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Findings from a Cross-Sectional Housing Risk-Factor Model

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Abstract Housing data from the last 25 years show that returns to residential real estate in the U.S. can be volatile and vary significantly among locations. The variations in returns are driven by economically as well as geographically and psychologically motivated factors, but so far, no asset pricing model that adequately explains systematic risks in cross-sectional housing returns is widely accepted. This paper proposes an asset pricing model for housing returns that includes a market-wide return factor, an economically motivated factor derived from income growth, a geographically based factor derived from land supply elasticity and a momentum factor, which is psychological in nature. The model explains well the systematic risks in housing returns and is robust to different portfolio segmentations. Moreover, the model illustrates that local risk factors indirectly capture the risk previously attributed to market-wide price changes. While housing is not actively traded when compared to other financial assets, understanding the risk-factors that explain housing return in cross-section provides important insight for real estate investors, builders, real estate future traders, homeowners, banks and other mortgage lenders.

Keywords Momentum · Residential real estate · Housing asset pricing model · Factor model

Introduction

Housing prices and their volatility vary significantly among U.S. markets. While the finance literature includes a long stream of research on risk-factor models that capture the cross-sectional risk-return differences in stocks, no model that explains the

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systematic cross-sectional variation in home prices is widely accepted by the real estate literature. Differences in housing returns from one location to another are not only a result of economic factors; they are also a result of factors that are geographically and psychologically driven. Therefore, a model that considers factors from all these sources is needed in order to explain the systematic variation in home prices in different locations through time.

This paper proposes a four-factor housing asset pricing model that is economically, geographically and psychologically motivated and reexamines the relation between raw housing returns and market sensitivity under the proposed model. Specifically, the model includes local risk factors derived from income growth, land supply elasticity and pricing momentum in addition to a risk factor that is based on U.S. market-wide housing return. The inclusion of the land supply elasticity factor as well as the housing price momentum factor is especially important to further the understanding of cross-sectional housing price fluctuations. Finding from Glaeser et al. (2008) suggests that housing price volatility is related to the amount of available developable land in a particular area and that price deviation from housing fundamentals is more likely to occur where land supply elasticity is low. Beracha and Skiba (2011) expand on Case and Shiller (1989) and illustrate that price momentum in housing is economically meaningful and may also cause deviation from housing fundamentals. The importance of controlling for housing price changes that are non-fundamentally driven is also noted by Koetter and Poghosyan (2010). The authors indicate that housing price deviation from their fundamentals significantly contributes to banks instability. The importance of understanding movements in housing prices has become particularly apparent in the aftermath of the housing market correction of 2007–2009.

The four-factor housing price model proposed in this paper captures most of the systematic variation in home prices in more than 90 large cities over the last 25 years. The analysis shows that all four factors are important in order to explain cross-sectional housing price changes, but the inclusion of the momentum factor is particularly important. Interestingly, the findings indicate that when all four systematic risk factors are included in the model, the sensitivity of local home prices to the broad housing U.S. market (beta) is not positively related to raw housing price changes as documented in the extant literature. This novel finding suggests that while local home prices generally tend to commove with the overall U.S. housing market, local risk factors can capture the same market-wide risk indirectly.

While it is true that housing markets cannot be traded as easily as stocks or REITs, a well-defined and robust housing risk-factor model still provides important practical implications in addition to being a useful benchmark for real estate researchers. Future contracts on different housing markets are currently being traded on the Chicago Board of Exchange (CBOE), and it seems very likely that housing financial innovation and expansion will provide additional housing related financial products. Benchmark performance models are useful for traders and investors who deal with such housing related products. Moreover, understanding the risk-factors that explain housing returns in different markets provides important insight to real estate investors, builders, homeowners, banks and other mortgage lenders.

The rest of the paper is organized as follows: "Trends in U.S. Housing Prices and Volatility" provides some background on U.S. housing markets. "Asset Pricing

Model and Related Literature" derives the asset pricing model while reviewing the relevant extant literature. "Data" presents the data used in the analyses. "Results" describes the results, and "Conclusion" closes this piece with some concluding remarks.

Trends in U.S. Housing Prices and Volatility

While housing rate of appreciation cannot significantly exceed income growth over the long run, the two may be materially different over the short to medium terms.[1] Figure 1 illustrates the trend in real home prices in the U.S. between 1890 and 2009. Over this 120-year period, housing appreciated at an average compounded annual real rate of about 0.3%. The home price index remained around 100 during most of the 20th century, with the exception of a sharp decline during the Great Depression and a significant increase from those values back to their original level after World War II. During the 94-year period spanning 1890–1983, home prices in the U.S. experienced near zero real price appreciation. Then, over the 23 following years (1984–2006) home prices roughly doubled in real terms only to immediately give back 70% of these returns during the sharp correction that took place between 2007 and 2009. Unarguably, the last 25 years in the housing market were very unusual and had a colossal effect on the overall world economy. Beltratti and Morana (2010), for example, provide evidence that house price shocks produce larger effects on the macroeconomy than stock market shocks do, and that the U.S. housing market is a driver of global fluctuations. Similarly, Miller et al. (2011) find that housing price changes materially affect metropolitan economic growth via both wealth and collateral effects.

Commenting on the recent housing bubble and its subsequent collapse, Shiller (2007) asserts that a significant factor in the housing boom was propelled by non-fundamental reasons and the notion that a house is a great investment. According to Shiller, a psychological feedback mechanism helped spread that notion and caused home prices to reach inflated levels. Shiller argues that fundamentals could not explain housing prices during the boom and offers the explanation of "social epidemic of optimism". This optimism, speculative psychology, and investors' overconfidence fuel positive momentum in housing prices, which in turn lead to sharper declines.

One of the puzzles in real estate finance is the behavioral patterns of housing prices, especially for the markets located on the West Coast and in the Northeast. Glaeser and Gyourko's (2006) recent study on housing dynamics concludes that researchers in real estate should especially focus their efforts on explaining high volatilities observed in coastal markets and the positive serial correlations of high frequency price changes. According to Sommervoll et al. (2010) housing markets display significant positive serial correlation along with high volatilities over time and during times of credit constraints the fluctuations in prices can be especially large. Glaeser et al. (2008) point out that higher price volatility is expected in areas with low land supply elasticity, but also argue that a prolonged pricing correction is

[1] Gyourko et al. (2006) argue that housing appreciation in a few "superstar" cities may exceed the national income growth for extended time periods mainly due to growth in high-income population in these cities.

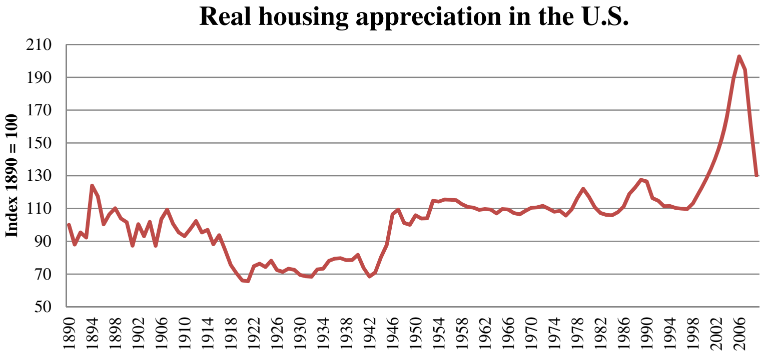

Fig. 1 Housing appreciation in the U.S. from 1890 to 2009 shows the trend in real home prices from 1890 to 2009 in the U.S. with the base value of 100 in 1890. Data are from Robert Shiller's "Irrational Exuberance" website (www.irrationalexuberance.com)

more likely in areas with plentiful developable land due to the excess of new housing supply created during a boom-period.

Regional differences in the price appreciations have been large from 1984 to 2009. Figure 2 illustrates the differences in housing price appreciation in nominal terms across seven Metropolitan Statistical Areas' (MSAs) housing markets. The seven markets in the figure correspond with the following total housing appreciation percentiles: 1%, 10%, 25%, 50%, 75%, 90%, and 100%. Oklahoma City's housing prices appreciated the least between 1984 and 2009, gaining only about 65% in nominal terms or an average annual compounded rate of 1.97%. Birmingham, Alabama is in the middle with a 3.99% average annual compounded appreciation, and San Francisco is the leading city in terms of price appreciation. Housing in San Francisco gained on average 6.67% during the 1984 to 2009 time period in spite of the sharp price correction the city experienced from 2007 to 2009. Generally speaking, the markets that appreciated the most during the housing boom also experienced the sharpest price correction during the bust period. The relatively smooth trends in housing prices shown in Figs. 2 and 3 are consistent with the notion that price momentum is significant in residential real estate (Beracha and Skiba 2011).

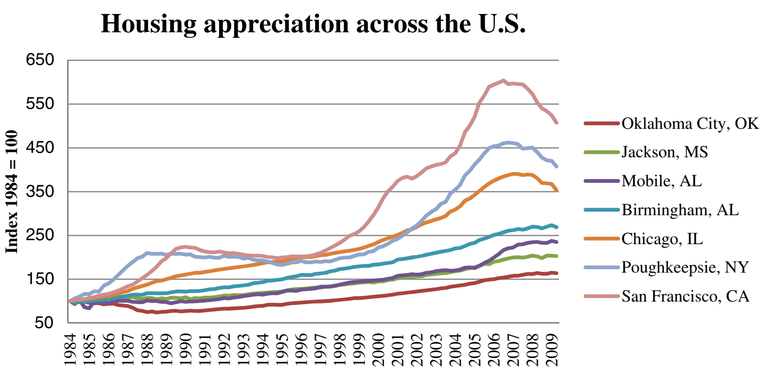

Fig. 2 Housing Appreciation in selected MSAs illustrates differences in home price appreciation in nominal terms across seven MSAs' housing markets. The Seven markets in the figure are chosen based on total appreciations during the Q1:1984 to Q2:2009 time period and correspond with the following return percentiles: 1%, 10%, 25%, 50%, 75%, 90%, and 100%

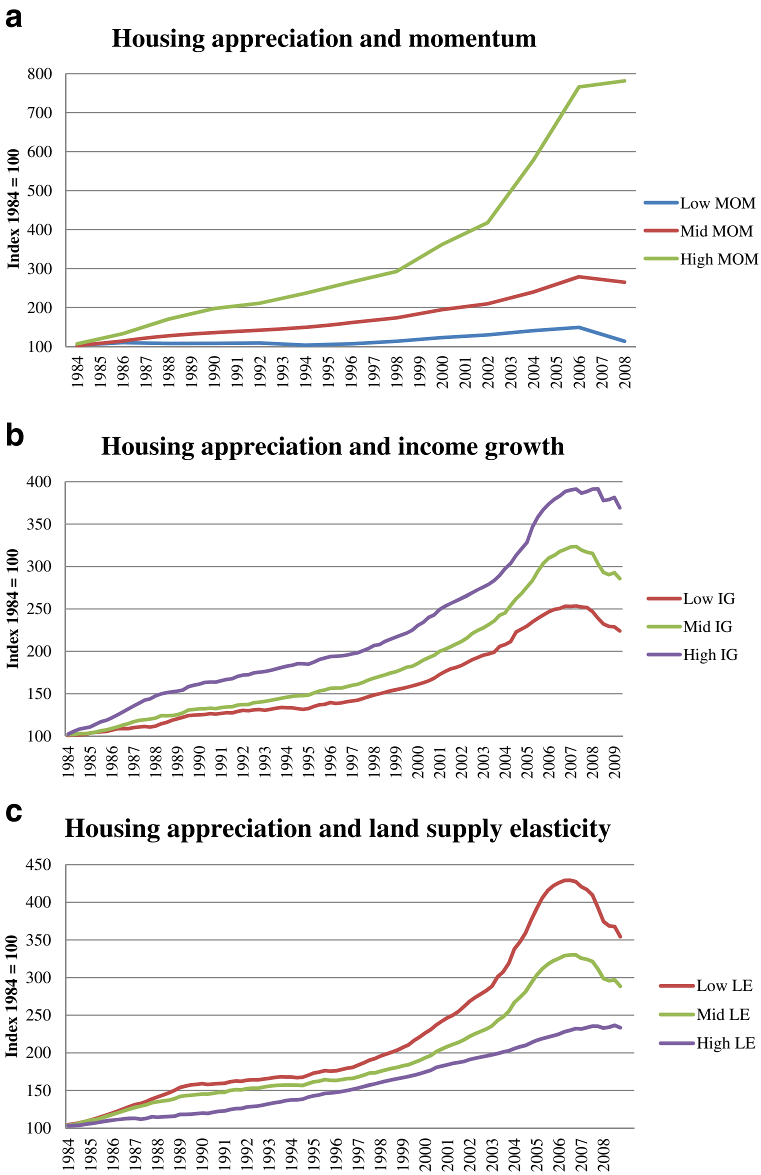

Fig. 3 Housing appreciation and risk factors illustrates housing appreciation given momentum, income growth rate and land elasticity during the Q1:1984 to Q2:2009 time period. Panel A shows housing appreciation in the top, middle and bottom thirds of housing markets ranked on previous 1-year performance and rebalanced every 3 quarters. Panel B shows housing appreciation in the top, middle and bottom thirds of housing markets ranked on previous 1-quarter income growth and rebalanced quarterly. Panel C shows housing appreciation in the top, middle and bottom thirds of housing markets ranked by land supply elasticity

Asset Pricing Model and Related Literature

Since the seminal works on risk-reward relationship in stocks and the derivation of the capital asset pricing model (CAPM), the finance literature has recognized market-wide return to be a systematic determinant of variation in security prices. According to portfolio theory, this systematic market risk is non-diversifiable and a security's sensitivity to the market risk determines the expected return to the security (Sharpe, 1964; Lintner, 1965). This risk-reward relationship has also been shown to matter in the cross-section of real estate returns (Cannon et al. 2006; Case et al. 2011)

Consistent with the CAPM and with Case et al. (2011), the dependent variable in the proposed model of this paper is defined as the excess return on housing during time *t* in MSA *i,* computed as the raw return to MSA *i*'s housing over the risk free rate. Cannon et al. (2006) as well as Case et al. (2011) show that the market-wide housing return is a significant systematic risk-factor in explaining the area-specific real estate returns and robust to inclusion of other explanatory factors. Hence, the first risk-factor is the excess return on the U.S. housing market at time *t*, computed as the broad market return to the U.S. housing over the risk free rate.

A stream of finance literature has merged in order to better explain the cross-section of stock returns (for example, Fama and French 1992, 1993; Carhart 1997) by including additional systematic risk-factors in the traditional CAPM, such as size (return differential between large and small U.S. stocks, SMB), value (return differential between high and low market-to-book ratio stocks, HML), and momentum (return differential between U.S. stocks that performed well and poorly in previous periods, UMD) factors. Similarly, three factors are included in the proposed model in addition to the market return. These factors are based on local income growth, land supply elasticity, and housing price momentum, which are motivated by economical, geographical and psychological forces, respectively.

The second factor in the model is the income growth risk-factor, motivated by Case and Shiller (2003). The authors point out that rapid increase in home prices since the late 1990s can be partially explained by fundamentals. In fact, income growth alone explains virtually all housing price increases in 40 states. Naranjo and Ling (1997) show that macroeconomic factors explain returns on commercial real estate and Capozza et al. (2004) specifically find income growth to be highly significant determinant of housing appreciation. The income growth factor is constructed for this asset pricing model, so that for each quarter we compute the average housing return differential between the given quarter's top third and bottom third areas in terms of income growth. We expect that the income growth risk-factor will mostly be positive, indicating that real estate in areas with relatively high income growth outperforms real estate in areas with relatively low income growth.

The third factor in the model is the land supply elasticity risk-factor, which is based on a measure of available developable land in each city. Several studies provide evidence that real estate markets in coastal cities function very differently from inland cities with less constraint supply of land. Gyourko et al. (2006) show that the rapid growth in housing prices in certain locations can be partially explained by inelastic land supply after controlling for other characteristics of the location. Capozza et al. (2004) find that land supply elasticity partially explains changes in housing prices in 62 cities. Similarly, Chen and Leung (2008) illustrate that land supply elasticity affects mortgage defaults. Albouy (2009) shows that amenities affect wages and housing costs, so that highly valuable cities are coastal (characterized by an inelastic supply of land). In this paper the land supply elasticity risk-factor is defined for each quarter as the quarter's housing return differential between the top third cities and bottom third cities in terms of their land supply elasticity value. The land supply elasticity factor is anticipated to be mostly positive, so that home prices in areas with inelastic supply of land appreciate faster than homes in areas with elastic land supply.

The fourth risk-factor is a psychologically motivated return momentum factor. Economically significant returns from momentum based trading have been documented in both finance and real estate research. Jegadeesh and Titman (1993) show that there exists a wide-spread momentum in the U.S. stock market. Momentum in stocks has been linked to behavioral characteristics such as overconfidence and self-attribution bias (Daniel et al. 1998; Gervais and Odean 2001; Chui et al. 2010; Piazzesi and Schneider 2009) and it is common practice to control for stocks' return momentum in benchmark models (Carhart 1997).

Because the market for residential real estate is dominated by inexperienced participants, who are likely to possess behavioral characteristics, such as overconfidence and self-attribution bias that have been linked to momentum in stocks, it is not surprising that the return momentum in housing is also large and persistent. Case and Shiller (1990) show that owner occupied home prices tend to change for over a year in same direction. Beracha and Skiba (2011) document economically significant momentum in 380 MSAs from 1983 to 2009 and show that a zero cost momentum based housing portfolio earns nearly 9% on an annual basis.

Observing housing prices in the 2000s, Shiller (2007) concludes that the boom in the U.S. housing market cannot be explained by fundamentals, but rather by psychological factors. Also, Clayton (1996) shows that rational expectations model of housing prices fails to capture observed housing price dynamics during boom cycles but track housing prices well in less volatile times. His findings also suggest that housing prices can temporarily deviate from fundamentals by a great amount during market cycles. Costello et al. (2011) document similar evidence in the Australian real estate markets, where the housing market experiences periods of sustained deviations from fundamental prices warranted by income growth.

The momentum risk-factor for each quarter is defined as the quarter's housing return differential between a portfolio constructed from previous year's top third cities in terms of their return and a portfolio that includes the previous year's bottom third cities in terms of their return.[2] Based on the existing literature, the momentum risk-factor is expected to be positive, on average, indicating that real estate in areas that performed well in the recent past will continue to perform well in the near future and real estate in areas that performed poorly in the recent past will continue to do so in the near future.

The following is the proposed four-factor housing price model that includes the broad housing market factor, income growth factor, land supply elasticity factor, and the momentum factor discussed above:

$$R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \lambda_i(HML_t) + \delta_i(IME_t) + \theta_i(UMD_t) + \varepsilon_{i,t} \quad (1)$$

Where $R\_MSA_{i,t}$ is the quarterly return to MSA i's housing price index in time t, RF_t is the risk free rate at time t, and R_USA_t is the quarterly return to the broad U.S.

[2] Beracha and Skiba (2011) show that portfolios based on performance from the previous four quarters experience the highest level of return momentum.

housing market at time t. HML_t (high minus low) is the income growth factor in time t, IME_t (inelastic minus elastic) is the land supply elasticity factor in time t, and UMD_t (up minus down) is the momentum factor in time t.

Data

The dataset used in the analysis is constructed from three different sources. Housing Price Indices (HPI) are obtained from the Federal Housing Finance Agency (FHFA).[3] The HPI observations are available on a quarterly basis for the U. S. and up to 380 MSAs from which quarterly housing price changes are derived for 102 quarters spanning the Q1:1984 to Q2:2009 time period. The FHFA uses weighted repeated sales methodology to construct each of the HPIs and includes only repeated sales or refinancings of single-family residential properties financed through a conforming loan.[4]

The source for supply elasticity index is Saiz (2008). Saiz assigns land supply elasticity values based on available developable land in each city while considering topographical constraints and regulatory barriers to development that are also positively correlated with each other. Land supply elasticity values are available for 95 U. S. metropolitan areas with populations of 500,000 or more.[5] Out of these 95 cities, 93 were matched with the HPI data for the purpose of calculating their associated housing price changes.

Finally, quarterly personal income growth is gathered at the state level from the Bureau of Economic Analysis (BEA). Income growth is assigned to each of the 93 MSAs included in our sample based on the state in which they are located.

Table 1 provides descriptive statistics on the average appreciation and standard deviation of the full sample as well as the top and bottom cities in terms of past price appreciation and land supply elasticity. The compounded annual price appreciation for the cities included in the sample ranges between 1.97% and 6.64% with an average (median) of 4.14% (3.94%). Table 1 shows that the top three cities in terms of price appreciation appreciated about 4.5% faster annually compared with the bottom three cities. Consistent with the theory of positive relation between risk and reward, the top performing cities are also associated with a standard deviation that is significantly larger than the return standard deviation of cities with the lowest performance. However, a closer look at the relationship between the raw housing return and standard deviation reveals that the relation between the two is not so straightforward. According to Fig. 4, housing return is increasing and then decreasing with housing volatility—measured by standard deviation of returns. As a result, some of the areas with the highest return volatility are associated with

[3] The index data are available at http://www.fhfa.gov.

[4] FHFA defines a repeated sale when the same physical address originates at least two mortgages and those mortgages are purchased by either Freddie Mac or Fannie Mae. The use of repeated sales of the same physical address controls for properties' characteristics, and reduces the effect of changes in construction quality over time on changes in housing prices. For more detail about the index construction see Calhoun (1996) and OFHEO's website at http://www.fhfa.gov.

[5] For the complete list of MSA land supply elasticities, see Saiz (2008).

Table 1 Descriptive statistics shows average annual price appreciation and standard deviation on selected cities from the 93 MSAs included in our sample. The housing price index data are obtained from the FHFA with quarterly frequency and include 102 quarters spanning the period between the first quarter of 1984 to the second quarter of 2009. Land supply elasticity values are from Saiz (2008)

		Appreciation	St. Deviation	MSA
Average (median) annual price appreciation		4.14% (3.94%)		
The top three cities in terms of annual price appreciations	1st	6.64%	8.90%	San Francisco, CA
	2nd	6.45%	8.35%	New York, NY
	3rd	6.33%	6.54%	Seattle, WA
The bottom three cities in terms of price appreciations	Last	1.97%	4.54%	Oklahoma City, OK
	2nd to last	2.13%	2.77%	Fort Worth, TX
	3rd to last	2.20%	3.28%	Dallas, TX
Cities with highest level of land supply elasticity	LSE=5.16	2.64%	2.03%	Wichita, KS
	LSE=5.13	2.94%	2.74%	Fort Wayne, IN
	LSE=3.36	3.48%	1.67%	Indianapolis, IN
Cities with lowest level of land supply lasticity	LSE=0.57	5.55%	10.88%	Los Angeles, CA
	LSE=0.57	4.99%	8.85%	Miami, FL
	LSE=0.59	6.64%	8.90%	San Francisco, CA

average returns from the middle to lower range of the sample during the 1984–2009 time period.

Table 1 shows that the MSAs associated with the highest level of land supply elasticity experience lower price volatility and appreciation compared with the cities with the lowest level of land supply elasticity. The differences in price volatility between the two extreme groups are especially large—about four times higher for the three most inelastic cities compared with the three most elastic cities.

Figure 3 further illustrates the relevance of momentum, income growth and land supply elasticity with respect to housing appreciation. Panel A shows the cumulative housing appreciation in the top, middle and bottom thirds of housing markets ranked on previous 1-year performance, when the portfolios are rebalanced every 3 quarters. Panel B shows housing appreciation in the top, middle and bottom thirds of housing markets ranked on previous 1-quarter income growth and rebalanced quarterly. Panel C shows housing appreciation in the top, middle and bottom thirds of housing markets ranked by land supply elasticity. In each of the three panels the relevant risk factor materially affects housing appreciation consistent with economic intuition. However, it appears that of these three factors the momentum factor has the greatest effect on housing return. For example, a portfolio that contains the top third cities ranked based on their previous year's performance, provides an accumulated appreciation of over 680% during the Q1:1984 to Q2:2009 time period, while the portfolio of the bottom third cities in terms of past performance appreciated less than 15% during the same time period.

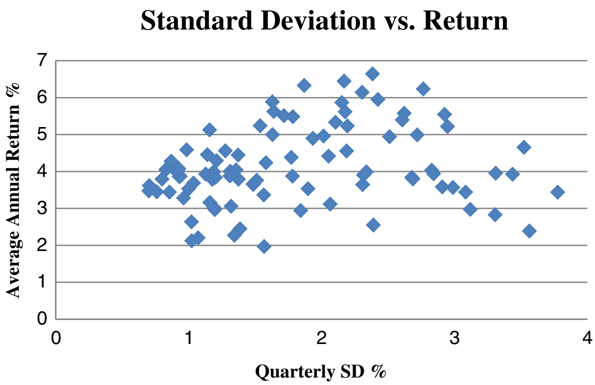

Fig. 4 Home price appreciation and volatility illustrates the relation between the raw average annual return on housing in different MSAs and their volatility—measured by the return standard deviation. The average annual housing returns and their standard deviations are based on the Q1:1984 to Q2:2009 time period

Results

Explanatory Power of Factors

To test the explanatory power of the individual factors and the four-factor model from Eq. 1, we run regressions using the time series of each of the 93 MSAs included in the sample. We then record the average value of each risk-factor coefficient as well as the value of the intercept term of the regressions, or the alpha coefficient, along with their respective statistical significances. To test whether the model captures all of the systematic return in the cross-section of U.S. housing markets, this analysis focuses on the statistical significance of the estimated intercepts, or the Jensen's (1969) alphas. A statistically significant, positive or negative alpha, would indicate that the model is misspecified and fails to capture all the systematic risk of housing returns. Consequently, an alpha that is statistically indifferent from zero would suggest that the model is generally well-defined and captures all but an insignificant portion of the systematic variation in housing returns.

Table 2 shows the results of seven different regression specifications based on the four-factor model defined in Eq. 1. Each of the first four specifications includes one risk-factor. The coefficient of each of the risk-factors in these specifications is statistically significant, which indicates that each of the risk-factors by itself has some explanatory power. However, the alpha intercept in all four single factor model specifications is also statistically significant, suggesting that no single risk-factor is able to capture the cross-sectional housing return variation. The alphas of the IME and UMD single factor specifications (3 and 4) are especially large in magnitude—−1.48% and −1.00% in annual terms respectively. Under the first specification, the beta coefficient, as expected, is close to one.

Specification 5 includes three risk-factors and only excludes the momentum factor from the analysis. The income and land elasticity risk-factors turn statistically insignificant and the alpha of this specification remains negative and statistically significant. In fact, the alpha coefficient of the three-factor model in specification 5 (−0.085) is similar in magnitude and slightly higher in absolute value than the alpha in specifications 1 (−0.071) and 2 (−0.081), where the market and income growth factors are present as single risk-factors. This suggests that while each of the three

Table 2 Risk-factors and risk-adjusted returns shows the results from several regression analyses based on the asset pricing model described in equation (1): $R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \lambda_i(HML_t) + \delta_i(IME_t) + \theta_i(UMD_t) + \varepsilon_t$. The dependent variable is the quarterly return to a housing market minus the risk free rate. Alpha is the Jensen's alpha that measures abnormal return or the misspecification of the model. *R_USA* is the estimated coefficient on the market wide return, *HML* is the estimated coefficient on the income growth risk-factor, *IME* is the estimated coefficient on the land elasticity risk-factor, and *UMD* is the estimated coefficient on the momentum risk-factor

Specification	Alpha	R_USA	HML	IME	UMD
(1)	−0.071 (−2.48)	1.043 (16.26)			
(2)	−0.081 (−2.78)		−0.066 (−2.04)		
(3)	−0.369 (−13.01)			0.592 (8.656)	
(4)	−0.251 (−6.99)				0.071 (3.42)
(5)	−0.085 (−3.71)	1.011 (28.01)	−0.026 (−0.85)	0.041 (0.58)	
(6)	0.016 (0.38)	1.051 (16.13)			−0.044 (−2.07)
(7)	−0.007 (−0.17)	1.015 (27.53)	−0.013 (−0.45)	0.046 (0.66)	−0.044 (−2.13)

factors by themselves explains some of the systematic variation of returns in cross-section, the three-factor model does not improve the single-factor market model of specification 1.

Specification 6 includes the market and the momentum risk-factors. Inclusion of only these two risk-factors seems to be sufficient to achieve an alpha that is statistically indistinguishable from zero. When all the four factors in the last specification (7), the alpha is even closer to zero (-0.007) and remains statistically indistinguishable from zero. As in the three-factor model presented in specification 5, the income growth and land elasticity factors are not statistically significant. Only the broad market return factor and momentum factor remain significant. Overall, the results presented in Table 2 indicate that when explaining cross-sectional variation in residential real estate returns, market return as documented by Case et al. (2011), is an important determinant. However, without the additional factors, the factor- model appears to be misspecified. Also, of the additional factors, the psychologically motivated momentum appears to be especially important.

Figure 5 provides a graphical illustration of how effective the four-factor model is compared with the simple market model in explaining the systematic risk in housing. In panel A, where alphas are estimated using the one-factor model of specification 1 of Table 2, the abnormal returns are strongly correlated with the raw returns. This suggests that the market model does not fully capture the systematic risk in housing. In panel B, where alphas are estimated using the four-factor model of Eq. 1, there is no clear relation between the alphas and the raw returns. The visible difference between panel A and panel B serves as an additional evidence that the four-factor model does a superior job in explaining systematic risk in housing.

Relation between Risk-Factors and Returns

The results presented in Table 3 provide more insight to the relation between housing return, housing risk-adjusted return (alpha), and each of the four housing risk-factors.

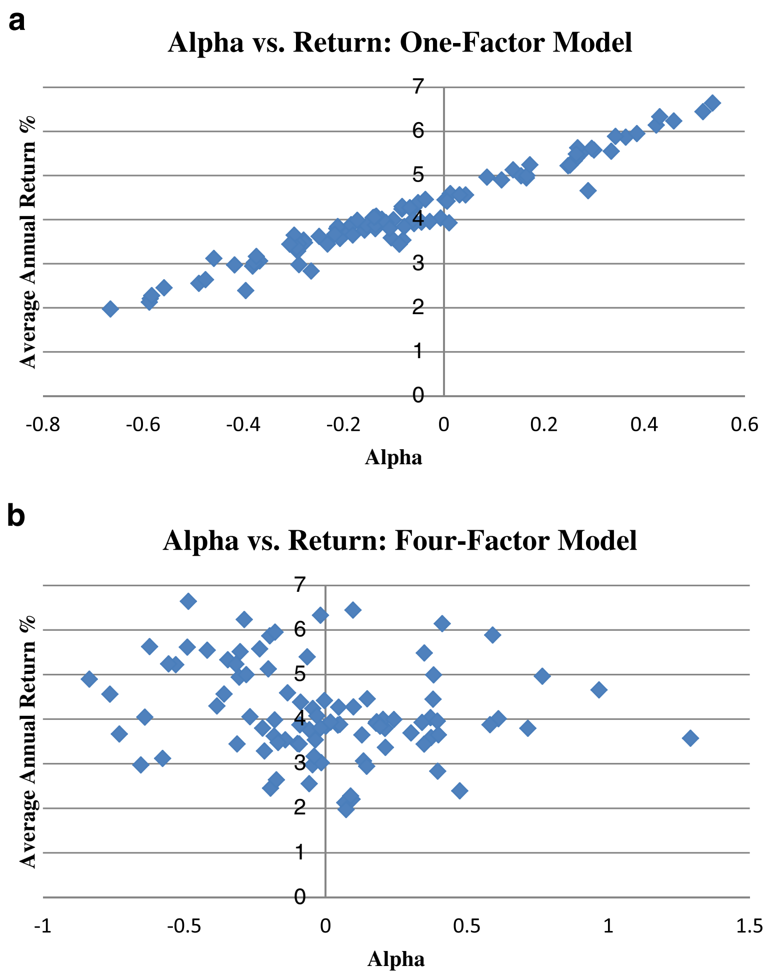

Fig. 5 Home Price Appreciation and Alpha illustrates the relation between the raw average annual return on housing in different MSAs and their risk-adjusted abnormal return—alpha. The alphas presented in panels A and B are estimated using the market model and a four-factor model as per equations (1) and (2) below, respectively. The average annual housing returns and alphas estimations are based on the Q1:1984 to Q2:2009 time period. $R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \varepsilon_t$ (1), $R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \lambda_i(HML_t) + \delta_i(IME_t) + \theta_i(UMD_t) + \varepsilon_t$ (2)

In order to observe the relation between the average risk-adjusted return (alpha), average HPI return, and each of the four risk-factors, the sample is sorted based on values of each estimated risk-factor coefficient. We then report the average return and the risk-adjusted return associated with cities that carry the highest, the lowest, and the middle estimated coefficient values of that specific risk-factor. Additionally, panel B's of Figs. 5 and 6 plot the relation between the estimated alphas and betas for each MSA against the average housing return to the MSAs respectively.

The first row of Table 3 shows risk-adjusted and average returns to areas associated with high, medium, and low betas where the cutoffs are determined based on the top, middle and bottom thirds of the sample. On a risk-adjusted basis, the average

Table 3 Average alpha and returns of factor sensitivities reports the average alphas and returns to portfolios that are sorted based on areas' estimated sensitivities to the four risk-factors in equation (1): Market return (*R_USA*), income growth (*HML*), land elasticity (*IME*), and the momentum (*UMD*). The alphas are computed for the high, medium and low sensitivity portfolios as arithmetic averages of the regression intercepts. The average returns are annualized returns to portfolios that have high, medium or low sensitivity to each of the factors in equation (1): $R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \lambda_i(HML_t) + \delta_i(IME_t) + \theta_i(UMD_t) + \varepsilon_t$

Factor Sensitivity	Average Alpha			Average Return		
	High	Medium	Low	High	Medium	Low
β	0.139	−0.005	−0.154	3.86%	4.15%	4.42%
λ	−0.163	0.110	0.034	4.40%	4.01%	4.02%
δ	−0.102	−0.040	0.122	4.84%	4.24%	3.35%
θ	−0.364	−0.007	0.351	4.55%	4.10%	3.78%

housing return increases with beta. On average, the alpha term for high beta areas is 0.139 compared to−0.154 for low beta areas. Interestingly, under the proposed four-factor model the average housing total return decreases as the betas increase from 3.86% in high beta areas to 4.42% in the low beta areas. This implies that the local risk factors included in the model indirectly capture the risk previously reflected in the market-wide risk factor. In other words, while our analysis confirms that the beta coefficient is positive and significant as per Cannon et al. (2006) as well as Case et al. (2011), the positive relation between beta and return no longer exist when local economical, geographical and psychological risk factors are included in the model.

Figure 6 allows us to take a closer look at the relation between the beta estimates and the total housing return under two different asset pricing specifications. Panel A illustrates the relation between housing betas and returns when the market model is used as a benchmark. Under this specification it is visible that the relation between the betas and raw returns is first positive and then turns negative. That is, in the lower range of observed betas (approximately from 0.5 to 1.5), as the beta increases, the average return increases as well. However, in the higher range of observed betas (approximately from 1.5 to 2.5) the average return decreases with an increasing beta. Panel B illustrates the relation between housing beta and the raw return when betas are estimated with the four-factor model. Here, it appears that the relation between the betas and the raw returns is not positive and even slightly negative across the full range of beta estimates. These results are new to the real estate literature. Our analysis shows that the relation between market-wide risk factor and local housing performance is captured indirectly by city-specific risk factors.

The second through the forth rows in Table 3 report the relation between the other risk-factors and risk-adjusted and raw returns. Areas with high sensitivities to income growth, land elasticity, and momentum earn higher total returns. These raw returns monotonically decrease with decreasing sensitivities to each risk factor. However, the risk-adjusted returns show the opposite result. Areas with high sensitivity to income, land elasticity and momentum earn lower risk-adjusted returns. For example, areas with high exposure to income growth factor earn 4.40% annual return, on average, but the risk-adjusted return to those areas is −0.163% (or −0.652% annually). Noticeably,

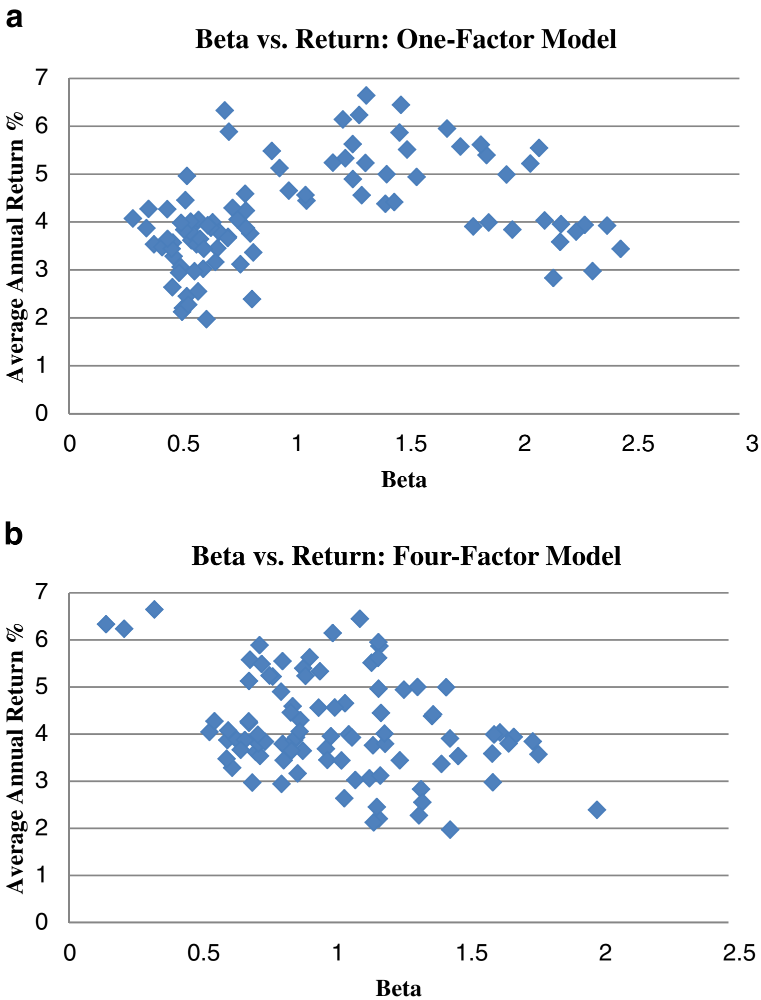

Fig. 6 Home price appreciation and beta illustrates the relation between the estimated betas of each MSA and the raw average annual return to housing. The betas presented in panels A and B are estimated using the market model and the four-factor model of equations (1) and (2) below, respectively. The average annual housing returns and beta coefficients are based on the Q1:1984 to Q2:2009 time period. $R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \varepsilon_t \quad (1), \quad R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \lambda_i(HML_t) + \delta_i(IME_t) + \theta_i(UMD_t) + \varepsilon_t$ (2)

the areas with high sensitivity to momentum, earn the highest total return of 4.55% compared with the areas with medium and low sensitivity to momentum that earn total returns of 4.10% and 3.78% respectively. The negative risk-adjusted return to areas with high momentum coefficient is large with alpha of −0.364 compared with areas with low sensitivity to momentum that are associated with an average alpha of 0.351.

Return Momentum and Factors' Explanatory Power

Next, we document the importance of momentum in real estate returns and the ability of the factor-model to explain systematic variation in housing returns by sorting portfolios of housing markets based on their past performance into performance portfolios. Prior literature suggests that return momentum in residential real estate is economically meaningful. We follow the methodology used by Derwall et al. (2009) in order to test whether market return, income growth, and land supply elasticity factors capture the momentum in housing returns, or whether a housing specific momentum factor should be included in the asset pricing model.

First, we confirm that momentum exists within our 93 MSAs' housing markets during the 25 year sample period. We construct three portfolios that include housing markets based on their performance in the previous year. P1 is the portfolio that invests in housing market indices that were the top third performers during the previous four quarters. P3 is the portfolio that invests in housing market indices that were the bottom third performers during previous four quarters, and P2 invests in housing market indices that in the previous year ranked in the middle third in terms of price appreciation. The three momentum sorted portfolios are held for a period between one to seven quarters before they are rebalanced. A material difference between the performance of P1 and P3 during the holding period indicates that housing momentum exists in the sample.

The results in Table 4 confirm a large and persistent momentum in the sample. The results show that P1 earns up to 8.51% return in annualized terms compared to P3 that earns only up to 1.56% in annualized terms. The difference in performance between P1 and P3 is economically significant and ranges from 6.88% to 7.85% on annual basis. The largest return differential is generated by the portfolio that holds the housing markets for three quarters before rebalancing.

After confirming the existence of the return momentum in the sample, we test the effectiveness of the risk-factor model in Eq. 1 in the momentum sorted portfolios P1, P2 and P3 similar to Derwall et al. (2009). Each factor's ability to explain the portfolios return is tested individually. In addition, we test the three-factor model's, which excludes the momentum factor, and the full four-factor model's ability to explain the systematic variation in P1, P2, and P3. An insignificant abnormal return difference between P1 and P3 suggests that the model is reasonably well specified and captures the momentum effect as well as other systematic drivers of housing returns.

Table 5 reports the regression results of different model specifications on momentum sorted housing portfolios. As in Table 4, P1 is invested in the housing indices of cities that rank in the top third in terms of housing price appreciation over the previous year, P2 and P3 are invested in housing indices of cities that rank in the middle and bottom thirds in terms of housing price appreciation over the previous year, respectively. Panel A reports the results of the market model. Panel B reports the results of the three-factor model that includes the broad-market return, income growth, and land elasticity risk-factors. Panel C and D report the results of the two- and four-factors models that both include the momentum risk-factor.

The results presented in panel A show that the model which includes only the broad market return as a risk-factor is not sufficient in explaining returns of momentum based portfolios. The market model does especially poor job explaining the returns of the past winners' portfolio, where the alpha term is positive and large in magnitude and of the past losers' portfolio. So, in both P1 and P3 the alpha terms are positive and negative respectively and economically as well as statistically significant. The quarterly abnormal return differential between P1 and P3 is 1.9%, or 7.6% in annual terms. This indicates that the market model does not capture the momentum in housing returns. The

Table 4 Momentum in real estate returns shows the magnitude and persistence of return momentum in the sample of 93 cities' housing markets. The returns are computed based on quarterly data from the FHFA. The table shows annualized returns to portfolios of housing indices that are constructed based on the cities' past returns during the last four quarters. The portfolios are held between one and seven quarters before rebalancing. P1 invests in housing market indices that were the top third performers during the previous four quarters, P3 invests in housing market indices that were the bottom third performers and P2 invests in housing market indices that in the previous year ranked in the middle third in terms of price appreciation

	1Q	2Q	3Q	4Q	5Q	6Q	7Q
P1 (TOP)	8.21%	8.40%	8.49%	8.51%	8.50%	8.48%	8.44%
P2	3.74%	3.91%	4.02%	4.12%	4.25%	4.38%	4.51%
P3(BOTTOM)	0.56%	0.57%	0.64%	0.82%	1.06%	1.31%	1.56%
TOP-BOTTOM	7.64%	7.82%	7.85%	7.69%	7.45%	7.17%	6.88%

average beta coefficient is the highest for the winners' portfolio (beta=1.254) and the lowest for P2 (beta=0.825). The explanatory power of the market model is significantly higher for P1 and P2 compared to the past losers' portfolio.

Panel B reveals that the three-factor model reduces the difference between P1 and P2's alphas compared with the market model results presented panel A. However, the alpha differential between P1 and P3 is still large—almost 7% annually. The alpha associated with P1 is positive and significant and the alpha associated with P3 is negative and significant. Unlike the results presented in Table 2, the income growth and land elasticity risk-factors are significant in the top and bottom portfolios. However, the adjusted R^2 increases by less than 1% compared with panel A. The small increase in adjusted R^2 indicates that while statistically significant, the income and land supply factors do not add much explanatory power to the model.

In panel C, we show the result from the two-factor model regression that includes the market and momentum risk-factors. It appears that while the alpha for all three portfolios is statistically significant, it is materially smaller in magnitude compared with than the alphas from panels A and B. Moreover, the difference between the alpha for P1 and P3 is now only 0.075% (or 0.3% annually), which no longer carries economic significance. In panel D, where all the four risk-factors are included in the model, the alpha associated with P1, P2 and P3 declines by about 0.25% annually compared with the two factor model presented in panel C. The differential between P1 and P3 also slightly reduces to a level of 0.28% in annual terms, and the alpha of P3 turns statistically insignificant. The income growth factor loses its significance with the inclusion of the momentum factor, but land elasticity remains positive and significant in P1 and negative and significant in P3. The explanatory power of the two-factor (and four-factor) models is also noteworthy compared with the models that exclude the momentum risk-factor. In P1, the explanatory power increases from 42.7% to 48.5% (49.1%) when the momentum factor is included. In P3, the explanatory power of the model increases from under 30% to over 40%, while in P2 the explanatory power increases only a little with the inclusion of the momentum factor.

Supply Land Elasticity and Factors' Explanatory Power

As a final robustness test, we examine the ability of the proposed four factor model to explain systematic changes in housing prices in housing portfolios that are

Table 5 Momentum sorted real estate portfolios and factor-models' performance reports the regression results of different model specifications on momentum sorted housing portfolios. Portfolio 1 (P1) is invested in the housing indices of cities that ranked in the top third in terms of housing price appreciation over the previous year. Similarly, portfolio 2 (P2) and portfolio 3 (P3) are invested in housing indices of cities that ranked in the middle and bottom thirds in terms of housing price appreciation over the previous year, respectively. Panels A, B, C and D report the results of each model as per equation (1), (2), (3) and (4) below, respectively. $R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \varepsilon_t$ (1), $R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \lambda_i(HML_t) + \delta_i(IME_t) + \varepsilon_t$ (2), $R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \theta_i(UMD_t) + \varepsilon_t$ (3), $R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \lambda_i(HML_t) + \delta_i(IME_t) + \theta_i(UMD_t) + \varepsilon_t$ (4)

	Alpha	R_USA	Adjusted R^2			
Panel A: One-Factor Model						
P1 (TOP)	0.943 (32.46)	1.254 (47.05)	41.56%			
P2	−0.181 (−9.85)	0.825 (48.77)	42.95%			
P3(BOTTOM)	−0.962 (−30.32)	1.052 (36.05)	29.12%			
TOP-BOTTOM	1.905					
Panel B: Three-Factor Model						
	Alpha	R_USA	HML	IME	Adjusted R^2	
P1 (TOP)	0.793 (22.81)	1.074 (29.50)	0.116 (4.09)	0.211 (7.30)	42.71%	
P2	−0.113 (−5.11)	0.949 (41.33)	−0.002 (−0.13)	−0.143 (−7.85)	43.99%	
P3(BOTTOM)	−0.931 (−24.29)	0.963 (24.25)	−0.158 (−5.11)	0.096 (3.04)	29.94%	
TOP-BOTTOM	1.724					
Panel C: Two-Factor Model						
	Alpha	R_USA	UMD	Adjusted R^2		
P1 (TOP)	0.179 (3.86)	1.180 (46.66)	0.389 (20.41)	48.45%		
P2	−0.242 (−7.79)	0.819 (47.93)	0.031 (2.43)	43.02%		
P3(BOTTOM)	0.104 (2.16)	1.158 (43.67)	−0.544 (−27.37)	42.69%		
TOP-BOTTOM	0.075					
Panel D: Four-Factor Model						
	Alpha	R_USA	HML	IME	UMD	Adjusted R^2
P1 (TOP)	0.113 (2.36)	1.032 (30.00)	0.002 (0.07)	0.172 (6.28)	0.383 (19.72)	49.07%
P2	−0.181 (−5.66)	0.944 (41.08)	−0.013 (−0.73)	−0.147 (−8.04)	0.038 (2.94)	44.13%
P3(BOTTOM)	0.044 (0.89)	1.030 (28.72)	0.000 (0.01)	0.150 (5.27)	−0.549 (−27.13)	43.16%
TOP-BOTTOM	0.069					

constructed based on areas' land supply elasticities. Prior real estate literature documents that cities with different amounts of available developable land exhibit varying degrees of volatility and ability to absorb housing demand shocks. We apply different specifications of the model to three housing portfolios constructed based on the land supply elasticity of the cities included in the portfolio.

Table 6 presents the results of the different regression specifications in land supply elasticity sorted portfolios. P1 is invested in indices of the top third cities in terms of land supply elasticity. These are cities where relatively plentiful developable land is available. P2 and P3 invest in cities associated with the middle and bottom thirds in terms of land supply elasticity, respectively. As in Table 5, panel A reports the results of the market model. Panel B reports the results of the three-factor model that includes the broad-market return, income growth, and land elasticity risk-factors. Panels C and D report the results of the two- and four-factors models that include the momentum risk-factor. Not surprisingly, the three- and four-factor models, which include the land supply elasticity risk factor yield the highest explanatory power, lowest alphas, and the smallest difference in alphas between P1 and P3. Particularly, the alphas of the the four-factor model are all statistically indistinguishable from zero and the difference between the alpha of the most elastic portfolio and the most inelastic portfolio is only 0.006%. As a comparison, the single-factor model yields alphas that are statistically different from zero in each of the three portfolios, and the difference in alphas between the least and most elastic portfolio is much higher (0.443%).

Overall, the results presented in Table 6 serve as additional evidence that the four-factor model's ability to explain systematic housing price changes is superior to the market model and that it is robust to different portions of U.S. cities with varying geographic characteristics.

Conclusion

The real estate literature has yet to adopt a widely accepted benchmark risk model that explains the systematic changes in the cross-section of housing returns. This paper proposes a model that explains the cross-sectional systematic variation in housing returns. Motivated by theory and evidence from the real estate and finance literatures, the model builds on a CAPM style market model of housing prices by adding other systematic risk-factors in addition to the market-wide return.

The proposed model explains the systematic changes in housing prices in over 90 large U.S. cities during a period of 25 years. The four factor model is robust to segmentations of the data based on momentum and land supply elasticity. Perhaps the most novel finding of the paper is the idea that the local risk factors indirectly capture the risk reward relation previously attributed to the market-wide risk factor.

The recent collapse of the housing market emphasizes the importance of understanding how different risk-factors relate to home price changes on a larger scale. While most housing markets are not easily tradable, the housing price model presented in this paper can provide important insight on the embedded risk in residential real estate to banks and other mortgage lenders, builders, real estate investors, and homeowners. Understanding the systematic risk in housing prices is especially

Table 6 Land supply elasticity sorted real estate portfolios and factor-models' performance reports the regression results of different model specifications in land supply elasticity sorted housing portfolios. Portfolio 1 (P1) is invested in the housing indices of cities that ranked in the top third in terms of land supply elasticity. Portfolio 2 (P2) and portfolio 3 (P3) are invested in housing indices of cities that ranked in the middle and bottom thirds in terms of land supply elasticity, respectively. Panels A, B, C and D report the results of the each model as per equation (1), (2), (3) and (4) below, respectively. $R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \varepsilon_t$ (1), $R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \lambda_i(HML_t) + \delta_i(IME_t) + \varepsilon_t$ (2), $R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \theta_i(UMD_t) + \varepsilon_t$ (3), $R\_MSA_{i,t} - RF_t = \alpha_i + \beta_i(R\_USA_t - RF_t) + \lambda_i(HML_t) + \delta_i(IME_t) + \theta_i(UMD_t) + \varepsilon_t$ (4)

	Alpha	R_USA	Adjusted R^2			
Panel A: One-Factor Model						
P1 (Elastic)	−0.291 (−8.86)	0.559 (21.16)	35.26%			
P2	−0.073 (−1.99)	1.155 (9.85)	42.15%			
P3(Inelastic)	0.152 (3.64)	1.415 (13.73)	41.89%			
Elastic-Inelastic	−0.443					
Panel B: Three-Factor Model						
	Alpha	R_USA	HML	IME	Adjusted R^2	
P1 (Elastic)	−0.053 (−1.72)	1.000 (15.81)	−0.057 (−1.42)	−0.499 (−7.22)	46.22%	
P2	−0.155 (−3.47)	1.023 (20.04)	0.022 (0.40)	0.153 (1.38)	48.96%	
P3(Inelastic)	−0.046 (−1.14)	1.011 (13.79)	−0.043 (−0.71)	0.467 (4.42)	49.06%	
TOP-BOTTOM	−0.007					
Panel C: Two-Factor Model						
	Alpha	R_USA	UMD	Adjusted R^2		
P1 (Elastic)	−0.172 (−3.24)	0.570 (22.10)	−0.060 (−2.24)	37.57%		
P2	0.021 (0.24)	1.164 (9.56)	−0.048 (−1.02)	42.90%		
P3(Inelastic)	0.199 (3.49)	1.420 (13.57)	−0.024 (−0.70)	42.03%		
Elastic-Inelastic	−0.371					
Panel D: Four-Factor Model						
	Alpha	R_USA	HML	IME	UMD	Adjusted R^2
P1 (Elastic)	0.012 (0.20)	1.000 (15.88)	−0.046 (−1.09)	−0.492 (−7.26)	−0.036 (−1.42)	47.36%
P2	−0.050 (−0.60)	1.031 (19.15)	0.039 (0.80)	0.159 (1.41)	−0.059 (−1.31)	49.12%
P3(Inelastic)	0.018 (0.30)	1.015 (13.52)	−0.033 (−0.54)	0.471 (4.46)	−0.036 (−1.04)	49.21%
Elastic-Inelastic	0.006					

important to financial institutions that face a contagion risk from the property sector (Pais and Stork 2011). Moreover, the model can be applied by investors and traders of futures contracts on housing markets via the Chicago Board of Exchange (CBOE).

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