other regions.

The overall findings provide strong evidence of US regional house prices being highly interrelated which is consistent with the findings of Pollakowski and Ray (1997). This implies that US regional housing market is inefficient and that shocks arising in one census division do cause the same and subsequent-period reactions in other census divisions. In addition, the DAG results indicate the importance of the information transfer for determination of the house prices. Furthermore, the causality results are not necessarily consistent with the geographical locations of the regions, i.e. regions do not necessarily influence the adjacent region more than the non-adjacent regions. This pattern of price diffusion is consistent with that of Pollakowski and Ray (1997) who showed that the price diffusion pattern does not differ for neighboring and non-neighboring census divisions in terms of their statistical significance.

Several possible explanations for the observed dynamics in the US housing market can be very exhaustive including migration, income, local economy, zoning restrictions, etc. Migration, which was offered mainly to interpret the empirical findings in UK, is often associated with the availability of jobs, unemployment, labor market, demographics, as well as the lifestyle (Minford et al., 1987, Bover, 1989, Gordon, 1990, Holmans, 1990, Giussani and Hadjimatheou, 1991, McDonalds and Taylor, 1993, Alexander and Barrow, 1993, Meen, 1999). Our findings regarding the nonspatial diffusion of the regional house prices changes are probably direct effect of the regional economic interactions (Pollakowski and Ray, 1997). In other words, innovations in particular regional economy will be directly affect that region's housing market in addition to transmitting the shock to other regions' economies which eventually will have their impact on the housing market. Moreover, some authors suggest that zoning restriction and the difficulty of getting building permits might explain the observed dynamics and high prices in east and west of the US. Although many possible causes for such findings can be offered as hypothesis, it will be interesting to study the actual cause if the data permits.