CAN METROPOLITAN HOUSING RISK BE DIVERSIFIED?
A CAUTIONARY TALE FROM THE HOUSING BOOM AND BUST

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ABSTRACT

Geographic diversification should reduce investment risks in housing, mortgages, and mortgage-related derivatives, but by how much? To characterize diversification potential, we estimate spatial correlation and integration across US metropolitan housing markets. We find a marked uptrend in housing market integration during the decade of the 2000s, especially among cities in California. Influential explanatory factors include eased residential lending standards and a growth in private mortgage securitizations. Portfolio simulations indicate substantially lower diversification potential and higher risk in the wake of increased market integration.

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I. Introduction

Geographic diversification has long been fundamental in risk mitigation among investors and insurers of housing, mortgages, and mortgage-related derivatives. The housing GSEs, Fannie Mae and Freddie Mac, now in government conservatorship, sought to geographically diversify portfolio holdings so as to reduce risks associated with their investments in a single asset class. Prominent Wall Street firms, including Bear Sterns, Merrill Lynch, and Citigroup, employed similar logic in assembling mortgage-backed CDOs and related derivative securities. Geographic diversification also has been central to the portfolio investment strategies of multi-family REITs and single-family housing investment funds.1

In the wake of the recent housing downturn, anecdotal evidence suggests that geographic diversification may have offered few benefits.2 The efficacy of diversification strategies is limited if metropolitan housing markets exhibit high levels of return correlation or integration. In such a circumstance, housing investors could face substantial losses owing to widespread and contemporaneous co-movements in returns across geographically-distinct markets.

The efficacy of geographic risk diversification also has important implications for the solvency of private and government-backed insurers of residential mortgages. Indeed, substantial geographic correlation of credit losses, when coupled with sizable insurer guarantee liabilities and constrained access to credit markets, could render private mortgage insurance less viable. If markets are well integrated, alternative mechanisms may

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1 Freddie Mac’s efforts to geographically diversify mortgage assets held in portfolio are discussed in their 2007 Annual Report, (pg 97). The 10-Ks of large residential REITs such as Mid-American Apartment Communities and Apartment Investments and Management Company similarly address the expected benefits of portfolio geographic diversification. Also, new single-family housing hedge funds (e.g., Colony Capital) employ geographic diversification of single-family holdings as a strategy of risk mitigation.

2 For example, sizable losses were recorded in the geographically diversified retained portfolios of the failed housing GSEs. As described by Michael Lewis (2010), the failure of diversified subprime mortgage-backed CDOs also figured importantly in the 2009 Bear Stearns, Merrill Lynch and Lehman insolvencies.
be necessary to assure liquidity and stability of the housing finance system in both good and bad times.

Despite the prevalence of geographic diversification of holdings among investors and insurers of mortgages and housing, only a few studies have explicitly examined such strategies. Examples include papers by Nadauld, Sherlund and Vorkink (2011) and Nadauld and Sherlund (2009), which examine loan collateral diversification in the context of sub-prime mortgage-backed securitization.

While those studies offer important insights, little is known about the potential for geographic risk diversification in housing and whether it has been eroded over the recent boom and bust. Indeed, while the finance literature has addressed issues of correlation and integration among global equity markets, little attention has been paid to the same issues among real estate markets. A few studies include assessment of integration between securitized real estate markets (see, for example, Liow (2010)) or between securitized real estate and equity markets (Lin and Lin, 2011). However, we are unaware of prior analysis of the magnitude or trend in housing market integration, as evidenced by the relative exposure of metro housing returns to fluctuations in the national economic, housing market, and housing finance factors. Further, we know little about the relative importance of various financial and non-financial drivers of housing market integration trends. Also, few studies have explicitly estimated temporal variation in risk associated with diversified housing investment portfolios.³

³However, the literature includes related analyses of real estate investment trusts (REITs) using equity factors such as those developed by Chen, Roll and Ross (1986) and Fama and French (1993). Such studies include Chan, Hendershott and Sanders (1990) and Karolyi and Sanders (1998) who find, inter alia, that changes in expected inflation influence REIT returns. Explanations of REIT returns by the Fama-French (1993) factors are reported in Peterson and Hsieh (1997); whereas this approach has been expanded to include a momentum factor (Hung and Glascock (2010)) and the influence of liquidity (Cannon and Cole (2011).
Measures of housing market integration and housing portfolio risk are important indicators of diversification benefits. Such indicators are relevant to the full spectrum of market participants, be they housing and housing derivative investors, homebuilders, and the like. They also provide policymakers with information about the geographic propagation of macroeconomic shocks and national economic policy. Measures of metro housing market integration are vital to policymakers seeking to re-structure the housing finance system and to mitigate catastrophic risk associated with severe housing downturns.

Our study commences with assessment of spatial correlation in house price returns. That analysis includes an examination of contemporaneous and lagged MSA return correlations, distinguishing between common and “extreme” movements (jumps). As discussed below, jumps in house prices were especially evident during the recent boom and bust, the latter owing to extreme price declines in certain MSAs. In California, for example, jumps became very prevalent by mid-decade, with close to 70 percent of the cities experiencing extreme movements in house prices. High levels of MSA return or jump return correlation raise concerns for mortgage or housing investors seeking to diversify risk associated with investment in this asset class.

Given evidence of spatial correlation in returns, we turn to assessment of integration of metropolitan housing markets. Our measure of integration is based on the proportion of an MSAs housing market returns that can be explained by an identical set of national factors (see Pukthuanthong-Le and Roll (2009)). The level of integration is indicated by the magnitude of R-square, with higher values representing higher levels of integration. Two MSAs are viewed as perfectly integrated if the same national factors fully explain housing market returns in both areas. In that case, the R-square would be 1.0, implying no diversification potential between the MSAs.
We identify variation in integration and in integration drivers over time and across MSA markets. Results of the integration analysis are then employed to construct alternative metropolitan housing investment portfolios and to assess portfolio risks over the recent period of boom and bust.

The data reveal a marked uptrend in US metropolitan housing market integration over the latter half of the 2000s. On average, integration held roughly steady around 45 percent over the 1992 – 2004 period. Starting in the mid-2000s, however, the uptrend brought average integration levels to around .63 in 2010, implying that U.S. housing markets were 63 percent integrated relative to the maximum possible level. In California the trend was stronger, moving from about .70 in 2004 to around .88 late in the decade. The measured trend is robust to variation in temporal cohorts of MSAs and to window length.

We are able to identify factors associated with the significant integration increase during the latter half of the 2000s. To do so, we compute the contribution to integration R-square associated with each factor. Particularly influential factors include private mortgage securitizations and residential building permits, which together accounted for roughly .25 of the .50 R-square recorded for the 2006-2007 period. The mortgage underwriting (LTV) factor similarly figured importantly during the latter years of the housing boom. These results coincide with arguments that the boom and bust in house prices was fuelled in no small measure by ease of mortgage qualification and availability of non-conforming secondary market liquidity. In the wake of the late decade housing downturn, the contribution of log personal income rose to one-half the integration R-square as fundamentals took on renewed importance for the integration of house price returns.

Analysis of equal-weighted portfolios of the longest-available U.S. and California metropolitan cohorts showed sharply rising levels of housing portfolio risk over the boom
years of the 2000s. Changes in U.S. portfolio risk correlate strongly with the degree of portfolio metropolitan housing market integration. Over the decade of the 2000s, the simple correlation between the integration R-square and the standard deviation of portfolio returns is .93! In other words, increases in housing market integration reduce the efficacy of geographic diversification. Indeed, by end of decade, housing portfolio diversification offered only limited benefits in risk diversification. Further, for the 2000s, the negative correlation between portfolio integration and diversification benefits rose to -.95. The combination of those outcomes left investors and insurers of housing credit risk exposed to the market downturn.

Taken together, our findings offer a cautionary tale about portfolio geographic diversification as a mechanism to mitigate housing risk. High levels of housing market integration suggest that local fundamentals are less important to MSA-specific returns than previously thought. The results have far-reaching implications for policymakers. They underscore the fact that investors and insurers of housing and mortgages must be able to withstand high levels of exposure to systemic risk. In the absence of such capacity, credit losses associated with a severe housing downturn may result in the withdrawal of substantial funding liquidity from the marketplace.

II. MSA Returns and Jumps: Magnitudes and Correlations

We use the 384 metropolitan housing price indices from the U.S. Federal Housing Finance Agency (FHFA) to assess spatial correlation and integration in MSA house price returns. The database has been used extensively in examination of US house prices (for example, see Clark and Coggin (2009); and Calomiris, Longhofer, and Miles (2008)). The FHFA series are weighted repeat-sale price indices associated with single-family homes. Home sales and refinancings included in the FHFA sample are associated with 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 restriction to GSE-conforming mortgages may reduce housing price volatility. Nevertheless, the FHFA data comprise the most extensive cross-sectional and time-series set of quality-adjusted house price indices available in the United States.  

We compute house price returns for each MSA in our sample as the log quarterly difference in its repeat home sales price index. The MSA level data are quarterly from 1975:Q1 – 2010:Q1. The number of MSAs in the database increases over time from 2 at the initiation of the database in 1975 to 384 by 1993. At the end of the sample in 2010, there are still 384 MSAs present.

Figure 1 plots the unweighted average index over the entire US and the corresponding average index for 28 California MSAs. There is a general uptrend in the national average all the way from 1975 through 2006 followed by a marked downturn through 2010. The California pattern is similar though the up- and down-swings are more pronounced.

4The HPI is a broad measure of the movement of single-family house prices. The HPI is a weighted, repeat-sales index that measures average price changes in repeat sales or refinancings on the same properties. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975. The HPI is updated each quarter as additional mortgages are purchased or securitized by Fannie Mae and Freddie Mac. The new mortgage acquisitions are used to identify repeat transactions for the most recent quarter and for each quarter since the first quarter of 1975. In contrast to the value-weighted Case-Shiller US house price index, FHFA's index includes data from a comprehensive set of metropolitan housing markets in the U.S. and weights price trends equally for all properties. For a full discussion of the FHFA house price index, see Calhoun (1996) and "A Comparison of House Price Measures", Mimeo, Freddie Mac, February 28, 2008. For a critique of the series in the context of alternative house price series see Nagaraja, Browny, and Wachter (2010).

5In 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.
We use the MSA series to provide evidence about correlations among house price returns, both contemporaneous and lagged, about the prevalence of extreme movements (jumps) and about the correlations among jumps. 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 well-diversified investors and would have little interest for policymakers. But if extreme movements are clustered in time and across regions, they would represent serious risks for mortgage and housing investors because diversification would offer limited protection. Other market players, including MBS originators and investors, likely would be similarly impacted by high correlations in jumps among their mortgage collateral. Jumps might be generated by economic or policy shocks at local or national levels and should be of interest to policymakers, especially when they can be traced to political events or policy perturbations.

Alternative jump measures have been proposed in the recent literature; (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) study these jump measures in an application to equity return indexes for 82 countries; however, we are not aware of prior analyses of jumps in metropolitan house price.

The Lee and Mykland measure 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.

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6 Earlier work on extreme returns and correlation of same focused on more ad-hoc approaches (see Longin and Solnik (2001); Bae, Karolyi and Stulz (2003); and Hartmann, Straetman and de Vries (2004).

7 We note that Pukthuanthong-Le and Roll (2010) did extensive simulations of the various jump statistics to ascertain their power in detecting correlated jumps. They found that the Lee and Mykland measure has adequate power and measures the direction of the jump, unlike the other statistics.
where higher frequency (eg. daily) observations are available. For the vast majority of sampled MSA housing markets, the most frequent quality-adjusted house price index is quarterly. Moreover, investor rebalancing of real estate portfolios tends to be of lower frequency as compared to 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.

With this in mind, we compute the Lee and Mykland (2008), (hereafter LM), measure to study extreme quarterly movements in US metropolitan house price indexes. Lee and Mykland’s (2008) method is based on bipower variation, which is used to estimate 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 $k$
- $R_{i,t,k}$, the return (log price relative) for MSA $i$ quarter $t$ in subperiod $k$

Bipower variation, $B_{i,k}$, is defined as follows:

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

LM suggest the computation of bipower variation using data just preceding a particular return observation being tested for a jump. The test statistic is $L = R_{i,T_k+1,k}/\sqrt{2B_{i,k}T_k}$. Under the null hypothesis of no jump at $t+1$, LM shows that $L$ converges to a unit normal. In addition, if there is a jump at $t+1$, $L$ 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)). Figure 2 plots the temporal incidence of large $L$ absolute values in house price returns for 384 US MSAs and for 28 California MSAs;
i.e., the percentage in each quarter that exceed 2.0. Since the L statistic is asymptotically unit normal when there are no jumps, we should observe roughly 4.55 percent of the L’s either greater than 2.0 or less than -2.0 just by chance.

Some evidence of jumps in house prices is indicated for the overheated housing markets of the late 1980s when the jump incidence occasionally exceeds 10 percent. But from 1989 through 2003, few if any US MSAs were characterized by statistical jumps in house prices. This quiescent period ended in the 2000s boom and bust, which 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 large declines in house prices. In contrast to the US as a whole, California shows virtually no jumps in house prices prior to 2003. However, during the early stages of the boom period (2003 – 2004), jumps suddenly became very prevalent, with close to 70 percent of California MSAs having significant extreme returns. Similarly, high levels of jumps were evidenced among California MSAs in 2008 as boom turned to bust for many localities. While the preceding indicates the marked incidence of house price jumps during the 2000s housing boom and bust, they provide little insight as regards contemporaneous or lagged MSA spatial correlations in those jumps, and returns in general. We turn now to these issues.

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, we compute contemporaneous and lagged correlations in LM jump statistics among pairs of MSAs where at least one MSA exhibited a jump.\(^8\) 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

\(^8\)A jump is indicated in those cases where the absolute value of the LM L statistics is greater than 2.0, given that L is unit normal.
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 1, we report summary information on MSA house price return and jump correlations. Panel A reports summary statistics for MSA return correlations, which provide a basis of comparison for MSA jump correlations. The results show the full sample and two sub-samples stratified by the correlation coefficient’s T-statistic. For the full sample, correlations are computed for quarterly returns among all house price return pairs (total sample N = 73,536 distinct pairs; i.e., 384(383)/2). The mean contemporaneous correlation among all MSAs return pairs is 0.20, with a considerable cross coefficient standard deviation of 0.18. However, the mean T-statistic 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.  

Panel B of Table 1 reports summary statistics for the corresponding jump correlations. For the full sample, correlation coefficients are computed for identified jumps in quarterly house price returns among US MSAs. There are 49,742 pairs for which at least one MSA has a jump in some quarter. The mean contemporaneous MSA jump correlation across MSA pairs is only 0.047 but it is significant with a T-statistic above 53.  

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9 The numbers of MSA pairs with return correlation T-statistics in excess of 2 and 3 are 33,460 and 18,126, respectively. Among these same sub-samples, mean correlations are 0.354 and 0.435, respectively.

10 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
We now turn to the geographical incidence of return and jump correlations in metropolitan housing returns. Panel A of Table 2, reports contemporaneous and leading MSA house return correlations coefficients computed for US census divisions. Further, we report separately for California, given above evidence of pronounced boom and bust in house prices as well as elevated housing jump incidence in the state. After carving out California MSAs, census division 1 less California is now non-standard. As is evident in the left 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 with mean correlation coefficients in the range of 0.2 – 0.3 and not more than 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 right panel of table 2, 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; three-quarters of California MSAs record significant lead return correlations with a mean correlation of .56.

and 3 are 8770 and 5405, respectively. Among these more significant sub-samples, mean correlations as expected are substantially higher (0.375 and 0.455, respectively.) And these samples are similarly characterized by significant MSA jump mean correlations, as indicated by T-statistics of 237 and 247, respectively.
Panel B of table 2 reports a similar assessment of contemporaneous and lead LM jump 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 regions, 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 contemporaneous correlations are significant among California MSAs at an occurrence rate above 34 percent, and with much larger values, averaging .22, substantially above the mean values for other regions. Moreover, the mean lead jump correlations are highest for California.\textsuperscript{11} Given evidence of elevated levels of jumps during the housing boom and bust as well as high levels of return and jump correlations among California MSAs, we turn now to assessment of MSA housing market integration.

III. Integration

Substantial research has studied the integration of international equity markets (for a comprehensive review of this topic and related research see Gagnon and Karolyi (2006)). The dynamics of equity market integration has been investigated by Harvey (1991), Chan, Karolyi, and Stulz (1992), Engle and Susmel (1993), Bekaert and Harvey (1995), Longin and Solnik (1995), and Errunza, Hogan, and Hung (2007). Papers have tended to vary in geographic focus, as some address integration in the European community (see, for example, Hardouvelis, Malliaropoulos, and Priestley (2006), and Schotman and Zalewska

\textsuperscript{11} The incidence of significant return correlations far exceeds jump correlations. 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 1). Across geographical cohorts, return correlations are larger with three exceptions, Divisions 3 through 5 for lead values (see Table 2). The results pertaining to the magnitude of correlations across return and jumps 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!
(2006), whereas others investigate emerging markets (see, for example, Bekaert and Harvey (1995), Chambet and Gibson (2008), Bekaert, Harvey, Lundblad and Siegel (2011)). Often there is a focus on markets that includes the US as a benchmark market (Ammer and Mei (1995) and Karolyi and Stulz (1996)). There is also considerable variation in methods. For instance, Carrieri, Errunza and Hogan (2007) use GARCH-in-mean to assess correlation in returns and volatility among markets, while Longin and Solnik (1995) use cointegration. Bekaert, Harvey and Ng (2005) is related to this paper in the use of multiple economic fundamental factors. Their paper documents contagion using the correlation of a factor model’s residuals. Integration is often described in terms of cross-country correlations in stock returns (for an early study see King and Wadhwani (1990)); however, correlation may be a misleading measure. When multiple factors drive returns, markets may be imperfectly correlated but perfectly integrated. 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.\(^\text{12}\)

Pukthuanthong-Le and Roll (2009) provide a simple intuitive measure of financial market integration based on 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.\(^\text{13}\) Clearly, to the extent global factors explain only a small

\(^{12}\) 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. Moreover, 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 consequence, the extent to which the multi-factors drive returns is a better indication of likely diversification benefits than a correlation measure.

\(^{13}\) 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
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)). In contrast, markets would be viewed as highly integrated to the extent their returns are well explained.

We extend this idea to US metropolitan housing markets. They should be regarded as highly integrated if identical US national factors explain a large portion of the variance in MSA-specific house price returns. Hence to measure US housing market integration, we employ the explained variance (r-square) from a regression of metropolitan house price returns on an identical set of national economic and housing market fundamentals.

a. Model Specification

For each MSA in the sample, the log percent change in the MSA-specific house price index is regressed on a common set of national economic, housing, and financial market factors. These factors represent macroeconomic and housing market fundamentals commonly employed in explaining aggregate house price returns (for example, Himmelberg, C., C. Mayer and T. Sinai (2005), Ortalo-Magne, and Rady (2006), Hua, C. and Craig, R. S. (2011), Gerdesmeier, Lenarcic and Roffia (2012) and Gyourko, Mayer and Sinai (2006)). Also included are common housing finance factors representing mortgage underwriting and secondary market liquidity. Indeed, many have argued that the contemporaneous and marked evolution in housing credit availability—as proxied by the underwriting and securitization factors—has been associated with the housing boom and bust. The factors and their definitions are displayed in Appendix Table 1. They include measures of private residential mortgage-backed securities issuance, average borrower loan-to-value ratio, payroll employment, equity markets (S&P500), industrial production, exposure to the national factors, e.g., unless the estimated coefficient vectors are exactly proportional across MSAs.

14 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.
PPI materials prices as well as personal income, consumer sentiment, single-family building permits, and the Federal Funds rate. All factor data are quarterly in frequency from 1975:Q1 – 2010:Q1 with the exception of consumer sentiment, which is available from 1977:Q4, and LTV and private MBS issuance, both available since 1985:Q1. 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), private MBS issuance (Federal Reserve Flow of Funds Accounts), LTV (FHFA), and personal income (US Department of Commerce National Income and Product Accounts).\textsuperscript{15} Integration is measured by the R-squares from the multi-factor model fit to a 30-quarter moving window for the samples of MSAs.\textsuperscript{16} The equal-weighted MSA average R-square portrays the mean level of integration during the period spanned by each moving window. Changes in individual MSA R-squares depict the evolution of integration. The contribution of individual common factors to integration is quantified by their separate influences on R-square.

b. Return Regressions on National Factors

The US national MSA housing market has become more integrated since 2004, (Figure 3.) Panel A of Figure 3 plots the average R-square over the 1992:Q2 – 2010-Q1 period for both the national and California samples. On the national level, measured integration held roughly steady around 45 percent over the 1992 – 2004 period. Starting in the mid-2000s, however, there is a strong uptrend that ends near .63.

In California this latest trend involved a corresponding upward movement from around .70 in 2004 to .88 in 2008. While some modest easing in average integration R-

\textsuperscript{15} We looked at factors both individually and in combination in their explanation of house price returns. That assessment was based on their relative contribution to the level of integration over time. Also, we tested for the effects of other factors, such as effects of changes in the industrial organization of the real estate industry, as reflected in a Herfindahl index of homebuilder concentration. That term yielded only limited increment to regression explanatory power and was not quantitatively important to the trend in integration R-square displayed in Figure 4.

\textsuperscript{16} In panel C of Figure 3 (below), we assess the robustness of the integration results to window length. Note there is no evidence of serial correlation in the regressions residuals.
square was evidenced among California MSAs late in the decade, those markets remained highly integrated.

To control for the possibility that newly introduced MSAs differ in their degree of integration (smaller cities were added later), we examined the trends in R-square for three separate cohorts. A similar procedure is followed by Jorion and Goetzmann (1999) to deal with the timing of market index inclusion into their databases. The cohorts include cities that were in the database continually from 1985:Q1 through 2010:Q1 (cohort 1), cities added from 1989:Q1 through 2010:Q1 (cohort 2), and those added from 1992:Q3 through 2010:Q1 (cohort 3). Panel B of Figure 3 shows the average R-square pattern for the 3 time cohorts. As the figure shows, the cohorts all display a similar pattern, a marked upward trend in housing market integration over the latter half of the 2000s.

We also assess the robustness of integration results to window length. Panel C of Figure 3 computes average house price integration for the US national sample across window lengths of 30, 40 and 50 quarters. While longer windows provide additional degrees of freedom, they also result in shorter integration time-series. As shown in the chart, all series display average integration levels in the range of .35 - .45 over the first half of the 2000s followed by a marked uptrend in housing market integration over the latter half of the decade.

MSA housing market cross-sectional and time-series summary statistics are reported in Table 3. The table reports mean quarterly house price returns, standard deviation of returns (sigma), mean first and last R-square measures for each of the integration time-series regressions, the change in R-square over the full timeframe of the analysis and for the decade of the 2000s, and the associated R-square time trend t-statistics (R-squares for each MSA are fit to a simple linear time trend for all available quarters).

17 The 3 cohorts are chosen such that the final integration series yields values starting in 2000:Q1.
Minimum values by quintile also are presented. First, it is important to note that risk and return associated with housing have been substantial. As shown, the average quarterly return for all MSA housing markets in the sample is positive at almost 1% with an average standard 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%.

The mean final period R-square of the integration model is .633, suggesting the importance of national influences on MSA house price returns. On average, R-squares increase by almost 25 percent from the beginning to end of sample. In some areas, however, national economic and housing market fundamentals fail to explain much of the variation in MSA-specific house price returns (min 2000s R-square = .093) At the other extreme, those same fundamentals explain more than 91 percent of MSA-specific house price returns in the decade of the 2000s. Further, there is also substantial variation in the change in R-square across the sample with a standard deviation of 0.221. Finally, as evidenced in stratification of summary measures across house price return quintiles, volatility of house price returns, integration R-square, and trend in integration R-square all increase monotonically by quintile mean house price return.\(^{18}\)

Table 4 presents integration details for the 28 California MSAs included in our dataset. In comparison to the full national sample of 384 MSAs, California housing markets are characterized by elevated returns, return volatility, and housing market integration. Indeed, the mean final period R-square for the California MSAs was .88, well in excess of the .63 estimated for the nation as a whole, suggesting the importance of national factors in determination of California house price returns. The average integration R-square in California similarly moved up over the decade of the 2000s by a full 25 percent. Indeed, as

\(^{18}\) Integration results for each of the 384 MSAs are available from the authors upon request.
shown in Table 4, the trend in California housing market integration over that period was highly statistically significant. As discussed below, the elevated level of average integration evidenced in the latter half of the 2000s may limit investor ability to diversify housing risk geographically among metropolitan markets. The Table also indicates substantial temporal and cross-MSA variation in the integration measure.

**c. Integration Drivers**

In this section, we seek to identify the drivers of the significant trending up in housing market integration estimated for the latter half of the 2000s. To do so, we compute the contribution to integration R-square associated with each factor in the model using ten factors and a 30-quarter moving window. We seek to ascertain the role of innovations in mortgage finance, particularly those associated with underwriting and securitization, in contributing to integration trends. Indeed, substantial media and policy discussions have pointed to the salience of such factors to the recent house price boom and bust.

As described above and evidenced in Panel A of Figure 4, US house price return integration trended up from .43 in 2000 to about .63 in 2010 with much of the upward movement in integration R-square occurring post-2004. The booming increment to R-square is explained by increased power of several factors notably including private mortgage securitizations and residential building permits. Indeed, numerous analysts have argued that the boom and bust in house prices were fuelled in no small measure by availability of non-conforming secondary market liquidity. Together, log dollar volume of private mortgage securitization and log single-family building permits accounted for roughly .25 of the .50 R-square recorded for the 2006 – 2007 boom period.

The mortgage underwriting (LTV) factor similarly figured importantly in the increment to integration R-square during the latter years of the housing boom. The boom period of the 2000s was associated with discrete changes in mortgage underwriting
whereby new non-conforming instruments allowed substantial numbers of previously unqualified households to obtain mortgage credit. Those credit flows were reversed late in the decade as underwriting was tightened and non-conforming originations fell away. Panel A further reveals the decline in contribution of the LTV and securitization factors to R-square as boom turned to bust. In their place, during the final years of the decade, the contribution of log personal income rose markedly to roughly one-half of the integration R-square. Indeed, income fundamentals took on new importance to integration of house price returns in the wake of the housing downturn.

Panel B of Figure 4 illustrates factor contribution to integration R-square for the 28 metropolitan areas in California, where integration R-square rose from about .63 in 2000 to in excess of .85 at end of decade. In the wake of long-standing constraints on housing supply and affordability (see, for example, Glaeser and Gyourko (2002)), eased credit qualification and enhanced mortgage credit availability unleashed substantial pent-up demand and a related 2000s boom in California markets. Early in the decade, two factors, reflecting ease of mortgage qualification (LTV) and growth in private (non-conforming) mortgage securitization, accounted for much of the marked trending up in California metropolitan housing return integration. Indeed, in 2003-2004, those factors comprised roughly .40 of the .70 integration R-square. By mid-decade, however, the contribution of private securitization markets to California housing market integration waned but was offset by the markedly increased R-square contribution of the permits series. Late in the decade, akin to trends for the entire US, the R-square contribution of the income term rose to account for roughly one-half of the total of all factors.
IV. **MSA Return Integration and Portfolio Risk Diversification**

Finally, we assess the relationship between portfolio diversification, integration, and risk for U.S. metropolitan housing markets. As suggested above, portfolio geographic diversification long has been fundamental to risk mitigation among investors and insurers of housing, mortgages, and mortgage-related derivatives. For example, Freddie Mac sought to geographically diversify their single-family loan portfolio to reduce credit risks. Wall St. investment banks similarly employed such logic in assembling mortgage-backed CDOs and related derivative securities. Newly-formed single-family housing investment funds and large, multifamily REITs also have employed geographic diversification as a strategy to mitigate portfolio risk.

To undertake this analysis, we comprise equal-weighted portfolios for our longest-running U.S. and California metropolitan house price returns cohorts (1992:Q2 – 2010:Q1). Per convention, we employ the standard deviation of housing returns as a measure of portfolio risk. Return volatility is computed for each MSA using a 30-quarter moving window. Diversification is measured by the degree of risk mitigation of the portfolio, computed as the difference between average MSA risk and portfolio risk, relative to average MSA risk.

Figures 5A and 5B provide evidence of portfolio risk, integration, and diversification for the cohort of U.S. metropolitan areas. As shown in the time-series, the integration and risk metrics track one another. Particularly evident is the strong upward movement in both

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19 See Freddie Mac Annual Report, 2007 (pg 97).

20 Colony Capital, for example, has sought to reduce risk via geographic diversification of the holdings of its single-family housing hedge fund.

21 See, for example, explicit statements on the intended benefits of geographic diversification that appear in the 10-Ks of large residential REITs including Mid-America Apartment Communities and Apartment Investment and Management Company (AIV).
measures during the housing boom years of the 2000s. Integration of metropolitan house price returns moved up from about .39 on average at start of decade to approximately .64 by decade's end. During that same period, portfolio risk, as proxied by sigma, rose from 0.4 to almost 1.6. The simple correlation coefficient between the R-square and sigma measures was in excess of .90 over both the full term of the time-series and during the decade of the 2000s.

The strong, positive correlation between portfolio integration and portfolio risk suggests limitations to portfolio geographic diversification as a method of risk mitigation. Trends in those estimates are displayed in panel 5B. The chart reveals a sizable inverse correlation between measures of portfolio integration and diversification; over the full timeframe of the analysis, the simple correlation coefficient was -.79. Further, the negative correlation between portfolio integration and diversification rose to -.95 during the 2000s. Over the decade of the 2000s, risk mitigation associated with US housing portfolio diversification fell by more than one-half.

Results of similar analyses for California MSAs are contained in panels 5C and 5D. As shown in panel 5A, trends in average integration of California housing markets appear to closely track California housing portfolio risk. The simple correlation between portfolio integration and risk for California MSAs was .83 for the full time-series and .93 for the decade of the 2000s. Integration of metropolitan house price returns moved up from about .64 on average at start of decade to approximately .88 by decade's end. During that same period, portfolio risk, as proxied by sigma, rose from 1.3 to almost 4.4. Similarly, as shown in panel 5D, California housing portfolio integration and diversification exhibit strong negative correlation. The simple correlation coefficient between those series increased to -

\[\text{Note the relationship between correlated jumps and diversification is similar; increased incidence of correlated jumps results in lower diversification possibilities. So when markets experience large and negative correlated price movements, the ability to diversify away this risk is reduced substantially, and at precisely the time when this mitigating effect is required most.}\]
.89 for the decade of the 2000s from -.80 for the full 1992–2010 timeframe. As is further evident in panel 5D, by the latter years of the 2000s, California portfolio diversification offered almost no benefit in risk mitigation.

In sum, analysis of simulated investment portfolios indicates sizable upward adjustment to measured risk in the context of the pronounced increase in portfolio integration over the 2000s housing boom. The increases in portfolio risk reflect sharp declines in opportunities for investment diversification. In short, the above findings suggest substantial limits for geographic diversification as a strategy for portfolio risk mitigation.

V. Conclusion

This paper evaluates the efficacy of geographic diversification as a strategy for risk mitigation among investors and insurers of housing. Using 384 US MSAs, it characterizes spatial correlation and integration among metropolitan U.S. housing markets. It then assesses the risk of alternative simulated housing investment portfolios.

Non-parametric analyses reveal high levels of MSA housing return and jump correlation during the boom and bust period of the 2000s. Estimation of a multi-factor model further indicates a marked uptrending in metropolitan housing market integration during that same period, especially in California. Influential factors include eased residential lending standards and growth in private mortgage securitizations. Portfolio simulation reveals reduced diversification potential and higher risk in the wake of increased metropolitan housing market integration.

Our research findings shed new light on the correlated non-performance of geographically-disparate housing and residential MBS investments during the late 2000s. Further, given the high levels of housing risk evidenced in the data, our results suggest that losses to private and government-backed mortgage insurers could reach unsustainable
levels in a severe housing downturn. A possible future structure, as discussed by Hancock and Passmore (2011) and Scharfstein and Sunderam (2011), might be to retain some form of broad-based government-backed mortgage insurance, but deeply subordinate taxpayer exposure by allowing only the assumption of catastrophic risk. Our findings underscore the importance of efforts to develop appropriate mechanisms to assure the liquidity and stability of the housing finance system during periods of severe housing downturn.
References


Hua, C. and Craig, R. S.  2011, Determinants of Property Prices in Hong Kong SAR: Implications for Policy, International Monetary Fund, IMF Working Papers: 11/277,


Figure 1: Average 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: US and LM Jump Statistics

Big LM House Price Return Jumps Proportion [% |LM| > 2] for US and California MSAs by Quarter

Notes: The Lee and Mykland (2008) (LM) jump measure is computed from quarterly observations for each of the 384 MSAs. The plot is for the US and 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).
Figure 3: 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 US MSAs for Different Window Sizes 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 30-quarter moving window. See Appendix Table 1 for details on the factors utilized in model estimation. Average levels of integration are presented for 1992:Q2 – 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 1985: Q1 (cohort 1), 1989:Q1 (cohort 2) and 1992:Q3 (cohort 3). Average levels of integration are also presented for 384 MSAs for different windows sizes, 30-quarters, 40-quarters and 50-quarters.
Figure 4: Contributions to US MSA Housing Return Integration Trends

Panel A: Factor Contributions to R-square

Panel B: Contribution to R-squares for CA MSAs for each factor

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 30-quarter moving window. The R-square contribution of each factor to the level of integration is plotted. See Appendix Table 1 for details on the factors utilized in model estimation. Contributing r-squares for each factor are presented for 1992:Q2 – 2010:Q1 for 384 US MSAs and for 28 California MSAs.
Figure 5: Housing Return Integration, Portfolio Risk and Diversification

Panel A: Integration and Portfolio Risk for US MSAs

Panel B: Integration and Diversification for US 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 30-quarter moving window. See Appendix Table 1 for details on the factors utilized in model estimation. Portfolio risk is measured using the standard deviation of housing returns for a 30-quarter moving window. The portfolio is constructed for an equally weighted grouping of MSAs. Diversification measures the degree of risk mitigation of the portfolio relative to the average risk of the MSAs. Values are presented for 1992:Q2 – 2010:Q1 for 384 US MSAs and for 28 California MSAs.
Table 1: MSA House Price Return and Jump Correlations

Panel A: Return Correlations

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Sigma</th>
<th>T-Stat</th>
<th>Maximum</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full sample</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>73536</td>
<td>0.201</td>
<td>0.182</td>
<td>299.735</td>
<td>0.946</td>
<td>-0.639</td>
</tr>
<tr>
<td><strong>Sample of correlations with T-statistic &gt; 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>33460</td>
<td>0.354</td>
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<td>0.946</td>
<td>0.173</td>
</tr>
<tr>
<td><strong>Sample of correlations with T-statistic &gt; 3</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>18126</td>
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<td>0.116</td>
<td>505.922</td>
<td>0.946</td>
<td>0.258</td>
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</table>
Table 1: MSA House Price Return and Jump Correlations

Panel B: Jump Correlations

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Sigma</th>
<th>T-Stat</th>
<th>Maximum</th>
<th>Minimum</th>
</tr>
</thead>
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<tr>
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<td>1.000</td>
<td>-0.924</td>
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<td>Sample of jump correlations with T-statistic &gt; 2</td>
<td>8770</td>
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<td>236.908</td>
<td>1.000</td>
<td>0.173</td>
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<tr>
<td>Sample of jump correlations with T-statistic &gt; 3</td>
<td>5405</td>
<td>0.455</td>
<td>0.135</td>
<td>247.201</td>
<td>1.000</td>
<td>0.259</td>
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</tbody>
</table>

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 2: Contemporaneous and Lagged MSA House Price Return and Jump Correlations by Geographical Cohort

Panel A: Return Correlations

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

Panel B: Jump (LM) Correlations

<table>
<thead>
<tr>
<th>Division</th>
<th>N</th>
<th>Number Significant</th>
<th>Percentage Significant</th>
<th>Mean Correlation</th>
<th>N</th>
<th>Number Significant</th>
<th>Percentage Significant</th>
<th>Mean Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Division 1</td>
<td>190</td>
<td>9</td>
<td>4.737</td>
<td>0.028</td>
<td>321</td>
<td>20</td>
<td>6.231</td>
<td>-0.029</td>
</tr>
<tr>
<td>Division 2</td>
<td>595</td>
<td>19</td>
<td>3.193</td>
<td>0.021</td>
<td>791</td>
<td>31</td>
<td>3.919</td>
<td>0.035</td>
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<tr>
<td>Division 3</td>
<td>496</td>
<td>5</td>
<td>1.008</td>
<td>0.006</td>
<td>552</td>
<td>23</td>
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<td>0.035</td>
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<tr>
<td>Division 4</td>
<td>903</td>
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<td>2.879</td>
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<td>Division 5</td>
<td>1953</td>
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<td>3.072</td>
<td>0.018</td>
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<td>111</td>
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<td>0.037</td>
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<tr>
<td>Division 6</td>
<td>2628</td>
<td>67</td>
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<td>Division 7</td>
<td>703</td>
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<td>4.694</td>
<td>0.033</td>
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<td>0.012</td>
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<tr>
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<td>561</td>
<td>15</td>
<td>2.674</td>
<td>0.016</td>
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<td>36</td>
<td>4.675</td>
<td>0.041</td>
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<tr>
<td>Division 9</td>
<td>153</td>
<td>13</td>
<td>8.497</td>
<td>0.047</td>
<td>252</td>
<td>13</td>
<td>5.159</td>
<td>0.095</td>
</tr>
<tr>
<td>CA</td>
<td>378</td>
<td>130</td>
<td>34.392</td>
<td>0.224</td>
<td>705</td>
<td>49</td>
<td>6.950</td>
<td>0.116</td>
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</tbody>
</table>

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 3: Summary Integration Measures for All MSAs

<table>
<thead>
<tr>
<th>MSA</th>
<th>Mean Return %/Quarter</th>
<th>Sigma</th>
<th>First R-Square</th>
<th>Last R-Square</th>
<th>Change in R-Square (Last-First)</th>
<th>Trend t-stat (Last-First)</th>
<th>R-Square (2000)</th>
<th>Change R-Square (2000s)</th>
<th>Trend t-stat (2000s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.988</td>
<td>2.450</td>
<td>0.377</td>
<td>0.633</td>
<td>0.256</td>
<td>4.121</td>
<td>0.428</td>
<td>0.218</td>
<td>5.553</td>
</tr>
<tr>
<td>Std Dev</td>
<td>0.259</td>
<td>0.890</td>
<td>0.211</td>
<td>0.214</td>
<td>0.221</td>
<td>5.479</td>
<td>0.177</td>
<td>0.206</td>
<td>6.181</td>
</tr>
<tr>
<td>Min/Quintile 1</td>
<td>0.430</td>
<td>0.980</td>
<td>0.023</td>
<td>0.078</td>
<td>-0.355</td>
<td>-</td>
<td>11.033</td>
<td>0.093</td>
<td>-0.415</td>
</tr>
<tr>
<td>Quintile 2</td>
<td>0.784</td>
<td>1.744</td>
<td>0.198</td>
<td>0.422</td>
<td>0.050</td>
<td>-0.427</td>
<td>0.261</td>
<td>0.058</td>
<td>0.791</td>
</tr>
<tr>
<td>Quintile 3</td>
<td>0.890</td>
<td>2.144</td>
<td>0.284</td>
<td>0.594</td>
<td>0.193</td>
<td>2.365</td>
<td>0.360</td>
<td>0.166</td>
<td>3.675</td>
</tr>
<tr>
<td>Quintile 4</td>
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<td>2.545</td>
<td>0.371</td>
<td>0.748</td>
<td>0.329</td>
<td>4.841</td>
<td>0.458</td>
<td>0.267</td>
<td>6.243</td>
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<td>Quintile 5</td>
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<td>2.958</td>
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<td>0.454</td>
<td>8.329</td>
<td>0.587</td>
<td>0.384</td>
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<td>Max</td>
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<td>9.258</td>
<td>0.972</td>
<td>0.954</td>
<td>0.805</td>
<td>28.595</td>
<td>0.914</td>
<td>0.685</td>
<td>25.880</td>
</tr>
</tbody>
</table>

Notes: Details for 3 integration characteristics (Mean, Sigma and R-Square Trend t-stat) are presented for the 384 US 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. Both the first R-Square and R-Square for the start of 2000 are used to examine the trends in integration. The final R-squares pertain to 2010:Q1 for all 384 US MSAs. The change in R-squares (Last-First) refers to the difference between estimates for 2010:Q1 and 1992:Q2 for each MSA. The change in R-squares (2000s) refers to the difference between estimates for 2010:Q1 and 1999: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 4: Summary Integration Measures for California MSAs

<table>
<thead>
<tr>
<th>MSA</th>
<th>Mean</th>
<th>Sigma</th>
<th>First R-Square</th>
<th>Last R-Square</th>
<th>Change in R-Square (Last-First)</th>
<th>Trend t-stat (Last-First)</th>
<th>R-Square (2000)</th>
<th>Change R-Square (2000s)</th>
<th>Trend t-stat (2000s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.264</td>
<td>3.231</td>
<td>0.669</td>
<td>0.880</td>
<td>0.211</td>
<td>2.459</td>
<td>0.635</td>
<td>0.245</td>
<td>6.478</td>
</tr>
<tr>
<td>Std Dev</td>
<td>0.368</td>
<td>0.485</td>
<td>0.171</td>
<td>0.051</td>
<td>0.169</td>
<td>3.669</td>
<td>0.224</td>
<td>0.222</td>
<td>8.178</td>
</tr>
<tr>
<td>Min</td>
<td>0.607</td>
<td>2.540</td>
<td>0.293</td>
<td>0.699</td>
<td>0.001</td>
<td>-2.294</td>
<td>0.238</td>
<td>-0.050</td>
<td>-6.646</td>
</tr>
<tr>
<td>Max</td>
<td>1.892</td>
<td>4.674</td>
<td>0.897</td>
<td>0.951</td>
<td>0.609</td>
<td>9.170</td>
<td>0.914</td>
<td>0.644</td>
<td>25.880</td>
</tr>
</tbody>
</table>

Notes: Details for 3 integration characteristics (Mean, Sigma and R-Square Trend t-stat) are presented for the 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. 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. Both the first R-Square and R-Square for the start of 2000 are used to examine the trends in integration. The final R-squares pertain to 2010:Q1 for all 28 California MSAs. The change in R-squares (Last-First) refers to the difference between estimates for 2010:Q1 and 1992:Q2 for each MSA. The change in R-squares (2000s) refers to the difference between estimates for 2010:Q1 and 1999:Q4 for each MSA. 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.
**Appendix Table 1: Integration Model Factors and Data**

<table>
<thead>
<tr>
<th>Data</th>
<th>Data Defined</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSA HP</td>
<td>log percent change in MSA house price index</td>
</tr>
<tr>
<td>PRIVMBS</td>
<td>log Private MBS</td>
</tr>
<tr>
<td>LTV</td>
<td>log LTV all buyers</td>
</tr>
<tr>
<td>FEDFUNDS</td>
<td>log Fed Funds Rate</td>
</tr>
<tr>
<td>INDPRO</td>
<td>log percent change in Industrial Production Index</td>
</tr>
<tr>
<td>PAYEMS</td>
<td>log percent change in US payroll employment</td>
</tr>
<tr>
<td>PERMIT1</td>
<td>log single-family building permits</td>
</tr>
<tr>
<td>PPIITM</td>
<td>log percent change PPI materials prices</td>
</tr>
<tr>
<td>UMCSENT</td>
<td>log University of Michigan Consumer Sentiment Index</td>
</tr>
<tr>
<td>SP500</td>
<td>log percent change in S&amp;P 500</td>
</tr>
<tr>
<td>INCOME</td>
<td>log personal income</td>
</tr>
</tbody>
</table>

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:Q4, and LTV and private MBS issuance both available since 1985:Q1. 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 SP500 (Datastream), PRIVMBS (Federal Reserve Flow of Funds), LTV (FHFA) and INCOME (US Dept of Commerce National Income and Product Accounts).