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House Price Dynamics and Excess Risk

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We examine the relation between risk and returns in the U.S. residential housing market. We find that the risk of house price changes and the magnitude relative to the risk of income changes vary with economic conditions. We measure the excess risk of house price changes by adjusting for the risk of income changes and economic variables associated with the real estate and financial sectors of the economy, and find a significant and positive relation between house price changes and excess risk. We also find that excess risk has significantly adverse effects on the short-run momentum and long-run reversal of house price changes across metro areas, thus implying that excess risk induces price rigidity and helps to explain for the serial correlations in price changes in the U.S. single-family housing market.

Keywords

Cross-Sectional Dispersion, Idiosyncratic Risk, Serial Correlations, House Price Movements

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1. Introduction

Numerous studies on asset markets have documented the importance of the relation between idiosyncratic risk in an asset market and returns on the market. Constantinides and Duffie (1996) show that asset pricing models with heterogeneous consumers and idiosyncratic risks can help to explain for equity premium if consumers cannot smooth over or self-insure against idiosyncratic risks. A number of economists have investigated whether uninsured idiosyncratic risk accounts for equity premium by using idiosyncratic income (Heaton and Lucas, 1996) or cross-sectional consumption growth (Cogley, 2002). Goyal and Santa-Clara (2003) find a significantly positive relation between average stock variance (largely idiosyncratic) and the return on the market. Ang et al. (2006, 2009) find that stocks with high idiosyncratic volatility have abysmally low average returns in the U.S. and international markets. In the real estate literature, Plazzi et al. (2008) find a statistically reliable positive relation between commercial real estate returns and their cross-sectional dispersion, thus suggesting that idiosyncratic fluctuations are priced into the commercial real estate market.

Surprisingly, little is known about the relation between idiosyncratic risk and returns in the U.S. residential housing market. However, it is imperative to understand the relation for the following three reasons. First, housing investment represents the largest asset in the overall portfolio of most households, so the risk of a house price change is unlikely to be diversified away in their portfolio. The Survey of Consumer Finances show that about two-thirds of U.S. households own homes and primary residence accounts for almost one-third of household assets but about 60% of the total assets of median homeowners in 2010. Second, compared with other financial assets such as bonds and stocks, housing investment is relatively illiquid because housing is not only an investment vehicle for the accumulation of home equity but also a durable consumption good for the owner to derive utility. The illiquidity of housing investment makes it least likely that a homeowner can circumvent the risk of house price fluctuations by trading his/her principal residence. Third, borrowing constraints and short sale restrictions in the securities and especially housing markets make it difficult for households to completely smooth over or self-insure against risks in the housing market through borrowing, lending or maintaining buffer stocks of securities.

The focus of this research are single-family housing markets in metro areas across the U.S. Many authors find that change in income is a highly significant determinant of house price change, and change in income alone explains most house price increases (Case and Shiller 2003; Capozza et al., 2004). In this article, we use cross-sectional dispersions (standard deviations) to measure the risk of price change in single-family homes and the risk of income change in metro areas at each point of time. To adjust for the risk of income change, we focus on the ratio of the risk of price change to risk of income change, dubbed as the risk ratio.

Unlike the existing literature on the housing price-income relation which is mostly focused on their first moments, our study explores the relation from their second moments. The second moment in measuring aggregate risk has been found important in the literature on the U.S. stock market. Behavioral studies including Daniel et al. (2001), Scheinkman and Xiong (2003) and Hong et al. (2006) suggest that in addition to the first moments (mean values) of fundamentals-price ratios at the firm-level, the second moments (standard deviation) of logarithmic fundamentals to price ratios in the cross section, or, dispersion, also capture information on price-fundamental relationships. The second moments are an indicator of investor overreaction and market mispricing; therefore, they should negatively forecast aggregate stock returns (which implies a positive relation between cross-sectional price dispersion to fundamental ratio and the aggregate return). Unlike these behavioral studies, Jiang (2013) predicts a negative relation between price dispersion to fundamental ratio and stock return by using a rational framework. For the housing market, we find similar patterns as in Jiang (2013); that is, the excess risk of housing price change relative to change in income may negatively affect housing market returns.

Note that the risk ratio (also termed as excess risk in our study) can measure one unique national risk in the housing market: if the cross-sectional diversification in the rate of changes in house price overly exceeds that in the rate of changes in household income, this indicates a potential aggregate risk as such that investors need to be cautious in housing investment. This might provide housing market investors with a feasible trading rule given that the cross-section dispersion of housing return and household income are not difficult to calculate or sense. We believe that this can be an important complement to the finding in the existing literature that the time-series variation of housing return in excess of change in income may negatively affect housing returns (which describes excess risk in a single market), and thus can potentially capture the "macro risks".

In this study, our first goal is to study the times series properties of the risks of price and income changes, and the risk ratio. To accomplish this, we employ time series regressions in which the risk ratio is related to macroeconomic variables, which capture risks unrelated to those associated with change in income in metro areas. The variables include, for example, unemployment rate, housing market distress (the mortgage delinquency rate) and financial market conditions. We find that the risk ratio is significantly related to shocks from both the real and the financial sectors of the national economy. More specifically, the risk ratio increases in adverse real economic conditions or tightening financial conditions. In contrast, the risk of a house price change is only related to financial conditions but risk of income change is insignificantly related to any of the macroeconomic variables.

Given the preceding results, we measure the idiosyncratic risk of a house price change in the single-family home market by using a component of the risk ratio, dubbed excess risk, which is unrelated to the risks in the real and the financial sectors of the national economy. We then investigate the relation between house price change and excess risk. We find the relation to be statistically significant and positive, thus implying that excess risk is priced in the single-family housing market, similar to that in the commercial real estate market (Plazzi et al., 2008). However, we find the relation to be positive only after we control for not only serial correlations in the short-run, but also those in the long- run in house price change.

Like for other financial assets, price changes in residential properties show positive serial correlations (momentum) in the short run but negative serial correlations (reversal) in the long run (Case and Shiller 1988, 1989; Capozza et al., 2004; Titman et al., 2014). Most of these studies examine the properties of serial correlations by using the idiosyncratic characteristics of the housing market in each area. For instance, Titman et al. (2014) find that local population density, regulation intensity and city size affect the magnitude of these serial correlations in house price change.

There are two possible explanations for serial correlations in returns on financial and real estate assets. One explanation is that market participants are rational so expected returns vary with the stage of a business cycle. The other is that market participants tend to underreact in the short run but overreact in the long run. Previous studies that have used local economic variables indicate that serial correlations in house price change vary with local characteristics but to a large extent, does not explain the issues of rationality. Unlike previous studies, we propose a model in which serial correlations can be related to excess risk in the housing market. We find that excess risk has significant adverse effects on short-run momentum and long-run reversal of house price changes across metro areas, even after we control for the effects of local housing market factors. The results suggest that excess risk induces price rigidity in the single-family housing market. In other words, price momentum and reversal are less pronounced once we take into consideration the housing market risk that is not explained by the risk of income changes and other economic fundamentals.

This research is related to several recent articles on house prices. Gathergood (2011) studies unemployment and house price risks, and the transition into home ownership in the United Kingdom. Dröesa and Hassink (2013) measure the magnitude of idiosyncratic risk in house price risk. As far as we know, this article is the first study to explore the time series properties of the risk of house price changes relative to the risk of income changes and how house price dynamics are related to the risks.

The next section presents a simple model to highlight the econometric foundation of our study and provides an introduction on the hypotheses and methodology of our empirical study. The third section is an analysis on the data and empirical results. The last section concludes.

2. Model

We study the cross-sectional dispersion of house price change (rate) relative to that of housing market fundamentals such as income change. Let $r_{j,t}$ denote the rate of house price change and $F_{j,t}$ the income change for a metro area *j* ($j = 1, 2, \cdots, N$) for period *t* ($t = 1, 2, \cdots, T$). The cross-sectional standard deviations (dispersions) of the rate of change in house price and income change are defined by the following, respectively:

$$SD_t(r) = \sqrt{\sum_{j=1}^{N}[r_{j,t} - \overline{r}_t]^2 / (N-1)} \tag{1}$$

$$SD_t(F) = \sqrt{\sum_{j=1}^{N}[F_{j,t} - \overline{F}_t]^2 / (N-1)} \tag{2}$$

where $\overline{r}_t$ is the cross-sectional average of the rate of change in house price and $\overline{F}_t$ is the cross-sectional average of income change for period *t*. As reported by Case and Shiller (1988, 1989), the systematic risks of residential properties are typically small and statistically insignificant. As a result, the cross-sectional dispersion, $SD_t(r)$, represents the cross-sectional estimate of the housing market-specific (unsystematic) risk in the metro-areas at each point in time.[1] Similarly, $SD_t(F)$ represents the cross-sectional estimate of the risk of income changes in the metro-areas at each point in time. Under the assumption that the rate of change in house price in each metro area is mostly determined by the income change in the metro area, the cross-sectional dispersion of the former should vary with that of the latter.

Compared to Malpezzi (1999), who focuses on the ratio of house price to income, we focus on the ratio of the cross-sectional standard deviation of the change in house price relative to that of change in income:[2]

$$RR_t \equiv \frac{SD_t(r)}{SD_t(F)} \tag{3}$$

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[1] Garcia et al. (2014) show that the cross-sectional variance of stock returns is a consistent and asymptotically efficient estimator for aggregate idiosyncratic volatility.

[2] Some authors assume that real house prices are cointegrated with the levels of local variables. See for e.g., Capozza et al. (2004), Gao et al. (2009), Oikarinen (2009). However, it remains controversial whether house prices and levels of local variables are stationary (e.g., Gallin, 2006; Mikhed and Zemcik. 2009a, 2009b; Li, 2015). We use changes in prices and income to obtain stationary variables.

While the price-to-income ratio indicates the housing market conditions at the price level, the risk ratio, RR_t, is an indicator of the conditions at the risk level. Like the price-to-income ratio, the risk ratio is not necessarily constant. Our first regression type is a time-series regression that explores the possible forces that drive temporal changes in the risk ratio. In the regression, the dependent variable is the risk ratio, and the explanatory variables are a set of macroeconomic indicators. The regression takes the following form

$$RR_t = a + \sum_{k=1}^{K} b_k Z_{k,t} + e_t \tag{4}$$

where a is an intercept, b_k is the slope coefficient of the k-th macroeconomic variable, Z_k $(k = 1, \ldots, K)$, and e_t is an error term (residual). If the risk ratio is constant, each slope coefficient b_k= 0. Otherwise, the risk ratio is related to one or more macroeconomic variables. The macroeconomic variables in Equation (4) capture the variation unrelated to the risk associated with change in income in the metro areas. The variables include, for example, the unemployment rate, housing distress (mortgage delinquency rate), and financial market conditions.[3]

The regression in Equation (4) generates a residual, $\hat{e}_t$, dubbed as "excess risk", which captures the component of the risk ratio that cannot be explained by the economic fundamentals in the housing market and general economy. Our second regression type is a panel regression, which we use to study the relation between change in house price and lagged risk ratio, which represents an aggregate idiosyncratic risk known as of the beginning of each period. The explanatory variables also include lagged rate(s) of the price change to control for the well-known serial correlations of the price change.

The regressions take the following form:

$$r_{j,t} = \alpha + \beta \hat{e}_{t-1} + \gamma_1 r_{j,t-1} + \varphi F_{j,t} + \varepsilon_{j,t} \tag{5}$$

$$r_{j,t} = \alpha + \beta \hat{e}_{t-1} + \gamma_1 r_{j,t-1} + \gamma_2 r_{j,t-2} + \gamma_3 r_{j,t-3} + \varphi F_{j,t} + \varepsilon_{j,t} \tag{6}$$

where the dependent variable $r_{j,t}$ is the annual rate of change in house price for metropolitan statistical area (MSA) j and year t; $\hat{e}_{t-1}$ is the one-year lagged excess risk; $r_{j,t-k}$ $(k = 1, 2, 3)$ is the k-year lagged rate of change in house price; $F_{j,t}$ is the local income change; and $\varepsilon_{j,t}$ is an error term. The intercept α and slope coefficients including β, γ_k and φ are constant. The coefficient β measures the effect of lagged excess risk on the rate of change in house price. Under the hypothesis that housing-market participants are indifferent to excess risk in the housing market, β should be indistinguishable from zero.

[3] Note that our later analysis shows that the risk of income change in the denominator of Equation (3) is weakly correlated with these macroeconomic variables.

Otherwise, a positive (negative) β indicates that the change in house price is positively (negatively) related to the lagged excess risk, which implies that housing-market participants require a premium (discount) for bearing the housing market risks that are not explained by fundamental economic variables. The coefficient γ_k is a *k*-th-order autoregressive correlation. A positive γ_1 is indicative of house price momentum in the short-run while a negative γ_3 is indicative of house price momentum and reversion in the long-run. The coefficient φ is the price elasticity with respect to income. MSA and year dummies are included in the regression to control for fixed effects.

In order to study the effect of excess risk on house price momentum and reversion, we consider the following alternative specifications

$$r_{j,t} = \alpha + \beta \hat{e}_{t-1} + \gamma_1 r_{j,t-1} + \lambda_1 \hat{e}_{t-1} r_{j,t-1} + \varphi F_{j,t} + \varepsilon_{j,t} \tag{7}$$

$$\begin{aligned} r_{j,t} &= \alpha + \beta \hat{e}_{t-1} + \gamma_1 r_{j,t-1} + \gamma_2 r_{j,t-2} + \gamma_3 r_{j,t-3} + \lambda_1 \hat{e}_{t-1} r_{j,t-1} \\ &+ \lambda_2 \hat{e}_{t-1} r_{j,t-2} + \lambda_3 \hat{e}_{t-1} r_{j,t-3} + \varphi F_{j,t} + \varepsilon_{j,t} \end{aligned} \tag{8}$$

where λ_k is a constant coefficient of the interaction term, $\hat{e}_{t-1} r_{j,t-k}$. Since $\gamma_k r_{j,t-k} + \lambda_k \hat{e}_{t-1} r_{j,t-k} = (\gamma_k + \lambda_k \hat{e}_{t-1}) r_{j,t-k}$, the combined term, $\gamma_k + \lambda_k \hat{e}_{t-1}$, represents a time-varying coefficient of $r_{j,t-k}$. If $\gamma_1 > 0$ but $\lambda_1 < 0$, the lagged excess risk has an adverse effect on the house price momentum. Similarly, if $\gamma_3 < 0$ but $\lambda_3 > 0$, the lagged excess risk has an adverse effect on house price reversion. Any adverse effect on house price momentum or reversion is indicative of price rigidity, which means that house price momentum or reversion would be less pronounced once we take into consideration the housing market risk that is not explained by the risks of income change and other economic fundamentals.

3. Empirical Results

3.1 Data

We calculate real annual house prices by using the house price index provided by the Federal Housing Finance Agency (FHFA), deflated by the MSA Consumer Price Index (CPI) for All Urban Consumers provided by the U.S. Bureau of Labor Statistics.[4] We measure the MSA income level with the MSA

[4] We refine the area to the MSA level by following the cross sectional analyses in most studies on the U.S. housing markets (such as Capozza et al. 2004; Plazzi et al., 2008; Titman et al., 2014). Like most of these studies, we use the quarterly housing price index

median household income (from the U.S. Census Bureau) deflated by the MSA CPI index. The availability of the FHFA house price data limits our empirical study to a sample of 121 MSAs that cover all 50 states in the U.S. over the sample period of 1979 to 2011.

Recent research (e.g., Igan et al., 2011) find that house price cycles are related to credit and real activity. The first macroeconomic variable that we use is the unemployment rate from the Bureau of Labor Statistics. The unemployment rate proxies for the risk of aggregate real activity in the U.S. The other macroeconomic variable that we use is the Chicago Fed's National Financial Condition Index (NFCI). This index provides comprehensive updates on U.S. financial conditions in the money, debt and equity markets, and conventional and "shadow" banking systems. Positive (negative) values of the index indicate financial conditions that are tight (loose). Increasing risk, tighter credit conditions and declining leverage are consistent with tightening financial conditions.

The alternative macroeconomic variables include the (overall) consumer, housing and employment distress indexes, all from the Federal Reserve Economic Data (FRED) database of the St. Louis Fed. The consumer distress index measures the 5 categories of personal finance that reflect or lead to a secure and stable financial life — employment, housing, credit, household budget and net worth. Each category is weighted equally. Consumer distress is measured on a 100-point scale and a score under 70 indicates financial distress. A lower score equals more distress and a weaker financial position. The housing and employment stress indexes are for sub-categories of the consumer distress index. We exclude 3 other sub-category indexes (credit distress, household budget distress and net worth) in our final analysis as they are insignificantly correlated at the 5 percent level with the cross-sectional deviations or the risk ratio. The key measures of the housing distress category are mortgage and rental delinquencies and housing as percent of budget. The employment distress category measures the impact of unemployment and underemployment on financial health.

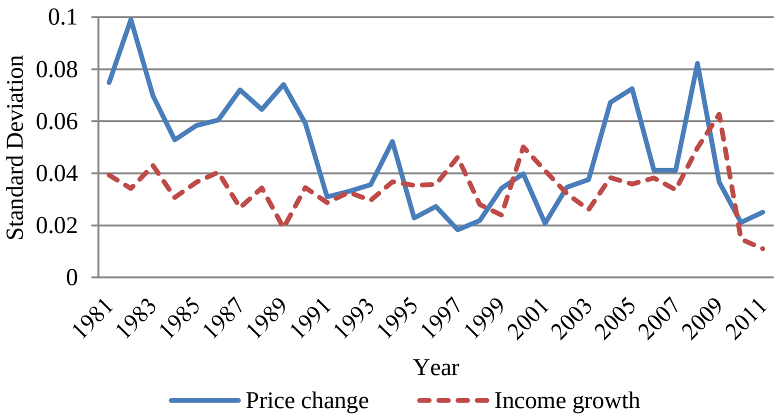
3.2 Summary Statistics

Figure 1 illustrates the cross-sectional dispersions (standard deviations) of changes in house price and income. As shown in Figure 1, house price change dispersion shows great variability. The dispersion is bigger during the 1980s and 2000s than the 1990s. The reduced dispersion in the 1990s might be associated with the growth of real estate market securitization, which could have dampened the importance of area-specific idiosyncratic risks to the housing market. The rise in the dispersion in the 2000s is likely to be associated

of the FHFA, which is popular in real estate studies due to its broad coverage of MSAs and long time periods.

with the events that led to the housing market bubble (e.g., increases in real estate loans, loosening of credit conditions) and the 2008-2009 global financial crisis. The pattern here is analogous to the finding in Plazzi et al. (2008) that in the commercial property markets, periods of economic downturns are followed by higher cross-sectional dispersions of changes in price and net operating income.

Figure 1 Cross-Sectional Dispersion of Changes in Housing Price and Income

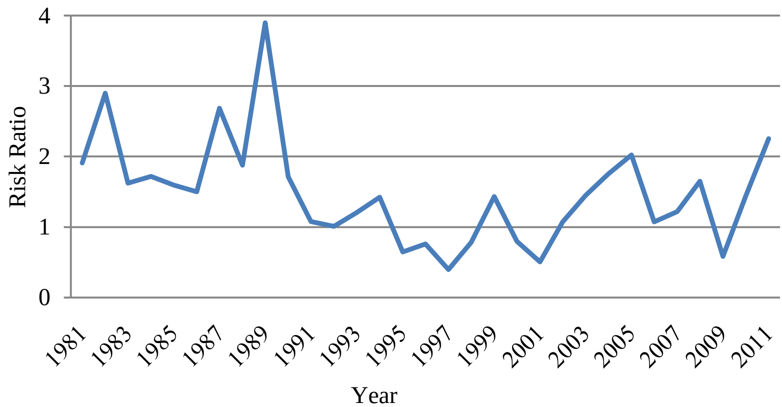


Note: The sample includes 121 MSAs over period of 1979-2011

As shown in Figure 1, the cross-sectional dispersion in income change is relatively more stable than the house price change dispersion. This implies that a large amount of the variation in the risk of price change is unexplained by the risks of income change. This is analogous to the fact that most of the time series variability of the price-to-dividend ratio or the price-to-earnings ratio is attributed to the variability of prices rather than to that of dividends or earnings in the stock market (e.g., Campbell and Shiller, 1988; Cochrane, 1992). The income change dispersion reaches a historical high of 6.27% in 2009, approximately one year after the surge in house price dispersion. The disparity in house price change dispersion and the income change dispersion is illustrated by the cross-sectional risk ratio in Figure 2, as the ratio of the house price change dispersion to the income change dispersion. The risk ratio peaks around 1990 and bottoms out around 1997. The large swings in the risk ratio appear to be associated more with the variation of the house price change dispersion than with that of the income change dispersion.

In Table 1, we present the summary statistics for the macroeconomic variables, cross-sectional standard deviations and risk ratio. The unemployment rate has a mean of 6.21 percent and a median of 5.75 percent. The consumer distress index has a mean of 79.50 and a median of 80.37. The housing and employment indexes have higher means and medians than the overall consumer distress index. Recall that a distress index of less than 70 indicates financial distress. The financial condition index has a mean of -0.31 and a median of -0.43. The negative values here indicate normal or loose financial conditions during the sample period. Each variable shows great variability, as shown by the range of the variable and its standard deviation. In particular, the financial condition index varies from -1.02 (loosest) to 2.60 (tightest), with a standard deviation (0.53) greater than the size (absolute value) of its mean (0.31). It is of interest to note that, if the mean of a variable is greater (less) than its median, the distribution of the variable exhibits positive (negative) skewness. As a result, there is some evidence of skewness in most variables.

Figure 2 Risk Ratio



Note: Risk ratio is cross-sectional standard deviation of rate of change in house price divided by that of change in income. The sample includes 121 MSAs over period of 1979-2011.

The mean (or median) of the cross-sectional standard deviation of the rate of change in house price is 4.53 (or 4.19) percent. The mean (or median) of the cross-sectional standard deviation of change in income is 4.22 (4.10) percent. Finally, the mean (or median) of the risk ratio is 1.19 (or 1.04). The fact that the mean or median of the risk ratio exceeds one is consistent with the fact that the cross-sectional dispersion of the rate of change in house price tends to exceed that of change in income. Like the macroeconomic variables, the cross-sectional dispersions and the risk ratio show great variability.

The first-order autocorrelations of all the variables and the χ^2 tests for the joint significance of the first six autocorrelations are reported in the last two columns of Table 1. Among the macroeconomic variables, the financial condition index shows the lowest first-order autocorrelation of 0.29 and its first six autocorrelations are jointly insignificant. The rest of the macroeconomic variables have first-order autocorrelations in the range of 0.72-0.88 and their first six autocorrelations are jointly significant at the 1 percent level.

The first-order autocorrelation of the cross-sectional dispersion of the change in house price is 0.50, which far exceeds that of the change in income (0.07). The first-order autocorrelation (0.76) of the risk ratio is higher than that of each of the cross-sectional standard deviations, and the autocorrelation is closer to those of the macroeconomic variables except for the financial condition index. Finally, the χ^2 tests reveal that the first six autocorrelations of the risk ratio are jointly significant at the 1 percent level, similar to those of most of the macroeconomic variables. However, the autocorrelations of the price change dispersion are jointly significant at the 5 percent level and those of the income change dispersion are jointly insignificant. The results suggest that the risk ratio likely varies with most of the macroeconomic variables more than the cross-sectional dispersion of price change or income change.

Table 1 Summary Statistics

Variable	Mean	Med.	Min.	Max.	Std.	ρ_1	*p*-value
U.S. (all metro areas):							
Unemployment rate, %	6.21	5.75	3.80	10.40	1.61	0.72	0.002
Consumer distress index	79.50	80.37	64.26	87.22	5.54	0.80	<0.001
Housing distress index	85.88	88.28	57.62	98.86	10.52	0.88	<0.001
Employment distress index	81.29	86.96	49.15	100.00	16.64	0.77	<0.001
Financial condition index	-0.31	-0.43	-1.02	2.60	0.53	0.29	0.538
Cross-sectional std. dev. of house price change, %	4.53	4.19	1.69	8.22	1.79	0.50	0.034
Cross-sectional std. dev. of income change, %	4.22	4.10	1.02	6.70	1.30	0.07	0.409
Risk ratio	1.19	1.04	0.30	3.90	0.62	0.76	<0.001

Note: Risk ratio is cross-sectional standard deviation of rate of house price change divided by that of income change. The sample includes 121 MSAs over period of 1979-2011. ρ_1 is first-order autocorrelation. The *p*-value is associated with testing of hypothesis that first six autocorrelations are jointly zero.

We then analyze the correlations among the macroeconomic variables to select explanatory variables for regression in Equation (4), and test the normality of the variables to ensure that they fit the linear regression form. In Panel A of Table 2, we report the correlations between pairs of macroeconomic variables and between the risk ratio and each macroeconomic variable. First note that there is a sizable negative correlation between the unemployment rate and the consumer distress index (-0.625), which is significant at the 1 percent level. This is because a lower stress index score means more stress. The result here implies that the financial distress of consumers is significantly and directly related to the unemployment rate. Most strikingly, the unemployment rate is more highly correlated with the employment stress index (-0.956) than the housing stress index (-0.564). The consumer stress index is more highly correlated with the housing stress index (0.937) than the employment stress index (0.544). All of the above correlations are significant at the 1 percent level.

Table 2 Correlations and Normality

Panel A Correlations

	Unemployment	Consumer distress	Housing distress	Employ. distress	Financial conditions
Consumer distress index	-0.625***				
Housing distress index	-0.564***	0.937***			
Employment distress index	-0.956***	0.544***	0.467**		
Financial condition index	0.087	-0.370**	-0.427**	-0.212	
Cross-sectional std. dev. of house price change	0.003	0.082	-0.056	-0.101	0.476***
Cross-sectional std. dev. of income change	-0.040	-0.114	-0.145	0.059	0.193
Risk ratio	0.578***	-0.594***	-0.666***	-0.580***	0.462**

Panel B Normality Tests

	Shapiro-Wilk	Kolmogorov-Smirnov	Cramer-von Mises	Anderson-Darling
Unemployment	0.0444**	0.0414**	0.0714*	0.0509*
Consumer distress index	0.0012***	0.0161**	<0.005***	<0.005***
Housing distress index	0.0017***	0.0133**	<0.005***	<0.005***
Financial condition index	<0.0001***	<0.010***	<0.005***	<0.005***
Risk ratio	0.0448**	0.0968*	0.0829*	0.0717*

Note: Panel A reports correlation coefficients among variables. Panel B reports p-values of various normality tests. Risk ratio is cross-sectional standard deviation of rate of change in house price divided by that of change in income. Lower stress index score means more distress. Sample includes 121 MSAs over period of 1979-2011. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

The financial condition index has a significant correlation with the consumer stress index (-0.370) or housing stress index (-0.427). However, the correlation between the financial condition index and unemployment rate is only 0.087 and that between the financial condition index and employment stress index is -

0.212. Both correlations are low and insignificant at the 10 percent level. Since the two correlations are moderate in size and statistically insignificant, the information revealed from the financial condition index, which reflects risks in the financial markets, is likely to be quite different from the information from real economic variables like the unemployment rate.

Interestingly, the risk ratio is positively correlated with the unemployment rate (0.578) or financial condition index (0.462) but negatively correlated with the consumer (-0.594), housing (-0.666) or the employment (-0.580) stress index. Each of the above correlations is significant at the 1 or 5 percent level. The signs of the correlations suggest that the risk ratio increases with tightening in the financial market conditions (credit and leverage), increasing financial stress of consumers, or a higher unemployment rate

It should be noted that, the cross-sectional standard deviation of change in house price is insignificantly correlated with most variables, except for the financial condition index (0.476). The cross-sectional standard deviation of income change is insignificantly correlated with each of the macroeconomic variables. As a result, the significant correlation between the risk ratio and the financial condition index is likely due to the cross-sectional standard deviation of the change in house price (but not change in income). The significant correlations between the risk ratio and each of the other variables (the unemployment rate and the stress indexes), however, are not caused by the cross-sectional standard deviation of the change in price or income.

Based on these correlation analyses, we choose unemployment rate, consumer and housing distress indexes and financial condition index as explanatory variables for the regression in Equation (4). Different sets of these variables will be used in different specifications of the regression to eliminate possible multicollinearity. We then conduct multiple normality tests for these explanatory variables as well as for the dependent variable, the risk ratio, to ensure that both dependent and independent variables follow normal distributions as such that the linear regression does fit their relationships. As reported in Panel B of Table 2, all of these variables pass the normality tests including the Shapiro-Wilk, Kolmogorov-Smirnov, Cramer-von Mises and Anderson-Darling tests, thus confirming that it is appropriate to use the linear regression model, the regression in Equation (4), to characterize the relations between the risk ratio and macroeconomic variables.

3.3 Results from Time-Series Regression of Risk Ratio

We now report the results of the time-series regressions of the excess risk on macroeconomic variables by using Equation (4). To eliminate the multicollinearity problem that results from high correlations, we use three regression models with subsets of explanatory variables, as shown in Table 3. In Model I, we include the unemployment rate and the financial condition index as the explanatory variables, as these two variables are not correlated and indicative of different sources of risks. In Model II, we include the consumer distress index as the only explanatory variable, since this index measures 5 categories of personal finance including employment, housing, credit, and so on and so forth. In Model III, the consumer distress index in Model II is replaced with the housing distress index. We also consider other combinations of the macroeconomic variables including the employment stress index and real estate loans. Since the results are similar to those based on Models I-III, they are not reported.

Table 3 Time-Series Regressions

	Model		
Explanatory variable	I	II	III
Intercept	0.218	6.612***	4.916***
	(0.62)	(4.84)	(6.40)
Unemployment rate	0.212***		
	(3.86)		
Consumer distress index		-0.066***	
		(3.81)	
Housing distress index			-0.042***
			(4.59)
Financial condition index	0.391***		
	(2.96)		
Adj. R-square	0.466	0.329	0.424

Note: The regression takes the following form

$$RR_t = a + \sum_{k=1}^{K} b_k Z_{k,t} + e_t \tag{4}$$

where a is intercept, b_k is slope coefficient of k-th macroeconomic variable, Z_k ($k = 1, \dots, K$), and e_t is an error term. Dependent variable is risk ratio, *RR*. Risk ratio is the cross-sectional standard deviation of rate of change in house price divided by the cross-sectional standard deviation of income change. A lower stress index score means more distress. Three model specifications are developed as robustness tests for each other to alleviate problems with error-in-model and omitted variables. Each specification includes a different set of variables which have no multicollinearity. We find that robust standard errors are similar after adjusting for heteroskedasticity and non-normality. The sample includes 121 MSAs over period of 1979-2011. *t*-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

In Model I, both explanatory variables are significant at the 1 percent level. The coefficients of the unemployment rate and the financial condition index are 0.212 (t = 3.86) and 0.391 (t = 2.96), respectively. The coefficient of the consumer distress and housing stress indexes is -0.042 (t = 4.59) and -0.066 (t = 3.81) in Models II and III, respectively. As a result, each variable used in the three models help to explain for the time variation of the risk ratio. We note that with the two variables in Model I, the intercept is 0.218 (t = 0.62) and statistically insignificant, thus implying that the average risk ratio is unrelated to the intercept but instead, entirely determined by the average unemployment rate and financial condition index. The adjusted R^2 of Models I, II and III is 0.466, 0.329 and 0.424, respectively. Thus, all of the models, especially Model I, capture substantial amounts of the time series variation of the risk ratio. The fact that the adjusted R^2 of Model III is greater than that of Model II is consistent with the result in Table 2, in that the risk ratio is more correlated with the housing stress index (-0.666) than the consumer stress index (-0.594). Hence, housing distress, measured mostly by mortgage and rental delinquencies as well as the housing cost as a percent of the budget, seems to be more important than the other distress categories for explaining the time variation of the risk ratio.

It is worthwhile to note that the sign of the coefficient of each macroeconomic variable here is the same as that of the correlation coefficient between the risk ratio and the variable. The result provides further evidence that the risk ratio is increased in adverse real economic conditions or tightening financial conditions. The fact that two macroeconomic variables in Model I enter the regressions with significant coefficients simultaneously suggests that the time variation of the risk ratio is related to shocks from both the real and the financial sectors of the national economy.

3.4 Results from Panel Regression of Rates of Change in House Price

In Table 4, we report the results of the panel regressions of rates of change in house price in Equations (5)-(8). The excess risk is the residual from the time-series regression of the risk ratio (Model I, II or III) in Table 3. The sample includes 121 MSAs over the period of 1979-2011. The t-statistics in parentheses are based on asymptotic standard errors adjusted for autocorrelations of residuals. In each regression in Equation (5) or (6) here, we focus on the effect of the lagged risk ratio on house price movements.

The results of estimating Equation (5) clearly demonstrate the existence of a positive serial correlation in the short-run in house price change. In each regression, the point estimates of the coefficient γ_1 associated with the 1-year lagged price change are always 0.528 with t-statistics 62.23-73.29, thus implying that the coefficient is significant at the 1 percent level or lower. The results are consistent with those in the literature. In addition, the rate of change in income enters each regression with an estimated coefficient φ of 0.079 with a t-statistic of 12.26, thus implying significantly positive price elasticity with respect to income. The results on the first-order autocorrelation and income elasticity are qualitatively similar to the evidence in the literature (e.g., Abraham and Hendershott, 1996; Malpezzi, 1999)

Table 4 Panel Regressions

		1 lagged price change, Eq. (5)			3 lagged price changes, Eq. (6)		
Variable	Coef.	Model I	Model II	Model III	Model I	Model II	Model III
Intercept	α	0.099***	0.125***	0.085***	-0.080***	-0.074***	-0.075***
		(12.21)	(11.14)	(8.60)	(-18.23)	(-15.41)	(-13.73)
Excess risk (-1)	β	-0.190***	-0.264***	-0.233***	0.087***	0.094***	0.109***
		(-23.92)	(-33.18)	(-29.28)	(8.45)	(9.44)	(10.70)
House price change (-1)	γ_1	0.528***	0.528***	0.528***	0.456***	0.456***	0.456***
		(69.27)	(62.23)	(73.29)	(78.64)	(81.43)	(80.50)
House price change (-2)	γ_2				0.005	0.005	0.005
					(0.82)	(0.83)	(0.83)
House price change (-3)	γ_3				-0.058***	-0.058***	-0.058***
					(-7.21)	(-7.19)	(-7.21)
Income change	φ	0.079***	0.079***	0.079***	0.052***	0.052***	0.052***
		(12.26)	(12.26)	(12.26)	(8.45)	(5.23)	(5.24)
Adj. R^2		0.608	0.608	0.608	0.558	0.558	0.558

Note: Regressions take following forms:

$$r_{j,t} = \alpha + \beta\hat{e}_{t-1} + \gamma_1 r_{j,t-1} + \varphi F_{j,t} + \varepsilon_{j,t} \qquad (5)$$

$$r_{j,t} = \alpha + \beta\hat{e}_{t-1} + \gamma_1 r_{j,t-1} + \gamma_2 r_{j,t-2} + \gamma_3 r_{j,t-3} + \varphi F_{j,t} + \varepsilon_{j,t} \qquad (6)$$

where dependent variable $r_{j,t}$ is annual rate of change in house price for MSA j and year t; $\hat{e}_{t-1}$ is one-year lagged excess risk; $r_{j,t-k}$ is k-year lagged rate of change in house price; $F_{j,t}$ is local change in rate of income; and $\varepsilon_{j,t}$ is error term. Excess risk is residual from time-series regression (Model I, II or III) in Table 3. Sample includes 121 MSAs over period of 1979-2011. t-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

More interestingly, while the estimates of the intercept α are all positive and significant at the 1 percent level, the lagged excess risk shows a negative effect on house price change, with an estimated coefficient β of -0.190 (t = -23.92, -0.264 (t = -33.18), or -0.233 (t = -29.28) in) in Models I, II, or III, respectively. The estimated coefficient of the lagged excess risk is significant at the 1 percent level in each regression. This implies that there is a discount of the price change associated with the lagged excess risk. We also find that the adjusted R^2 of each regression is 0.608, regardless of the model used to obtain the fitted excess risk in the time series regressions of the risk ratio. The similarity of the estimates of the coefficient of the excess risk and the adjusted R^2 s suggest that the results on the relation between excess risk and house price change are robust to the specifications of the time-series regressions of the risk ratio.

A different picture on the estimates of α and β emerges when we include 3 lags of house price change in Equation (6). The estimates of the intercept α all become negative and significant at the 1 percent level but those of β all become positive and significant at the 1 percent level (0.087-0.109). Since the estimates of γ_1 and φ remain positive and qualitatively unchanged, the difference in the estimates of α and β are due to the inclusion of the high-order lags (the 3rd year lag) of house price change.[5] The estimates of γ_2 are 0.005 (t = 0.82-0.83), which are insignificant at the 10 percent level but those of γ_3 are all -0.058 (t = -7.19 or -7.21), which are significant at the 1 percent level. The negative values of the estimated γ_3 are indicative of price reversal in the long-run. The results here, therefore, suggest that the inclusion of house price reversion helps to reveal a positive relation between price change and lagged excess risk, which implies a premium in the price change associated with the risk in the housing market unexplained by the economic variables. In other words, the negative estimates of β in Equation (5), which includes only one lag of the price change, are caused by the well-known omitted-variables problem.

Next, we examine the results of estimating Equations (7)-(8). First, we note that in Table 5, the estimated coefficients of the lagged excess risk, along with those of other explanatory variables, including the lagged price change and change in income, are similar to the estimates reported in Table 4. Hence, the effect of the lagged excess risk on house price change is largely unaffected by the inclusion of the interactions term in Equation (7) or (8). With the lagged excess risk in Model I, the estimated coefficient λ_1 of the interaction of the excess risk with

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[5] We include up to 3-year lagged terms in the regression of the rate of change in house price, following Case and Shiller (1989), Campbell et al. (2009), and Titman et al. (2014), who find that 1-year or 6-month lagged terms positively affect the rate of change in house price , while reversal usually occurs after 6 months until the 3rd year.

the 1-year lagged house price change in Equation (7) is 0.012, which is small and insignificant at the 10 percent level (*t* = 1.49). However, the coefficient is -0.130 (*t* = -16.27) in Model II and -0.143 (*t* = -18.04) in Model III. The estimates of λ_1 in Equation (8) is -0.185 (*t* = -23.48) in Model I, -0.322 (*t* = -40.25) in Model II, and -0.401 (*t* = -50.13) in Model III. The results suggest that the coefficient λ_1 of the interaction term is negative and significant at the 1 percent level. The result here suggests that the lagged excess risk diminishes the short run momentum of house price change. Finally, the estimates of the coefficient λ_3 of the interaction term with the 3-year lagged price change is 0.220 (*t* = 21.49) in Model I, 0.171 (*t* =16.13) in Model II and 0.214 (*t* = 20.05) in Model III. The results of estimating Equation (8), hence, indicate that the estimates of the coefficient are positive and significant at the 1 percent level. Coupled with the negative estimates of the coefficient γ_3, the results suggest the lagged excess risk also diminishes the long run reversal of house price change.

3.5 Other Results

Given the effects of the excess risk on house price change, a question may arise: are the results sensitive to the variables used in both the risk ratio regression and the regression of the rate of change in house price? As we have shown, the results in the panel regressions of rates of change in house price are very similar for the three different sets of economic variables used in the time-series regressions of risk ratio. When we consider other variables, including the employment distress index or the credit distress index, we mostly obtain similar results in the panel regressions of rate of change in house price.

Instead of using income change as a metro-level variable in the panel regressions, we also use the rate of change in the gross metropolitan product at the metro-level. The results are similar. However, if excess risk is replaced with the fitted value of the risk ratio in the risk ratio regression, the signs of the estimates of the coefficient β often become inconsistent with respect to different sets of variables used in the risk ratio regressions. Alternatively, if excess risk is replaced with the risk ratio or the cross-sectional standard deviation of house price change, the estimates of the coefficient β become insignificant. The results suggest that the dynamics of house price change are more related to the component of the housing market risk that is unexplained by economic fundamentals than the total risk or the component of the risk explained by the fundamentals.

Table 5 Panel Regressions with Interaction Terms

Variable	Coef.	1 lagged price change, Eq. (7)			3 lagged price changes, Eq. (8)		
		Model I	Model II	Model III	Model I	Model II	Model III
Intercept	α	0.100	0.120*	0.081	-0.081***	-0.079***	-0.081***
		(1.40)	(1.94)	(1.24)	(-13.50)	(-11.79)	(-10.25)
Excess risk (-1)	β	-0.191***	-0.259***	-0.230***	0.077***	0.089***	0.104***
		(-29.39)	(-40.57)	(-35.99)	(8.56)	(14.77)	(18.83)
House price change (-1)	γ_1	0.529***	0.535***	0.530***	0.471***	0.512***	0.512***
		(60.11)	(45.54)	(52.37)	(6.12)	(8.39)	(7.64)
House price change (-2)	γ_2				0.008	0.018	0.012
					(0.17)	(0.32)	(0.19)
House price change (-3)	γ_3				-0.098***	-0.141***	-0.146***
					(2.61)	(-25.18)	(-4.56)
Excess risk (-1)							
× price change (-1)	λ_1	0.012	-0.130***	-0.143***	-0.185***	-0.322***	-0.401***
		(1.49)	(-16.27)	(-18.04)	(-23.48)	(-40.25)	(-50.13)
× price change (-2)	λ_2				-0.090***	-0.012***	0.015
					(-9.03)	(11.80)	(1.49)
× price change (-3)	λ_3				0.220***	0.171***	0.214***
					(21.49)	(16.13)	(20.05)
Income change	φ	0.079***	0.079***	0.080***	0.042***	0.042***	0.040***
		(8.68)	(8.53)	(10.38)	(7.40)	(7.50)	(7.18)
Adj. R^2		0.608	0.611	0.628	0.572	0.580	0.584

(Continued…)

(Table 5 Continued)

Note: Regressions take following forms:

$$r_{j,t} = \alpha + \beta \hat{e}_{t-1} + \gamma_1 r_{j,t-1} + \lambda_1 \hat{e}_{t-1} r_{j,t-1} + \varphi F_{j,t} + \varepsilon_{j,t} \tag{7}$$

$$r_{j,t} = \alpha + \beta \hat{e}_{t-1} + \gamma_1 r_{j,t-1} + \gamma_2 r_{j,t-2} + \gamma_3 r_{j,t-3} + \lambda_1 \hat{e}_{t-1} r_{j,t-1} + \lambda_2 \hat{e}_{t-1} r_{j,t-2} + \lambda_3 \hat{e}_{t-1} r_{j,t-3} + \varphi F_{j,t} + \varepsilon_{j,t} \tag{8}$$

where dependent variable $r_{j,t}$ is annual rate of change in house price for MSA *j* and year t; $\hat{e}_{t-1}$ is one-year lagged excess risk; $r_{j,t-k}$ is *k*-year lagged rate of change in house price; $\hat{e}_{t-1} r_{j,t-k}$ is interaction term; $F_{j,t}$ is rate of change in local income; and $\varepsilon_{j,t}$ is error term. Excess risk is residual from time-series regression (Model I, II or III) in Table 3. Sample includes 121 MSAs over period of 1979-2011. *t*-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

4. Conclusions

In this study, we investigate the time series properties of the housing market risk ratio, defined as the cross-sectional dispersion in house price change relative to that in income change. We first study the relation between the risk ratio and the macroeconomic variables. Using the component of the risk ratio that is not explained by the macroeconomic variables to measure the idiosyncratic risk of the housing market, we investigate impacts of the idiosyncratic risk on house price dynamics.

In the time-series regressions of risk ratio, we regress the risk ratio on different sets of macroeconomic variables. The results reveal that the risk ratio is not only inversely related to the aggregate economic conditions, but also positively related to the tightening financial conditions in the aggregate capital markets. We find that real economic and financial conditions explain up to approximately 50% of the time variation of the risk ratio. We then measure the idiosyncratic risk of the housing market by using the residuals from the risk ratio regressions, which captures the excess risk that is not explained by the macroeconomic risks. In the panel regression of rate of change in the house price, we regress the rate of change in house price on this excess risk and its interactions with other determinants of price change, including lagged rates of change in price. We find a significantly positive relation between house price change and lagged excess risk, which suggests that idiosyncratic risk is priced into the local housing markets. In addition, excess risk reduces both the positive serial correlation in the short-run and the negative serial correlation of house price change in the long-run. Our study supplements the existing literature that explains housing market dynamics with local characteristics and extends the existing literature on the importance of idiosyncratic risks in the financial and real estate markets.

References

Abraham, J. and Hendershott, P.H. (1996). Bubbles in Metropolitan Housing Markets, *Journal of Housing Research*, 7, 191–207.

Ang, A., Hodrick, R., Xing, Y. and Zhang, X. (2006). The Cross-Section of Volatility and Expected Returns, *Journal of Finance*, 61, 259-300.

Ang, A., Hodrick, R., Xing, Y., and Zhang. X. (2009). High Idiosyncratic Volatility and Low Returns: International and further U.S. evidence, *Journal of Financial Economics*, 91, 1-23.

Campbell, S., Davis, M., Gallin, J. and Martin, R. (2009). What Moves Housing Markets: A Variance Decomposition of the Rent-Price Ratio, *Journal of Urban Economics*, 66, 90-102.

Campbell, J.Y. and Shiller, R.J. (1988). Stock Prices, Earnings, and Expected Dividends, *Journal of Finance*, 43, 661–676.

Capozza, D, Hendershott, P.H. and Mack, C. (2004). An Anatomy of Price Dynamics In Illiquid Markets: Analysis and Evidence from Local Housing Markets, *Real Estate Economics*, 32, 1-32.

Case, K.E. and Shiller, R.J. (1988). The Behavior of Home Buyers in Boom and Post Boom Markets, *New England Economic Review*, 29-46.

Case, K.E, and Shiller, R.J. (1989). The Efficiency of the Market for Single Family Homes, *American Economic Review*, 79, 125-37.

Case, K.E, and Shiller, R.J. (2003). Is There a Bubble in the Housing Market? *Brookings Papers on Economic Activity*, 2, 299–342.

Cochrane, J.H. (1992). Explaining the Variance of Price–Dividend Ratios, *Review of Financial Studies*, 5, 243-280.

Cogley, T. (2002). Idiosyncratic Risk and the Equity Premium: Evidence from the Consumer Expenditure Survey, *Journal of Monetary Economics*, 49, 309–334.

Constantinides, G. and Duffie. D. (1996). Asset Pricing with Heterogeneous Consumers, *Journal of Political Economy*, 104, 219–240.

Daniel, K.D., Hirshleifer, D. and Subrahmanyam, A. (2001). Overconfidence, Arbitrage, and Equilibrium Asset Pricing, *Journal of Finance*, 54, 921–965.

Dröesa, M. I., and Hassink. W.H.J. (2013). House Price Risk and the Hedging Benefits of Home Ownership, *Journal of Housing Economics*, 22, 92-99.

Gathergood, J. (2011). Unemployment Risk, House Price Risk and the Transition into Home Ownership in the United Kingdom, *Journal of Housing Economics*, 20, 200–209.

Gallin, J. (2006). The Long-Run Relationship between House Prices and Income: Evidence from Local Housing Markets, *Real Estate Economics*, 34, 417-438.

Gao, A., Lin, Z. and Na, C.F. (2009). Housing Market Dynamics, Evidence of Mean Reversion and Downward Rigidity, *Journal of Housing Economics*, 18, 256–266.

Garcia, R., Mantilla-García, D. and Martellini. L. (2014). A Model-Free Measure of Aggregate Idiosyncratic Volatility and the Prediction of Market Returns, *Journal of Financial & Quantitative Analysis*, 49, 1133-1165.

Goyal, A. and Santa-Clara. P. (2003). Idiosynchratic Risk Matters! *Journal of Finance*, 58, 975–1007.

Heaton, J. and Lucas, D.J. (1996). Evaluating the Effects of Incomplete Markets on Risk Sharing and Asset Pricing, *Journal of Political Economy*, 104, 443–487.

Hong, H., Scheinkman, J. and Xiong, W. (2006). Asset Float and Speculative Bubbles, *Journal of Finance*, 61, 1073–1117.

Igan, D., Kabundi, A., Nadal De Simone, F., Pinheiro, M. and Tamirisa, N. (2011). Housing, Credit, and Real Activity Cycles: Characteristics and Comovement, *Journal of Housing Economics*, 20, 210-231.

Jiang, D. (2013). The Second Moment Matters! Cross-Sectional Dispersion of Firm Valuations and Expected Returns, *Journal of Banking & Finance*, 37 (10), 3974-3992.

Li, Y. (2015). The Asymmetric House Price Dynamics: Evidence from the California Market, *Regional Science and Urban Economics*, 52, 1-12.

Malpezzi, S. (1999). A Simple Error Correction Model of House Prices, *Journal of Housing Economics*, 8, 27–62.

Mikhed, V. and Zemcik, P. (2009a). Do House Prices Reflect Fundamentals? Aggregate and Panel Data Evidence, *Journal of Housing Economics*, 18, 140–149.

Mikhed, V. and Zemcik, P. (2009b). Testing for Bubbles in Housing Markets: A Panel Data Approach, *Journal Real Estate Finance and Economic*, 38, 366–386.

Oikarinen, E. (2009). Household Borrowing and Metropolitan House Price Dynamics – Empirical Evidence from Helsinki, *Journal of Housing Economics*, 18, 126–139.

Plazzi, A., Torous, W. and Valkanov, R. (2008). The Cross-Sectional Dispersion of Commercial Real Estate Price Change and Rent Growth: Time Variation and Economic Fluctuations, *Real Estate Economics*, 36, 403-439.

Scheinkman, J.A. and Xiong. W. (2003). Overconfidence and Speculative Bubbles, *Journal of Political Economy*, 111, 1183–1219.

Titman, S., Wang, K. and Yang, J. (2014). The Dynamics of House Prices, *Journal of Real Estate Research*, 36, 283-317.