UCD GEARY INSTITUTE
DISCUSSION PAPER SERIES

Integration and Contagion in US Housing Markets

John Cotter
School of Business
University College Dublin

Stuart Gabriel
Anderson School of Management
University of California, Los Angeles

Richard Roll
Anderson School of Management
University of California, Los Angeles

Geary WP2011/31
November 2011

INTEGRATION AND CONTAGION IN US HOUSING MARKETS

John Cotter[1], Stuart Gabriel[2] and Richard Roll[3]

ABSTRACT

This paper explores integration and contagion among US metropolitan housing markets. The analysis applies Federal Housing Finance Agency (FHFA) house price repeat sales indexes from 384 metropolitan areas to estimate a multi-factor model of U.S. housing market integration. It then identifies statistical jumps in metropolitan house price returns as well as MSA contemporaneous and lagged jump correlations. Finally, the paper evaluates contagion in housing markets via parametric assessment of MSA house price spatial dynamics.

A R-squared measure reveals an upward trend in MSA housing market integration over the 2000s to approximately .83 in 2010. Among California MSAs, the trend was especially pronounced, as average integration increased from about .55 in 1997 to close to .95 in 2008! The 2000s bubble period similarly was characterized by elevated incidence of statistical jumps in housing returns. Again, jump incidence and MSA jump correlations were especially high in California. Analysis of contagion among California markets indicates that house price returns in San Francisco often led those of surrounding communities; in contrast, southern California MSA house price returns appeared to move largely in lock step.

The high levels of housing market integration evidenced in the analysis suggest limited investor opportunity to diversify away MSA-specific housing risk. Further, results suggest that macro and policy shocks propagate through a large number of MSA housing markets. Research findings are relevant to all market participants, including institutional investors in MBS as well as those who regulate housing, the housing GSEs, mortgage lenders, and related financial institutions.

This draft: October 12 2011

Keywords: integration, correlation, contagion, house price returns

JEL Classification: G10, G11, G12, G14, R12, R21

[1]UCD School of Business, University College Dublin, Blackrock, Co. Dublin, Ireland. Email: john.cotter@ucd.ie and Research Fellow, Ziman Center for Real Estate, UCLA Anderson School of Management.

[2]Anderson School of Management, University of California, Los Angeles, 110 Westwood Plaza, Los Angeles, California 90095, stuart.gabriel@anderson.ucla.edu

[3] Anderson School of Management, University of California, Los Angeles, 110 Westwood Plaza, Los Angeles, California 90095, rroll@anderson.ucla.edu.

The authors gratefully acknowledge research support from the UCLA Ziman Center for Real Estate. Cotter also acknowledges the support of Science Foundation Ireland under Grant Number 08/SRC/FM1389. The authors thank Tom Conlon, Tom Davidoff, Stijn Van Nieuwerburgh and Robert Shiller for comments.

I. Introduction

The boom and bust of house prices defined the opening decade of the 21st century. As reported in Shiller (http://www.econ.yale.edu/shiller/data.htm)), US national house prices recorded a decline of 31 percent over the 2006 - 2010 period, about on par with the peak-to-trough contraction during the Great Depression. Implosion in house prices figured importantly in the 2007 meltdown in mortgage and capital markets and the downturn in the global economy. As shown in Figure 1, the fall-off in house prices and related economic decline were especially severe in California.

Neither analysts on Wall St., regulators in Washington, D.C., nor most academic economists anticipated the magnitude of the house price cycle, its geographic reach, or related housing market contagion. Indeed, while urban economists long have addressed linkages among a system of cities (see, for example, Henderson (1977)), few studies have focused on the spatial-temporal structure of the house price cycle. For example, little is known about the relative exposure of MSA housing markets to fluctuations in the national economy, despite the importance of such to investor diversification or to economic policy propagation. Also, few analyses have provided insights as regards the metropolitan geography of house price returns, notably including incidence of extreme (jump) returns and the directions of contagion.

We address those questions via analyses of integration, correlation, and contagion in US metropolitan housing markets. Those estimates are important to investors as they provide an indication of opportunities to diversify away metropolitan-specific housing risk. For example, high levels of MSA integration and contagion among geographically distinct residential markets could mitigate the efficacy of geographic diversification strategies implemented by investors in mortgage-backed securities. An improved understanding of metropolitan housing market integration also could provide new insights regarding the spatial incidence of national economic policy. In general, measures of integration and contagion in housing markets provide signals for price return performance and are relevant for the full spectrum of market participants, be they lenders, housing and mortgage investors, homebuilders, and the like.

Following Pukthuanthong-Le and Roll (2009), we compute a simple intuitive measure of housing market integration, based on the proportion of an MSA's housing market returns that can be explained by an identical set of national factors. The level of integration is associated with the magnitude of R-Square, with higher values indicating higher levels of integration. Two MSAs are viewed as perfectly integrated if those same national factors fully explain housing market returns in both those areas. In that case, there would be a R-square of 1 so there is no diversification potential between the MSAs.

Results of the analysis indicate elevated and increasing MSA housing market integration. For the US as a whole, housing market integration trended up over the decade of the 2000s to about .83 in 2010.[1] In California the trend was marked; there average housing market integration moved up from about .55 in 1997 to close to .95 in 2008! Also noteworthy, however, was the abrupt downward adjustment in California integration, to approximately .75, in the wake of the recent severe implosion in house prices. Further disaggregation of California trends revealed more pronounced declines in integration among coastal markets in the context of the housing bust. That result likely reflects special factors associated with coastal markets (supply constraint, presence of amenities, and lack of subprime lending) in the context of ongoing weakness in national economic and housing market fundamentals.

Using the Lee and Mykland (2008) measure to characterize extreme returns, we find that the 2000s bubble period also was distinguished by a relatively high incidence of jumps in housing returns. Jumps were especially evident early in the boom during 2004-2005 as well as in 2008 in the wake of the bust in house prices, the latter likely owing to extreme declines in returns in certain MSAs. During early stages of the boom (2003 – 2004), return jumps in California suddenly become very prevalent with close to 70 percent of cities having significant extreme housing returns; further, during that period, the jumps were ubiquitous among coastal and inland California cities. In marked contrast, during the 2007-2008 bust and among California MSAs, only inland cities witnessed extreme movements in housing returns. Inland cities are characterized by a lack of constraint on housing supply and, in hindsight, they had been substantially overbuilt. Further, those areas had been the focus of substantial boom period subprime lending. As boom turned to bust, inland areas of California quickly and largely imploded.

As would be expected, both in the US overall and in California, metropolitan return correlations are dramatically larger than jump return correlations in both incidence and magnitude. California, however, stands apart from the rest of the US in both returns and extreme returns. Research findings indicate relatively high levels of housing return and jump return correlations in California compared to the rest of the US. For example, contemporaneous housing return correlations are generally in the range of 0.2 – 0.3 with about 20 percent significant for MSAs outside California. In marked contrast, in excess of 92 percent of California MSA returns were significantly correlated with a mean correlation level of about .66! Similar results are obtained for lead (one quarter ahead) MSA correlations. Among areas outside California, less than 10 percent of lead correlations were statistically significant with mean lead correlation levels at or below 0.20. In California, more than three-quarters of MSAs recorded significant lead return correlations with a mean correlation level of about .57.

California also was markedly different as regards contemporaneous and lead LM jump correlations. Among areas outside of California, significant contemporaneous jump correlations were small in number and in the range of only .02 – .03. Large lead jump

[1] A measure of 1.0 would indicate perfectly integrated markets while zero would indicate no integration at all; hence, the observed average of 0.83 implies that U.S. housing markets are 83% integrated relative to the maximum possible level.

correlations outside California similarly occurred infrequently in any census division with mean correlation coefficients (except for New England) of .04 or less. In contrast, both the incidence and magnitude of contemporaneous and lead jump correlations were greater for California.

Given the above aberrant nature of integration, jump incidence, and MSA jump correlations among California MSAs, the analysis turns to parametric assessment of spatial and temporal contagion among California cities. Regression analyses over the full sample timeframe indicate that house price returns for Los Angeles and surrounding areas largely move in lock-step. In contrast, findings for Bay Area regional housing markets provide some evidence of a spatial term structure of contagion. In that region, housing returns in San Francisco lead those of many northern California communities. Contagion findings are robust to controls for booms and busts in California housing markets.

The plan of the paper is as follows. Section II provides assessment of integration of US MSA house price returns. In Section III, we report on analyses of both contemporaneous and lagged correlations and jump correlations in MSA house price returns. Section IV provides tests of geographic-temporal contagion among MSA housing markets in California. In section V, we provide concluding remarks.

II. Integration

Substantial research has been undertaken as regards integration of international equity markets. The applications vary in geography of focus, as some papers address integration in the European community (see, for example, Hardouvelis, Malliaropoulos, and Priestley (2006), and Schotman and Zalewska (2006)), whereas others investigate emerging markets (see, for example, Bakaert and Harvey (1995), Chamber and Gibson (2006), Bakaert, Harvey, Lundblad and Siegel (2008)). The analyses also vary widely in methodological approach. For instance, Carrieri, Errunza and Hogan (2007) use GARCH-in-mean methods to assess correlation in returns and volatility between markets, whereas Longin and Solnik (1995) use cointegration techniques. While integration is often described in terms of cross-country correlations in stock returns (for an early study see King and Wadhwani (1990)), such a measure is argued to be flawed. Indeed, in the case where multiple factors drive returns, markets may be imperfectly correlated but perfectly integrated.[2]

[2] As shown by Pukthuanthong and Roll (2009), while perfect integration implies that identical global factors fully explain index returns across countries, some countries may differ in their sensitivities to those factors and accordingly not exhibit perfect correlation. An easy intuitive example would be an energy-exporting country such as Saudi Arabia and an energy-importing country such as Hong Kong. Both countries might be positively associated with global factors such as consumer goods or financial services. Morever, both countries could be fully integrated in the global economy; yet the simple correlation between their stock market returns could be relatively small, or even negative, because higher energy price increase Saudi equity values and decrease Hong Kong equity values. As a

As suggested by Pukthuanthong-Le and Roll (2009), a simple intuitive measure of financial market integration is the proportion of a country's returns that can be explained by an identical set of [global] factors. This measure of integration focuses on the magnitude of country-specific residual variance in a factor model seeking to explain a broadly-defined country equity return index.[3] Clearly, to the extent global factors explain only a small proportion of variance in a country's returns, the country would be viewed as less integrated (see, for example, Stulz (1981) and Errunza and Losq (1985)).[4] In contrast, markets would be viewed as highly integrated to the extent their returns are explained. We below describe US metropolitan housing markets as highly integrated if identical US national factors explain a large portion of the variance in MSA house price returns. To compute US housing market integration, we regress metropolitan house price returns on an identical set of national economic and housing market fundamentals.

Integration is viewed as important to investors, policymakers, and market participants in general. A measure of housing market integration provides some indication of the benefits to investor diversification among MSA markets. While there may be some benefit to diversifying away MSA-specific housing market risk, those benefits would decline with increases in integration. Indeed, high levels of integration may mitigate strategies of geographic diversification among investors in mortgage-backed securities. Also, among other things, a measure of metro housing market integration would provide national economic policymakers with some indication of the geographic ubiquity of policy propagation. High levels of MSA housing return integration imply that those markets largely are driven by national factors, notably including monetary policy and other housing fundamentals. Similarly, elevated levels of metro housing market integration imply that macro and financial shocks will propagate through a larger number of MSA housing markets. This will have relevance for all market participants, including institutional investors in residential MBS as well as those who regulate housing, the housing GSEs, mortgage lenders, and related financial institutions.

a. Model Specification and Data

MSA-specific house price returns are computed using the U.S. Federal Housing Finance Agency (FHFA) metropolitan indices, previously known as the OFHEO house price series.

---

consequence, the extent to which the multi-factors drive returns is a better indication of likely diversification benefits than a correlation measure.

[3] In contrast, in the presence of multiple national factors, the simple correlation between MSA house price return indexes could be a flawed measure of integration unless those MSAs have identical exposure to the national factors, e.g., unless the estimated coefficient vectors are exactly proportional across MSAs.

[4] According to this definition, a country is perfectly integrated if the country-specific variance is zero after controlling for global factors. In the case of two perfectly integrated countries, market indexes would have zero residual variance. See Pukthuanthong and Roll (2009) for discussion and details.

The FHFA series are weighted repeat-sale price indices associated with single-family homes. Home sales and refinancing activity included in the FHFA sample derive from conventional home purchase mortgage loans conforming to the underwriting requirements of the housing Government Sponsored Enterprises—the Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac). The FHFA data comprise the most extensive cross-sectional and time-series set of quality-adjusted house price indices available in the United States.[5] We compute house price returns for each MSA in our sample as the log quarterly difference in its repeat home sales price index.[6] The MSA level data are quarterly from 1975:Q1 – 2010:Q1. The number of MSAs in the database increases over time from 2 in 1975 to 380 by 1993. By the end of the sample timeframe, there are 384 MSAs in the dataset.

Per above, for each MSA in the sample, log percent change in the MSA-specific house price indices is regressed on a common set of national economic, financial and housing market factors. The specific factors and their definitions are displayed in Appendix Table 1. The factors include measures of change in population, payroll employment, unemployment rate, S&P500, industrial production, CPI, and PPI materials prices as well as personal income, consumer sentiment, single-family building permits, Fed Funds rate, 10-year constant maturity Treasury yields, and the like. All factor data are quarterly in frequency from 1975:Q1 – 2010:Q1 with the exception of consumer sentiment, which is available from 1977:Q4. Data for the factors are obtained from the Federal Reserve Bank of St. Louis FRED (Federal Reserve Economic Data) with the exception of the S&P500 (Datastream) and personal income (US Department of Commerce National Income and Product Accounts). The MSA returns series are pre-whitened to remove serial correlation. A VAR(1) is employed based on optimal AIC/BIC criteria from running the factor model on each individual MSA. The average level of integration is measured by the R-squares from the multi-factor model fitted for a 20-quarter moving window for the samples of MSAs (the use of other window sizes gave the same qualitative results). The R-squares in these moving windows indicate the corresponding levels of housing market integration.

b. Return Regressions on National Factors

Estimation results indicate that U.S. MSA housing market integration has increased over time. Figure 2 provides information on trends in housing market integration for the MSAs in our sample. Panel A of Figure 2 shows that trend for the 1983:Q4 – 2009-Q4 period both for the national and California samples. Very little trend in US MSA housing market

---

[5] For a full discussion of the OFHEO house price index, see "A Comparison of House Price Measures", Mimeo, Freddie Mac, February 28, 2008.

[6] In principle, it would be desirable to model house prices at higher frequencies. Unfortunately, monthly quality-adjusted house price indices are available from OFHEO only for Census Divisions (N=18) and only for a much shorter time frame.

integration appeared during the decades of the 1980s and 1990s. In contrast, the 2000s provides graphic evidence of trending up in housing market integration among US MSAs, from about .70 in 2000 to approximately .83 by decade's end. In California the trend in housing market integration was even more marked moving up from about .55 in 1997 to close to .95 in 2008! Further noteworthy, however, was the abrupt downward adjustment in California housing market integration, to approximately .75, in the wake of the recent severe implosion in house prices. Indeed, localized factors associated with the California housing bust resulted in some disassociation of California metropolitan housing returns from national economic fundamentals.

We control for potential bias in the FHFA data in terms of when an MSA was included in the database. Regardless, the finding of increased integration still holds. Panel B of Figure 2 shows the average R-square pattern for 3 time cohorts. This categorization of MSAs into cohorts assesses the robustness of results to the timeframe of city inclusion in the sample. In this regard, it is possible that MSAs that entered the sample later were characterized by lower or higher R-squares. If that were the case, averaging all MSAs together could move the trend in the average either up or down. We plotted trends in the average level of integration for three time-based cohorts. The cohorts included the full timeframe of 1983:Q4 – 2010:Q1 (cohort 1), 1989:Q2 – 2010:Q1 (cohort 2), and 1992:Q1 – 2010:Q1 (cohort 3). The cohorts yielded roughly similar results and indicated a longer-term trend towards MSA housing market integration. In cohort 2, for example, the average R-square moved up from about .65 in 1989 to almost .82 in 2010.

MSA housing market cross-sectional and time-series summary statistics are contained in Table 1. For the sample of MSAs, we display mean quarterly house price returns, standard deviation of returns (sigma), the R-square measure of integration, the change in R-square over the timeframe of the analysis, and the associated time trend t-statistic (R-squares for each MSA are fit to a simple linear time trend for all available quarters). Minimum values by quintile are also presented. First, it is important to note that risk and return associated with housing has been substantial. As shown, the average quarterly return for all MSA housing markets in the sample is positive at almost 1% with an average deviation of about 2.5%. Moreover, we see substantial cross sectional variation in those measures; for example, mean house price return varies from a minimum 0.43% to a sample maximum of 1.89%.

As evidenced in Table 1, the mean final period R-square of the integration model is .82, suggesting the importance of national factors in determination of MSA house price returns. The Table also indicates substantial temporal and cross-MSA variation in the integration measure. On average R-squares increase by almost 10 percent from the beginning to end of sample. In some areas, national economic and housing market fundamentals fail to explain the majority of variation in MSA-specific house price returns (min R-squared = .35) At a maximum, those same fundamentals explain a full 99 percent of variation in MSA-specific house price returns. There is also substantial variation in the change in R-squared across the sample with a standard deviation of .187. Appendix Table 2 contains integration details for all 384 MSAs.[7]

Table 2 presents integration details for the 28 California MSAs included in our dataset. Relative to the full national sample of 384 MSAs, California metropolitan areas are characterized by elevated mean house price returns, return volatility, and integration time trend t-statistic. Further discernable in Table 2 are distinct coastal versus inland housing market phenomena. Comparing coastal MSAs (see, for example, San Francisco, Oakland, San Jose, Los Angeles, Santa Ana, and Santa Barbara) with inland MSAs (for example, Bakersfield, Fresno, Madera, Merced, Modesto, Riverside, and Sacramento), note that the former are roughly characterized by relatively higher mean house price returns, lower return volatility, damped levels of integration, and lower integration trend t-statistics. Among California coastal MSAs, mean quarterly returns averaged an elevated 1.6 percent; further, integration R-squared averaged .69 with an insignificant time trend t-statistic. In marked contrast, California Central Valley and Inland Empire cities displayed substantially lower mean house price returns, elevated return volatility, higher levels of integration, and higher integration trend t-stats. In inland areas, mean quarterly house price returns were a damped 1 percent with an elevated sigma of 3.4 percent; further, the t-statistic on the integration time trend was 2.2, well in excess of t-statistics for California coastal MSAs and for the nation as a whole.

Panel C of Figure 2 shows trends in average R-square for inland and coastal MSAs in California. As is evident, average integration for MSAs in both areas trended up over the late-1990s through 2008 period. Striking is an up and down pattern in integration that roughly coincided with the boom and bust in housing markets overall. While integration levels for California MSAs moved up from about .75 to in excess of .90 in the context of the 2000s cyclical boom in housing, those same measures fell back markedly during the subsequent bust as California housing returns became increasingly divorced from national economic fundamentals. Further, the chart is suggestive that localized factors recently played a substantially greater role in determination of coastal California house price returns, as suggested in the divergence in integration between coastal and inland areas in the context of the implosion in housing markets. That divergence likely reflected special factors supportive of the performance of coastal markets (supply constraint, desirable natural amenities, shorter commutes, and the like) in the context of ongoing weakness in national economic and housing market fundamentals. As was broadly reported, Central Valley and Inland Empire cities collectively comprised the epicentre of the 2000s boom-bust cycle in California housing markets. Those areas were characterized by high levels of subprime lending, elastic land and housing supply, longer commutes, and substantial overbuilding. In many cases, the interior MSAs are outer-ring bedroom communities for employment centers closer to the coast. The results suggest distinctions in housing return

[7] The table further provides the quintile and rank (from lowest to highest) across the 384 MSAs of returns, sigma, and integration time trend t-statistic.

phenomena both within and between California MSAs and the nation as a whole. We return to that below, in discussion of MSAs house price return correlations and contagion.

III. MSA Return and Jump Return Correlations

In this section, we investigate the magnitude of metropolitan house price returns, distinguishing between common and extreme movements (jumps). Those results are benchmarked by a discussion of contemporaneous and lagged correlations in MSA house price returns. The analysis provides insights about temporal and geographic variations in those measures; we pay particular attention to California MSAs.

To the extent that extreme movements in MSA house price returns are few in number or geographically random, they would be of limited consequence to either private investors or policymakers. On the other hand, higher levels of ubiquity in return or jump return correlations raise concerns for mortgage or housing investors seeking to diversify risks associated with extreme house price movements. In a similar vein, other market players including MBS originators and investors would be similarly impacted by high correlations in returns or jump returns among their mortgage assets. Note further that jumps or jump correlations may be driven by economic or policy shocks at local or national levels. Jumps in house price returns should be of interest to policymakers especially in those cases where jumps can be traced to political events or policy perturbations.

Prior analyses have proposed alternative measures of jump test statistics (see, for example, Barndorff-Nielson and Shepard (2006), Lee and Mykland (2008), Jiang and Oomen (2008), and Jacod and Todorov (2009)). In a recent paper, Pukthuanthong-Le and Roll (2010) assess the various jump statistics in application to stock return indexes for 82 countries.[8] Unlike the other measures, Lee and Mykland works well with single observations (as opposed to a sample of several observations). This is important for our application because we have only quarterly data and hence the sample size is more limited than in the case of equities, where daily observations are available. While results vary across alternative jump statistics, results of of the above cited research suggest that jumps are largely idiosyncratic in international equity indexes. We are not aware of prior analyses of jumps in metropolitan house prices returns.

For the vast majority of sampled MSA housing markets, the most frequent quality-adjusted house price index available to investors is quarterly. Moreover, investor rebalancing of real estate portfolios tends to be of lower frequency relative to that of equities, and commonly is at a quarterly interval. Consequently, we view such frequency as appropriate to investor and policymaker market assessment and hence for the jump analysis.

[8] Earlier work on extreme returns and correlation of same focused on more ad-hoc approaches (see Longin and Solnik, 2001).

With that in mind, we apply the Lee and Mykland (2008), (hereafter LM), method in assessment of extreme movements in US metropolitan house price indexes. Like Barndorff-Nielson and Shephard (2006), Lee and Mykland's (2008) test is based on bipower variation. Bipower variation is used to proxy the instantaneous variance of the continuous non-jump component of prices.

To understand the test, consider the following notation:

t, subscript for quarter

T_k, the number of quarters in subperiod k

K, the total number of available subperiods

$R_{i,t,k}$, the return (log price relative) for MSA i quarter t in subperiod k

The Barndorff-Nielson and Shepard (2006) and Lee and Mykland (2008) bipower variation, $B_{i,k}$, is defined as follows:

$$B_{i,k} = \frac{1}{T_k - 1} \sum_{t=2}^{T_k} | R_{i,t,k} \| R_{i,t-1,k} |$$

LM suggest the computation of bipower variation using data preceding a particular return observation being tested for a jump. The test statistic is $L = R_{i,t+1,k} / \sqrt{B_{i,k}}$. Under the null hypothesis of no jump at t+1, LM show that $L\sqrt{2/\pi}$ converges to a unit normal. In addition, if there <u>is</u> a jump at t+1, $L\sqrt{2/\pi}$ is equal to a unit normal plus the jump scaled by the standard deviation of the continuous portion of the process.

Jumps in housing returns, although frequent, do not occur as often as in equity returns (see Roll and Pukthuanthong-Le (2010)). In Figure 3, we describe the temporal incidence of big LM jumps in house price returns for US MSAs. For each quarter, we plot the percentage of LM statistics in excess of 2.0. That percentage is plotted from 1983:Q4 – 2010:Q1. Since the L statistic is asymptotically unit normal, we adopt a 10 percent criterion for each tail. In other words, we identify a non-normal (jump) quarter for each MSA when the absolute value of the LM statistic exceeds the 10 percent level for the unit normal (1.65).

Panel A of Figure 3 plots the quarterly incidence of big LM jumps for the full sample of 384 MSAs. Some evidence of jumps in house price returns is indicated for the overheated housing markets of the late 1980s with an incidence rate often in excess of 10 percent. Jumps fell back during the downturn of the early 1990s and were similarly damped from the mid-1990s through about 2003. In fact, results indicate a large number of quarters during the 1995 – 2003 period for which few if any US MSAs were characterized by statistical jumps in house prices returns.

As is evident, the 2000s bubble period was characterized by substantial jump incidence. Jumps were especially evident early in the boom during 2004-2005 as well as in 2008 in the wake of the bust in house prices. The latter set of jumps likely was associated with extreme declines in house price returns in a small percentage of metropolitan areas.

As in the above integration analysis, we assess jumps across inland and coastal California MSAs (Figure 3, panel B). In contrast to the US as a whole, analysis for within California suggests virtually no statistical jumps in house price returns prior to 2003. However, during the early stages of the boom period (2003 – 2004), return jumps suddenly became very prevalent with close to 70 percent having significant extreme returns. The jumps in returns were evidenced among both coastal and inland California cities; indeed, the plots reveal little difference in either the timing or incidence of house price jumps among MSAs in those areas. In marked contrast, substantially elevated incidence of significant extreme values (LM return jumps) was indicated during the bust 2007-2008 period only for inland California MSAs! Indeed, there is no evidence of jumps in returns during the latter period for coastal cities. The jumps evidenced for inland California cities during the bust period likely reflect the sharp house price declines that were common in those areas. Such outcomes were consistent with the implosion in housing market drivers. As suggested above, unlike coastal areas, inland cities were characterized by lack of (regulatory or natural) constraint on housing supply and were substantially overbuilt. Further, inland areas shared a common feature of substantial boom period subprime lending. As boom turned to bust, inland areas of California quickly and largely imploded. While the preceding indicates the marked incidence of house price return jumps during the 2000s housing boom and bust, they provide little insight as regards contemporaneous or lagged MSA correlations in those jumps, and returns in general. It is to those analyses that we now turn.

First, a word on methodology. Per above and following Pukthuanthong-Le and Roll (2010), we identify periods when the L statistic indicates a likely jump. After classifying each sample quarter for each MSA as jump or non-jump (jump indicated in those cases where the absolute value of the LM L statistics is greater than 2.0, given that L is unit normal), we compute contemporaneous and lagged correlations in LM jump statistics among pairs of MSAs where at least one MSA had a jump. If the companion MSA also had a jump in the same quarter (or in the lagged quarter) the product of their LM measures contributes to the contemporaneous (or lagged) correlation. Otherwise, the contribution for that month is zero. Note that we do not count the LM statistic for a given quarter unless it is significant; this is appropriate, otherwise the resulting correlation would simply measure the total return correlation. The result of our procedure is a pure measure of jump correlation for every pair of MSAs.

We find extensive evidence of strong correlations in returns and jumps. But jumps occur infrequently and have smaller correlations than returns. California exhibits particularly large return and jump correlations. In Table 3, we report summary information on MSA house price return and jump return correlations. Panel A reports summary statistics for

MSA return correlations, which provide a basis of comparison to MSA jump correlations. Those results are stratified by level of T-statistic for cross-coefficient independence. For the full sample, correlation coefficients are computed for quarterly returns among all house price return pairs (total sample N = 73,536). The mean contemporaneous correlation among all MSAs return pairs is 0.20, with considerable cross coefficient standard deviation of 0.18. However, the T-statistic for the mean correlation, assuming cross-coefficient independence, is almost 300, indicating very significant average correlation among MSA returns. The table further indicates sizable numbers of individual MSA pairs with house price return correlations at high levels of statistical significance. The numbers of MSA pairs with return correlation T-statistics in excess of 2 and 3 are 33,460 and 18,126, respectively. Among those same sub-samples, mean correlations are 0.35 and 0.44, respectively.

Panel B of Table 3 reports summary statistics for the corresponding jump return correlations stratified by T-statistic. For the full sample, correlation coefficients are computed for identified jumps in quarterly house price returns among US MSAs. There are 49,742 pairs. The summary statistics are computed across all available coefficients. The mean contemporaneous MSA jump correlation across MSA jump return pairs is only about 0.05 but is significant with a T-statistic of about 53. The Table further indicates the existence of MSA house price jump return correlations at higher levels of statistical significance. The numbers of MSA pairs with jump return correlation T-statistics in excess of 2 and 3 are 8770 and 5405, respectively. Among these more significant sub-samples, mean correlations as expected are substantially higher (0.38 and 0.46, respectively.) And these samples are similarly characterized by significant MSA jump mean correlations, as indicated by T-statistics of 237 and 247, respectively.

We now turn to identify the geographical incidence of significant return and jump correlations in metropolitan housing returns. We find strong evidence for a high incidence of significant return and jump return correlations for California. In panel A of Table 4, contemporaneous and lead MSA house price index return correlations coefficients are computed for US census divisions. In that analysis, we break out California MSAs. Accordingly, the definition of census division 1 is now non-standard, as we remove California from that division. As is evident in the top left-hand panel, the incidence of MSA house price return correlations varies substantially across US census divisions. For each division, the number and proportion of significant correlations (using a T-stat of 5 or above) are reported. The mean correlation for each region is also given. The vast majority of census divisions, including divisions 1 – 8, report only limited contemporaneous correlations in MSA house price returns. Specifically, divisions 1 – 8 report a mean correlation coefficient in the range of 0.2 – 0.3 with not more than around 20 percent highly significant. California appears to be different from the rest of the U.S. in that 92 percent of the MSA paired returns are significantly contemporaneously correlated! Further, the mean correlation level for California MSAs is about .66!

As reported in the top right-hand panel of table 4, intertemporal (lead one quarter ahead) correlations are similarly damped in most census divisions. Among divisions 1 - 8, less than 10 percent of lead correlations are statistically significant. Further, mean lead correlation levels remain at or below .20. In marked contrast, MSAs in New England (division 9) and California are characterized by relatively high percentages of significant and elevated lead correlations. Again California is the outlier, as in excess of three-quarters of California MSAs recorded significant lead return correlations with a mean correlation level of about .57.

Panel B reports a similar assessment of contemporaneous and lead LM jump return correlations among MSAs stratified by census division. As shown in the bottom panels, California is conspicuously different from the rest of the U.S. For census divisions 1 – 8, significant contemporaneous jump correlations are small in number (less than 10 percent in any division) and mean correlations coefficients are in the range of only .02 – .03. In those same areas, lead jump correlations are limited to an incidence of 6 percent or less in any division with mean correlation coefficients (except for New England) of .04 or less. In marked contrast, jump return contemporaneous correlations are significant among California MSAs at an occurrence rate of 34 percent, and with much larger values, reaching .22, substantially in excess of levels discussed above for other regions. Moreover, the mean lead jump correlations are highest for California.

Another clear message results from the correlation analysis in US housing markets and when broken down into geographical cohorts. The incidence of significant return correlations far exceeds jump correlations. To illustrate, the percentage with significant t-statistics greater than 2 is in excess of 45 percent for return correlations compared to approximately 18 percent for jump return correlations (see Table 3). When we break out the analysis into geographical cohorts we find that the ratio of significant t-statistics far greater for return correlations with three exceptions, that occur in Divisions 3 through 5 for lead values (see Table 4). The results pertaining to the magnitude of correlations across return and jump returns are even more clear-cut. In all comparisons, we find that the return correlations far exceed their jump counterparts, usually by a ratio of 5 or more!

In addition, analyses of contemporaneous and lead jumps in house price returns again suggest that California is different. Also, levels of contemporaneous and lead return and jump correlations in California were well in excess of levels recorded in other census divisions. Given the anomalous behavior of California metropolitan housing markets thus documented we now turn to identify further insights as regards the temporal – spatial structure of house price return contagion in this state.

IV. Contagion in Housing Market Returns

The above analyses suggest the outlier status of California MSAs in assessment of recent house price phenomena. Specifically, our analyses point to rising levels of integration as well as elevated return correlation and jump return correlation, both lead and contemporaneous, among California MSAs. However, the spatial dimensions of those relationships were not specified. Below we address that issue via parametric assessment of the spatial dynamics of housing returns among MSAs in northern and southern California.

We report some interesting findings for the metropolitan housing markets in California. In particular, spatial return spillovers are largely efficient across MSAs, especially in Southern California, coming from Los Angeles to surrounding areas. Results of a first set of analyses are contained in Table 5. There we test the simple hypothesis that house price returns among primary California coastal MSAs lead those of surrounding areas. That hypothesis is consistent with a mechanism whereby increases in house price returns (and related declines in affordability) in expensive, supply-constrained, coastal metropolitan areas lead to out-migration, related demand-side pressures, and subsequent increases in returns in more affordable inland suburbs. In our test of that hypothesis for southern California, for example, we estimate city-specific regressions whereby we regress returns for each inner- and outer-ring suburb of the larger LA area on contemporaneous and lead Los Angeles MSA house price returns. We undertake identical analyses for the Bay Area and central California using San Francisco and Santa Barbara as primary coastal cities. As shown in Table 5, we estimate those equations over the full timeframe of the metro-specific data sets. In each case, MSA returns are regressed on contemporaneous and 3 quarterly lags of primary coastal MSA returns.

Results of the analysis for LA region MSAs are contained in the top panel of Table 5. Those findings indicate a market efficiency in metropolitan spillover returns in that the most significant effects are contemporaneous. Overall, the regressions are characterized by high levels of explanatory power. In all of LA's surrounding cities, including Bakersfield, Fresno, Oxnard-Thousand Oaks, Riverside, San Diego, Santa Ana, and Santa Barbara, sizable and highly significant coefficients are estimated for contemporaneous Los Angeles house price returns. In Bakersfield and Fresno, located further from Los Angeles in California's great central valley, the contemporaneous coefficients on Los Angeles house price returns are about .60 and highly significant; further, a positive and significant coefficient of about .30 is estimated on the first quarterly lag of Los Angeles house price returns. In marked contrast, in closer-in areas, only the contemporaneous coefficient was statistically significant. Indeed, in those cities, the estimated coefficients on contemporaneous (quarterly) changes in Los Angeles house price returns were close to 1! These analyses indicate a high degree of contemporaneous correlation in house price returns among Los Angeles and its suburbs.

Results of the analysis diverge somewhat for San Francisco and environs where the level of market efficiency appears to be somewhat lower. In most areas of northern California, including Oakland, Sacramento, Salinas, San Jose, Santa Rosa, and Santa Cruz, both contemporaneous and 1-quarter lagged San Francisco house price returns play a sizable and significant role in determination of house price returns. In a few places, including both Oakland and Santa Cruz, contemporaneous as well as 1- and 2-quarter lagged San Francisco house prices returns significantly affect surrounding outcomes. San Francisco house price returns lead those of the outer-ring Central Valley boom town of Modesto by 1-quarter. In short, findings for Bay Area regional housing markets suggest a spatial term structure of contagion, whereas results for Los Angeles indicate a southern California region where metropolitan housing returns largely move in lock-step.

The above findings, however, may not be robust to periods of boom and bust in California housing markets. Indeed, it is plausible that the spatial or temporal path of house price contagion might accelerate during a boom or decelerate and even reverse during a bust. We test for such effects in Table 6. The regression equations estimated in Table 6 are identical to those in Table 5, except that each regression contains 4 additional terms. The additional variables comprise interactions between the primary (explanatory) city's return (contemporaneous and 3 quarterly lags) and a contemporaneous residual from a time trend fit of the log of an equal-weighted index of California house prices.

Findings contained in table 6 indicate that results of the California MSA house price contagion analysis are largely robust to the inclusion of the boom and bust interactive terms. In southern California, an exception is Bakersfield, where a sizable and significant coefficient is estimated on second quarterly lagged interaction term. In northern California, there exists little to report other than significant coefficients on contemporaneous interactive terms for Santa Rosa and Santa Cruz. Accordingly, an explicit accounting for boom and bust periods in California's housing markets has little effect on conclusions regarding the temporal path of house price contagion among California MSAs.[9]

V. Conclusion

This paper applies data from 384 US MSAs to examine integration and contagion among metropolitan housing markets. The paper first examines the level and change in housing market integration as reflected in the response of MSA house price returns to a national multi-factor model. It then investigates the incidence of large house price return and jump return correlations for the MSAs. Finally, as a result of the earlier integration and contagion analysis, it isolates California and further examines contagion characteristics from leading coastal cities to their inland neighbors.

Research findings reveal a highly integrated set of US metropolitan housing markets. Furthermore, the susceptibility of MSA housing markets to national economic and policy shocks trended up over time and was especially evident in the decade of the 2000s. Also, high levels and elevated trends in housing market integration limit the efficacy of strategies to diversify MSA-specific risk on the part of mortgage and housing investors.

[9] We undertook yet another robustness check whereby we created an interaction between the explanatory's city's return (including four lags) and a contemporaneous residual from a time trend fit of the log of an equal-weighted California MSA (N=28) FHFA house price index. That interaction term was substituted for the primary coastal city boom and bust interaction term estimated in Table 6. Results here differed little from those reported in table 6, as the house price index for the state as a whole differed little from those for the primary coastal California cities.

California emerges as somewhat of an outlier, in terms of elevated trends in integration, jumps in house price returns, and MSA contemporaneous and lagged return and jump return correlations. In addition, high levels of short-term contagion appear endemic to major California markets, especially in Los Angeles. Inland California MSAs appear to behave as one and exhibit a high degree of market efficiency in the response to return movements in the large coastal metropolitan areas.

References

Barndorff-Nielsen, O., and Shephard, N. 2006. Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics* 4, 1-30.

Bekaert, G., and Harvey, C., 1995. "Time-Varying World Market Integration", *Journal of Finance* 50, 403-444.

Bekaert, G., Harvey, C., Lundblad, C., and Siegel, S., 2008. What Segments Equity Markets? AFA 2009 Meetings Paper. Available at SSRN: http://ssrn.com/abstract=1108156.

Case, K., Cotter, J., and Gabriel, S., Housing Risk and Return: Evidence from a Housing Asset Pricing Model, *Journal of Portfolio Management*, forthcoming, 2011.

Carrieri, F., Errunza, V., and Hogan, K., 2007, Characterizing World Market Integration Through Time. *Journal of Financial and Quantitative Analysis*, 42, 915-940.

Chambet, A., and Gibson, R., 2008, Financial Integration, Economic Instability, and Trade Structure in Emerging Markets, *Journal of International Money and Finance* 27, 654-675.

Hardouvelis, G., Malliaropoulos, D., and Priestley, R., 2006. EMU and European stock market integrations *Journal of Business* 79, 369-392.

Henderson, V., Economic Theory and the Cities, Academic Press, New York, 1977.

Jacod, J., and Todorov, V. 2009. Testing for common arrivals of jumps for discretely observed multidimensional processes. *The Annals of Statistics* 37, 1792-1838.

Jiang, G., and Oomen, R. 2008. Testing for jumps when asset prices are observed with noise – a "swap variance" approach. *Journal of Econometrics* 144, 352-370.

King, M. A., and S. Wadhwani, 1990, Transmission of volatility between stock markets, *Review of Financial Studies* 3, 5-33.

Lee, S., and Mykland, P., 2008. Jumps in financial markets: A new nonparametric test and jump dynamics, *Review of Financial Studies* 21, 2535-2563.

Longin, F., Solnik, B., 1995. Is the correlation in international equity returns constant: 1960-1990? *Journal of International Money and Finance* 14, 3-26.

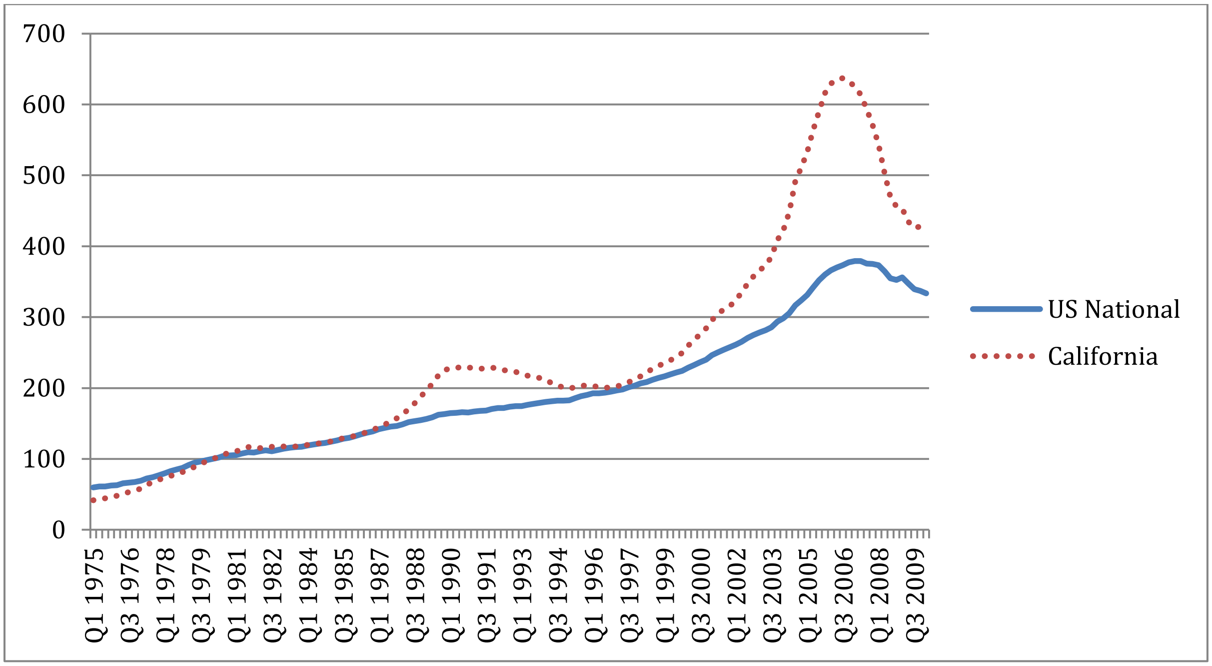
Longin, F., and Solnik, B., 2001, Extreme correlation of international equity markets, *Journal of Finance*, 56: 649-676.

Pukthuanthong-Le, K., and Roll, R. Global Market Integration: An Alternative Measure and Its Application, *Journal of Financial Economics*, 2009, 94(2), 214-232.

Pukthuanthong-Le, K., and Roll, R., Internationally Correlated Jumps, Working Papers in Finance, UCLA Anderson School of Management, July 2010.

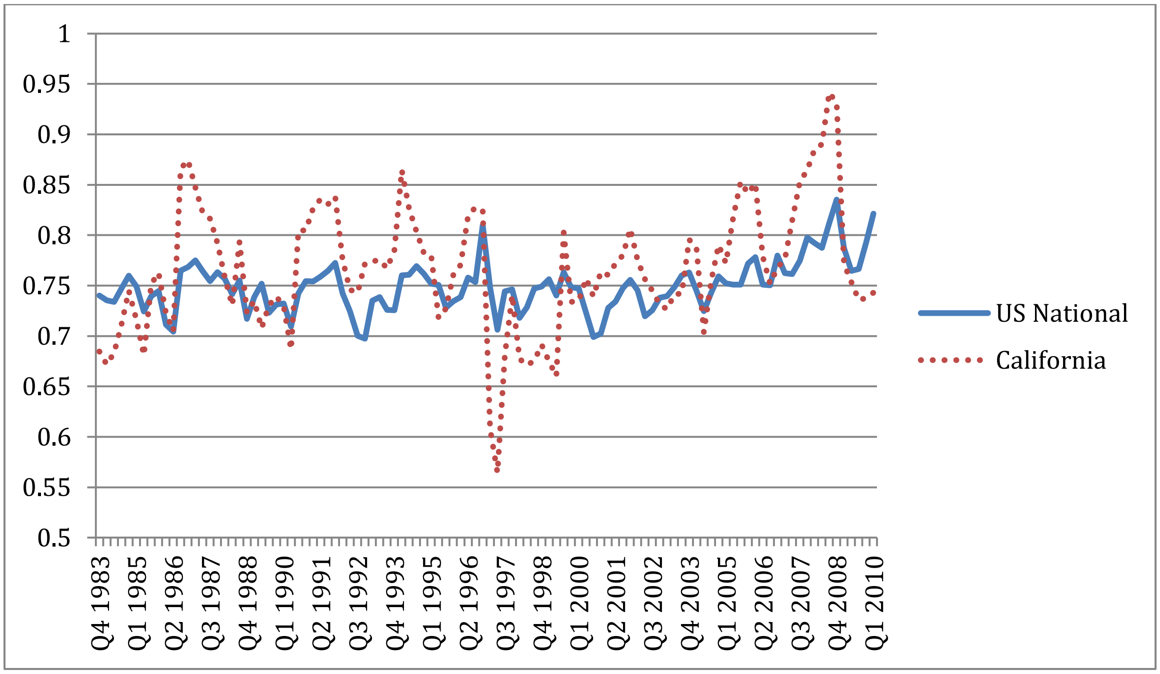
Schotman, P., and Zalewska, A., 2006, Non-synchronous trading and testing for market integration in Central European emerging markets, *Journal of Empirical Finance* 13, 462-494.

Figure 1: US and California House Price Indices

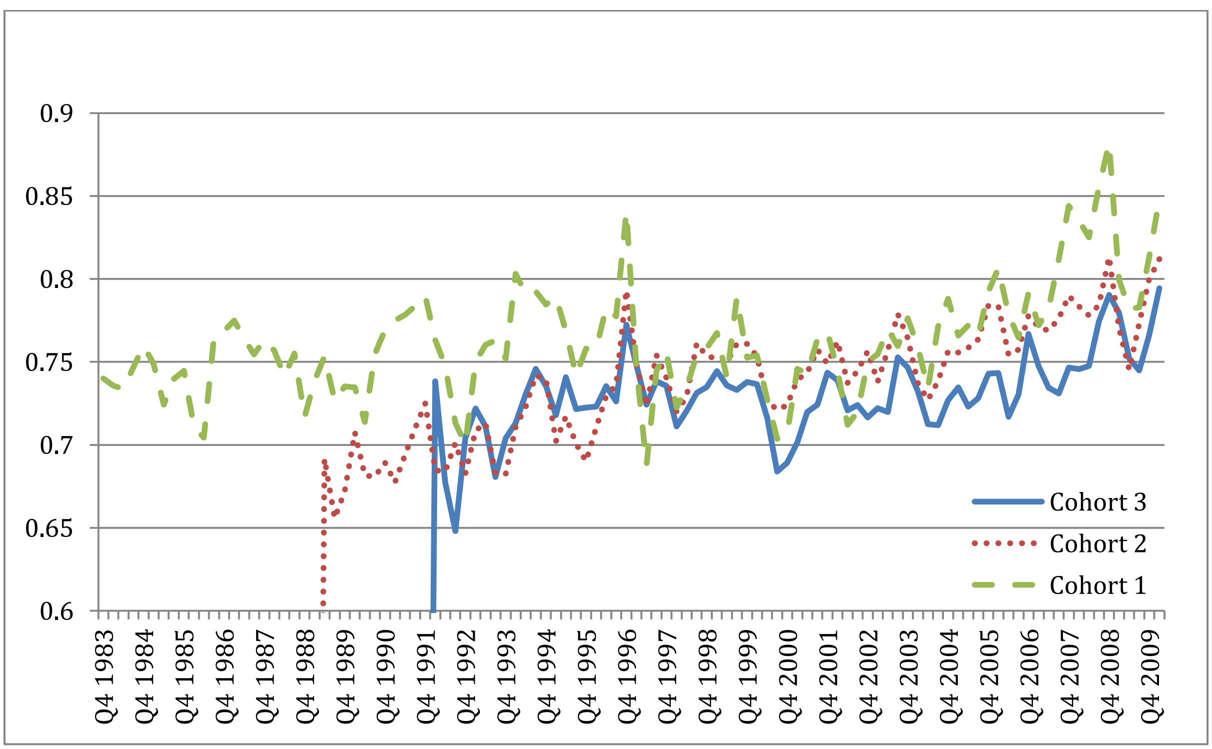


Notes: The chart depicts the time series of US national and California index levels (1975: Q1 - 2010:Q1) based on repeat sales house price indexes from the Federal Housing Finance Agency (FHFA). The prices are normalized to 100 in 1980:Q1.

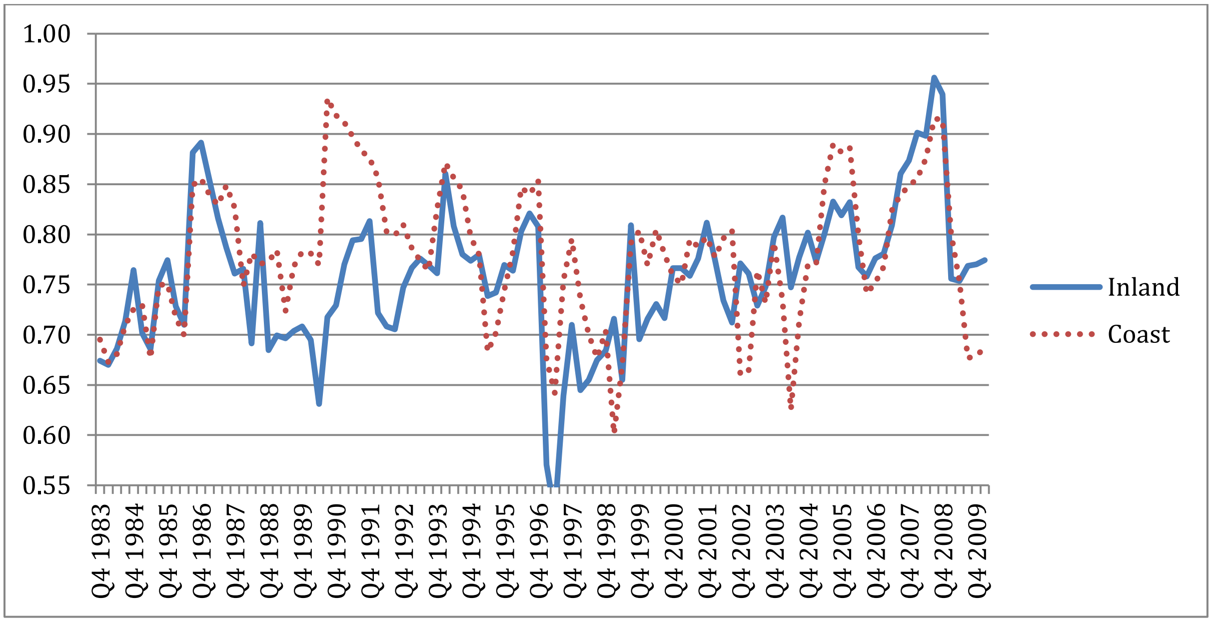
Figure 2: Housing Return Integration Trends
Panel A: Average R-squares for US MSAs and California MSAs



Panel B: Average R-squares for US MSA Time Cohorts

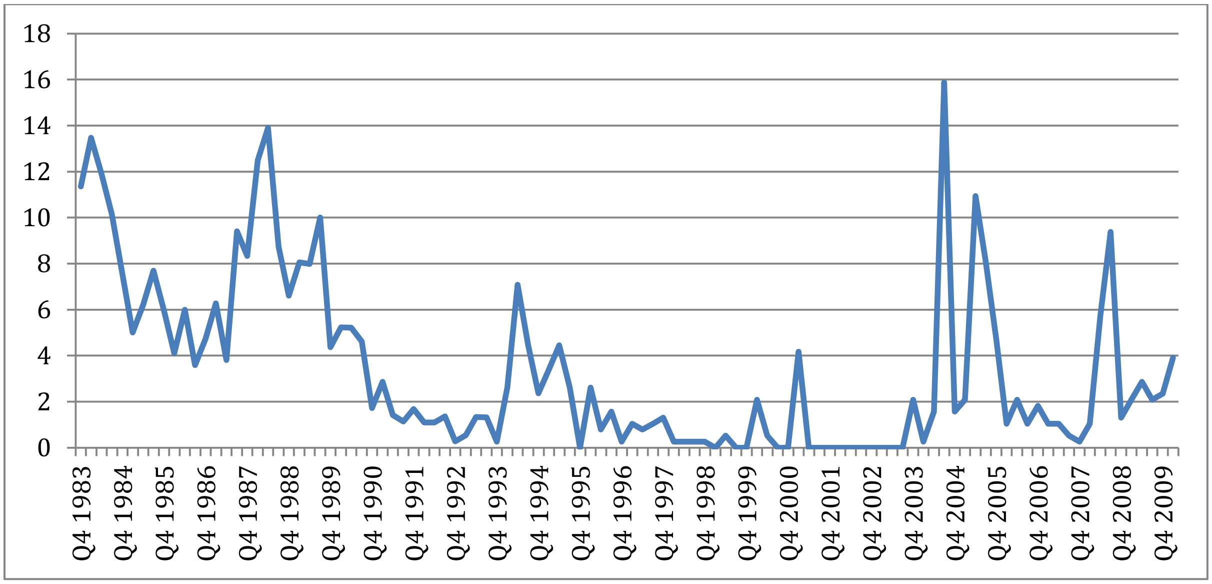


Panel C: Average R-squares for California Inland and Coastal MSAs

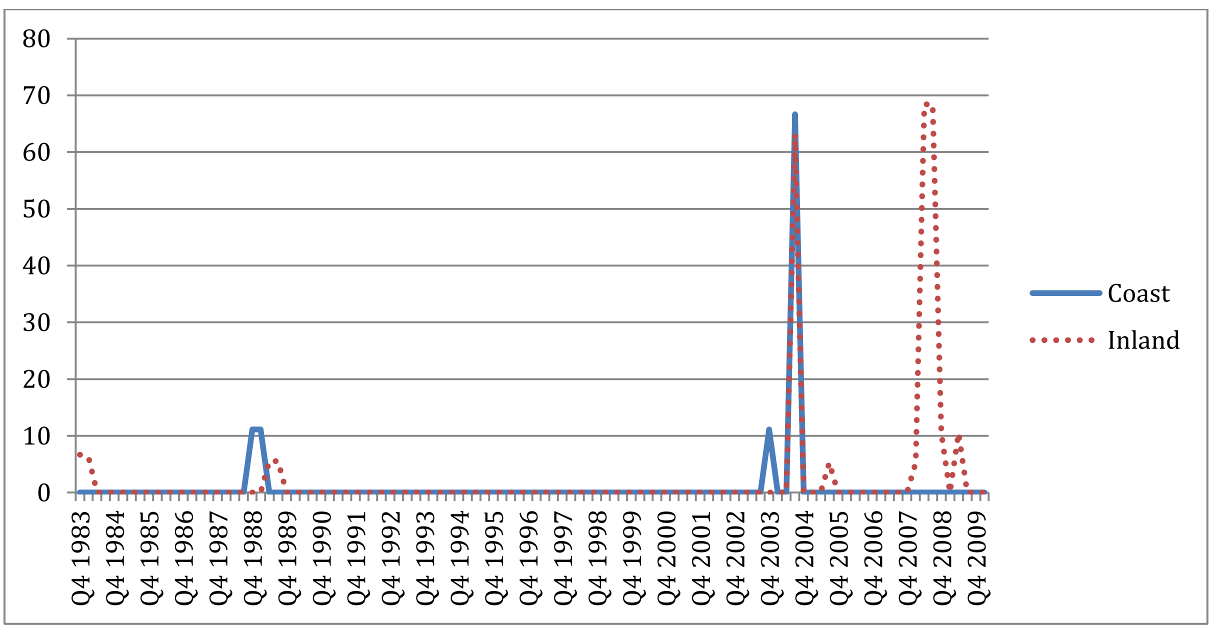


Notes: The level of integration is measured by the R-squares from the multi-factor housing returns model fitted for the full sample of MSAs using a 20-quarter moving window. See Appendix Table 1 for details on the factors utilized in model estimation. Average levels of integration are presented for 1983:Q4 – 2010:Q1 for 384 US MSAs and for 28 California MSAs. Average levels of integration are presented for time cohorts based on when the MSA entered the database and had sufficient time series to execute the moving window regression. The cohorts begin at 1983: Q4 (cohort 1), 1989:Q2 (cohort 2) and 1992:Q1 (cohort 3). Average levels of integration are also presented for California Interior MSAs and California Coast MSAs. California Coastal MSAs include Los Angeles, Oakland, Oxnard, San Diego, San Francisco, San Jose, San Luis Obispo, Santa Ana, Santa Barbara and Santa Cruz with the remainder of the 28 MSAs categorized as California Inland MSAs.

Figure 3: US and California LM Jump Statistics
Panel A: Big LM House Price Return Jumps Proportion [% |LM| > 2] for US MSAs by Quarter



Panel B: Big LM House Price Return Jumps Proportion [% |LM| > 2] for Coastal and Inland California MSAs by Quarter



Notes: The Lee and Mykland (2008) (LM) jump measure is computed from quarterly observations for each of the 384 MSAs. Plots are given for the US National, and for inland and coast California MSAs. The plots are from 1983:Q4 and show the percentage of LM statistic that exceed 2.0. The percentage classified as a jump quarter is when the absolute value of the LM statistic exceeds the 10% level for a unit normal (1.65).

Table 1
Summary Integration Measures for All MSAs

	Mean	Sigma	Final R-Square	Change in R-Square	R-Square Trend T-stat
Mean	0.988	2.450	0.822	0.093	1.222
Std Dev	0.259	0.890	0.118	0.187	2.879
Min/Quintile 1	0.430	0.980	0.349	-0.616	-7.246
Quintile 2	0.784	1.744	0.738	-0.046	-1.167
Quintile 3	0.890	2.144	0.817	0.053	0.501
Quintile 4	0.998	2.545	0.864	0.120	2.035
Quintile 5	1.185	2.958	0.930	0.236	3.436
Max	1.892	9.258	0.993	0.695	10.469

Summary details for 5 integration characteristics (Mean, Sigma, Final R-square, Change in R-square, and R-Square Trend T-stat) are presented for the 384 MSAs. Mean is the average quarterly house price return. We compute house price returns for each MSA in our sample as the log quarterly difference in its FHFA repeat home sales price index. Sigma is the standard deviation of returns. We use R-Squares as the measure of integration and these are applied to obtain R-square trend t-statistics. R-squares are obtained from fitting MSA returns to the factors described in Appendix Table 1. The time trend t-statistics are estimated by regressing the R-squares for each MSA on a simple linear time trend for all available quarters of data. The final R-squares pertain to 2010:Q1 for all 384 US MSAs. The change in R-squares refers to the difference between estimates for 2010:Q1 and 1983:Q4 for each MSA. Summary details report the time-series cross-sectional summary statistics (mean, standard deviation, minimum/quintile 1, quintile 2, quintile 3, quintile 4, quintile 5 and maximum) of the characteristics. The minimum values of each quintile are presented.

Table 2
Summary Integration Measures for California MSAs

MSA	Mean	US Rank Mean	CA Rank Mean	Sigma	US Rank Sigma	CA Rank Sigma	Final R-Square	Change in R-Square	Trend t-stat	US Rank Trend t-stat	CA Rank Trend t-stat
Bakersfield	0.864	136	4	3.197	330	16	0.898	0.166	4.228	335	26
Chico	1.066	273	11	3.077	321	13	0.832	0.169	-0.844	87	7
El Centro	0.607	11	1	4.240	370	27	0.912	0.114	2.365	258	18
Fresno	1.075	276	12	3.198	331	17	0.833	-0.004	2.174	241	16
Hanford	0.909	172	8	3.098	324	15	0.619	0.226	4.120	331	25
Los Angeles	1.736	380	26	2.839	286	5	0.558	-0.339	2.172	239	15
Madera	0.879	146	6	3.548	351	23	0.826	-0.121	8.208	380	28
Merced	0.790	84	2	4.674	376	28	0.889	0.111	2.937	282	20
Modesto	1.005	236	9	4.006	364	26	0.820	0.168	2.994	286	22
Napa	1.424	358	18	2.989	312	9	0.838	0.158	3.463	310	24
Oakland	1.699	378	25	2.638	250	2	0.577	-0.115	0.744	167	12
Oxnard	1.635	374	23	2.991	313	10	0.768	0.099	2.353	255	17
Redding	0.879	148	7	3.063	319	12	0.947	0.388	-1.395	68	5
Riverside	1.296	332	14	3.438	343	21	0.713	0.177	-1.260	74	6
Sacramento	1.354	345	17	2.894	299	8	0.649	-0.176	2.980	284	21
San Diego	1.541	369	16	3.013	314	24	0.868	-0.114	0.253	141	14
San Francisco	1.892	384	20	2.540	229	11	0.638	-0.143	-2.069	50	10
San Jose	1.877	383	28	2.789	274	1	0.759	0.123	-2.379	42	3
San Luis Obispo	1.303	334	27	3.326	337	4	0.637	-0.134	-0.826	88	1
Santa Ana	1.674	376	15	2.718	265	19	0.626	0.051	-1.713	58	8
Santa Barbara	1.470	364	24	2.879	295	3	0.779	0.090	0.256	142	4
Santa Cruz	1.599	373	19	3.093	323	7	0.657	0.065	2.422	262	11
Santa Rosa	1.590	371	22	2.855	291	14	0.678	0.251	0.990	182	19
Stockton	1.050	266	21	3.696	359	6	0.669	0.238	-0.537	108	13
Vallejo	1.133	293	10	3.419	342	25	0.796	0.074	-2.146	47	9
Visalia	0.872	142	13	3.244	334	20	0.828	-0.013	3.380	303	2

Yuba City	0.833	113	5	3.448	345	18	0.579	0.030	5.775	361	23
	Mean			***Sigma***			***Final R-Square***	***Change in R-Square***	***Trend t-stat***		
Mean	1.264			3.231			0.741	0.057	1.447		
Std Dev	0.368			0.485			0.118	0.158	2.590		
Min	0.607			2.540			0.558	-0.339	-2.379		
Max	1.892			4.674			0.947	0.388	8.208		

Notes: Details for 3 integration characteristics (Mean, Sigma and R-Square Trend t-stat) are presented for all 28 California MSAs. Mean is the average quarterly house price return. We compute house price returns for each MSA in our sample as the log quarterly difference in its FHFA repeat home sales price index. Sigma is the standard deviation of returns. R-Squares are the estimates of integration and are used to obtain R-Square trend t-statistics. R-squares are obtained from fitting MSA returns to the factor model described in Appendix Table 1. The time trend t-statistics are estimated by regressing the R-squares for each MSA on a simple linear time trend for all available quarters of data. The final R-Squares pertain to 2010:Q1 for all 28 California MSAs. The change in R-Squares refers to the difference between estimates for 2010:Q1 and 1983:Q4 for each MSA. Each characteristic is ranked from lowest to highest in comparison both to all 384 US MSAs and all 28 California MSAs. The last four rows provide the time-series cross-sectional summary statistics (mean, standard deviation, minimum and maximum) of the characteristics with reference to all CA MSAs.

Table 3—MSA House Price Return and Jump Correlations

Panel A: Return Correlations

Full sample					
N	**Mean**	**Sigma**	**T-Stat**	**Maximum**	**Minimum**
73536	0.201	0.182	299.735	0.946	-0.639
Sample of correlations with T-statistic > 2					
N	**Mean**	**Sigma**	**T-Stat**	**Maximum**	**Minimum**
33460	0.354	0.125	517.703	0.946	0.173
Sample of correlations with T-statistic > 3					
N	**Mean**	**Sigma**	**T-Stat**	**Maximum**	**Minimum**
18126	0.435	0.116	505.922	0.946	0.258

Table 3—MSA House Price Return and Jump Correlations

Panel B: Jump Correlations

Full sample					
N	**Mean**	**Sigma**	**T-Stat**	**Maximum**	**Minimum**
49742	0.047	0.194	53.528	1.000	-0.924
Sample of jump correlations with T-statistic > 2					
N	**Mean**	**Sigma**	**T-Stat**	**Maximum**	**Minimum**
8770	0.375	0.148	236.908	1.000	0.173
Sample of jump correlations with T-statistic > 3					
N	**Mean**	**Sigma**	**T-Stat**	**Maximum**	**Minimum**
5405	0.455	0.135	247.201	1.000	0.259

Notes: Notes: Panel A shows the house price return correlations. Correlation coefficients are computed from quarterly returns for all pairs of 384 MSAs (total sample N = 73536). Sigma is the cross-coefficient standard deviation. T is the T-statistic that tests for cross-coefficient independence. Panel B shows the jump correlations. Correlation coefficients are computed from quarterly returns for Lee and Mykland's (2008) (LM) jump measure. Sigma is the cross-coefficient standard deviation. T is the T-statistic that tests for cross-coefficient independence.

Table 4
Contemporaneous and Lagged MSA House Price Return and Jump Correlations by Geographical Cohort

Panel A: Return Correlations

	Contemporaneous correlation				Lead correlation			
	N	Number Significant	Percentage Significant	Mean Correlation	N	Number Significant	Percentage Significant	Mean Correlation
Division 1	190	37	19.474	0.304	400	34	8.500	0.182
Division 2	595	83	13.950	0.314	1225	88	7.184	0.222
Division 3	496	14	2.823	0.211	1024	6	0.586	0.100
Division 4	903	29	3.212	0.180	1849	19	1.028	0.091
Division 5	1953	129	6.605	0.268	3969	49	1.235	0.148
Division 6	2628	237	9.018	0.251	5329	295	5.536	0.171
Division 7	703	62	8.819	0.237	1444	62	4.294	0.154
Division 8	561	100	17.825	0.317	1156	104	8.997	0.213
Division 9	153	114	74.510	0.629	324	193	59.568	0.501
CA	378	349	92.328	0.656	784	596	76.020	0.565

Table 4
Contemporaneous and Lagged MSA House Price Return and Jump Correlations by Geographical Cohort

Panel B: Jump (LM) Correlations

	Contemporaneous correlation				Lead correlation			
	N	Number Significant	Percentage Significant	Mean Correlation	N	Number Significant	Percentage Significant	Mean Correlation
Division 1	190	9	4.737	0.028	321	20	6.231	-0.029
Division 2	595	19	3.193	0.021	791	31	3.919	0.035
Division 3	496	5	1.008	0.006	552	23	4.167	0.035
Division 4	903	26	2.879	0.017	1124	60	5.338	0.025
Division 5	1953	60	3.072	0.018	2479	111	4.478	0.037
Division 6	2628	67	2.549	0.017	3772	84	2.227	0.034
Division 7	703	33	4.694	0.033	1068	17	1.592	0.012
Division 8	561	15	2.674	0.016	770	36	4.675	0.041
Division 9	153	13	8.497	0.047	252	13	5.159	0.095
CA	378	130	34.392	0.224	705	49	6.950	0.116

Notes: Panel A presents the return correlations including both contemporaneous and lead (one quarter ahead) correlations. Correlation coefficients are computed from quarterly returns for each geographical division where N is the sample size. The number and proportion of significant correlations with a t-statistic greater than 5 are reported. The mean correlation is also given. Panel B presents the jump correlations including both contemporaneous and lead (one quarter ahead) correlations. Correlation coefficients are computed from quarterly returns for Lee and Mykland's (2008) (LM) jump measure for each geographical division where N is the sample size. The number and proportion of significant correlations with a t-statistic greater than 5 are reported. The mean correlation is also given. The geographical divisions are based on the 9 US census divisions. However the definition of division 1 is not standard, in that we remove California from census division 1 and report it separately in a cohort by itself (CA). The states in the 9 census divisions are: Division 1 (AK HI OR WA), Division 2 (AZ CO ID MT NM NV UT WY), Division 3 (IA KS MN MO ND NE SD), Division 4 (AR LA OK TX), Division 5 (IL IN MI OH WI), Division 6 (AL KY MS TN), Division 7 (DC DE FL GA MD NC SC VA WV), Division 8 (NJ NY PA) and Division 9 (CT MA ME NH RI VT).

Table 5—Housing Return Contagion Regressions for California MSAs
Panel A: Explanatory MSA - Los Angeles

	N	Constant	Lag0	Lag1	Lag2	Lag3	R-Squares
Bakersfield	130	-0.460	0.600	0.350	-0.210	0.120	0.516
		(-2.010)	(4.360)	(2.050)	(-1.220)	(0.880)	
Fresno	131	-0.280	0.600	0.290	-0.230	0.190	0.509
		(-1.200)	(4.320)	(1.730)	(-1.340)	(1.400)	
Oxnard	135	0.100	1.070	0.070	-0.120	-0.090	0.867
		(0.850)	(16.420)	(0.890)	(-1.430)	(-1.300)	
Riverside	135	-0.540	0.950	0.110	0.100	-0.060	0.788
		(-3.300)	(10.100)	(0.970)	(0.810)	(-0.640)	
San Diego	136	0.190	0.900	-0.190	0.030	0.060	0.564
		(0.940)	(7.610)	(-1.270)	(0.200)	(0.510)	
Santa Ana	136	0.100	0.900	0.020	0.010	-0.010	0.895
		(1.040)	(17.170)	(0.250)	(0.140)	(-0.270)	
Santa Barbara	129	0.220	0.890	-0.080	0.070	-0.050	0.649
		(1.240)	(8.390)	(-0.590)	(0.550)	(-0.450)	

Panel B: Explanatory MSA - San Francisco

	N	Constant	Lag0	Lag1	Lag2	Lag3	R-Squares
Merced	117	-1.130	0.340	0.670	0.190	-0.050	0.285
		(-2.430)	(1.190)	(2.100)	(0.690)	(-0.210)	
Modesto	131	-0.950	-0.020	0.650	0.410	0.050	0.380
		(-2.640)	(-0.130)	(3.480)	(2.160)	(0.290)	
Napa	125	-0.100	0.370	0.130	0.400	0.010	0.439
		(-0.380)	(2.820)	(0.910)	(2.760)	(0.050)	
Oakland	135	-0.290	0.670	0.140	0.110	0.120	0.821
		(-2.280)	(11.330)	(2.170)	(1.710)	(2.090)	
Sacramento	134	-0.260	0.400	0.290	-0.070	0.260	0.447
		(-1.050)	(3.500)	(2.310)	(-0.590)	(2.240)	
Salinas	129	-0.440	0.610	0.480	-0.260	0.220	0.427
		(-1.430)	(3.880)	(2.880)	(-1.530)	(1.480)	
San Jose	135	-0.170	0.710	0.310	0.030	0.040	0.831
		(-1.350)	(11.750)	(4.620)	(0.380)	(0.730)	
Santa Cruz	127	-0.030	0.360	0.380	0.300	-0.070	0.473
		(-0.130)	(2.780)	(2.610)	(2.060)	(-0.520)	
Santa Rosa	133	-0.230	0.440	0.410	0.070	0.090	0.623
		(-1.160)	(4.710)	(3.930)	(0.680)	(0.940)	
Stockton	131	-0.900	0.590	0.250	0.100	0.180	0.423
		(-2.840)	(3.790)	(1.510)	(0.570)	(1.190)	
Vallejo	127	-0.630	0.550	0.050	0.520	-0.070	0.465
		(-2.240)	(3.790)	(0.310)	(3.240)	(-0.490)	

Panel C: Explanatory MSA - Santa Barbara

Oxnard	126	0.040	0.550	0.270	0.130	-0.020	0.673
		(0.250)	(7.400)	(3.700)	(1.750)	(-0.250)	
San Luis Obispo	126	0.180	0.230	0.130	0.190	0.260	0.379
		(0.680)	(2.060)	(1.210)	(1.750)	(2.280)	

Notes: Regression results for a selection of California MSAs on contemporaneous and lagged returns (3 lags) of large coastal California MSAs. The three large coastal leading cities used in the regressions are Los Angeles (Panel A), San Francesco (Panel B) and Santa Barbara (Panel C). N is the number of quarters in each regression. Regression coefficients and t-statistics in parentheses are given. R-squares of each regression are also reported. Results for some MSAs required a Cochrane-Orcutt adjustment for error term serial correlation. Durbin-Watson statistics for all presented MSA regressions allow us to reject the null hypothesis of first order serial correlation.

Table 6— Housing Return Contagion Regressions Across Booms and Busts for California MSAs

Panel A: Explanatory MSA - Los Angeles

	N	Constant	Lag0	Lag1	Lag2	Lag3	Lag0	Lag1	Lag2	Lag3	R-Square
Bakersfield	130	-0.35	0.60	0.26	-0.14	0.10	0.08	2.27	-2.67	1.03	0.523
		(-1.34)	(3.87)	(1.49)	(-.81)	(0.68)	(0.07)	(1.64)	(-2.13)	(1.13)	
Fresno	121	0.07	0.58	-0.19	0.05	0.29	0.49	-0.98	-0.41	0.030	0.294
		(0.22)	(3.09)	(-0.93)	(0.22)	(1.58)	(0.36)	(-0.58)	(-0.25)	(0.03)	
Oxnard	131	-0.37	0.62	0.30	-0.25	0.21	-1.16	-0.25	1.82	-1.31	0.518
		(-1.47)	(4.06)	(1.76)	(-1.43)	(1.47)	(-1.03)	(-0.19)	(1.51)	(-1.43)	
Riverside	135	0.14	1.01	0.10	-0.14	-0.050	0.26	0.010	0.13	-0.96	0.882
		(1.210)	(15.55)	(1.32)	(-1.78)	(-0.80)	(0.67)	(0.02)	(0.25)	(-2.34)	
San Diego	135	-0.50	0.96	0.110	0.10	-0.070	-0.10	0.94	-0.91	0.13	0.786
		(-2.80)	(9.44)	(0.91)	(0.83)	(-0.68)	(-0.16)	(1.18)	(-1.09)	(0.20)	
Santa Ana	136	0.25	0.82	-0.15	-0.02	0.13	1.49	-2.28	1.64	-1.46	0.594
		(1.19)	(7.04)	(-1.03)	(-0.11)	(1.11)	(2.24)	(-2.46)	(1.83)	(-2.28)	
Santa Barbara	136	0.13	0.87	0.030	0.00	0.00	0.11	0.34	-0.31	-0.51	0.904
		(1.40)	(16.83)	(0.50)	(-0.01)	(0.020)	(0.38)	(0.84)	(-0.77)	(-1.81)	

Panel B: Explanatory MSA - San Francisco

	N	Constant	Lag0	Lag1	Lag2	Lag3	Lag0	Lag1	Lag2	Lag3	R-Square
Merced	117	-0.92	0.36	0.72	-0.04	0.10	0.88	0.81	2.46	-2.35	0.292
		(-1.88)	(1.18)	(1.90)	(-0.10)	(0.34)	(0.41)	(0.31)	(0.96)	(-1.19)	
Modesto	131	-0.84	-0.01	0.67	0.39	0.06	0.15	1.51	0.51	-1.33	0.387
		(-2.30)	(-0.08)	(3.31)	(1.85)	(0.33)	(0.13)	(1.27)	(0.39)	(-1.17)	
Napa	125	-0.10	0.55	-0.18	0.46	0.09	-2.05	3.18	-0.33	-1.18	0.458
		(-0.39)	(3.61)	(-0.92)	(2.29)	(0.56)	(-2.00)	(2.46)	(-0.24)	(-1.10)	
Oakland	135	-0.29	0.67	0.14	0.12	0.11	-0.40	0.53	0.07	-0.21	0.821
		(-2.23)	(10.98)	(2.04)	(1.80)	(1.84)	(-1.23)	(1.53)	(0.17)	(-0.56)	
Sacramento	129	-0.31	0.56	0.53	-0.36	0.30	1.04	0.24	0.96	-2.06	0.432
		(-0.97)	(3.11)	(2.81)	(-1.85)	(1.88)	(0.86)	(0.20)	(0.72)	(-2.02)	
Salinas	135	-0.22	0.71	0.30	0.04	0.04	-0.34	-0.34	0.060	0.42	0.831
		(-1.66)	(11.36)	(4.34)	(0.52)	(0.60)	(-1.02)	-(0.96)	(0.15)	(1.12)	
San Jose	127	-0.15	0.54	0.19	0.29	-0.03	-2.51	1.74	0.41	-0.21	0.483
		(-0.56)	(3.53)	(0.99)	(1.52)	(-0.19)	(-2.43)	(1.36)	(0.31)	(-0.20)	
Santa Cruz	133	-0.26	0.42	0.39	0.07	0.10	-1.20	0.77	0.69	-0.85	0.646
		(-1.31)	(4.48)	(3.74)	(0.64)	(1.05)	(-2.27)	(1.28)	(1.12)	(-1.47)	
Santa Rosa	131	-0.67	0.46	0.43	-0.04	0.25	3.29	-1.25	0.74	-1.56	0.457
		(-2.13)	(2.88)	(2.43)	(-0.21)	(1.58)	(3.27)	(-1.21)	(0.64)	(-1.58)	
Stockton	127	-0.59	0.54	0.12	0.37	0.02	0.30	-0.33	1.58	-1.07	0.456
		(-1.97)	(3.14)	(0.54)	(1.70)	(0.13)	(0.26)	(-0.23)	(1.06)	(-0.90)	
Vallejo	117	-0.92	0.36	0.72	-0.04	0.10	0.88	0.81	2.46	-2.35	0.292
		(-1.88)	(1.18)	(1.90)	(-0.10)	(0.34)	(0.41)	(0.31)	(0.96)	(-1.19)	

Panel C: Explanatory MSA - Santa Barbara

	N	Constant	Lag0	Lag1	Lag2	Lag3	Lag0	Lag1	Lag2	Lag3	
Oxnard	126	0.16	0.55	0.22	0.11	0.01	-0.07	0.80	0.31	-0.59	0.671
		(0.79)	(5.71)	(2.70)	(1.27)	(0.11)	(-0.09)	(1.29)	(0.53)	(-0.93)	
San Luis Obispo	126	-0.01	0.30	0.16	0.15	0.25	-1.19	-0.45	0.86	0.18	0.371
		(-0.04)	(2.03)	(1.29)	(1.17)	(1.68)	(-1.06)	(-0.47)	(0.95)	(0.19)	

Notes: Regression results for a selection of California MSAs on contemporaneous and lagged returns (3 lags) of large coastal California MSAs. In addition the regressions contain four more variables, each one being an interaction between the explanatory city's return (including 3 lags) and a contemporaneous residual from a time trend fit of the log of the large coastal city's house price index. The three large coastal leading cities used in the regressions are Los Angeles (Panel A), San Francesco (Panel B) and Santa Barbara (Panel C). N is the number of quarters in each regression. Regression coefficients and t-statistics in parentheses are given. R-squares of each regression are also reported. Results for some MSAs required a Cochrane-Orcutt adjustment for error term serial correlation. Durbin-Watson statistics for all presented MSA regressions allow us to reject the null hypothesis of first order serial correlation.

Appendix Table 1
Factor Model Data and Specification

Data	Data Defined
MSA HP	log percent change in MSA house price index
CNP16OV	log percent change civilian non-institutional population
CPILFESL	log percent change in CPI
FEDFUNDS	log Fed Funds Rate
GS10	log 10-year constant maturity Treasury
INDPRO	log percent change in Industrial Production Index
PAYEMS	log percent change in US payroll employment
PERMIT1	log single-family building permits
PPIITM	log percent change PPI materials prices
UMCSENT	log University of Michigan Consumer Sentiment Index
UNRATE	log unemployment rate
SP500	log percent change in S&P 500
INCOME	log personal income

Notes: MSA level data are quarterly and the start of the database is 1975 quarter 1 and the end is 2010 quarter 1. The number of MSAs in the database increases over time beginning with 2 in 1975 and reaches 380 by 1993. At the end of the sample there are 384 MSAs. All factor data are quarterly from 1975:Q1 – 2010:Q1 with the exception of UMCSENT which is available since 1977 quarter 4. The MSA house price data is provided by the Federal Housing Finance Agency (FHFA). MSA house price returns are computed as the log quarterly difference in the MSA repeat home sales price index. Data for the factors are obtained from the Federal Reserve Bank of St. Louis FRED (Federal Reserve Economic Data) except the SP500 (Datastream) and INCOME (US Dept of Commerce National Income and Product Accounts).

Appendix Table 2
Integration Details for All MSAs

MSA	State	Mean	Rank Mean	Quintile Mean	Sigma	Rank Sigma	Quintile Sigma	Final R-Square	Change in R-Square	Trend t-stat	Rank Trend t-stat	Quintile Trend t-stat
Abilene	TX	0.615	16	1	3.115	325	5	0.962	0.274	-0.379	111	2
Akron	OH	0.957	200	3	1.688	68	1	0.897	0.049	-1.964	52	1
Albany	GA	0.699	36	1	2.040	137	2	0.846	0.364	-1.417	32	1
Albany	NY	1.337	341	5	2.590	241	4	0.871	0.134	-2.847	67	1
Albuquerque	NM	1.152	298	4	1.961	116	2	0.938	0.062	0.783	171	3
Alexandria	LA	0.790	83	2	2.186	160	3	0.954	0.102	7.057	373	5
Allentown	PA	1.050	264	4	3.357	340	5	0.952	0.304	-1.944	53	1
Altoona	PA	1.027	252	4	2.526	225	3	0.956	0.058	-2.983	31	1
Amarillo	TX	0.779	73	1	2.894	298	4	0.734	-0.012	0.174	136	2
Ames	IA	0.952	195	3	1.380	26	1	0.555	0.111	-3.058	29	1
Anchorage	AK	0.728	51	1	3.811	360	5	0.777	-0.047	2.316	249	4
Anderson	SC	0.829	110	2	2.131	41	1	0.851	0.197	1.453	203	3
Anderson	IN	0.872	140	2	1.513	150	2	0.944	0.576	6.308	366	5
Ann Arbor	MI	0.977	213	3	2.351	189	3	0.969	0.202	1.343	196	3
Anniston	AL	0.910	173	3	1.983	121	2	0.762	0.181	0.132	133	2
Appleton	WI	0.843	122	2	1.094	5	1	0.766	0.095	1.781	219	3
Asheville	NC	1.265	325	5	1.459	32	1	0.882	0.447	5.743	360	5
Athens	GA	0.904	165	3	1.255	12	1	0.814	-0.104	-2.158	46	1
Atlanta	GA	1.010	241	4	1.494	39	1	0.925	0.061	-1.147	79	1
Atlantic City	NJ	1.176	304	4	2.407	203	3	0.954	0.356	1.468	204	3
Auburn	AL	0.858	131	2	2.223	167	3	0.965	0.574	6.963	372	5
Augusta	GA	0.876	143	2	3.216	332	5	0.967	0.383	0.653	159	3
Austin	TX	1.220	314	5	3.056	318	5	0.776	0.254	1.595	210	3
Bakersfield	CA	0.864	136	2	3.197	330	5	0.898	0.166	4.228	335	5

Baltimore	MD	1.364	349	5	1.846	103	2	0.750	0.035	2.692	272	4
Bangor	ME	0.721	46	1	2.700	261	4	0.964	0.440	3.558	316	5
Barnstable Town	MA	1.390	354	5	2.540	227	3	0.836	0.252	2.816	276	4
Baton Rouge	LA	0.915	177	3	1.704	70	1	0.786	-0.095	2.360	257	4
Battle Creek	MI	0.897	159	3	2.136	151	2	0.855	0.342	2.565	269	4
Bay City	MI	0.899	161	3	2.513	221	3	0.860	0.243	1.847	221	3
Beaumont	TX	0.729	52	1	2.435	209	3	0.853	0.028	-1.434	66	1
Bellingham	WA	1.337	342	5	2.565	235	4	0.743	-0.080	-3.500	20	1
Bend	OR	1.367	350	5	3.076	320	5	0.797	0.022	0.986	181	3
Bethesda	MD	1.438	361	5	2.232	168	3	0.760	-0.038	-0.973	83	2
Billings	MT	1.006	238	4	2.501	219	3	0.768	0.142	-0.485	109	2
Binghamton	NY	0.809	101	2	2.516	223	3	0.739	0.102	-2.385	41	1
Birmingham	AL	0.954	197	3	2.397	201	3	0.975	0.450	0.435	153	2
Bismarck	ND	0.967	205	3	1.349	21	1	0.666	-0.177	-6.109	2	1
Blacksburg	VA	0.996	227	3	1.519	42	1	0.716	-0.081	-1.746	57	1
Bloomington	IN	1.019	81	2	1.765	6	1	0.815	0.141	5.729	209	3
Bloomington	IL	0.788	247	4	1.108	82	2	0.787	0.043	1.593	359	5
Boise City	ID	0.849	126	2	3.337	338	5	0.896	-0.039	3.439	308	5
Boston	MA	1.738	381	5	2.578	238	4	0.880	0.022	2.660	270	4
Boulder	CO	1.325	339	5	2.238	170	3	0.597	-0.372	-0.683	94	2
Bowling Green	KY	0.840	117	2	1.630	59	1	0.898	0.278	-4.927	7	1
Bremerton	WA	1.187	308	5	2.817	280	4	0.914	0.039	-2.616	37	1
Bridgeport	CT	1.428	360	5	2.703	262	4	0.857	0.098	1.992	227	3
Brownsville	TX	0.750	55	1	2.642	251	4	0.718	-0.278	-4.158	11	1
Brunswick	GA	1.162	302	4	1.966	118	2	0.817	-0.096	0.653	160	3
Buffalo	NY	1.050	265	4	2.201	162	3	0.618	-0.234	3.434	307	5
Burlington	NC	0.792	85	2	1.541	46	1	0.838	0.086	0.302	145	2
Burlington	VT	1.232	317	5	1.569	49	1	0.749	0.022	1.701	214	3
Cambridge	MA	1.712	379	5	2.386	196	3	0.671	-0.261	0.720	165	3

Camden	NJ	1.358	348	5	2.466	214	3	0.800	0.204	3.116	293	4
Canton	OH	0.834	114	2	2.285	178	3	0.766	-0.102	-3.296	24	1
Cape Coral	FL	0.655	28	1	3.659	358	5	0.738	0.019	2.754	274	4
Cape Girardeau	MO	0.807	99	2	2.030	134	2	0.856	0.040	-3.712	14	1
Carson City	NV	0.967	206	3	2.827	283	4	0.916	0.078	1.869	223	3
Casper	WY	0.727	49	1	4.553	375	5	0.835	0.198	0.360	149	2
Cedar Rapids	IA	0.842	119	2	2.035	136	2	0.757	-0.119	3.680	320	5
Champaign	IL	0.833	112	2	1.279	14	1	0.897	0.397	5.474	354	5
Charleston	WV	0.755	60	1	1.800	90	2	0.865	0.378	0.954	178	3
Charleston	SC	1.254	322	5	5.619	381	5	0.957	0.189	7.573	377	5
Charlotte	NC	1.169	303	4	1.762	80	2	0.935	0.011	2.510	267	4
Charlottesville	VA	1.231	316	5	2.136	152	2	0.700	-0.044	-3.595	19	1
Chattanooga	TN	1.029	253	4	2.635	249	4	0.934	0.462	-2.258	44	1
Cheyenne	WY	0.992	222	3	2.794	275	4	0.843	0.297	2.197	245	4
Chicago	IL	1.250	320	5	1.948	114	2	0.913	0.038	3.457	309	5
Chico	CA	1.066	273	4	3.077	321	5	0.832	0.169	-0.844	87	2
Cincinnati	OH	0.997	228	3	1.206	10	1	0.953	0.695	3.113	292	4
Clarksville	TN	0.950	191	3	1.308	17	1	0.845	0.311	0.402	151	2
Cleveland	TN	0.983	203	3	1.900	109	2	0.898	0.084	-1.074	80	2
Cleveland	OH	0.964	216	3	2.009	131	2	0.885	0.095	2.333	251	4
Coeur d'Alene	ID	1.298	333	5	2.756	271	4	0.813	-0.110	3.304	301	4
College Station	TX	0.632	21	1	1.806	93	2	0.448	-0.022	0.302	144	2
Colorado Springs	CO	1.046	261	4	2.590	242	4	0.946	-0.004	-0.257	115	2
Columbia	SC	0.765	68	1	1.413	30	1	0.764	0.121	-1.292	72	1
Columbia	MO	0.994	223	3	1.669	65	1	0.957	0.320	1.381	199	3
Columbus	OH	0.817	103	2	1.258	11	1	0.845	0.072	1.199	113	2
Columbus	GA	0.943	186	3	1.254	13	1	0.915	0.283	2.103	188	3
Columbus	IN	0.995	225	3	1.491	38	1	0.960	0.090	-0.331	236	4
Corpus Christi	TX	0.688	35	1	3.129	327	5	0.564	-0.371	-1.678	60	1

Corvallis	OR	1.305	335	5	2.222	166	3	0.913	0.190	2.860	278	4
Crestview	FL	0.940	184	3	3.041	317	5	0.690	-0.238	4.394	337	5
Cumberland	MD	1.029	254	4	3.039	316	5	0.576	0.042	2.087	234	4
Dallas	TX	1.048	263	4	2.596	243	4	0.812	0.167	-0.779	90	2
Dalton	GA	0.836	116	2	2.416	206	3	0.760	0.085	-2.072	49	1
Danville	IL	0.730	53	1	2.446	200	3	0.931	0.304	4.740	27	1
Danville	VA	0.787	80	2	2.393	211	3	0.774	-0.085	-3.151	346	5
Davenport	IA	0.687	34	1	2.581	240	4	0.812	-0.047	0.145	134	2
Dayton	OH	0.903	164	3	2.119	148	2	0.943	0.195	2.107	237	4
Decatur	AL	0.664	30	1	1.332	18	1	0.533	-0.387	-7.246	1	1
Decatur	IL	0.716	42	1	1.843	102	2	0.953	0.081	-2.301	43	1
Deltona	FL	1.035	257	4	5.225	379	5	0.819	0.155	0.347	147	2
Denver	CO	1.345	344	5	1.824	98	2	0.948	0.389	6.511	369	5
Des Moines	IA	0.876	144	2	2.984	311	5	0.848	0.113	2.340	252	4
Detroit	MI	0.927	180	3	2.568	237	4	0.866	0.049	2.476	266	4
Dothan	AL	0.802	94	2	1.990	125	2	0.775	0.220	2.475	265	4
Dover	DE	0.940	185	3	2.274	176	3	0.712	-0.004	4.168	332	5
Dubuque	IA	1.031	255	4	1.611	56	1	0.790	-0.038	-2.245	45	1
Duluth	MN	1.320	337	5	1.607	53	1	0.858	0.104	1.756	216	3
Durham	NC	0.985	218	3	2.376	194	3	0.976	0.111	0.551	158	3
Eau Claire	WI	1.061	269	4	1.820	97	2	0.945	0.163	3.184	297	4
Edison	NJ	1.489	368	5	2.335	187	3	0.753	0.013	-0.223	117	2
El Centro	CA	0.607	11	1	4.240	370	5	0.912	0.114	2.365	258	4
El Paso	TX	0.706	39	1	2.167	158	3	0.937	0.300	-0.949	85	2
Elizabethtown	KY	0.977	214	3	1.741	76	1	0.876	0.212	6.697	370	5
Elkhart	IN	0.760	64	1	1.600	52	1	0.637	-0.096	-5.684	3	1
Elmira	NY	0.681	33	1	2.876	294	4	0.417	-0.348	-3.711	15	1
Erie	PA	0.909	171	3	2.077	141	2	0.832	0.255	8.267	381	5
Eugene	OR	1.248	319	5	3.941	363	5	0.874	0.135	5.615	358	5

Evansville	IN	0.573	7	1	2.126	149	2	0.836	0.092	0.275	143	2
Fairbanks	AK	0.655	29	1	5.709	382	5	0.873	0.057	-3.731	13	1
Fargo	ND	0.808	100	2	1.731	74	1	0.847	0.193	1.563	208	3
Farmington	NM	1.078	277	4	2.853	289	4	0.855	0.040	2.519	268	4
Fayetteville	NC	0.763	66	1	1.485	36	1	0.835	-0.031	0.355	148	2
Fayetteville	AR	0.805	96	2	4.157	368	5	0.970	0.233	7.112	375	5
Flagstaff	AZ	1.287	329	5	2.754	270	4	0.794	-0.075	2.174	242	4
Flint	MI	0.753	58	1	4.387	374	5	0.912	0.166	3.693	321	5
Florence	SC	0.851	61	1	1.402	29	1	0.730	0.338	0.746	168	3
Florence	AL	0.757	127	2	1.851	105	2	0.865	0.231	2.414	260	4
Fond du Lac	WI	1.002	234	4	2.027	133	2	0.738	0.011	-1.549	63	1
Fort Collins	CO	1.200	309	5	3.222	333	5	0.975	0.526	6.259	365	5
Fort Smith	AR	0.797	89	2	2.326	183	3	0.847	0.115	3.089	290	4
Fort Wayne	IN	0.704	38	1	2.672	254	4	0.858	0.327	3.293	300	4
Fort Worth	TX	0.896	157	3	1.519	43	1	0.943	-0.006	-2.453	40	1
Fresno	CA	1.075	276	4	3.198	331	5	0.833	-0.004	2.174	241	4
Ft. Lauderdale	FL	1.025	251	4	5.088	378	5	0.815	0.048	1.599	211	3
Gadsden	AL	0.978	215	3	1.842	101	2	0.813	0.020	0.708	164	3
Gainesville	GA	0.961	70	1	2.845	140	2	0.775	0.277	6.331	175	3
Gainesville	FL	0.772	202	3	2.072	288	4	0.779	0.042	0.879	367	5
Gary	IN	0.856	130	2	1.970	120	2	0.889	0.067	2.084	233	4
Glens Falls	NY	0.901	162	3	2.958	307	5	0.855	0.016	-1.242	75	1
Goldsboro	NC	0.800	90	2	1.608	54	1	0.738	0.083	0.976	179	3
Grand Forks	ND	1.013	242	4	1.900	110	2	0.460	-0.037	-3.287	25	1
Grand Junction	CO	0.896	158	3	5.445	380	5	0.983	0.070	0.770	169	3
Grand Rapids	MI	0.881	150	2	2.374	193	3	0.929	0.109	-0.681	96	2
Great Falls	MT	1.067	274	4	1.644	62	1	0.789	-0.083	0.186	137	2
Greeley	CO	0.801	91	2	2.716	264	4	0.848	0.330	3.230	298	4
Green Bay	WI	0.866	137	2	1.081	2	1	0.857	0.039	-0.187	119	2

Greensboro	NC	0.889	153	2	1.740	75	1	0.982	0.047	-1.261	73	1
Greenville	NC	0.725	48	1	1.371	24	1	0.755	-0.109	0.666	36	1
Greenville	SC	0.884	152	2	3.439	344	5	0.985	0.100	-2.684	162	3
Gulfport	MS	1.022	248	4	2.533	226	3	0.658	-0.166	1.406	201	3
Hagerstown	MD	0.952	196	3	2.379	195	3	0.850	0.285	0.660	161	3
Hanford	CA	0.909	172	3	3.098	324	5	0.619	0.226	4.120	331	5
Harrisburg	PA	1.006	239	4	3.261	335	5	0.934	0.588	3.974	329	5
Harrisonburg	VA	1.073	275	4	2.083	142	2	0.945	0.189	3.182	296	4
Hartford	CT	1.355	346	5	2.659	252	4	0.831	0.077	0.419	152	2
Hattiesburg	MS	0.792	86	2	2.262	175	3	0.884	0.102	-0.090	125	2
Hickory	NC	0.933	181	3	1.435	31	1	0.935	0.393	2.348	254	4
Hinesville	GA	1.211	311	5	4.162	369	5	0.744	0.196	-1.160	78	1
Holland	MI	0.955	198	3	2.232	169	3	0.942	-0.012	3.628	317	5
Honolulu	HI	1.595	372	5	9.258	384	5	0.953	0.541	7.366	376	5
Hot Springs	AR	1.057	268	4	2.008	130	2	0.718	-0.033	3.123	294	4
Houma	LA	0.919	178	3	2.608	247	4	0.715	-0.100	5.211	351	5
Houston	TX	0.872	141	2	1.960	115	2	0.723	-0.149	1.216	189	3
Huntington	WV	0.881	151	2	2.201	163	3	0.791	0.119	-1.353	70	1
Huntsville	AL	0.776	71	1	0.980	1	1	0.968	0.200	3.545	314	5
Idaho Falls	ID	0.823	107	2	1.924	112	2	0.883	0.251	-5.266	6	1
Indianapolis	IN	0.987	219	3	1.460	33	1	0.925	0.437	3.772	325	5
Iowa City	IA	0.946	188	3	1.636	61	1	0.779	-0.005	2.072	232	4
Ithaca	NY	0.901	163	3	2.736	267	4	0.848	0.234	-1.675	61	1
Jackson	TN	0.971	14	1	2.217	37	1	0.879	0.553	4.549	8	1
Jackson	MI	0.612	19	1	3.510	165	3	0.958	0.239	3.866	327	5
Jackson	MS	0.625	209	3	1.490	347	5	0.884	0.134	-4.466	341	5
Jacksonville	NC	1.080	278	4	2.249	173	3	0.941	0.117	3.549	264	4
Jacksonville	FL	1.131	292	4	2.623	248	4	0.936	0.202	2.457	315	5
Janesville	WI	0.895	156	3	1.471	35	1	0.925	0.448	2.681	271	4

Jefferson City	MO	0.795	87	2	1.561	48	1	0.828	0.114	3.368	302	4
Johnson City	TN	1.062	270	4	1.670	67	1	0.972	0.523	5.340	352	5
Johnstown	PA	0.834	115	2	2.691	258	4	0.529	-0.093	-4.440	9	1
Jonesboro	AR	0.675	32	1	1.886	107	2	0.756	0.085	0.865	174	3
Joplin	MO	0.713	41	1	1.540	45	1	0.784	0.291	-3.193	26	1
Kalamazoo	MI	0.951	193	3	2.023	132	2	0.940	0.047	5.508	356	5
Kankakee	IL	1.130	291	4	1.850	104	2	0.862	-0.059	2.347	253	4
Kansas City	MO	0.970	208	3	1.653	64	1	0.914	0.350	1.539	207	3
Kennewick	WA	1.000	232	4	3.631	357	5	0.713	-0.180	-0.297	114	2
Killeen	TX	0.582	8	1	2.543	230	3	0.790	-0.083	-5.326	5	1
Kingsport	TN	0.951	194	3	1.841	100	2	0.791	0.133	0.525	156	3
Kingston	NY	1.018	246	4	2.928	303	4	0.753	0.010	2.195	244	4
Knoxville	TN	0.906	167	3	1.133	7	1	0.840	0.083	-3.359	22	1
Kokomo	IN	0.585	10	1	2.147	155	2	0.484	-0.139	-2.471	39	1
La Crosse	WI	0.987	220	3	1.177	8	1	0.817	0.006	3.754	324	5
Lafayette	LA	0.817	15	1	1.190	9	1	0.644	-0.182	1.264	190	3
Lafayette	IN	0.612	104	2	2.559	233	4	0.629	-0.119	2.022	230	3
Lake Charles	LA	0.938	183	3	2.412	204	3	0.895	0.013	-0.607	103	2
Lake County	IL	1.005	235	4	2.143	154	2	0.941	0.095	3.017	287	4
Lake Havasu City	AZ	0.781	76	1	3.162	328	5	0.862	0.130	5.943	363	5
Lakeland	FL	0.716	43	1	2.759	272	4	0.847	0.100	6.884	371	5
Lancaster	PA	0.995	226	3	2.459	212	3	0.947	0.132	2.834	277	4
Lansing	MI	0.851	128	2	2.968	309	5	0.864	-0.078	-1.301	71	1
Laredo	TX	0.666	31	1	2.826	282	4	0.847	-0.148	0.216	139	2
Las Cruces	NM	0.823	108	2	1.839	99	2	0.824	0.101	3.516	313	5
Las Vegas	NV	0.750	56	1	4.303	372	5	0.735	0.240	4.830	348	5
Lawrence	KS	1.054	267	4	1.784	85	2	0.876	0.147	2.928	280	4
Lawton	OK	0.806	97	2	2.549	232	4	0.849	0.054	2.412	259	4
Lebanon	PA	0.997	229	3	1.999	128	2	0.676	0.343	-2.508	38	1

Lewiston	ID	1.286	175	3	2.094	145	2	0.632	0.166	0.127	131	2
Lewiston	ME	0.914	328	5	2.696	259	4	0.876	0.108	0.775	170	3
Lexington	KY	0.795	88	2	2.690	257	4	0.855	0.410	-0.675	99	2
Lima	OH	0.716	44	1	1.962	117	2	0.813	0.097	4.578	342	5
Lincoln	NE	0.801	92	2	1.669	66	1	0.918	0.091	0.500	154	2
Little Rock	AR	0.949	189	3	2.469	215	3	0.826	0.376	1.046	184	3
Logan	UT	1.063	271	4	1.988	124	2	0.724	0.099	-0.679	97	2
Longview	WA	0.644	25	1	2.661	253	4	0.727	-0.231	4.030	330	5
Longview	TX	1.023	249	4	5.746	383	5	0.966	0.100	6.257	364	5
Los Angeles	CA	1.736	380	5	2.839	286	4	0.558	-0.339	2.172	239	4
Louisville	KY	1.122	289	4	1.350	22	1	0.955	0.190	1.296	193	3
Lubbock	TX	0.607	12	1	2.579	239	4	0.955	0.124	-3.671	17	1
Lynchburg	VA	1.024	250	4	1.578	51	1	0.958	0.215	5.011	349	5
Macon	GA	0.908	169	3	2.705	263	4	0.922	-0.034	-1.708	59	1
Madera	CA	0.879	146	2	3.548	351	5	0.826	-0.121	8.208	380	5
Madison	WI	1.115	286	4	2.327	184	3	0.867	0.074	-0.056	127	2
Manchester	NH	1.214	313	5	2.420	207	3	0.918	0.051	-1.910	54	1
Manhattan	KS	1.032	256	4	2.833	285	4	0.755	-0.013	-3.702	16	1
Mankato	MN	1.007	240	4	1.787	87	2	0.937	0.053	0.982	180	3
Mansfield	OH	0.770	69	1	2.248	172	3	0.636	0.025	-0.337	112	2
McAllen	TX	0.541	4	1	3.393	341	5	0.921	0.202	1.472	205	3
Medford	OR	1.177	305	4	3.127	326	5	0.933	0.276	3.274	299	4
Memphis	TN	0.889	154	2	3.081	322	5	0.943	0.058	1.716	215	3
Merced	CA	0.790	84	2	4.674	376	5	0.889	0.111	2.937	282	4
Miami	FL	1.308	336	5	3.823	361	5	0.935	0.106	-0.133	124	2
Michigan City	IN	1.064	272	4	2.373	192	3	0.898	0.064	7.098	374	5
Midland	TX	0.493	2	1	2.869	293	4	0.742	-0.083	4.516	340	5
Milwaukee	WI	1.047	262	4	1.755	79	1	0.945	0.508	5.614	357	5
Minneapolis	MN	1.213	312	5	1.814	95	2	0.900	-0.025	-0.616	102	2

Missoula	MT	1.439	362	5	2.860	292	4	0.993	0.316	-0.682	95	2
Mobile	AL	0.855	129	2	2.844	287	4	0.956	0.217	1.288	192	3
Modesto	CA	1.005	236	4	4.006	364	5	0.820	0.168	2.994	286	4
Monroe	MI	0.780	75	1	1.852	106	2	0.797	0.227	0.240	140	2
Monroe	LA	0.959	201	3	2.726	266	4	0.930	0.136	3.468	312	5
Montgomery	AL	0.617	17	1	1.283	15	1	0.853	0.159	-0.894	86	2
Morgantown	WV	0.998	230	3	2.333	186	3	0.645	-0.182	2.098	235	4
Morristown	TN	0.937	182	3	1.609	55	1	0.775	0.032	0.502	155	2
Mount Vernon	WA	1.424	357	5	3.485	346	5	0.940	0.003	0.380	150	2
Muncie	IN	0.553	5	1	2.007	129	2	0.622	-0.107	-5.328	4	1
Muskegon	MI	0.817	105	2	1.697	69	1	0.867	0.142	-1.178	77	1
Myrtle Beach	SC	0.879	147	2	2.174	159	3	0.878	-0.045	-1.896	56	1
Napa	CA	1.424	358	5	2.989	312	5	0.838	0.158	3.463	310	5
Naples	FL	0.956	199	3	3.544	350	5	0.649	-0.318	1.046	183	3
Nashville	TN	1.042	259	4	1.553	47	1	0.963	0.234	0.072	130	2
Nassau	NY	1.680	377	5	2.389	198	3	0.798	0.144	0.532	157	3
New Haven	CT	1.399	355	5	2.674	255	4	0.832	0.211	-0.584	104	2
New Orleans	LA	1.087	279	4	2.153	156	3	0.855	0.292	2.428	263	4
New York	NY	1.673	375	5	2.428	208	3	0.638	-0.085	1.319	195	3
Newark	NJ	1.574	370	5	2.321	181	3	0.677	-0.166	1.994	228	3
Niles	MI	1.184	307	5	1.762	81	2	0.757	-0.168	-0.571	106	2
North Port	FL	1.014	243	4	4.257	371	5	0.699	-0.084	3.639	318	5
Norwich	CT	1.001	233	4	2.279	177	3	0.887	0.342	0.130	132	2
Oakland	CA	1.699	378	5	2.638	250	4	0.577	-0.115	0.744	167	3
Ocala	FL	0.722	47	1	2.808	278	4	0.776	0.103	-0.071	126	2
Ocean City	NJ	1.477	366	5	2.829	284	4	0.831	-0.028	3.466	311	5
Odessa	TX	0.430	1	1	3.843	362	5	0.726	-0.099	5.413	353	5
Ogden	UT	0.974	212	3	2.931	304	4	0.952	0.167	3.948	328	5
Oklahoma City	OK	0.944	187	3	2.203	164	3	0.851	0.194	1.668	213	3

Olympia	WA	1.290	330	5	3.530	349	5	0.979	0.112	1.613	212	3
Omaha	NE	0.904	166	3	2.597	244	4	0.873	0.154	1.298	194	3
Orlando	FL	1.106	284	4	2.682	256	4	0.798	0.245	-0.751	92	2
Oshkosh	WI	0.846	123	2	1.332	19	1	0.912	0.313	2.979	283	4
Owensboro	KY	0.727	50	1	2.289	179	3	0.697	-0.101	2.932	281	4
Oxnard	CA	1.635	374	5	2.991	313	5	0.768	0.099	2.353	255	4
Palm Bay	FL	0.830	111	2	4.069	365	5	0.821	-0.015	4.499	339	5
Palm Coast	FL	0.619	18	1	3.604	355	5	0.816	-0.163	-0.580	105	2
Panama City	FL	0.919	179	3	2.895	300	4	0.856	0.179	8.038	379	5
Parkersburg	WV	0.847	124	2	1.901	111	2	0.872	0.147	-0.618	101	2
Pascagoula	MS	1.087	280	4	2.196	161	3	0.747	0.115	3.391	304	4
Peabody	MA	1.480	367	5	2.485	218	3	0.856	0.141	-1.394	69	1
Pensacola	FL	0.860	132	2	2.247	171	3	0.798	-0.036	2.014	229	3
Peoria	IL	0.641	23	1	4.077	366	5	0.900	0.175	9.310	383	5
Philadelphia	PA	1.343	343	5	1.742	77	1	0.749	-0.113	2.172	240	4
Phoenix	AZ	1.104	283	4	2.979	310	5	0.726	-0.026	4.721	345	5
Pine Bluff	AR	0.785	79	1	2.346	188	3	0.774	0.207	2.224	246	4
Pittsburgh	PA	1.005	237	4	1.998	127	2	0.957	0.409	1.779	218	3
Pittsfield	MA	0.898	160	3	2.937	306	4	0.970	0.051	2.360	256	4
Pocatello	ID	1.116	287	4	1.745	78	1	0.968	0.170	0.732	166	3
Port St. Lucie	FL	0.783	77	1	4.322	373	5	0.924	-0.028	3.061	288	4
Portland	ME	1.356	347	5	2.083	143	2	0.853	0.075	1.972	226	3
Portland	OR	1.457	363	5	2.386	197	3	0.862	0.067	4.181	334	5
Poughkeepsie	NY	1.252	321	5	3.027	315	5	0.947	0.220	-0.733	93	2
Prescott	AZ	1.036	258	4	2.566	236	4	0.916	0.331	1.124	186	3
Providence	RI	1.476	365	5	2.753	269	4	0.915	0.142	-0.181	120	2
Provo	UT	0.990	221	3	2.402	202	3	0.960	0.308	10.469	384	5
Pueblo	CO	0.803	95	2	4.139	367	5	0.925	0.377	3.162	295	4
Punta Gorda	FL	0.759	62	1	3.562	353	5	0.817	0.072	3.738	323	5

Racine	WI	0.965	204	3	1.374	25	1	0.865	0.083	2.986	285	4
Raleigh	NC	1.098	281	4	1.628	58	1	0.949	-0.008	3.406	305	4
Rapid City	SD	1.245	318	5	1.775	83	2	0.864	0.117	-2.758	34	1
Reading	PA	0.983	217	3	2.523	224	3	0.964	0.340	-1.570	62	1
Redding	CA	0.879	148	2	3.063	319	5	0.947	0.388	-1.395	68	1
Reno	NV	0.789	82	2	2.907	302	4	0.834	0.296	0.336	146	2
Richmond	VA	1.149	297	4	1.783	84	2	0.889	0.226	0.861	173	3
Riverside	CA	1.296	332	5	3.438	343	5	0.713	0.177	-1.260	74	1
Roanoke	VA	1.384	353	5	3.614	356	5	0.927	0.215	6.352	368	5
Rochester	NY	0.825	109	2	1.344	20	1	0.848	0.104	2.182	35	1
Rochester	MN	0.863	134	2	1.784	86	2	0.671	-0.001	-2.716	243	4
Rockford	IL	0.763	67	1	2.540	228	3	0.875	0.220	2.712	273	4
Rockingham County	NH	1.183	306	4	2.320	180	3	0.943	0.066	-0.379	110	2
Rocky Mount	NC	0.630	20	1	1.790	88	2	0.776	-0.054	1.393	200	3
Rome	GA	0.848	125	2	2.439	210	3	0.696	0.112	1.807	220	3
Sacramento	CA	1.354	345	5	2.894	299	4	0.649	-0.176	2.980	284	4
Saginaw	MI	0.637	22	1	1.986	123	2	0.749	0.102	4.324	336	5
Salem	OR	1.138	294	4	2.771	273	4	0.934	0.582	1.920	224	3
Salinas	CA	1.336	340	5	3.570	354	5	0.613	0.044	1.866	222	3
Salisbury	MD	0.998	231	4	2.372	191	3	0.349	-0.136	1.415	202	3
Salt Lake City	UT	1.274	327	5	2.413	205	3	0.968	0.121	3.851	326	5
San Angelo	TX	0.740	54	1	2.804	277	4	0.783	-0.017	-1.504	65	1
San Antonio	TX	0.784	78	1	3.354	339	5	0.866	0.266	5.040	350	5
San Diego	CA	1.541	369	5	3.013	314	5	0.868	-0.114	0.253	141	2
San Francisco	CA	1.892	384	5	2.540	229	3	0.638	-0.143	-2.069	50	1
San Jose	CA	1.877	383	5	2.789	274	4	0.759	0.123	-2.379	42	1
San Luis Obispo	CA	1.303	334	5	3.326	337	5	0.637	-0.134	-0.826	88	2
Sandusky	OH	0.863	135	2	2.855	290	4	0.853	0.023	3.731	322	5

Santa Ana	CA	1.674	376	5	2.718	265	4	0.626	0.051	-1.713	58	1
Santa Barbara	CA	1.470	364	5	2.879	295	4	0.779	0.090	0.256	142	2
Santa Cruz	CA	1.599	373	5	3.093	323	5	0.657	0.065	2.422	262	4
Santa Fe	NM	1.101	282	4	2.032	135	2	0.819	0.195	3.650	319	5
Santa Rosa	CA	1.590	371	5	2.855	291	4	0.678	0.251	0.990	182	3
Savannah	GA	1.223	315	5	2.513	222	3	0.932	0.295	2.239	247	4
Scranton	PA	1.264	324	5	2.351	190	3	0.885	0.252	1.373	198	3
Seattle	WA	1.744	382	5	2.508	220	3	0.925	0.271	2.038	231	4
Sebastian	FL	0.711	40	1	3.554	352	5	0.770	0.108	4.677	343	5
Sheboygan	WI	0.949	190	3	1.390	27	1	0.845	0.019	2.152	238	4
Sherman	TX	0.533	3	1	2.887	297	4	0.843	0.031	-2.842	33	1
Shreveport	LA	0.582	9	1	1.711	71	1	0.865	0.006	0.159	135	2
Sioux City	IA	0.910	174	3	1.721	73	1	0.618	-0.170	-0.643	100	2
Sioux Falls	SD	0.894	155	2	1.810	94	2	0.834	0.152	-0.559	107	2
South Bend	IN	0.876	145	2	1.353	23	1	0.866	0.194	1.774	217	3
Spartanburg	SC	0.801	93	2	1.391	28	1	0.832	0.105	3.112	291	4
Spokane	WA	1.159	300	4	2.696	260	4	0.877	-0.095	1.088	185	3
Springfield	IL	0.702	37	1	1.089	3	1	0.897	0.057	8.489	12	1
Springfield	MA	1.293	63	1	2.605	4	1	0.852	0.088	4.770	129	2
Springfield	OH	0.759	138	2	1.082	217	3	0.888	0.032	0.067	347	5
Springfield	MO	0.870	331	5	2.475	246	4	0.717	-0.069	-3.873	382	5
St. Cloud	MN	0.971	210	3	1.575	50	1	0.748	-0.091	-0.676	98	2
St. George	UT	0.842	120	2	3.517	348	5	0.835	0.005	1.517	206	3
St. Joseph	MO	1.017	245	4	1.994	126	2	0.545	-0.404	1.933	225	3
St. Louis	MO	1.139	295	4	3.304	336	5	0.927	0.138	7.950	378	5
State College	PA	0.950	192	3	1.650	63	1	0.635	-0.113	-1.534	64	1
Steubenville	WV	0.777	72	1	2.881	296	4	0.638	-0.038	4.716	344	5
Stockton	CA	1.050	266	4	3.696	359	5	0.669	0.238	-0.537	108	2
Sumter	SC	0.842	121	2	1.805	92	2	0.816	-0.046	-1.999	51	1

Syracuse	NY	1.014	244	4	1.793	89	2	0.786	0.214	-3.324	23	1
Tacoma	WA	1.425	359	5	2.460	213	3	0.929	0.035	-0.210	118	2
Tallahassee	FL	0.908	170	3	2.328	185	3	0.914	0.180	2.861	279	4
Tampa	FL	1.117	288	4	2.597	245	4	0.744	-0.190	-2.146	48	1
Terre Haute	IN	0.643	24	1	2.139	153	2	0.764	0.238	-0.785	89	2
Texarkana	TX	0.779	74	1	1.713	72	1	0.697	-0.170	-4.316	10	1
Toledo	OH	0.717	45	1	2.934	305	4	0.965	0.439	2.414	261	4
Topeka	KS	0.754	59	1	1.815	96	2	0.823	0.084	2.331	250	4
Trenton	NJ	1.324	338	5	2.470	216	3	0.834	0.242	0.910	176	3
Tucson	AZ	1.203	310	5	4.682	377	5	0.844	-0.037	0.704	163	3
Tulsa	OK	0.907	168	3	1.969	119	2	0.799	0.243	0.804	172	3
Tuscaloosa	AL	0.994	224	3	1.293	16	1	0.954	0.140	-0.768	91	2
Tyler	TX	0.568	6	1	2.087	144	2	0.592	-0.290	-1.031	81	2
Utica	NY	0.840	118	2	2.389	199	3	0.653	-0.304	-0.952	84	2
Valdosta	GA	0.914	176	3	2.071	139	2	0.855	-0.010	-0.143	123	2
Vallejo	CA	1.133	293	4	3.419	342	5	0.796	0.074	-2.146	47	1
Victoria	TX	0.760	65	1	2.063	138	2	0.787	-0.107	-0.237	116	2
Vineland	NJ	1.146	296	4	2.821	281	4	0.886	-0.052	-3.110	28	1
Virginia Beach	VA	1.379	352	5	1.985	122	2	0.733	-0.085	0.214	138	2
Visalia	CA	0.872	142	2	3.244	334	5	0.828	-0.013	3.380	303	4
Waco	TX	0.610	13	1	2.109	147	2	0.357	-0.616	-1.185	76	1
Warner Robins	GA	0.644	26	1	1.465	34	1	0.682	-0.018	2.302	248	4
Warren	MI	0.968	207	3	2.322	182	3	0.927	0.110	1.372	197	3
Washington	DC	1.411	356	5	2.101	146	2	0.569	-0.025	-3.617	18	1
Waterloo	IA	1.128	290	4	2.738	268	4	0.457	-0.511	-3.028	30	1
Wausau	WI	0.971	211	3	1.623	57	1	0.597	-0.037	-0.159	122	2
Wenatchee	WA	1.161	301	4	2.795	276	4	0.976	0.090	4.428	338	5
West Palm Beach	FL	1.113	285	4	2.902	301	4	0.911	0.156	3.084	289	4
Wheeling	WV	0.871	139	2	3.177	329	5	0.638	-0.301	2.796	275	4

Wichita	KS	0.648	27	1	2.545	231	4	0.733	0.156	1.160	187	3
Wichita Falls	TX	0.806	98	2	1.804	91	2	0.697	0.159	-3.458	21	1
Williamsport	PA	0.809	102	2	1.937	113	2	0.829	0.080	-0.018	128	2
Wilmington	NC	1.269	323	5	2.255	108	2	0.796	-0.061	-1.902	55	1
Wilmington	DE	1.257	326	5	1.889	174	3	0.825	0.061	5.477	355	5
Winchester	VA	0.751	57	1	2.958	308	5	0.840	0.107	1.275	191	3
Winston	NC	0.880	149	2	1.630	60	1	0.857	-0.075	3.410	306	4
Worcester	MA	1.376	351	5	2.561	234	4	0.970	0.314	-0.160	121	2
Yakima	WA	1.156	299	4	2.159	157	3	0.914	0.286	4.177	333	5
York	PA	1.042	260	4	1.509	40	1	0.800	0.114	-0.984	82	2
Youngstown	OH	0.821	106	2	1.533	44	1	0.957	0.369	0.937	177	3
Yuba City	CA	0.833	113	2	3.448	345	5	0.579	0.030	5.775	361	5
Yuma	AZ	0.862	133	2	2.808	279	4	0.873	0.252	5.885	362	5

Notes: Details for 3 integration measures (Mean, Sigma and R-Square Trend t-stat) are presented for all 384 MSAs. Mean is the average quarterly house price return. We compute house price returns for each MSA in our sample as the log quarterly difference in its FHFA repeat home sales price index. Sigma is the standard deviation of returns. R-Squares are the estimates of integration and are used to obtain R-Square trend t-statistics. R-Squares are obtained from fitting MSA returns to the factor model described in Appendix Table 1. The time trend t-statistics are estimated by regressing the R-squares for each MSA on a simple linear time trend for all available quarters of data. The final R-Squares pertain to 2010:Q1 for all 384 US MSAs. The change in R-Squares refers to the difference between estimates for 2010:Q1 and 1983:Q4 for each MSA. Each characteristic is ranked from lowest to highest in comparison to all 384 US MSAs. Each characteristic is also binned by quintile in comparison to all 384 US MSAs.