National, Regional and Metro-Specific Factors of the U.S. Housing Market

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Abstract

We build a dynamic latent factor model to decompose housing prices in major U.S. metropolitan areas into national, regional, and metro-specific idiosyncratic factors, in order to distinguish the different dynamics behind housing price movements. We find that there is a distinctive national factor that has contributed about one-fourth of the individual metropolitan's housing price volatility. The regional factor accounts for another one-fourth and the idiosyncratic factor explains about half of housing price fluctuations. However, at the regional level, the factors' contributions vary across a fairly wide range. Although it only has modest explanatory power of housing price volatility, the national factor seems to account for much of the price increase in the current housing boom. Interestingly, the regional factor exerts negative influence on housing prices in a fairly large number of metros lately, only to be outweighed by the national factor's positive contribution. We also explore the possible forces influencing the national factor of housing price movements, including monetary policy, population growth, real economic activity, general inflation and other asset prices.

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1 Introduction

The recent fast pace of housing price increases in the U.S. and a number of countries has raised serious concerns about possible housing price bubbles (McCarthy and Peach 2004, Case and Shiller 2004, Duca 2005). In May 2005, then Federal Reserve Chairman Alan Greenspan assured the public that there was no indication of a national housing price bubble. However, he acknowledged that there were signs of froth in some local markets where home prices seemed to have risen to unsustainable levels.

Bubbles have been a long-time research topic in asset pricing. Depending on the definition, a bubble can be very hard to identify or prove, except maybe in retrospect (Blanchard and Watson 1982, Ferguson 2005). Gurkaynak (2005) provides an overview of testing for asset price bubbles, concluding that econometric detection of rational asset price bubbles remains difficult. In addition, the proposed tests do not produce a time series of the bubble itself; thus, making it hard to evaluate the implied properties of the bubble component. Wu (1997) tries a different approach by estimating the bubble component as an unobserved variable, in effect, a catch-all for deviations of price from the assumed fundamentals. However, in most cases, we are unable to distinguish bubbles from time-varying or regime-switching fundamentals.

The determinants of residential property prices are similar to those of other assets, namely the expected future rent cash flow (or consumption service stream) and the discount factor. However, housing property also has a number of distinctive features compared with other types of assets (Zhu 2003), including inelastic and limited local supply, a long product cycle, sticky rents and high transaction costs. Therefore, a housing price bubble may be even more difficult to prove. Rosen (2005) explains recent changes in home prices by falling mortgage interest rates and changes in household income. "The State of the Nation's Housing 2005," published by the Joint Center for Housing Studies of Harvard University, further points out immigration as another factor for the underlying strength of the housing market. Himmelberg, Mayer and Sinai (2005) compare the local annual cost of owner-occupied housing to local incomes and rents and conclude there is little evidence of housing bubbles in the U.S.

Instead of focusing on detecting a bubble, in this paper, we try to distinguish the different dynamics in the U.S. housing market. Strictly speaking, there is no such thing as a U.S. national housing market, unlike a centralized stock or futures market. The housing market is a composite of many smaller local markets (Case and Wachter 2003, McCarthy and Peach 2004). To analyze the state of the housing market we need to rely more heavily on regional and local prices rather than an aggregated national price. Individual local markets can have vastly different current situations and historical experiences versus the nation as a whole. We stress the importance of identifying the national factor in local housing price movements. It can be used to determine, for example, whether economic policies at the national level can have any detectable influence on housing prices. Meanwhile regional and idiosyncratic factors may be used to analyze, for example, the effects of local regulations and resource constraints.

We decompose real housing price movements in major U.S. metropolitan areas into components attributed to national, regional, and local idiosyncratic factors. The national factor is embodied in price movements in all local housing markets. The regional factor is shared only by the price movements in the local markets belonging to the same region. And the idiosyncratic factor affects only the local market. We follow Geweke (1977), Sargent and Sims (1977), Stock and Watson (1989), and Kose, Otrok and Whiteman (2003) in constructing a dynamic latent factor model in the state space form. We then use the classical Maximum Likelihood method to estimate the model, employing Kalman filter techniques, different from the Bayesian approach adopted by Kose, Otrok and Whiteman (2003).

We find that there is a distinctive national factor that has contributed to an individual metropolitan area's housing price movement. Over the sample period, on average, it accounts for about one fourth of the volatility in housing prices. At the census-region level, the national factor's contribution to the volatility in housing prices varies from almost nil to over one-third. Although its influence on the volatility of prices remains modest on average, the national factor seems to explain much of the recent uptick in metro housing prices relative to the long term mean. This applies to both metro areas that have seen fast price increases and those that have seen slower price increases.

The regional factor accounts for about another one-fourth of the volatility in housing prices. At the census-region level, the regional factor's contribution to the volatility in housing prices varies from 20 percent to 45 percent, a much narrower range than in the case of the national factor. One interesting phenomenon is that, during the current housing boom since the late 1990s and early 2000s, several regions have seen negative influence lately from the regional factor on the metro housing prices. In these cases, the positive influence exerted by the national factor outweighs the negative contribution of the regional factor, resulting in housing price gains above the long term mean in the metro areas within the region.

Consistent with the notion of local housing markets, our findings show that the idiosyncratic factor specific to an individual metro-area does explain, on average, half of the volatility in the housing price movements. At the census-region level, the idiosyncratic factor's contribution to the volatility of metro housing price movements is much more uneven, varying from less than one-fourth to two-thirds across different regions.

As we proceed to investigate the relationship between the national housing factor and other economic indicators—U.S. monetary policy, population growth, real economic activity, general inflation and other asset prices—we find monetary expansion does seem to affect national home price appreciation. Increases in real economic activity are positively correlated with increases in housing prices. Yet, past housing price increases do not seem to help explain consumption growth. Stock price appreciation doesn't have any effect on housing price gains. In addition, population growth is found to be negatively correlated with our estimated national housing factor.

The rest of the paper is organized as follows. Section 2 first discusses data issues and then lays out the model. Section 3 reports our estimates of the U.S. national, regional and metro-specific factors in housing price movements. Section 4 investigates the connections between the national factor of housing price movements and other economic variables. Section 5 concludes.

2 Modeling Housing Price Increases Using Metro Data

2.1 General Issues on Housing Prices

Studies of the recent state of the U.S. housing market have reached quite different conclusions partly because of the different data sets being used by researchers. Case and Wachter (2003) explore the methods used to construct residential real estate price indexes in detail. Hereafter, we concentrate on the single-family home price. There are four major sources of U.S. housing price data. The National Association of Realtors (NAR) publishes existing single family home price in current dollar term, covering the U.S. (starting from 1968 M1), 4 regions (starting from 1968 M1) and selected metropolitan areas (starting from 1980 Q1). The Bureau of the Census and the Department of Housing and Urban Development (HUD) jointly publish new home prices in current dollar terms, covering the U.S. (starting from 1963 M1 and Q1) and 4 regions (starting from 1963 Q1). In addition to the difference between existing homes and new homes, the timing of recorded prices in the NAR series is different from that in the Census-HUD series[1]. The two series do share the same disadvantages, including not adjusting for seasonality, and not adjusting for the quality differences either between homes sold at the same time, or between homes sold at different points in time.

As an improvement, the Census and HUD publish the Price Index of New One-Family Houses

[1] "Comparing New Home Sales and Existing Home Sales", http://www.census.gov/const/www/existingvsnewsales.html.

Sold, a Lasperyes type price index with constant quality[2]. The quality includes not only the physical size and amenities of the house, but also its geographic location, thus providing a more accurate measure of housing price changes[3]. The index's weakness is that it only covers new homes. In addition, data is only available for the U.S. at a quarterly frequency starting from 1977 Q1 and for 4 regions at an annual frequency starting from 1977. An alternative measure of housing price changes over time is the repeated sales price index published by the Office of Federal Housing Enterprise Oversight (OFHEO), which covers the U.S. (starting from 1975 Q1), 50 states (starting from 1975 Q1), 9 regions (starting from 1975 Q1) and selected metropolitan areas (with various starting dates ranging from 1975 Q1 to early-1980s)[4]. It is a weighted price index, measuring average price changes in repeated sales or refinancing on the same properties (Calhoun, 1996). The weakness of the OFHEO series is that it may not reflect fully home improvements on the same house between sales. As Case and Wachter (2003) point out, there are also important measurement disadvantages such as the need for frequent transactions. In comparison with the Census-HUD Price Index of New One-Family Houses Sold, the OFHEO repeated sales price index tends to over-estimate the price increases (Figure 1).

If one wants to determine if there is a bubble, the constant-quality Census-HUD Price Index is a more appropriate measure, as pointed out by McCarthy and Peach (2004). Haubrich and Craig (2005) show that the price-to-rent ratio based on OFHEO data is exaggerated compared with the one based on the Census-HUD constant-quality Price Index. In this paper, however, we focus on disentangling the effects of the national, regional and local factors on housing prices. The OFHEO data offer detailed regional, state and metro level data, which will greatly facilitate our analysis of factors influencing housing prices.

[2] The Census and HUD also publish a price index of new single family houses under construction in two forms: Laspeyres-Price Index and Fisher-Price Deflator in monthly frequency. However, both only cover at the U.S. national level with no regional, state, or metro level data available.

[3] "General Information About Price Indexes", "Description of Price Index for New One-Family Houses Sold", http://www.census.gov/const/www/constpriceindex.html.

[4] Freddie Mac publishes a very similar index called the Conventional Mortgage Home Price Index (single unit residential), covering the U.S. (starting from 1970 Q1), 50 states plus D.C. (starting from 1970 Q1), 9 regions (starting from 1975 Q1) and selected metropolitan areas (starting from 1975 Q1). Freddie Mac also publishes a purchase-transaction only Conventional Mortgage Home Price Index series, but it does not cover states or metro areas. See http://www.freddiemac.com/finance/cmhpi/faq.htm.

2.2 Data

We use the metro-level OFHEO data according to the Metropolitan Statistical Areas (MSAs) defined by the Office of Management and Budget as of December 2003. We first pick all MSAs with a population larger than 1 million according to the latest census estimates[5]. There are 50 of them, 11 of which the census further divides into smaller Metropolitan Divisions, totalling 29. In 2004 Q3, the OFHEO discontinued the repeated sales price index of these 11 MSAs and instead started to report the data on the Metropolitan Divisions which make up the 11 MSAs. Some of these Metropolitan Divisions are very small. To prevent them from skewing the data, we exclude them from the sample. The final sample we use contains 62 series; each represents either a MSA or a Metropolitan Division within a large MSA, with a population exceeding 1 million. Himmelberg, Mayer and Sinai (2005) also use OFHEO metro-level data, including 46 metropolitan areas, in their studies. Alternatively, Negro and Otrok (2005) use the state-level OFHEO data. We prefer metro data to state data because the state data smooth out the differences across different metro areas within each state. In addition, we want our results to bear significance in analyzing the metro level housing markets, which have drawn the greatest attention from both the public and the media.

Although theoretically we cannot entirely discount other smaller MSAs' influences on the national and regional factors we try to extract, in practice, including more MSAs in our sample presents some problems. As illustrated in Kose, Otrok and Whiteman (2003), to prevent the relative size of the local economy or the local housing market from affecting the weight of each series in forming the factors, we use the data in log difference. This way, the model treats all series the same *a priori*. However, a large number of smaller MSAs may lead to overrepresentation. While we do not want to underweigh the influence of smaller MSAs, neither do we want to overweigh them. By any measure, it is the major metropolitan areas that account for most of the nation's wealth, consumption and investment. Moreover, it is also the major metropolitan areas that are most vulnerable in the event of a housing market correction in terms of the impact on domestic consumption and investment. We argue that our sample series are good representations of the national, regional and local housing markets. In fact, combined, our chosen MSAs and Metropolitan Divisions account for 51 percent of the U.S. total population and 65 percent of the U.S. urban population. They spread over 36 states in 9 census regions (Table 1).

Secondly, even with the current sample containing 62 series, we are already approaching the limit

[5] No. 24. Largest Metropolitan Statistical Areas–Population: 1990 to 2003, U.S. Census Bureau, Statistical Abstract of the United States: 2004-2005.

of the classical Maximum Likelihood estimation method employed in this paper (Stock and Watson, 1998). The benefit from including more MSAs is overshadowed by the complication arising from estimating an even larger system. An alternative is to use the Bayesian approach adopted by Kose, Otrok and Whiteman (2003) and Negro and Otrok (2005). However, their method has difficulty in handling large time variations.

Our sample spans from 1980 Q1 to 2005 Q1[6]. In comparison, Negro and Otrok (2005) use state-level data but the sample period is limited to only post-1986. Their choice of a shorter sample period is mainly because the Bayesian methodology they adopt cannot deal with the large time variations exhibited by the OFHEO indexes in the early 1980s. However, we believe the earlier sample period contains valuable information in shaping the underlying factors in the long term. The classical Maximum Likelihood estimation method we use can handle the earlier volatility with ease, because the noise in the series is simply captured by the idiosyncratic component. Negro and Otrok (2005) also argue for using the post 1986 sample because of credit market and monetary policy regime changes in the mid 1980s. However, as a pure statistical tool, the dynamic factor model does not hinge on the assumption of absence of regime change. In fact, adding the earlier period to the sample in the process of extracting the national, regional and local factors of housing price changes will serve to assess the effect of any possible regime shift, if necessary.

The OFHEO repeated sales price index is a nominal index. The X12 seasonality test performed on the 62 sample metro price indexes returns negative results in all but 2 cases (Table 2). For practical purposes, all are treated as with no seasonality. We transform them into real terms using the seasonally adjusted core PCE deflator, a preferred measure of long term general inflation. Because the raw data are indices, we take log difference to express the data in terms of real housing price changes. Finally we demean the data as we are more interested in measuring real housing price movements relative to the long term mean over the movement itself. This way, the factors are expressed as deviations from their means. Demeaning the data also reduce the number of unknown parameters by eliminating intercepts in both the observation equation and the state equation of the state space model we construct. This facilitates identification and estimation considering the large dimension of our state space model.

[6] The period between 1975 Q1 and 1979 Q4 is not included because the starting dates of the OFHEO repeat sales price indices vary across different MSAs. Here we avoid missing observations for convenience. In theory the Kalman filter technique we use can handle missing observations, though it complicates things in practice. We leave the case for future research to explore.

2.3 Stationarity and Principal Components

Before diving into the dynamic factor model, we need to evaluate the time series properties of the data. The Augmented Dickey-Fuller (ADF) test rejects the unit root null in the majority of the cases, as shown in Table 2. Because we use demeaned data, the ADF test is done with no intercept or trend. The lag length is based on the Schwarz Information Criterion. Considering the finite sample power and size of the ADF test, and also for convenience in practice, we regard all data series as stationary. As shown in the next subsection, the stationary property is useful in formulating parsimonious representations of the underlying processes of housing price movements in the form of a dynamic latent factor model.

Next, we analyze the comovements among the 62 sample housing price series from the principal component point of view. This is also built upon the data's stationary property we have established above. As illustrated by Stock and Watson (1998), the presumption of stationarity is built in implicitly in such models. Following Stock and Watson (1998, 1999, 2002a, 2002b), we assume that the housing price series i at time t (in log difference), denoted by $dp_{i,t}$, with $i = 1, 2, ..., 62$, can be expressed in the following factor representation:

$$dp_{i,t} = \omega_{i,1} \cdot f_{1,t} + \omega_{i,2} \cdot f_{2,t} + ... + \omega_{i,k} \cdot f_{k,t} + e_{i,t} \tag{1}$$

where $f_{j,t}$ stands for common factor j with $j = 1, 2, ..., k$, and $\omega_{i,j}$ for the loading of factor j into $dp_{i,t}$. $e_{i,t}$ is the idiosyncratic factor. By construction, the common factors are orthogonal to each other and to the idiosyncratic factors. However, the idiosyncratic factors can be correlated across different price series. This is known as the approximate factor model. Computation wise, Stock and Watson (1998) illustrate how to estimate the approximate factor model in its static form, which is equivalent to estimating the principal components. In our case, it is done by solving the eigenvalue problem of the correlation matrix of $dP = (dp_{1,t}, dp_{2,t}, ..., dp_{62,t})'$. The first principal component $f_{1,t}$ is calculated as a linear combination of $dp_{1,t}, dp_{2,t}, ..., dp_{62,t}$ with the loadings given by the eigenvector corresponding to the largest eigenvalue (subject to standardization), and $f_{2,t}$ with the loadings given by the eigenvector corresponding to the second largest eigenvalue, and so on and so forth. Bai and Ng (2002) develop criteria to determine the number of factors in approximate factor models. At this stage, we only want to get a rough idea of how to characterize the comovements among the data series using the underlying factors. We leave the exact representation of the factor model to the next subsection. Our results show the first 10 principal components account for 76.7 percent of the comovements among the 62 price series, with the 10th largest principal component accounting for 3.3 percent. This suggests the possibility of characterizing the comovements among the metro level housing price changes with a modest number of common factors.

2.4 Dynamic Latent Factor Model

To distinguish the different dynamics behind the metro housing price movements, we build a dynamic latent factor model, following Kose, Otrok and Whiteman (2003). For an individual metro area j within census region i, the housing price (log difference) is denoted by $dp_t^{i,j}$ at time t. It is assumed to be composed of three parts. The first part is due to f_t^{us}, a common factor that reflects the U.S. national housing price trend, with loading $\alpha_{i,j}$. The second part is due to f_t^i, a factor that is common among the metro areas in the same census region, with loading $\beta_{i,j}$. And the third part is due to $e_t^{i,j}$, the idiosyncratic factor of a particular metro area's housing price, with standardized loading 1.

$$dp_t^{i,j} = \alpha_{i,j} \cdot f_t^{us} + \beta_{i,j} \cdot f_t^i + e_t^{i,j} \tag{2}$$

$i = 1...9$, stands for the region, and $j = 1...n^i$ stands for the individual metro series within census region i, which encompasses n^i metro areas. We collect all $dp_t^{i,j}$ equations and write them into the observation equation of the state space model

$$Y_t = H \cdot S_t \tag{3}$$

with $Y_t = (dp_t^{1,1}, ..., dp_t^{1,n^1}, dp_t^{2,1}, ..., dp_t^{2,n^2}, ..., dp_t^{8,1}, ..., dp_t^{8,n^8}, dp_t^{9,1}, ..., dp_t^{9,n^9})'$

$S_t = (f_t^{us},\ f_t^1, ...\ f_t^9,\ e_t^{1,1}, ..., e_t^{1,n^1}, e_t^{2,1}, ..., e_t^{2,n^2}, ..., e_t^{8,1}, ..., e_t^{8,n^8}, e_t^{9,1}, ..., e_t^{9,n^9})'$ and H is set up according to (2).

We assume that the factors f_t^{us}, f_t^i and $e_t^{i,j}$ all follow AR(1) processes with autoregressive coefficients ρ_f^{us}, ρ_f^i and $\rho_e^{i,j}$, and innovations $\nu_{f,t}^{us}$, $\nu_{f,t}^i$ and $\nu_{e,t}^{i,j}$, respectively. We assume the factors are orthogonal to each other. The state equation is then simply

$$S_t = F \cdot S_{t-1} + V_t \tag{4}$$

with $V_t \sim N(0, Q)$ where Q is diagonal. The variances on the diagonal are denoted by $\sigma_{us,f}^2$, $\sigma_{i,f}^2$ and $\sigma_{e,i,j}^2$. This marks the difference from the approximate factor model discussed in the previous subsection, where the idiosyncratic factors are allowed to be correlated across different price series. F has all the AR(1) coefficients ρ_f^{us}, ρ_f^i and $\rho_e^{i,j}$ on the diagonal and zeros elsewhere. This parsimonious representation of the factors' dynamics helps to reduce the burden of estimating such a large system using the classical Maximum Likelihood estimation method. Considering the data's stationary property shown above, we expect the AR(1) coefficients to fall inside the unit circle[7]. Our results reported in section 3 below show that all estimated AR(1) coefficients indeed fall inside the unit circle.

Identification is achieved by assuming the variances corresponding to the national factor ($\sigma^2_{us,f}$) and the regional factors ($\sigma^2_{i,f}$) all take a value of 1 in the variance-covariance matrix Q, following Sargent and Sims (1977) and Stock and Watson (1989, 1993). In addition, because the factor loading coefficients and factors' signs cannot be separately determined, we can impose sign restrictions on either the factor loadings or the corresponding factors. However, this identification scheme doesn't affect the products of the factors and their loadings in calculating the factors' contributions to the housing price series. As we focus on analyzing a factor's property in term of its contribution to housing prices, we do not impose explicit restrictions. Instead, we simply take the signs given as part of the estimation results.

3 U.S. National, Regional and Metro-Specific Factors

3.1 Parameter Estimation

We use the classical Maximum Likelihood method to estimate the model, following Koopman, Shephard and Doornik (1999, 2002)[8]. Our multivariate series are converted to a univariate series and the Kalman update equations are applied to the resulting univariate series. This offers significant computational savings and avoids running into memory problems because of the large dimension of our state space model. The Kalman filter is started with the standard non-diffuse initialization. We test with different initial values for the unknown parameters in the optimization process. Convergence is achieved in all cases and the parameter estimates are very similar. Thus we have more confidence in reaching a global optimum rather than a local optimum. Table 3 shows the parameter estimates with standard errors. All the AR(1) coefficients fall inside the unit circle.

[7] In the event of an AR(1) coefficient falling out of the unit circle, the factor is nonstationary and we can deal with the problem in alternative ways such as introducing a unit root process as done in Balke and Wohar (2002).

[8] SsfPack 3.0 developed by Koopman, Shephard and Doornik (2002) is used. The likelihood function is adjusted by the sample size to avoid dependency on the sample size in the convergence criteria (Koopman, Shepard and Doornik, 1999)

3.2 National and Regional Factors

Using the estimated parameters, we can calculate the factors based on information available at the end of the sample period, i.e., the smoothed state vector $S_{t|T}$. Here we focus on analyzing the national factor and the regional factors. Figure 2 shows the national housing factor f_t^{us} we estimate in comparison with the OFHEO U.S. national index. The latter is also in log difference, transformed into the real term by using the core PCE deflator and demeaned. The difference between the two series is that the OFHEO U.S. national index is a weighted average using weights based on market sizes while the national factor we estimate is based on no ex ante information on weights. The two series are highly correlated with a correlation coefficient of 0.83[9]. However, the national factor f_t^{us} picks up a larger up movement in the mid 1980s, and a milder subsequent drop in the late 1980s than the OFHEO U.S. national index does. Judging from the OFHEO U.S. national index, the housing price increases have been consistently above the long term mean since late 1990s. Our estimated national housing factor f_t^{us} suggests the current housing boom didn't start until 2000 on the national level.

We also compare the estimated regional factors and the 9 OFHEO regional price indexes (all in log difference, transformed into real terms using the core PCE deflator and demeaned). The correlation is much lower, with the correlation coefficient ranging from 0.37 to 0.77 in absolute value, compared with the correlation between the national factor and the OFHEO national price index. This is not surprising, considering that the OFHEO regional price indexes contain not only regional, but also national and idiosyncratic components, while our estimated regional factors are designed to capture only the region-specific components of metro housing price movements.

Figure 3 shows the regional factors, some of which share similar historical trends. In fact, regional factors f_t^1 (New England) and f_t^2 (Mid-Atlantic) are closely correlated with a correlation coefficient of -0.88. Because we do not impose any sign restriction on the factors, it is the absolute value of the coefficient that matters. The loadings for f_t^1 are all negative, while the loadings for f_t^2 are all positive (Table 3). If we flip the sign of f_t^1, then the two factors are positively correlated. This suggests the two regions may be considered as one bigger region as far as housing price movements are concerned, experiencing a boom in the mid 1980s and a bust in the late 1980s.

Similarly, the regional factor f_t^4 (West-North-Central) is closely correlated with f_t^7 (West-South-

[9] As we have already shown earlier, the OFHEO repeated sales price index tends to over-estimate the price increases when compared with the Census-HUD constant quality price index. Since the national factor we estimate here is highly correlated with the OFHEO index, it is likely also upwardly biased in comparison with the Census-HUD constant quality price index.

Central) with a correlation coefficient of 0.62, and also with f_t^8 (Mountain) with a correlation coefficient of -0.78. And the regional factor f_t^7 (West-South-Central) is closely correlated with f_t^8 (Mountain) with a correlation coefficient of -0.78. Again, because we do not impose any sign restriction on the factors, it is the absolute values of the coefficients that matter. The loadings for f_t^4 and f_t^7 are all positive while loadings for f_t^8 are negative (Table 3). If we flip the sign of f_t^8, then the factors are positively correlated. This suggests these three regions may be considered as a combined region, containing many states in the Heartland of America. The regional factors all show a severe decline in the late 1980s and a recovery since the 1990s.

The regional factor f_t^3 (East-North-Central) remains remarkably flat during much of the sample period (loadings for f_t^3 are mostly negative from Table 3). This may not be surprising, as this region consists largely of so-called rust belt states, such as Illinois, Michigan and Ohio. The regional factor f_t^6 (East-South-Central) also shows relative stability (loadings are positive from Table 3). On the other hand, the regional factor f_t^5 (South-Atlantic) shows a steady upward trend, recovering since the 1990s (loadings are positive from Table 3).

The one that really stands out is the regional factor f_t^9 (Pacific), largely due to the unique business cycle of California (loadings are mostly positive from Table 3). It shows two drastic jumps. The recent one appears in the late 1990s and early 2000s, most likely related to the dot-com boom. An earlier jump appears in the late 1980s[10], drawing a sharp contrast with most other regions, which were in busts then. Lately, f_t^9 is poised to rise quickly again.

3.3 Variance Decomposition

In our state space model, we have assumed the innovations to the factors are not correlated. So, the unconditional variance-covariance matrix Q should be strictly diagonal. Then, the variance of the price series $dp_t^{i,j}$ can be decomposed into three parts, each due to the variance of a factor. According to (2), we have

$$Var(dp_t^{i,j}) = (\alpha_{i,j})^2 \cdot Var(f_t^{us}) + (\beta_{i,j})^2 \cdot Var(f_t^i) + Var(e_t^{i,j}) \tag{5}$$

However, in reality, the estimated variance-covariance matrix Q is conditional on the realized sample observations. Because of sampling errors, the resulting conditional covariances between f_t^{us} and f_t^i, between f_t^i and $e_t^{i,j}$, and between f_t^{us} and $e_t^{i,j}$ are not zeros. In order to calculate the variance decomposition correctly, we need to orthogonalize the estimated variance-covariance matrix

[10] The peak coincides with the 1989 San Francisco earthquake, which hit the Bay area on October 17, measuring 7.1 on the Richter scale.

corresponding to a particular housing price series. The correlation between factors matters for the ordering of factors in the orthogonalization. The majority of the correlation coefficients among factor pairs and across different housing price series are fairly small. However, there are 6 cases where the correlation between f_t^i and $e_t^{i,j}$ exceeds 0.2 in absolute value, with the maximum at 0.41. There are 11 cases where the correlation between f_t^{us} and f_t^i exceeds 0.2 in absolute value, with the maximum at 0.38. In contrast, there is no case where the correlation between f_t^{us} and $e_t^{i,j}$ exceeds 0.2 in absolute value. The results reported in Table 4 are based on ordering the national factor first, the regional factor second and the idiosyncratic factor last in the orthogonalization. Alternative orderings generally yield similar results, but are not reported.

We find that there is a distinctive national factor that has contributed to individual metropolitan's housing price movement. Over the sample period, on average, it accounts for 23.1 percent of the volatility in housing price movements. However, the national factor's contribution to volatility varies widely across the regions (Figure 4-1). On average, the national factor accounts for only 0.8 percent of the sample variance in the West-South-Central region ($i = 7$). But it accounts for 38.9 percent of the sample variance in the Pacific region ($i = 9$).

The regional factor accounts for 27.2 percent of the volatility in the individual metropolitan's housing price movement on average. At the census region level, the regional factor's contribution to the volatility varies from 20.2 percent in the South-Atlantic region ($i = 5$) to 45.6 percent in the New England region ($i = 1$), a much narrower range than in the case of the national factor (Figure 4-2).

Previous studies, such as Case and Wachter (2003) and McCarthy and Peach (2004), have emphasized that the U.S. housing market is comprised of many heterogeneous regional markets. Consistent with this heterogeneity, our findings show that the idiosyncratic factor does explain on average, the largest portion—49.7 percent—of the volatility in metro housing price movements. However, at the census region level, the idiosyncratic factor's contribution to the volatility is much more uneven (Figure 4-3), varying from 23.8 percent in the New England region ($i = 1$) to 66.7 percent in the East-South-Central region ($i = 6$).

3.4 The Current Housing Boom

To present a more thorough analysis of the factors' impacts on housing price movements, it is not enough to only look at the variance decomposition, we also need to look at the factors' contributions to the housing price movements according to (2). Particularly, we concentrate on the recent housing price changes in order to understand the relative significance of each factor in the current housing boom. Figure 5-1 to Figure 5-9 show the factor contributions to metro housing prices grouped by regions in recent years.

Based on our estimated national housing factor f_t^{us}, the current housing boom didn't start until 2000 on the national level. Since 2000 Q1, the national factor f_t^{us} has remained positive. Meanwhile, in all 62 metro series, the loading factors $\alpha_{i,j}$ are all positive (Table 3). So the national factor's contribution to all metro housing price series has been positive. In other words, the national factor has made positive contributions to housing prices in both the metro areas that have seen rapid price increases and those that have seen slower price increases (Figure 5-1 to Figure 5-9).

To measure this contribution formally, the simple ratio of $(\alpha_{i,j} \cdot f_t^{us})/dp_t^{i,j}$ wouldn't work because, as the denominator, not all the metro series $dp_t^{i,j}$ remain positive at all times after 2000 Q1. Instead, we calculate the accumulated national factor's contributions over the subsample period between 2000 Q1 and 2005 Q1. We also calculate accumulated housing price changes, which are positive for all metros during the same period. The ratio between the two series describes the importance of the national factor in explaining the recent run-up of housing prices relative to the long term means. We can also think of it as the ratio between the mean of the national factor's contribution $\alpha_{i,j} \cdot f_t^{us}$ and the mean of the price series $dp_t^{i,j}$. Figure 6 indicates that on average, the national factor f_t^{us} explains 87 percent of the housing price increase beyond the long term mean since 2000 Q1 across all metros[11]. This contrasts with our earlier finding based on variance decomposition. Although its average contribution to the volatility of housing price movements remains modest in the entire sample period, the national factor seems to account for much of the housing price increases across a large number of local markets in the more recent subsample period.

Another interesting finding is that, lately, some local markets have seen negative influences from the regional factor on metro housing price movements. These include all 4 metros in the New England region ($i = 1$) since 2002 Q3, all 9 in the Mid-Atlantic region ($i = 2$) since 2002 Q3, 6 of 8 in the East-North-Central region ($i = 3$) since 2001 Q4, all 3 in the West-North-Central region ($i = 4$) since 2004 Q1, and all 7 in the West-South-Central region ($i = 7$) since 2003 Q3. In addition, the regional factor's contribution only recently turned positive in 4 metros in the Mountain region ($i = 8$) in 2004 Q4 after being negative from 2002 Q2 to 2004 Q3. It also turned positive in 9 of

[11]Because the numerator, the national factor's contribution to each series—$\alpha_{i,j} \cdot f_t^{us}$—is positive for all i and j at all times after 2000 Q1, we can calculate an alternative measure by taking the ratio $(\alpha_{i,j} \cdot f_t^{us})/dp_t^{i,j}$ when it's positive and zero otherwise. We calculate the average of the resulting series, containing positive ratios and zeros, over the subsample period between 2000 Q1 and 2005 Q1. It is essentially a lower bound of the average ratio between the national factor's contribution and price series $dp_t^{i,j}$. By this measure, on average, the national factor f_t^{us} explains an even bigger portion of housing price increases.

10 in the Pacific region ($i = 9$) in 2004 Q2 after being negative from 2002 Q3 to 2004 Q1. In all these cases, however, the positive influence exerted by the national factor outweighs the negative contribution of the regional factor, resulting in still housing price gains above the long term means. On the other hand, the regional factor reinforces the national factor in contributing to the metro housing price increases in some local markets. Particularly, all 13 metros in the South-Atlantic region ($i = 5$) have seen persistent push on housing prices from the regional factor since 1998 Q3. The regional factor's contribution has been generally hovering around zero in the 4 metros in the East-South-Central region ($i = 6$).

Still, the idiosyncratic factors account for a sizeable portion of the recent housing price increases in some metropolitan areas, notably, in Fort Lauderdale-Pompano Beach-Deerfield Beach (var #25), Virginia Beach-Norfolk-Newport (#34), Oklahoma City (#48), Phonex-Mesa-Scottdale (#49), Las Vegas-Paradise (#51), Salt Lake City (#52), Riverside-San Bernadino-Ontario (#57) and Portland-Vancouver-Beaverton (#60).

Strong demand and low interest rates have likely played a role in recent fast housing price increases in these local markets, but their effect may have already been largely reflected in the common national and regional factors. Still, some argue that local housing markets may be affected by the variation of mortgage rates[12]. Others look into issues such as economic shocks, government regulation and resource constraint in local markets. For example, Shiller (2003) points out the finding of a sharp distinction between states due to the relative abundance of buildable land. Davis and Heathcote (2004, 2005) also show home price movements are dominated by swings in land, rather than structure, costs. Negro and Otrok (2005) combine the regional and idiosyncratic components based on state level data into a single local component and compare it with its counterpart in personal income (as a proxy for local business cycle) and try to explain the relationship between local housing movements and local business cycles.

Even with all these factors considered, it is hard not to think that at least part of the idiosyncratic factors can be attributed to local speculative bubbles. Indeed, the more the idiosyncratic factor accounts for a metro's housing price movements, the harder it seems to exclude the possibility of a local bubble. This brings us back to the same question—what portion of the idiosyncratic factors' contribution to housing price increases is justified by economic fundamentals and what is not? That is beyond the scope of this paper.

[12] "Mortgage Rates Vary Widely by State," Wall Street Journal, June 14, 2005. Negro and Otrok (2005) also touch on this, pointing out the segmentation in the mortgage markets up until the mid-90s.

4 National Housing Factor in Connection with Other Economic Indicators

Past studies have related housing prices to other economic indicators. Generally speaking, in the long run, housing prices depend on the cost of construction, land availability and the quality of existing stock of homes on the supply side. On the demand side, prices depend on national income, the average discount rate and population growth (possibly in large part due to immigration). The recent U.S. housing boom has highlighted two salient issues: the impact on consumption from housing prices and the interaction between monetary policy and the housing market.

Case, Quigley and Shiller (2005) demonstrate that variations in housing market wealth have important effects on consumption. In their view, changes in housing prices should be considered to have a larger and more important impact than changes in stock market prices in influencing household consumption in the U.S. and in other developed countries. Some believe that the current U.S. housing boom has in fact bolstered consumption and largely prevented the economy from sliding into a more serious recession after the NASDAQ bubble burst in the early 2000s. Particularly, housing price gains sparked cash-out refinances and home equity borrowing, boosting consumer spending.

The condition of the housing market has deep implications for the U.S. monetary policy (Bernanke and Gertler 2000 and 2001, Bernanke 2002, Zhu 2003, Aoki, Proudman and Vlieghe 2004). So far, the Federal Reserve, and many other central banks in the world, have focused on a conventional form of inflation defined in terms of goods and services price increases. By this measure, inflation has remained low in the U.S., thus helping the Fed to maintain a measured pace of raising interest rates in the current cycle. This has prompted worries that the extra liquidity has spilled, and possibly still is spilling, over into asset prices, particularly in the housing market.

In this section, we try to shed light on some of the forces possibly contributing to U.S. housing market movements. We focus on analyzing the connection between our estimated national housing factor and other economic indicators with national scopes. Our chosen indicators fall into five major categories: money and interest rates, population, the real economy, general prices and asset prices. Table 5 shows the detailed definitions and transformations of the variables. Note that we define the real fed funds rate and the real mortgage rate based on annualized realized core PCE inflation to avoid handling the ex-ante inflation expectations issue. We also define real asset price appreciation using realized core PCE inflation. All variables are demeaned to maintain consistency with our estimated national housing factor, which is interpreted as relative to its long term mean.

4.1 Correlation Analysis

First, we analyze the simple correlation relationships. The correlograms (Figure 7) show the correlations between f_t^{us} and the lags and leads of the chosen variables based on the entire sample from 1980 Q1 to 2005 Q1. We take the maximum lag (lead) length as 16, that is, four years. Table 6 reports the Q-statistics based on increasing lags and leads with an increment of 4.

f_t^{us} is positively correlated with lagged $M2$ (significant between lag 5 and 8), suggesting a monetary expansion does seem to coincide with subsequent housing price increases. Furthermore, f_t^{us} is negatively correlated with both lags and leads of $FFED$ and FCM (significant at lag 4 and lead 4)[13]. It is also negatively correlated with both lags and leads of $RFFED$ and $RFCM$ (significant at lag 4 and lead 4).

POP is correlated with f_t^{us}, albeit negatively in both lags and leads (significant at lag 4 and lead 4). It turns out that population growth has actually slowed down since the 1990s while housing prices have accelerated in contrast. Thus, despite popular belief, the current housing boom doesn't appear to be closely tied with population growth.

On the real economy side, $RGDP$ is positively correlated with f_t^{us} between lag 4 and lead 4. However, the correlation is marginally significant with a p-value of 0.07 (not included in Table 6). Further lags of $RGDP$ are positively correlated with f_t^{us}, but the correlation is only significant when the lags are long enough (exceeding 12). Meanwhile, further leads of $RGDP$ are significantly negatively correlated with f_t^{us} if the leads are long enough (exceeding 8). Similarly, lagged RDI is only significantly positively correlated with f_t^{us} when the lag is long enough (exceeding 12); the lead of RDI is significantly negatively correlated with f_t^{us} if the lead is long enough (exceeding 12). $UNEMP$ is negatively correlated in both lags and leads with f_t^{us} (significant at lag 4 and lead 4). So it seems that if there are positive effects from real economic or income growth on the national housing factor, they likely come with considerable lags, while the effects from employment conditions are more timely. We also find that $RPCE$ is significantly positively correlated at lag 4 and negatively correlated at lead 12 with f_t^{us}.

Both lags and leads of the two general inflationary measures—DEF and $PCEC$—are significantly negatively correlated (at lag 4 and lead 4) with f_t^{us}. These sound reasonable—as the national housing factor is based on the real price, it is likely to move in the opposite direction as inflation does. Asset price wise, neither $DJ30$ nor $SP500$ shows any significant correlation with f_t^{us}. The same applies to $RDJ30$ and $RSP500$, but are not reported in Table 6.

[13]Arguably, conventional mortgage rates have become less important in the current housing boom as borrowers increasingly jump from fixed-rate loans into a growing menu of adjustable rate alternatives.

4.2 Causality Analysis

To go beyond simple correlations, we need to understand more about the causal relationships between the national housing factor f_t^{us} and the other economic indicators. Thus we conduct a series of causality tests, exploring whether these economic indicators can help to explain the movements of f_t^{us} beyond what its own history could do, or vice versa. We narrow the indicators down to four categories: money and interest rates, population, the real economy and asset prices.

First, we regress the national housing factor f_t^{us} on its own lags and lags of a chosen economic indicator, denoted by x_t, according to

$$f_t^{us} = a^f + \sum_{i=1}^{l} b_i^f \cdot f_{t-i}^{us} + \sum_{i=1}^{l} c_i^x \cdot x_{t-i} + \varepsilon_t^f \qquad (6)$$

Table 7 reports the joint significance level of lags of f_t^{us} (LHS) and that of lags of x_t (RHS). Table 8 reports results in the other direction of the Granger causality test based on regressing a chosen individual indicator x_t (LHS) on its own lags and lags of f_t^{us} (RHS), according to

$$x_t = a^x + \sum_{i=1}^{l} b_i^x \cdot x_{t-i} + \sum_{i=1}^{l} c_i^f \cdot f_{t-i}^{us} + \varepsilon_t^x \qquad (7)$$

We use the entire sample from 1980 Q1 to 2005 Q1. We pick the lag length l of 16, as was done in the earlier correlation analysis. We present only the cases with a clear direction of Granger causality. Under $l = 16$, only RDI is shown to Granger cause f_t^{us}. Looking at individual lags, lag 9 and lag 12 are both significant with a positive coefficient c_i^x. This suggests real disposable income growth helps to explain subsequent increases in the national housing price, confirming the correlation analysis.

Based on the finding that most significant correlations between f_t^{us} and other indicators occur with lags and leads under 8, we also run the test with the alternative lag length of 8. One benefit of doing so is that we lose fewer observations in the early sample period[14]. Under $l = 8$, $M2$ Granger causes f_t^{us}, albeit with marginal significance. Looking at individual lags, only lag 1 of $M2$ is marginally significant with a positive coefficient c_i^x, suggesting a monetary expansion may have some positive effect on the national housing price factor. This again confirms the correlation analysis.

On the other hand, under $l = 8$, f_t^{us} is shown to Granger cause RDI, in the opposite direction of the case under $l = 16$. Looking into the details, lag 4 of f_t^{us} is significant with a positive coefficient

[14] We can also pick some optimal lag length based on the Akaike or Schwarz Information Criterion, which offers a more parsimonious representation. However, as the purpose here is to see if there is a causal relationship and if so, what direction it goes, we are less worried about the fitting.

c_i^f, while lag 5 of f_t^{us} is significant with a negative coefficient c_i^f. It is not clear what effects f_t^{us} has on real disposable income just based on this regression. In addition, earlier analysis has shown that the correlation between RDI and f_t^{us} is only significant with a lead exceeding 12. So, the finding that RDI Granger causes f_t^{us} under $l = 16$ sounds more reasonable.

Under $l = 8$, f_t^{us} is also shown to marginally Granger cause $RGDP$. Lag 1 and lag 3 of $RGDP$ are both significant with a positive coefficient c_i^f, suggesting past f_t^{us} increases somehow may have explanatory power of current real GDP growth. Considering that $RGDP$ is marginally positively correlated with f_t^{us} between lag 4 and lead 4, this may not be surprising.

Last, under $l = 8$, f_t^{us} is shown to Granger cause $RFCM$. However, with c_i^f significantly negative for lag 1 and significantly positive for lag 4 of f_t^{us}, it is not clear what effects f_t^{us} has on real mortgage rates based on only this regression.

4.3 Summary

We draw some tentative conclusions based on the correlation and causality analysis. Monetary policy does have some influence on the national housing price factor f_t^{us}. Money growth ($M2$) is positively correlated in lags with, and Granger causes (albeit marginally) f_t^{us}. Nominal and real interest rates ($FFED$, FCM, $RFFED$ and $RFCM$) are negatively correlated with f_t^{us}.

On the real economy side, real GDP growth ($RGDP$) is positively correlated with f_t^{us}. f_t^{us}'s historical values may contain some information on $RGDP$ too. Real personal income growth (RDI) helps to explain subsequent increases in the national housing price, but only in long lags. Unemployment ($UNEMP$) is negatively correlated with f_t^{us}. Real personal consumption expenditure ($RPCE$) is positively correlated with f_t^{us}. However, past values of f_t^{us} do not seem to help explain current $RPCE$. The national housing price increase doesn't appear to be closely tied with population growth. In fact, f_t^{us} and POP are negatively correlated.

General inflation (DEF and $PCEC$) is negatively correlated with f_t^{us}, while stock price appreciation ($DJ30/RDJ30$ and $SP500/RSP500$) doesn't seem to have any effect on f_t^{us}.

Again, these tentative conclusions are based on *only* the correlation and causality analysis performed so far. It is entirely possible that the relationship between a particular indicator and the national housing price factor f_t^{us} is more complicated in nature and involves many other variables at the same time. We will pursue that avenue in future research.

5 Conclusion

By decomposing the housing prices in major metropolitan areas into national, regional, and metro-specific idiosyncratic factors, we can achieve a better understanding of the underlying dynamics of the U.S. housing market. Historically, the national factor contributes about one-fourth of metro housing price volatility. The regional factor accounts for another one-fourth and the idiosyncratic factor explains about half of housing price fluctuations. However, during the current housing boom starting from year 2000, our estimated national housing factor seems to account for the major portion of housing price increases. The regional factor has exerted negative influence on housing prices in a fairly large number of metros lately. Some metro housing markets are also heavily influenced by the local factor.

We also explore connections between the national housing factor and other economic indicators including U.S. monetary policy, population growth, real economic activity, general inflation and other asset prices. Particularly, we find monetary expansion does seem to affect national home price appreciation. Increases in the pace of real economic activity are positively correlated with housing prices, while stock price appreciation doesn't have any apparent link with housing price gains. However, past housing price increases do not seem to help explain consumption growth. Despite popular belief, national housing price movements do not appear to be closely tied with population growth. In fact, they are found to be negatively correlated. These are tentative results based on limited correlation and causality analysis. To draw more concrete conclusions, more elaborate modeling of the interactions between the national housing price factor and various economic variables is needed. Future research is also called for to analyze in greater detail regional and idiosyncratic factors' connection with various economic variables at regional and local levels.

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Table 1: Metro-level OFHEO Data

Var #	Variable	i	Region	j	Metro	State
1	BOQ	1	New England	1	Boston-Quincy	MA
2	CNF	1		2	Cambridge-Newton-Framingham	MA
3	PRI	1		3	Providence-New Bedford-Fall River-Warwick	RI
4	HTF	1		4	Hartford-West Hartford-East Hartford	CT
5	EDI	2	Mid-Atlantic	1	Edison	NJ
6	NSU	2		2	Nassau-Suffolk	NY
7	NUN	2		3	Newark-Union	NJ
8	NYW	2		4	New York-Wayne-White Plains	NY
9	CDN	2		5	Camden	NJ
10	PHI	2		6	Philadelphia	PA
11	PIT	2		7	Pittsburgh	PA
12	BUF	2		8	Buffalo-Niagra Falls	NY
13	ROH	2		9	Rochester	NY
14	CNJ	3	East-North-	1	Chicago-Naperville-Joliet	IL
15	DLD	3	Central	2	Detroit-Livonia-Dearborn	MI
16	WFT	3		3	Warren-Farmington Hills-Troy	MI
17	CVL	3		4	Cleveland-Elyria-Mentor	OH
18	CTI	3		5	Cincinnati-Middletown	OH-KY-IN
19	COL	3		6	Columbus	OH
20	IND	3		7	Indianapolis	IN
21	MWK	3		8	Milwaukee-Waukesha-West Allis	WI
22	MSP	4	West-North-	1	Minneapolis-St Paul-Bloomington	MN
23	STL	4	Central	2	St. Louis	MO-IL
24	KNC	4		3	Kansas City	MO-KS
25	FPD	5	South-Atlantic	1	Fort Laudrdle-Pompano Bch-Deerfld Bch	FL
26	MMK	5		2	Miami-Miami Beach-Kendall	FL
27	WBB	5		3	W Palm Beach-Boca Raton-Boynton Bch	FL
28	BFG	5		4	Bethesda-Frederick-Gaithersburg	MD
29	WAA	5		5	Washington-Arlington-Alexandria	DC
30	ATL	5		6	Atlanta-Sandy Springs-Marietta	GA

Table 1 (continued)

Var #	Variable	i	Region	j	Metro	State
31	BTM	5	South-Atlantic	7	Baltimore-Towson	MD
32	TMA	5		8	Tampa-St Petersburg-Clearwater	FL
33	ORL	5		9	Orlando	FL
34	NFK	5		10	Virginia Beach-Norfolk-Newport News	VA-NC
35	CGR	5		11	Charlotte-Gastonia-Concord	NC-SC
36	JAX	5		12	Jacksonville	FL
37	RCP	5		13	Richmond	VA
38	NVL	6	East-South-	1	Nashville-Davidson-Murfreesboro	TN
39	MPH	6	Central	2	Memphis	TN-MS-AR
40	LOI	6		3	Louisville	KY-IN
41	BIR	6		4	Birmingham-Hoover	AL
42	DPI	7	West-South-	1	Dallas-Plano-Irving	TX
43	FWR	7	Central	2	Fort Worth-Arlington	TX
44	HTN	7		3	Houston-Baytown-Suger Land	TX
45	SAT	7		4	San Antonio	TX
46	NOR	7		5	New Orleans-Metairie-Kenner	LA
47	AUS	7		6	Austin-Round Rock	TX
48	OKC	7		7	Oklahoma City	OK
49	PHX	8	Mountain	1	Phoenix-Mesa-Scottdale	AZ
50	DNV	8		2	Denver-Aurora	CO
51	LSV	8		3	Las Vegas-Paradise	NV
52	SLC	8		4	Salt Lake City	UT
53	LLG	9	Pacific	1	Los Angeles-Long Beach-Glendale	CA
54	SAI	9		2	Santa Ana-Anaheim-Irvine	CA
55	OFH	9		3	Oakland-Fremont-Hayward	CA
56	SSR	9		4	San Francisco-San Mateo-Redwd Cty	CA
57	RSB	9		5	Riverside-San Bernadino-Ontario	CA
58	SBE	9		6	Seattle-Bellevue-Everett	WA
59	SDI	9		7	San Diego-Carlsbad-San Marcos	CA
60	POR	9		8	Portland-Vancouver-Beaverton	OR-WA

Table 1 (continued)

Var #	Variable	i	Region	j	Metro	State
61	SAC	9	Pacific	9	Sacramento-Arden-Arcade-Roseville	CA
62	SSC	9		10	San Jose-Sunnyvale-Santa Clara	CA

Table 2: Unit Root and Seasonality Tests

Var #	i (Region)	j (Metro)	Variable	t-Statistic	p-value	Seasonality
1	1	1	BOQ	-1.884014	0.0571	N
2	1	2	CNF	-1.847978	0.0618	N
3	1	3	PRI	-3.101078	0.0022	N
4	1	4	HTF	-3.226821	0.0015	N
5	2	1	EDI	-1.829482	0.0643	N
6	2	2	NSU	-1.233954	0.1983	N
7	2	3	NUN	-1.955634	0.0487	N
8	2	4	NYW	-1.855755	0.0608	N
9	2	5	CDN	-5.394219	0.0000	N
10	2	6	PHI	-2.184618	0.0285	N
11	2	7	PIT	-9.682567	0.0000	N
12	2	8	BUF	-9.347895	0.0000	N
13	2	9	ROH	-7.517401	0.0000	N
14	3	1	CNJ	-2.512600	0.0123	N
15	3	2	DLD	-2.646274	0.0085	N
16	3	3	WFT	-3.705404	0.0003	N
17	3	4	CVL	-2.975108	0.0033	N
18	3	5	CTI	-5.810164	0.0000	N
19	3	6	COL	-3.477165	0.0007	N
20	3	7	IND	-2.135379	0.0321	N
21	3	8	MWK	-2.332373	0.0198	N
22	4	1	MSP	-2.121866	0.0332	N
23	4	2	STL	-3.550930	0.0005	N
24	4	3	KNC	-1.072811	0.2545	N
25	5	1	FPD	-0.332685	0.5629	N
26	5	2	MMK	-3.562538	0.0005	N
27	5	3	WBB	-0.718938	0.4028	N
28	5	4	BFG	-1.482333	0.1287	N
29	5	5	WAA	-1.036640	0.2685	N
30	5	6	ATL	-2.825868	0.0051	N

Table 2 (continued)

Var #	i (Region)	j (Metro)	Variable	t-Statistic	p-value	Seasonality
31	5	7	BTM	-1.278315	0.1843	N
32	5	8	TMA	-0.092336	0.6493	N
33	5	9	ORL	-2.953640	0.0035	N
34	5	10	NFK	-0.701442	0.4105	N
35	5	11	CGR	-15.02330	0.0000	N
36	5	12	JAX	0.228769	0.7505	N
37	5	13	RCP	-1.484462	0.1282	N
38	6	1	NVL	-3.162175	0.0019	N
39	6	2	MPH	-5.421363	0.0000	N
40	6	3	LOI	-4.455827	0.0000	N
41	6	4	BIR	-5.219870	0.0000	N
42	7	1	DPI	-2.471856	0.0137	N
43	7	2	FWR	-1.898137	0.0554	N
44	7	3	HTN	-2.556808	0.0109	N
45	7	4	SAT	-8.459864	0.0000	N
46	7	5	NOR	-3.339264	0.0010	N
47	7	6	AUS	-3.018558	0.0029	N
48	7	7	OKC	-2.895236	0.0042	N
49	8	1	PHX	-2.335096	0.0196	N
50	8	2	DNV	-1.746846	0.0766	Y
51	8	3	LSV	-2.654953	0.0083	N
52	8	4	SLC	-2.382820	0.0173	N
53	9	1	LLG	-3.329506	0.0011	N
54	9	2	SAI	-2.526446	0.0119	N
55	9	3	OFH	-3.777277	0.0002	N
56	9	4	SSR	-4.168495	0.0001	N
57	9	5	RSB	-3.046136	0.0026	N
58	9	6	SBE	-8.598475	0.0000	N
59	9	7	SDI	-2.931628	0.0037	N
60	9	8	POR	-2.687838	0.0076	N

Table 2 (continued)

Var #	i (Region)	j (Metro)	Variable	t-Statistic	p-value	Seasonality
61	9	9	SAC	-3.451204	0.0007	N
62	9	10	SSC	-3.352802	0.0010	Y

Note: for seasonality test, "N" stands for no obvious seasonality, "Y" otherwise.

Table 3: Parameter Estimates

#	i	j	$\alpha_{i,j}$	$\beta_{i,j}$	$\rho_e^{i,j}$	$\sigma_{e,i,j}$
1	1	1	0.00901 (0.00133)	-0.00797 (0.00110)	-0.27052 (0.14108)	-0.00662 (0.00079)
2	1	2	0.00757 (0.00129)	-0.00790 (0.00110)	-0.19151 (0.14732)	0.00695 (0.00076)
3	1	3	0.01409 (0.00156)	-0.00474 (0.00086)	-0.42236 (0.10061)	0.01690 (0.00135)
4	1	4	0.01180 (0.00147)	-0.00441 (0.00089)	-0.14098 (0.11305)	0.01562 (0.00118)
5	2	1	0.01140 (0.00136)	0.00718 (0.00112)	-0.10122 (0.13424)	0.00796 (0.00069)
6	2	2	0.00806 (0.00140)	0.00811 (0.00114)	0.14324 (0.13611)	0.01010 (0.00084)
7	2	3	0.01042 (0.00133)	0.00750 (0.00115)	-0.06661 (0.12713)	0.00653 (0.00064)
8	2	4	0.00961 (0.00130)	0.00783 (0.00113)	-0.14633 (0.14367)	0.00575 (0.00065)
9	2	5	0.01009 (0.00129)	0.00087 (0.00078)	-0.25784 (0.09858)	0.01757 (0.00130)
10	2	6	0.00982 (0.00095)	0.00231 (0.00057)	-0.20890 (0.11808)	0.00814 (0.00065)
11	2	7	0.00455 (0.00130)	0.00020 (0.00099)	-0.02666 (0.10231)	0.01832 (0.00130)
12	2	8	0.00613 (0.00111)	0.00012 (0.00078)	-0.12306 (0.10131)	0.01577 (0.00114)
13	2	9	0.00416 (0.00104)	0.00301 (0.00082)	-0.17434 (0.09913)	0.01478 (0.00105)
14	3	1	0.00674 (0.00099)	-0.00158 (0.00129)	0.09439 (0.11809)	0.01090 (0.00081)
15	3	2	0.00416 (0.00169)	-0.01984 (0.00207)	-0.15205 (0.29782)	-0.00629 (0.00327)
16	3	3	0.00400 (0.00151)	-0.01704 (0.00159)	-0.56204 (0.12401)	0.00998 (0.00149)
17	3	4	0.00327 (0.00094)	-0.00352 (0.00186)	-0.36423 (0.09565)	0.01587 (0.00117)
18	3	5	0.00288 (0.00078)	-0.00070 (0.00090)	0.53038 (0.10544)	0.00747 (0.00053)
19	3	6	0.00289 (0.00093)	0.00082 (0.00157)	0.16529 (0.12611)	0.01145 (0.00082)
20	3	7	0.00246 (0.00073)	-0.00536 (0.00104)	-0.40428 (0.10028)	0.01066 (0.00077)
21	3	8	0.00581 (0.00124)	0.00108 (0.00201)	0.01823 (0.12603)	0.01568 (0.00113)
22	4	1	0.00446 (0.00122)	0.00417 (0.00206)	-0.14087 (0.11609)	-0.01100 (0.00108)
23	4	2	0.00469 (0.00107)	0.00346 (0.00175)	-0.28458 (0.12086)	0.01146 (0.00105)
24	4	3	0.00314 (0.00115)	0.00380 (0.00179)	-0.57015 (0.08574)	0.01468 (0.00114)
25	5	1	0.00743 (0.00136)	0.00518 (0.00230)	0.17314 (0.13866)	0.01464 (0.00108)
26	5	2	0.00561 (0.00210)	0.01661 (0.00299)	-0.32191 (0.10048)	0.02498 (0.00206)
27	5	3	0.00916 (0.00139)	0.00781 (0.00149)	0.21702 (0.11152)	0.01162 (0.00094)
28	5	4	0.01026 (0.00115)	0.00393 (0.00147)	-0.19871 (0.10552)	0.01246 (0.00095)
29	5	5	0.01016 (0.00112)	0.00629 (0.00126)	-0.00595 (0.13101)	0.00780 (0.00071)
30	5	6	0.00189 (0.00071)	0.00362 (0.00100)	-0.01227 (0.10417)	0.00915 (0.00066)

Table 3 (continued)

#	i	j	$\alpha_{i,j}$	$\beta_{i,j}$	$\rho_e^{i,j}$	$\sigma_{e,i,j}$
31	5	7	0.00868 (0.00089)	0.00344 (0.00105)	-0.33701 (0.10589)	0.00838 (0.00067)
32	5	8	0.00440 (0.00143)	0.01239 (0.00173)	-0.44213 (0.10280)	0.01580 (0.00133)
33	5	9	0.00369 (0.00133)	0.01289 (0.00153)	-0.38450 (0.11549)	0.00958 (0.00109)
34	5	10	0.00717 (0.00118)	0.00236 (0.00164)	0.22596 (0.11718)	0.01200 (0.00087)
35	5	11	0.00179 (0.00068)	0.00259 (0.00110)	-0.42581 (0.09085)	0.01239 (0.00088)
36	5	12	0.00322 (0.00117)	0.00984 (0.00145)	-0.38252 (0.10034)	0.01358 (0.00109)
37	5	13	0.00540 (0.00087)	0.00446 (0.00115)	-0.53765 (0.08661)	0.01335 (0.00096)
38	6	1	0.00058 (0.00122)	0.01369 (0.00286)	-0.63205 (0.21886)	0.01004 (0.00373)
39	6	2	0.00197 (0.00118)	0.00021 (0.00258)	-0.49999 (0.08725)	0.02429 (0.00171)
40	6	3	0.00211 (0.00082)	0.00527 (0.00138)	-0.27151 (0.10580)	0.01194 (0.00096)
41	6	4	0.00282 (0.00135)	0.01047 (0.00208)	-0.23992 (0.10605)	0.01784 (0.00148)
42	7	1	0.00241 (0.00108)	0.00669 (0.00092)	-0.30908 (0.13294)	0.00652 (0.00070)
43	7	2	0.00315 (0.00105)	0.00619 (0.00090)	-0.27071 (0.11191)	0.00721 (0.00065)
44	7	3	0.00326 (0.00161)	0.00587 (0.00147)	0.14734 (0.10596)	0.01642 (0.00121)
45	7	4	0.00408 (0.00290)	0.00980 (0.00268)	0.08349 (0.10145)	0.03256 (0.00235)
46	7	5	0.00462 (0.00152)	0.00693 (0.00133)	-0.14087 (0.10740)	0.01593 (0.00121)
47	7	6	0.00151 (0.00217)	0.01100 (0.00195)	-0.39073 (0.09493)	0.02459 (0.00185)
48	7	7	0.00143 (0.00151)	0.00708 (0.00132)	-0.41503 (0.10001)	0.01893 (0.00144)
49	8	1	0.00706 (0.00166)	-0.00362 (0.00114)	0.01457 (0.11003)	0.01704 (0.00128)
50	8	2	0.00156 (0.00128)	-0.00453 (0.00114)	-0.21836 (0.14220)	-0.00916 (0.00104)
51	8	3	0.00944 (0.00243)	-0.00259 (0.00140)	-0.13783 (0.09982)	0.03327 (0.00238)
52	8	4	0.00034 (0.00152)	-0.00361 (0.00108)	-0.14683 (0.10773)	0.01889 (0.00141)
53	9	1	0.01206 (0.00121)	0.00326 (0.00104)	0.67865 (0.09502)	0.00723 (0.00074)
54	9	2	0.01047 (0.00124)	0.00464 (0.00106)	0.61186 (0.09167)	0.00821 (0.00068)
55	9	3	0.00766 (0.00120)	0.00865 (0.00087)	-0.18174 (0.17276)	0.00429 (0.00064)
56	9	4	0.00727 (0.00155)	0.00871 (0.00132)	0.39936 (0.11464)	0.01024 (0.00079)
57	9	5	0.01045 (0.00162)	0.00537 (0.00129)	0.17365 (0.10338)	0.01618 (0.00117)
58	9	6	0.00453 (0.00164)	0.00275 (0.00145)	0.02945 (0.10297)	0.02209 (0.00156)
59	9	7	0.01167 (0.00145)	0.00510 (0.00103)	-0.24685 (0.10004)	0.01738 (0.00127)
60	9	8	0.00206 (0.00196)	-0.00188 (0.00180)	0.24293 (0.09915)	0.02285 (0.00162)

Table 3 (continued)

#	i	j	$\alpha_{i,j}$	$\beta_{i,j}$	$\rho_e^{i,j}$	$\sigma_{e,i,j}$
61	9	9	0.00914 (0.00174)	0.00723 (0.00159)	0.52148 (0.09332)	0.01382 (0.00101)
62	9	10	0.00580 (0.00147)	0.01153 (0.00117)	0.74371 (0.08610)	0.00654 (0.00090)

Note: the reported value for $\sigma_{e,i,j}$ is the corresponding element in the Choleski decomposition of the variance-covariance matrix Q.

Table 3 (continued)

ρ_f^{us}	0.74610 (0.07001)
ρ_f^1	0.90399 (0.04535)
ρ_f^2	0.86747 (0.05805)
ρ_f^3	0.20028 (0.13457)
ρ_f^4	0.86220 (0.12059)
ρ_f^5	0.34199 (0.13517)
ρ_f^6	0.19608 (0.17550)
ρ_f^7	0.80052 (0.07708)
ρ_f^8	0.92641 (0.04407)
ρ_f^9	0.81514 (0.06329)

Table 4: Variance Decomposition

#	i	j	f_t^{us}	f_t^i	$e_t^{i,j}$
1	1	1	0.2087	0.7254	0.0659
2	1	2	0.1430	0.7786	0.0785
3	1	3	0.4579	0.1364	0.4058
4	1	4	0.4156	0.1836	0.4008
5	2	1	0.4745	0.4156	0.1099
6	2	2	0.2109	0.5922	0.1969
7	2	3	0.4270	0.5003	0.0727
8	2	4	0.3664	0.5793	0.0543
9	2	5	0.4223	0.0005	0.5772
10	2	6	0.7059	0.0736	0.2206
11	2	7	0.1262	0.0003	0.8735
12	2	8	0.2631	0.0003	0.7366
13	2	9	0.1169	0.1326	0.7505
14	3	1	0.4674	0.0174	0.5152
15	3	2	0.0978	0.8810	0.0212
16	3	3	0.0752	0.6970	0.2278
17	3	4	0.0696	0.0176	0.9128
18	3	5	0.2452	0.0852	0.6696
19	3	6	0.1215	0.0003	0.8782
20	3	7	0.0937	0.1273	0.7790
21	3	8	0.2404	0.0038	0.7558
22	4	1	0.1899	0.3612	0.4489
23	4	2	0.2045	0.2424	0.5531
24	4	3	0.0465	0.1904	0.7631
25	5	1	0.3226	0.1373	0.5401
26	5	2	0.0487	0.3842	0.5671
27	5	3	0.4642	0.2101	0.3257
28	5	4	0.5843	0.0353	0.3804
29	5	5	0.7092	0.1386	0.1522
30	5	6	0.0771	0.1578	0.7651

Table 4 (continued)

#	i	j	f_t^{us}	f_t^i	$e_t^{i,j}$
31	5	7	0.6561	0.0630	0.2809
32	5	8	0.0897	0.3133	0.5970
33	5	9	0.0950	0.6788	0.2262
34	5	10	0.4066	0.0504	0.5430
35	5	11	0.0428	0.0691	0.8881
36	5	12	0.0800	0.3504	0.5696
37	5	13	0.2381	0.0414	0.7204
38	6	1	0.0030	0.7165	0.2805
39	6	2	0.0127	0.0167	0.9706
40	6	3	0.0578	0.1543	0.7879
41	6	4	0.0496	0.3217	0.6287
42	7	1	0.0028	0.7675	0.2297
43	7	2	0.0068	0.6922	0.3010
44	7	3	0.0028	0.2463	0.7509
45	7	4	0.0000	0.1936	0.8064
46	7	5	0.0176	0.3451	0.6374
47	7	6	0.0163	0.3411	0.6427
48	7	7	0.0102	0.2490	0.7408
49	8	1	0.1268	0.2332	0.6399
50	8	2	0.0123	0.6820	0.3057
51	8	3	0.1158	0.0418	0.8424
52	8	4	0.0158	0.2209	0.7633
53	9	1	0.7363	0.1166	0.1471
54	9	2	0.6248	0.1856	0.1896
55	9	3	0.4523	0.5190	0.0287
56	9	4	0.4027	0.3641	0.2331
57	9	5	0.4763	0.1203	0.4034
58	9	6	0.0994	0.0392	0.8614
59	9	7	0.4968	0.0776	0.4256
60	9	8	0.0124	0.0128	0.9748

Table 4 (continued)

#	i	j	f_t^{us}	f_t^i	$e_t^{i,j}$
61	9	9	0.3770	0.1726	0.4503
62	9	10	0.2121	0.6427	0.1452

Table 5: Economic Indicators in Connection with the National Housing Factor

Category	Variable	Definition	Transformation
Money &	M2	Money Stock: M2 (SA)	log difference
Interest Rate	FFED	Federal Funds Rate (Effective)	
	FCM	Conventional 30-Year Mortgage Rate	
	RFFED	Real Federal Funds Rate = FFED – 400*PCEC	
	RFCM	Real Mortgage Rate = FCM – 400*PCEC	
Population	POP	Civilian Population (All Ages, SA)	log difference
Real	RGDP	Real GDP (SAAR)	log difference
Economy	RDI	Real Disposable Personal Income (SAAR)	log difference
	UNEMP	Civilian Unemployment Rate (Age 16+, SA)	
	RPCE	Real Personal Consumption Expenditure (SAAR)	log difference
General Price	DEF	Implicit GDP Price Deflator (SA)	log difference
	PCEC	Chain Price Index for Core PCE (SA)	log difference
Asset Price	DJ30	Dow Jones 30 Industrial Stock Price Index	log difference
	SP500	Standard & Poor's 500 Composite Index	log difference
	RDJ30	Real DJ30 Appreciation = DJ30 – PCEC	
	RSP500	Real SP500 Appreciation = SP500 – PCEC	

Table 6: Q-Statistics for Testing Cross Correlations between Lags and Leads of Economic Indicators with the National Housing Factor f_t^{us}

Lags/Leads	-16 to -1	-12 to -1	-8 to -1	-4 to -1	1 to 4	1 to 8	1 to 12	1 to 16
M2	110.83	69.50	26.87	3.17	1.79	6.65	12.66	22.73
	(.00)	(.00)	(.00)	(.53)	(.77)	(.57)	(.39)	(.12)
FFED	157.86	157.67	149.36	99.79	56.84	67.33	68.99	70.30
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
FCM	107.89	107.66	102.81	72.46	66.95	89.44	97.65	99.44
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
RFFED	103.76	90.30	88.26	74.09	62.52	81.72	91.86	107.63
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
RFCM	61.95	40.30	31.14	29.39	76.23	127.69	168.41	194.28
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
POP	177.66	162.57	122.96	60.29	41.94	51.10	54.66	86.55
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
RGDP	30.39	15.68	11.81	6.89	6.55	11.71	29.66	49.22
	(.02)	(.21)	(.16)	(.14)	(.16)	(.16)	(.00)	(.00)
RDI	29.19	12.81	3.39	0.90	1.42	7.92	14.30	26.51
	(.02)	(.38)	(.91)	(.92)	(.84)	(.44)	(.28)	(.05)
UNEMP	64.60	61.11	50.83	31.93	76.24	134.64	150.78	153.52
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
RPCE	86.62	51.63	31.91	12.66	2.08	13.91	36.69	61.44
	(.00)	(.00)	(.00)	(.01)	(.72)	(.08)	(.00)	(.00)
DEF	182.65	169.36	143.13	66.45	12.07	13.38	19.69	30.09
	(.00)	(.00)	(.00)	(.00)	(.02)	(.10)	(.07)	(.02)
PCEC	202.90	183.01	148.54	70.49	21.27	22.14	24.69	31.70
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.02)	(.01)
DJ30	7.95	7.20	5.34	1.03	7.71	8.49	10.74	12.35
	(.95)	(.84)	(.72)	(.90)	(.10)	(.39)	(.55)	(.72)
SP500	14.39	13.03	9.90	0.37	7.54	8.20	10.27	11.64
	(.57)	(.37)	(.27)	(.98)	(.11)	(.41)	(.59)	(.77)

Table 7-1: Causality Test—Part I

		Joint Sig. Lvl. with $l = 16$		Joint Sig. Lvl. with $l = 8$	
LHS	RHS (x_t)	lagged LHS	lagged RHS	lagged LHS	lagged RHS
f_t^{us}	M2	0.0000	0.2209	0.0000	0.0844
f_t^{us}	FFED	0.0000	0.9752	0.0000	0.8859
f_t^{us}	FCM	0.0000	0.5518	0.0000	0.2165
f_t^{us}	RFFED	0.0000	0.6648	0.0000	0.7068
f_t^{us}	RFCM	0.0000	0.3698	0.0000	0.5746
f_t^{us}	POP	0.0000	0.5412	0.0000	0.4820
f_t^{us}	RGDP	0.0000	0.9383	0.0000	0.6084
f_t^{us}	RDI	0.0000	0.0224	0.0000	0.5136
f_t^{us}	UNEMP	0.0000	0.7675	0.0000	0.4536
f_t^{us}	RPCE	0.0000	0.8831	0.0000	0.8662
f_t^{us}	DJ30	0.0000	0.6261	0.0000	0.6944
f_t^{us}	SP500	0.0000	0.4088	0.0000	0.5730

Table 7-2: Causality Test—Part II

		Joint Sig. Lvl. with $l = 16$		Joint Sig. Lvl. with $l = 8$	
LHS (x_t)	RHS	lagged LHS	lagged RHS	lagged LHS	lagged RHS
M2	f_t^{us}	0.0000	0.2725	0.0000	0.6526
FFED	f_t^{us}	0.0000	0.8399	0.0000	0.7674
FCM	f_t^{us}	0.0000	0.9973	0.0000	0.4710
RFFED	f_t^{us}	0.0000	0.4266	0.0000	0.3456
RFCM	f_t^{us}	0.0000	0.2115	0.0000	0.0315
POP	f_t^{us}	0.0000	0.3708	0.0000	0.6957
RGDP	f_t^{us}	0.0240	0.1517	0.0003	0.0899
RDI	f_t^{us}	0.4252	0.4084	0.2902	0.0147
UNEMP	f_t^{us}	0.0000	0.8960	0.0000	0.4907
RPCE	f_t^{us}	0.7235	0.4383	0.3491	0.3460
DJ30	f_t^{us}	0.8972	0.6340	0.3908	0.1499
SP500	f_t^{us}	0.9128	0.5765	0.8595	0.1888

Figure 1

OFHEO Index in Comparison with Census-HUD Index

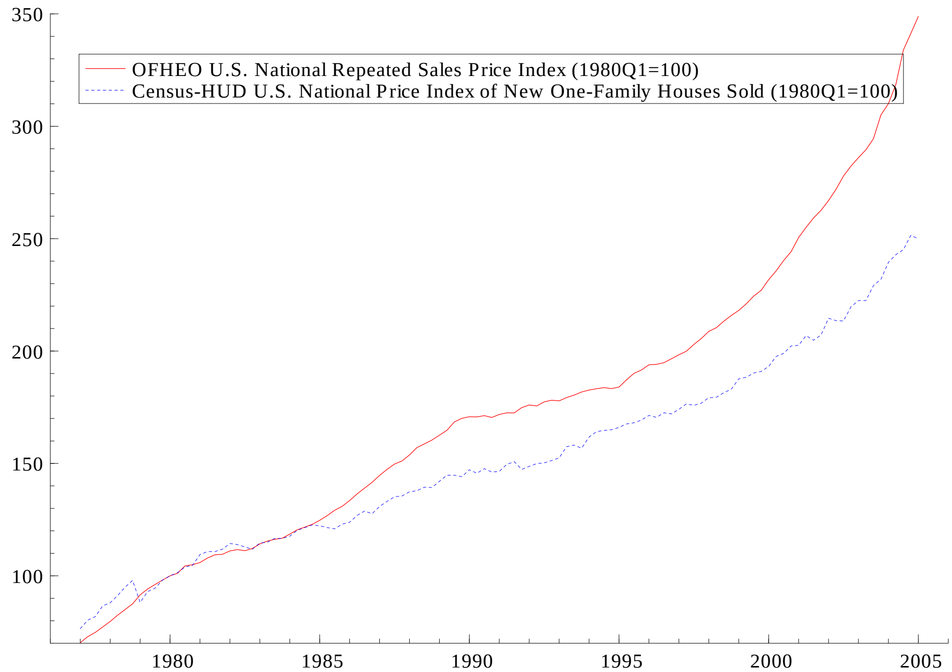

Figure 2

National Factor in Comparison with OFHEO National Index

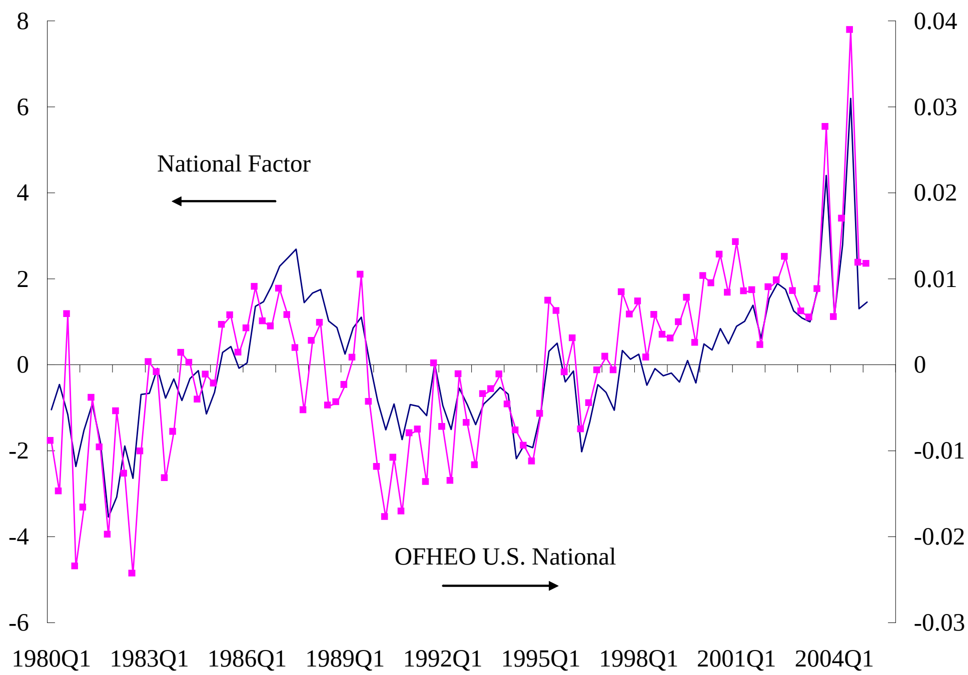

Figure 3

Regional Factors

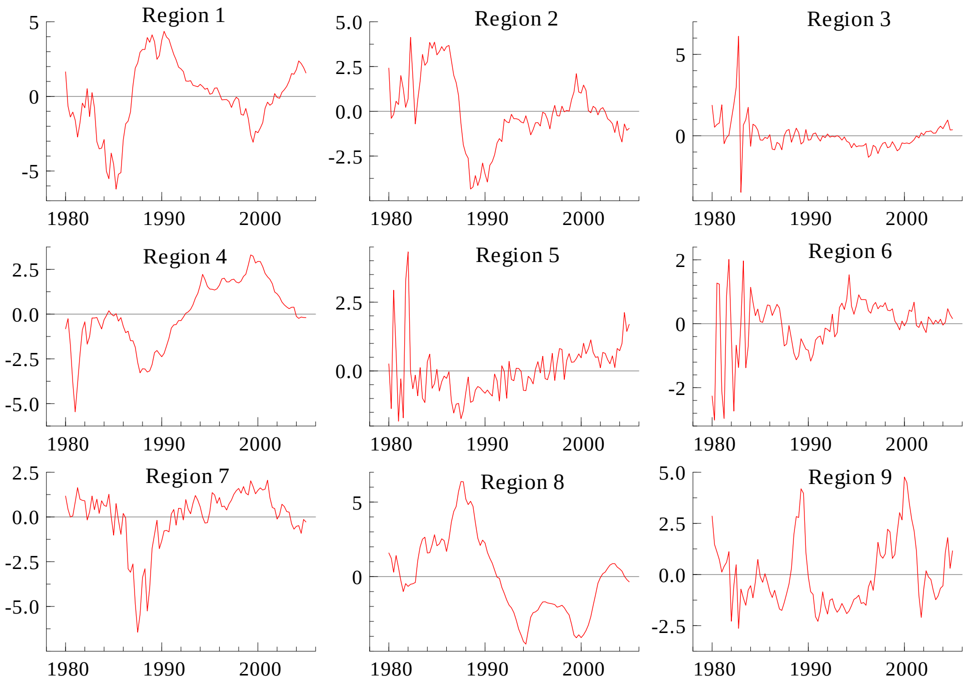

Figure 4-1

Variance Decomposition—National Factor

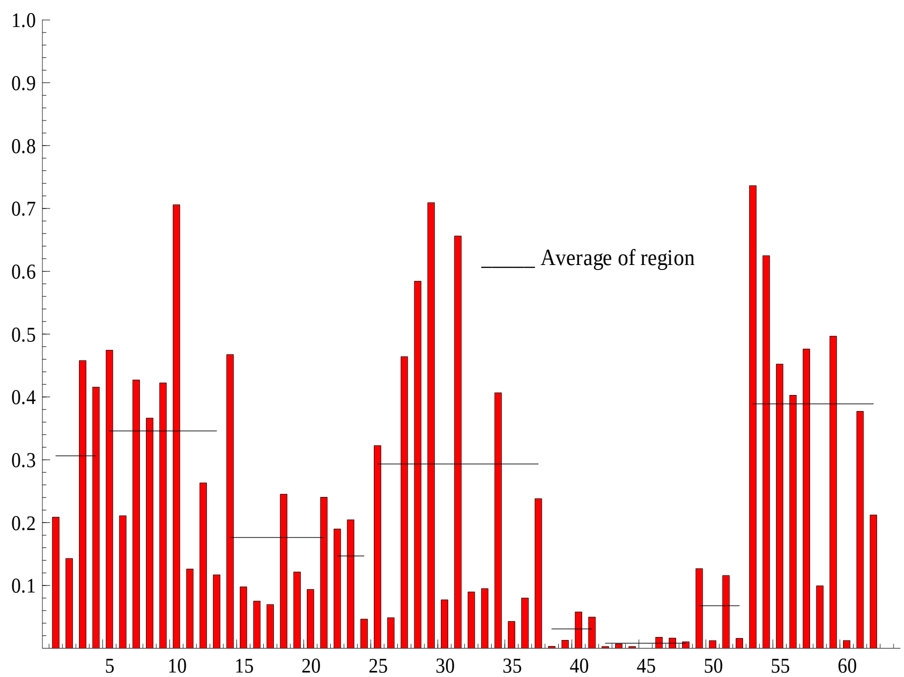

Figure 4-2

Variance Decomposition—Regional Factor

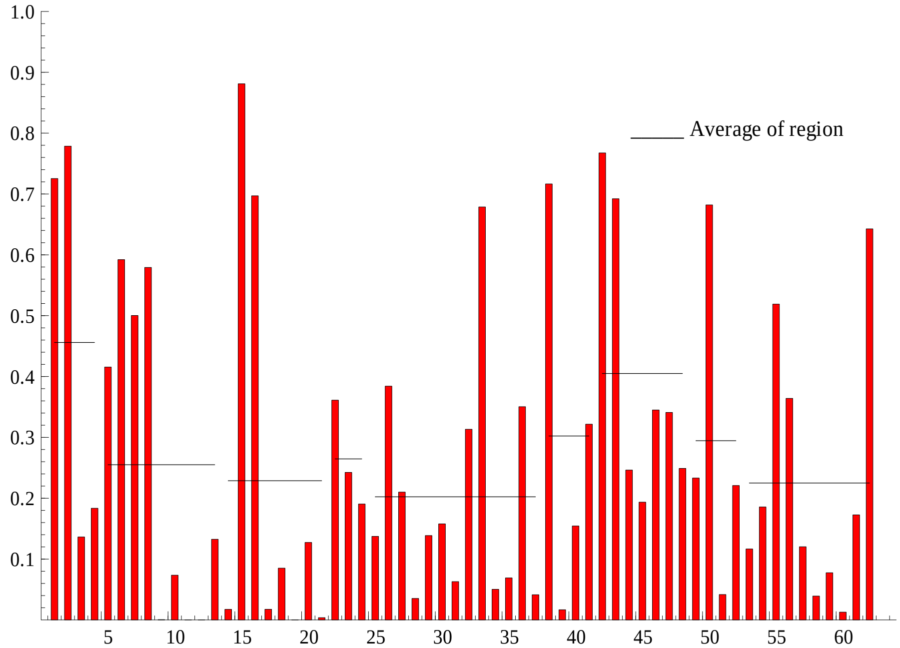

Figure 4-3

Variance Decomposition—Idiosyncratic Factor

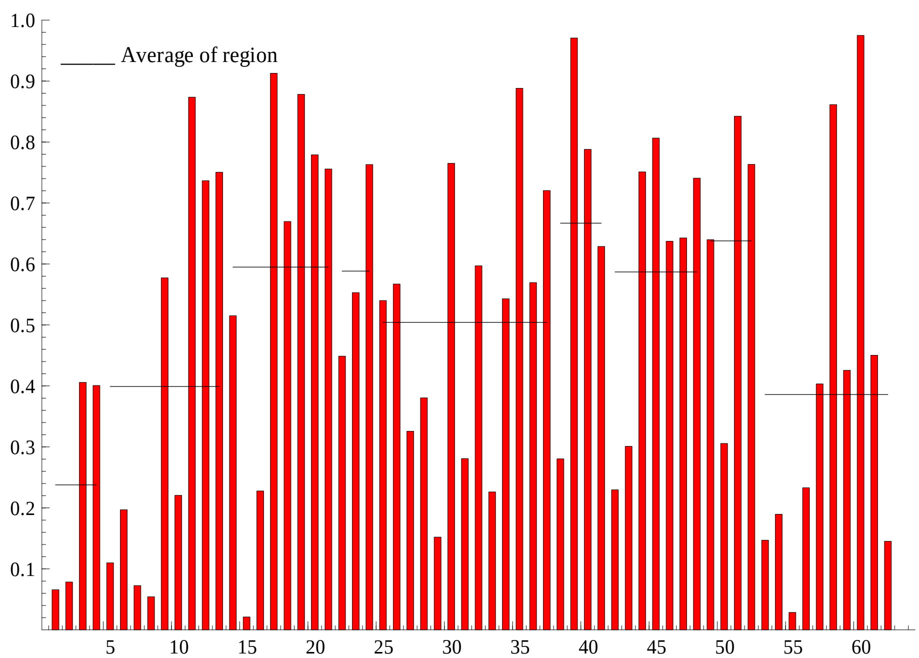

Figure 5-1

Factor Contributions—Region 1: New England

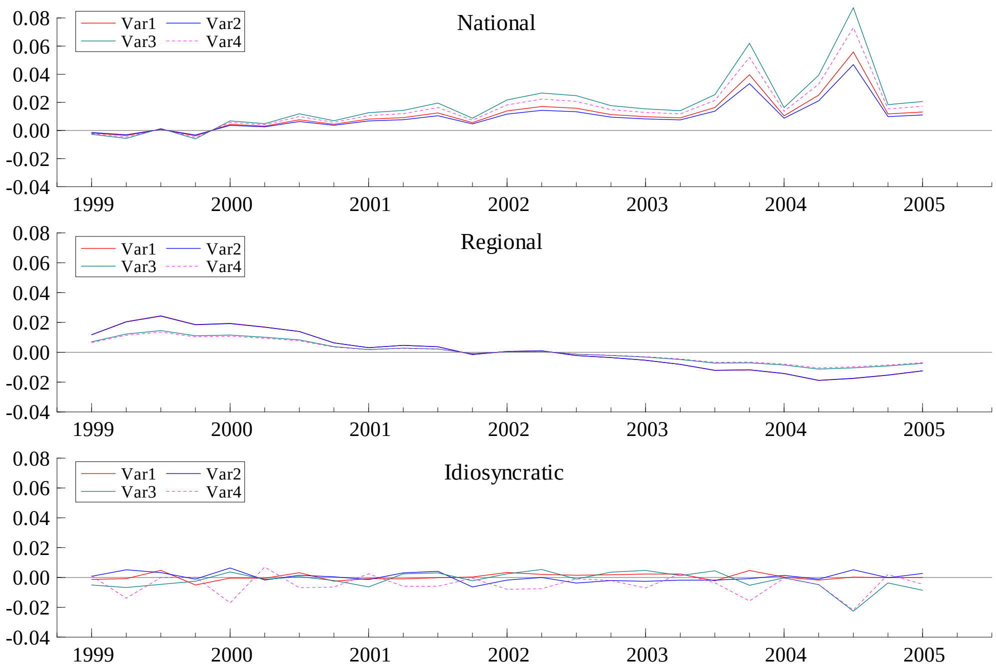

Figure 5-2

Factor Contributions—Region 2: Mid-Atlantic

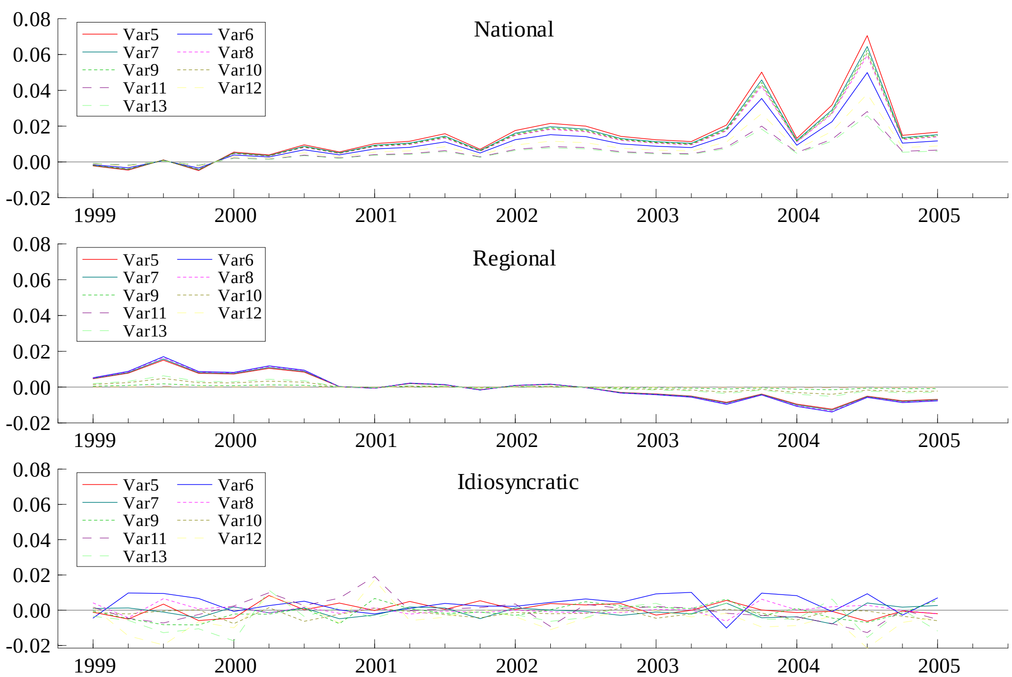

Figure 5-3

Factor Contributions—Region 3: East-North-Central

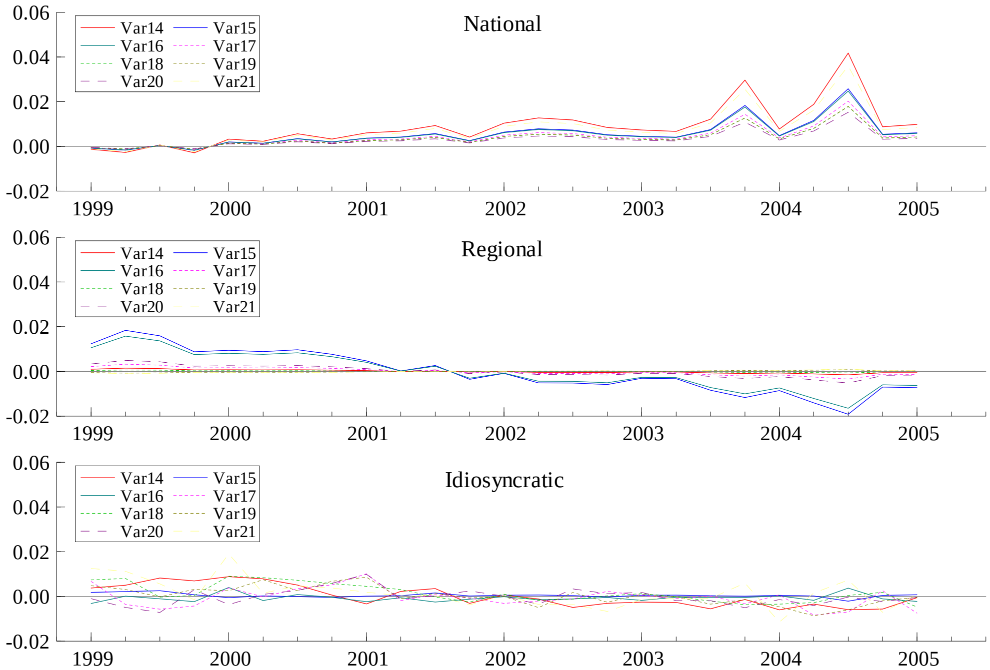

Figure 5-4

Factor Contributions—Region 4: West-North-Central

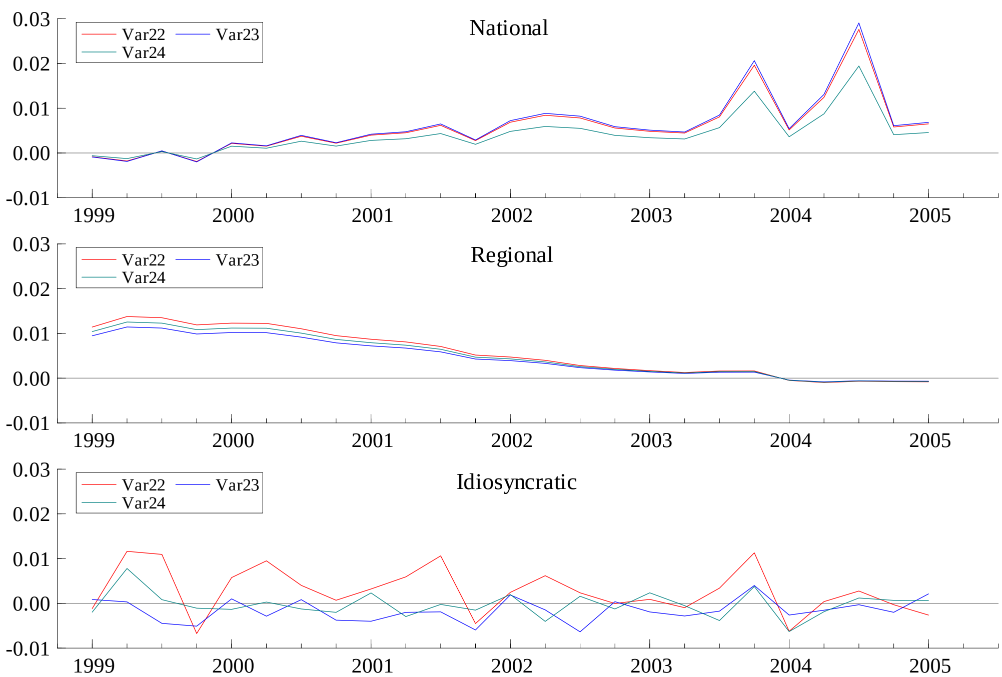

Figure 5-5

Factor Contributions—Region 5: South-Atlantic

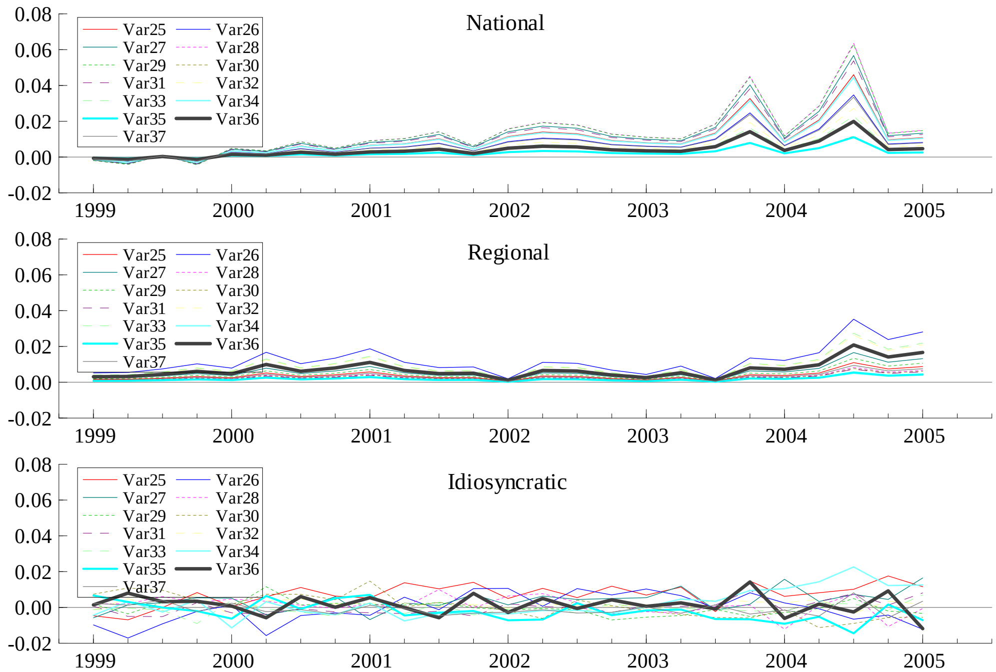

Figure 5-6

Factor Contributions—Region 6: East-South-Central

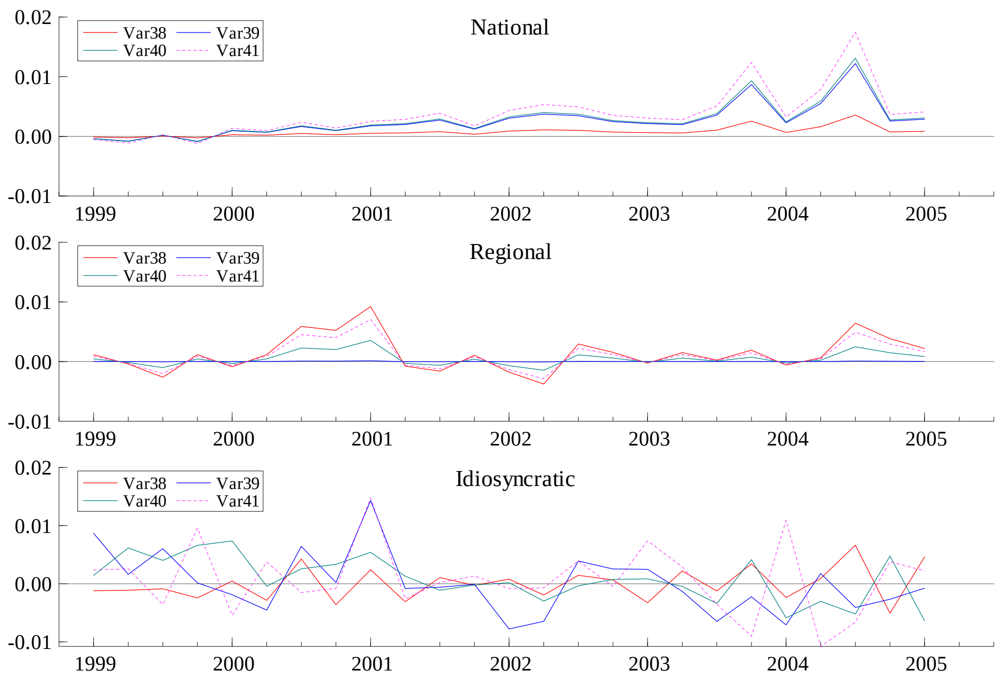

Figure 5-7

Factor Contributions—Region 7: West-South-Central

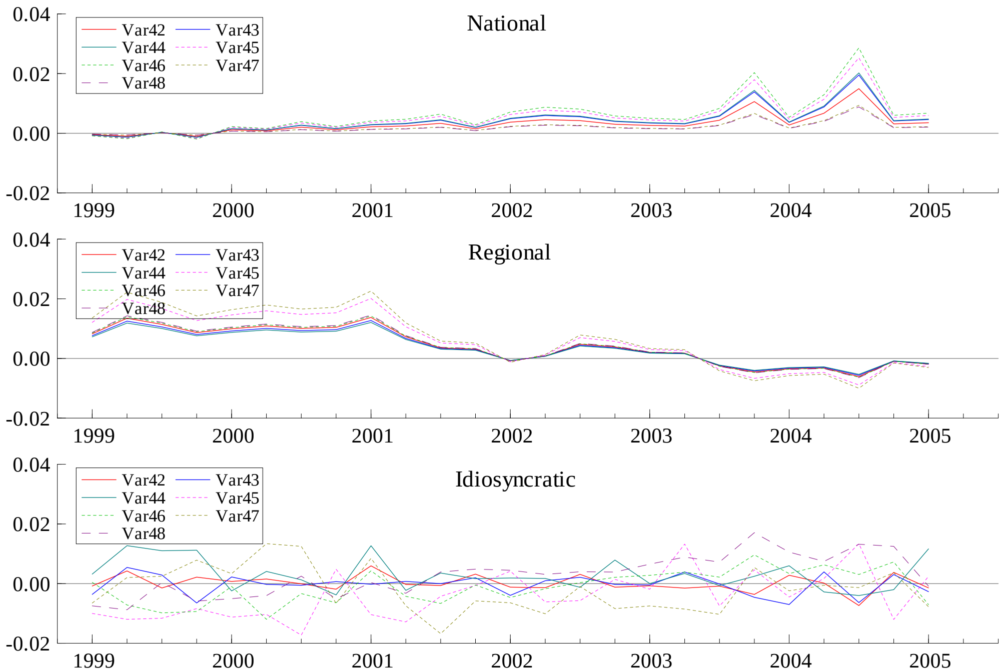

Figure 5-8

Factor Contributions—Region 8: Mountain

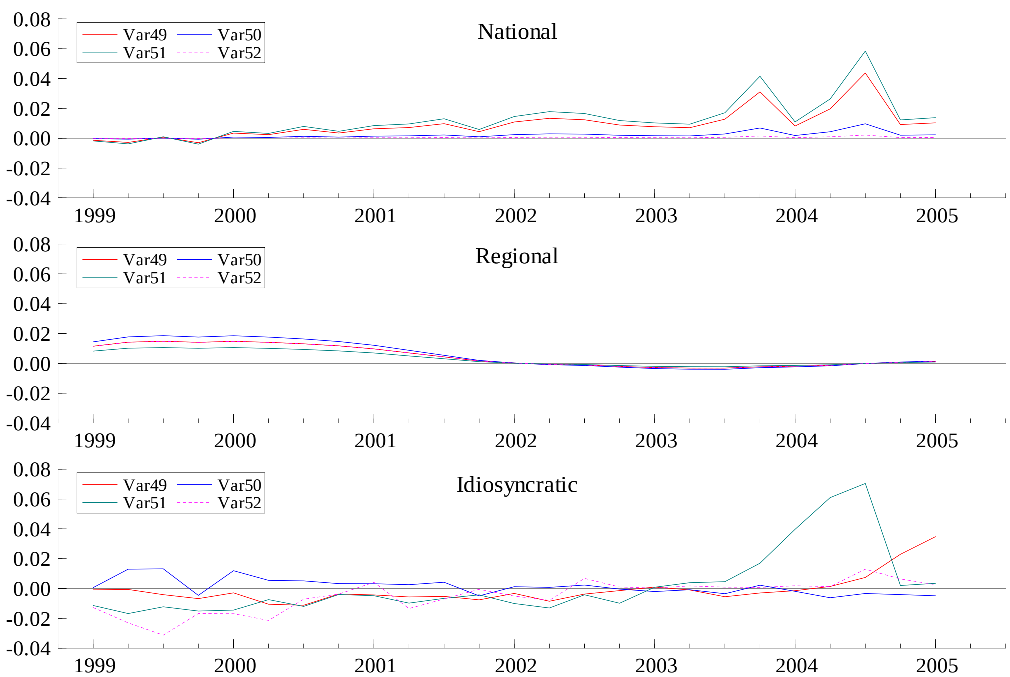

Figure 5-9

Factor Contributions—Region 9: Pacific

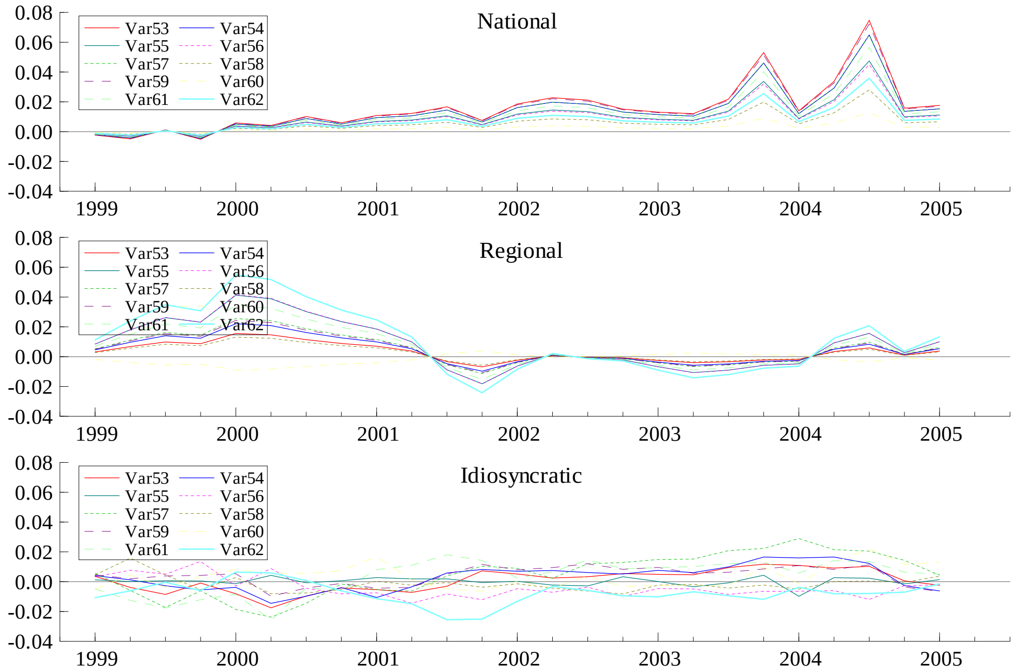

Figure 6

The Ratio between Accumulated National Factor's Contributions and Metro Price Changes

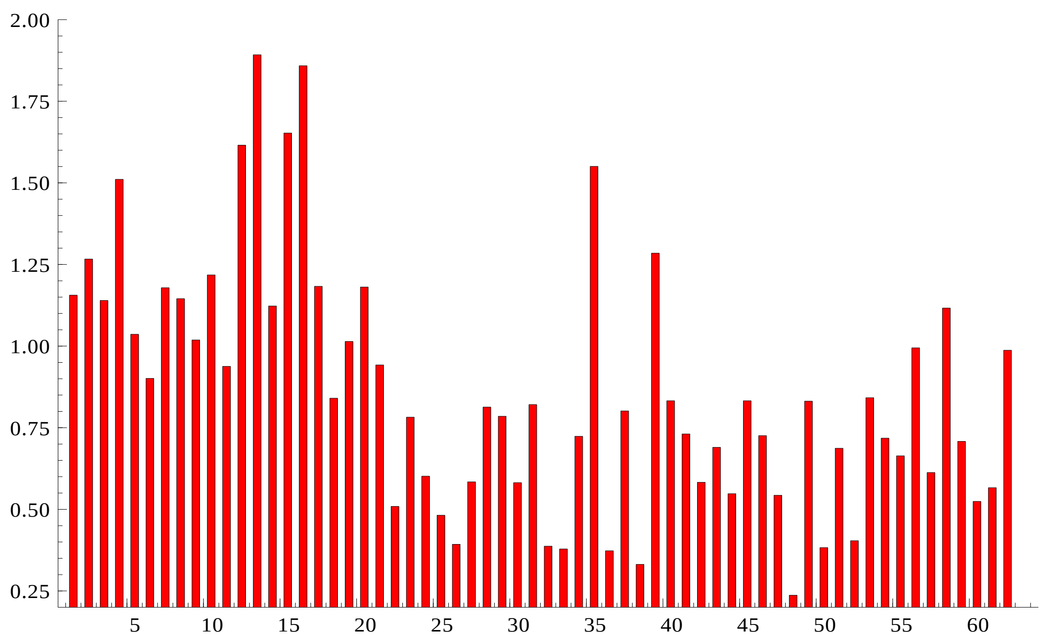

Figure 7

Correlations between the National Factor and the Chosen Variables