Risk Dynamics of Housing Market: Cross-sectional Variations, Time Variations and Economic Fluctuations

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Abstract

This paper estimates both the conditional systematic and idiosyncratic risks in the housing market using the monthly housing price data on U.S metropolitan areas over the sample period Jan 1987 to Oct 2008. Different to previous studies, this paper decomposes the total risk in housing market into both the systematic and the non-systematic parts by introducing new model-independent approaches for the measure of aggregate systematic and idiosyncratic risks, the PCA approach, the portfolio approach as well as the cross-section dispersion approach which do not depend on any parametric specifications of the return generating process such as the CAPM model or three-factor capital asset pricing model. The time-series properties of conditional risks in the housing market are found to be time varying and highly persistent as following a random walk process. Furthermore, the housing risk fluctuations can be largely explained by macroeconomic variables such as the credit spread and the inflation rate. In addition, using the portfolio sorting methodology, this paper finds that the housing portfolio with high idiosyncratic volatility has high expected returns. The results offer the new evidences supporting Merton's (1987) proposition that idiosyncratic volatility should be positively related to the cross-section of expected returns if investors demand compensation for imperfect diversification in presence of incomplete information.

Keyword Risk Dynamics; Housing; Cross-sectional Returns; PCA; Portfolio; Time-Varying

JEL Code G11; G12; G15

1. INTRODUCTION

Time variation in housing price level and its relation to the state of the economy have been well documented at both the national and Metropolitan Statistical Areas (MSAs) levels (see, among others, DiPasquale and Wheaten, 1994; Englund and Ioannides, 1997; Laakso, 2000; Capozza, et al. 2002; and Meese and Wallace, 2003). Comparatively little, however, is known about risk dynamics in the housing market and their links to prevailing economic conditions.

This absence of empirical research is not due to the unimportance of this question. To the contrary, the risk of the housing market is among the largest personal economic risks faced by individuals, as Shiller (1998) argues, because housing assets compose the majority of the U.S household's wealth. In fact, almost two-thirds of the typical household's portfolio in the United States is represented by housing (Tracy, et al., 1999), with Federal Reserve Board data showing that more than $18 trillion of real estate, most of it residential in nature, was owned by the household sector at the end of 2005[1]. Meanwhile there have been lots of literatures addressing the extreme important effects of housing asset on household's savings and portfolio choice[2]. Moreover, the "wealth effect" of housing on consumption is significant and larger than the wealth effect of financial assets (See e.g. Case et al. 2001, Benjamin et al. 2004, Compbell and Cocco, 2004). Furthermore, because the volatility of housing price is one of the key determinants of the options value realized by mortgage default and prepayment (e.g. Foster and Van Order, 1984, 1985; Crawford and Rosenblatt, 1995), the risks of housing market will affect mortgage and mortgage related securities market and consequently as well as the institutional investors since they usually hold a notable part of their funds invested in mortgage related securities. Quite recently the financial market turmoil driven by the sub-prime mortgage and credit crisis has indicated again that the variations in housing market are extremely crucial to overall economy, the mortgage capital markets and the welfare of the society.

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[1] This figure includes primary homes, second homes, vacant homes for sales, and vacant land. See Table B.100 Balance Sheet of Households and Nonprofit Organization at http://www.federalreserve.gov/RELEASES/z1/Current/data.htm

[2] See Cocco (2005), Hu (2005), Bond et al. (2003), Campbell and Cocco (2003), Kullmann and Siegel (2003), Davidoff (2002), Flavin and Yamashita (2002), Gu (2002), Capozza et al. (1997), Goetzmann (1993), and Goetzmann and Ibbotson (1990) among others.

This study empirically investigates risk dynamics in housing market and their relationship to the fluctuations in macroeconomic variables across U.S. metropolitan areas. Although a number of recent studies have examined the temporal aspects of housing price dynamics and volatility (Dolde, and Tirtioglu, 1997, 2002; Capozza, et al. 2004; Malpezzi and Wachter, 2005; Bourassa, et al. 2005; Miller and Peng, 2006 and others), some important questions about the risks dynamics in the housing market have not been sufficiently answered. The questions include how to measure the risks of the housing market accurately; what are the temporal and the cross-sectional characteristics of these risks in the housing market; what are the key economic fundamentals driving risks dynamics; how housing risk dynamics affect the cross-sectional housing returns. Moreover, most of existing studies focus only on the total risk of housing markets by using time series variance of housing returns as the measure of risk, the unique risk structure of housing market and the intrinsic heterogeneity risk characteristics of housing assets have been overlooked.

One innovation in this paper is to decompose total risk into both the systematic and non-systematic parts and evaluate systematic risk and idiosyncratic risk dynamics of housing market respectively. It is widely accepted that different from other financial assets, such as stocks, housing assets have more restrictions to diversification due to high transaction costs and liquidity risk. These distinct features of housing assets and the implied lack of diversification suggest that idiosyncratic risk may also play an important role in housing returns. In addition, for the cross-sectional properties of housing markets, due to the differences in the composition of local industry, the distribution of household income, as well as other social-economic factor, such as demographics, employments, etc, the effects of macroeconomic fluctuations and their speeds of propagation should vary across metropolitan areas (Redfearn, 2001; Carlino and DeFina, 2003; Carlino and Sill, 2001; Owyang, et al., 2003; Fratantoni and Schuh, 2003). Therefore, estimating both systematic and idiosyncratic risks can give a full picture about the risks inherent in housing markets driven by not only common aggregate factors but also idiosyncratic fluctuations arising from local shocks, which improves the further understanding of dynamic risk pattern of housing market and its links to fluctuations of macroeconomic variables.

To obtain an accurate and unique measure of idiosyncratic risk and systematic risk, this paper firstly introduces the model-independent measures of idiosyncratic risk, which do not require estimation of market betas or correlations: (1) the portfolio approach is based on the concept of gain from portfolio diversification; (2) the Principal Component Analysis (PCA) approach tries to extract meaningful information from the correlation matrix of housing returns; (3) the cross-sectional dispersion of housing returns measures the cross-sectional variance of housing return which is actually a measure of heterogeneity across MSAs in housing market. The previous studies compute the average idiosyncratic volatility based on the variance decomposition or using the residuals from the one-factor capital asset pricing model (CAPM) or three-factor model of Fama and French (1993) assuming a certain parametric specification for the return generation. However, some critical assumptions of CAPM or three-factor model obviously contradict with the market experience[3], therefore, using the factor or CAPM based models in estimating idiosyncratic volatility may lead to inaccurate or inconsistent measures of diversifiable risk.

A three-stage analysis framework is implemented by this study. As a first step of investigation, I estimate the conditional volatility series (systematic and idiosyncratic risk) in housing market using three different model-independent approaches. The housing return data are from S&P/Case-Shiller home price indices (HPI), which are available at monthly frequency over Jan 1987 to October 2008 sample period for a number of U.S metropolitan areas. While the Case-Shiller HPI data are not without limitations, they have more advantages of providing information across a large cross-section of metropolitan areas compared to Office of Federal Housing Enterprise Oversight (OFHEO) quarterly house price index, which is also widely documented in real estate literature. Then the time-series properties of risk dynamics in housing market are analyzed. In particular, I carry out the Augmented Dickey-Fuller (ADF) unit root test and the KPSS test to determine whether the risk dynamics of housing market is non-stationary and follows a random walk process or not. The answer to this question has special meaning to measure the expected risk values in housing market. Thirdly, I then run the predictive regressions of estimated risk series on macroeconomic variables respectively to investigate whether changes in economic conditions systematically affect the systematic/idiosyncratic volatilities in housing market.

[3] See Fama and French (2004) for a good summary about the shortcoming of CAPM and three factor models.

In addition, to the extent that households are more difficult to diversify their housing investment naturally due to the high unit cost of housing assets and economic constraints, theoretically housing investors may require compensation for such risk, thus I also test whether idiosyncratic risk is priced in housing market using the portfolio sorting methodology. This question is directly related to the on-going debate in the asset pricing literature about the existence and direction of a tradeoff between idiosyncratic risk and the cross-section of expected asset returns. Consistent with earlier research such as Lehmann (1990), Lintner (1965), Tinic and West (1986), and Merton (1987), a number of recent studies (e.g., Malkiel and Xu, 1997, 2006; Goyal and Santa-Calra, 2003; Fu, 2005; Jiang and Lee, 2004; Spiegel and Wang, 2006) find a positive relation between idiosyncratic volatility and expected returns at the firm or portfolio level in the stock market. Other studies, however, do not support this positive relation, where the cross-sectional relation has been found insignificant (e.g., Fama and Macbeth, 1973; Longstaff, 1989; Bali, et al., 2008). While more recently utilizing the portfolio sorting methodology, Ang et al. (2006, 2008) find a statistically significant negative relationship between the lagged idiosyncratic risk and the cross-section of expected stock returns.

The results of this study provide several new insights and contributions to empirical literature about the U.S housing market. First, this paper introduces three model-independent approaches to decompose total risk into the systematic and non-systematic parts for a better understanding of risk dynamics of the housing market. The PCA approach mainly relies on the estimation of the largest eigenvalue of the covariance return matrix for all local housing markets; the portfolio approach of the measure of idiosyncratic risk is defined as the difference between the variances of the non-diversified and fully diversified housing portfolios. The cross-sectional dispersion of housing returns approach is to calculate the cross-sectional variance of housing returns in market. The key innovation and advantage for new measures is that the new measure does not depend on any parametric specifications of the return generating process such as the CAPM model or three-factor capital asset pricing model.

Second, as for the time-series properties of risk dynamics in housing market measured by the PCA, the portfolio approaches and the cross-sectional dispersion of housing returns, this paper finds that they are volatile and time varying but highly persistent as following a random walk process.

Third, the results indicate that a significant fraction of the previously documented variations in systematic and idiosyncratic risks in housing market can be explained by fluctuations in macroeconomic variables such as the tem and credit spreads, inflation and the short rate of interest, as well as the underlying real estate market performance. In particular, both the housing idiosyncratic and systematic volatilities are increasing when the credit spread widens with tightening conditions in credit markets and more expensive external debt financing.

Finally, this study finds that, contrary to CAPM theory, a positive relationship between idiosyncratic risk and the cross-section of housing returns is found based on the portfolio sorting methodology. Although there is plenty of finance literature about the pricing of idiosyncratic risk in the cross section of stocks, to the best knowledge, this is the first study that examines the role of idiosyncratic risks in housing returns using the model-independent approaches for the measurement of idiosyncratic risk.

This study relates to and builds upon several very important literatures and has policy implications especially considering current fragile conditions in U.S. housing markets. First, it improves the understanding of risk and return characteristics of housing market (See Bond, et al. 2003; Capozza, et al. 2002; Capozza and Seguin, 2003; Chaudry, et al., 2004; Clayton and MacKinnon, 2003; among others) for this paper decomposes total risk into systematic and idiosyncratic parts and analyzes the these two risk dynamics in housing market respectively; second, it expands the literatures on the relations between the economic fundamentals and housing price volatility (See, for example, Case and Mayer, 1996; Clapp and Giaccotto, 1994; Leung, 2003; Miller and Peng, 2006) by investigating the economic determinants and impacts of risk dynamics in housing market; third, it adds to the literature regarding theoretical asset pricing models and the role of idiosyncratic risks in pricing assets returns (see, for example, Malkiel and Xu, 1997, 2006; Ali, et al., 2003; Goyal and Santa-Clara, 2003; Bali and Cakici, 2008; and Fu, 2005, among others) for this paper models idiosyncratic risk in housing market by firstly introducing model-independent measures, which is different to measuring idiosyncratic risks directly by utilizing FF 3-factor model in previous literature. Furthermore, this study has implications for mortgage markets and household portfolio choice, especially on mortgage default choice due to the intrinsic relationship between housing market and mortgage market; Finally, since May 2005, the housing price index derivatives market has been established in the Chicago Mercantile Exchange (CME) based on the Case & Shiller housing price indexes analyzed in this paper, the understanding of risk dynamics in the housing market will have more practical implications because the pricing of housing price derivatives is closely related to volatility.

The remainder of this paper is organized as follows. Section 2 reviews related studies to provide the relevant theoretical and empirical background for the research design. Section 3 presents the descriptive analysis of the data. Section 4 introduces the alternative measure methodologies of aggregate idiosyncratic and systematic risk: the portfolio approach, the PCA approach and the cross-sectional dispersion of housing returns; Section 5 summarizes the empirical findings of the time series properties of risks in housing market. The estimated results for the relationship between risk dynamics and economic variables are presented in Section 6. Section 7 sets up the portfolio sorting methodology to analyze the interactions between risks and the cross-sectional housing returns. Section 8 concludes the paper.

2. RELATED RESEARCH

This study attempts to draw together two strands of housing and financial asset pricing literature on the risk characteristics of housing assets and housing market. The first strand is the housing literature that involves examination of the causes and the temporal aspects of volatility and housing price within metropolitan areas, the efficiency of housing market, and house price predictability. Among a few empirical papers that study the risk dynamics of the housing market, most of them apply econometric time series technologies to model the conditional housing price volatility then use the time variations of housing price volatility[4] as the measure of risk dynamics in housing market. While the time-series of housing return volatility considers the deviations of the local housing market from its long-term means, which is actually a measure of total risk in a housing submarket, the risk microstructure of housing market, that is to say, systematic and non-systematic risk characteristics in housing market are totally ignored.

For example, Dolde and Tirtiroglu (1997a) reject the null hypothesis of time-

[4] Volatility is used informally as a synonym for either variance or standard deviation of a time series of returns in much of literature.

invariant volatility by using a Generalized Autoregressive Conditional Hetroskedasticity (GARCH)[5] model and find a positive relationship between conditional variance and returns. Then Dolde and Tirtiroglu (1997b) empirically examine the temporal and spatial information diffusion in housing price volatility, estimated with GARCH-M model. Furthermore, Dolde and Tirtiroglu (2002) identify 36 volatility events, most of which are purely regional and find significant associations between these volatility events and economic conditions, especially national and regional income growth, inflation and interest rates. Capozza et al. (2004) explore dynamics of real house prices by estimating serial correlation and mean reversion coefficients from a panel data set of 62 metro areas from 1979 to 1995. They find heterogeneity in terms of the price trend responses to these economic variables based on the time period and the specific MSAs. By examining supply constraints in the natural or political sense, Malpezzi and Wachter (2005) demonstrate that price elasticity of supply plays a key role in housing volatility. They conclude that when supply is less elastic, speculation has more significant effects on housing price volatility. Miller and Peng (2006) use GARCH models and Granger Causality test to analyze possible time variations of the volatility of single-family home value appreciation and they find the volatility is Granger-caused by the home appreciation rate and GMP growth rate and volatility also Granger-causes the personal income growth. Unfortunately, however their estimation of the GARCH model converges in only 34 MSAs of the 227 MSAsn in the sample.

Recently some studies began to pay close attention to the idiosyncratic risk instead of total risk (house price volatility) in housing market due to the obvious heterogeneity in housing market. Miller and Pandher (2008) provide the first analysis of idiosyncratic risk in housing market. Using classical Fama and French (1993) three factors model to measure the idiosyncratic risk in housing market, they find that in housing market idiosyncratic risk plays a positive role on housing returns in the cross-section and that relation is robust to the price level and socioeconomic variation among housing submarkets. However, they did not test the interactions between risk dynamics in housing market and the economic fluctuations as well as the time-series

[5] Bollerslev (1986) and Taylor (1986) independently proposed the GARCH process for modeling the stochastic volatility of asset return. Since then, the model has been generalized and used extensively in the finance literature on the modeling of financial time series; see Bollerslev, Chou, and Kroner (1992) and Bollerslev, Engle and Nelson (1994) for a review of theory.

properties of the risk dynamics. Other scholars investigate idiosyncratic risk dynamics in the real estate market in an indirect way by evaluating the time-varying cross-sectional dispersion of real estate returns across U.S. metropolitan areas. Replying on a commercial real estate panel data set drawn from a number of U.S. metropolitan areas over the 1986 to 2002 sample period, Plazzi, et al. (2004) find the cross-sectional dispersion are significantly driven by the fluctuations in the macroeconomic variables and the dynamics of the cross-sectional dispersions are positively related to subsequent commercial real estate return. Their findings indicate the cross-sectional dispersion of housing return is a more appropriate measure of the risk inherent in housing market because the cross-sectional dispersions of real estate return can captures idiosyncratic fluctuations associated with real estate that are unlikely to be diversified away. Not from the risk measure angle, Nieuwerburgh and Weill (2006) also investigate the cross-sectional dispersion of house prices across U.S. metropolitan areas in a calibrated general equilibrium island model and find that the pattern in wage dispersion could generate the house price dispersion across metropolitan areas.

The second stand is the financial literatures that focus on the role of idiosyncratic risk in asset pricing. The core research question is whether investors are compensated for their idiosyncratic risk exposure. The traditional CAPM theory prescribes that only systematic risk should be priced in equilibrium; any role for idiosyncratic risk is completely excluded through diversification. In reality, however, CAPM theory has been questioned by a growing number of both theoretical and empirical evidences for its inadequacy to capture the complexity of rationality in investors' behaviors (e.g. Levy, 1978; Merton, 1987; Malkiel and Xu, 2002; Rhodes-Kropf, 2003; Jagannathan and Wang, 1996; Heaton and Lucas, 1997, 2000; Storesletten, et al., 2001; Barberis and Huang, 2001, etc.). One of the best-known theories against CAPM model put forward by Merton (1987) is that in the presence of market frictions and incomplete information, stocks with high idiosyncratic volatility have high expected returns because investors cannot fully diversify away firm-specific risk and demand a premium for holding stocks with high idiosyncratic risk[6]. Moreover, Malkiel and Xu

[6] In addition to incomplete information, there are a number of other factors that could also attribute to why investors hold undiversified portfolios. They include market segmentation and institutional restrictions including limitations on short sales, taxes, transaction cost, liquidity, imperfect divisibility of securities (Merton, 1987; p488).

(2002) and Jones and Rhodes-Kropf (2003) demonstrate that if one group of investors fails to hold the market portfolio for exogenous reasons, the remaining investors will also be unable to hold the market portfolio. Therefore, traditional CAPM model may not hold and idiosyncratic risk should be priced to compensate rational investors for not being able to perfectly diversify risk.

On the empirical front, Lintner (1965) is perhaps the first study that considers the role of idiosyncratic risk. The early works like Douglas (1969), Linter (1965), Tinic and West (1986), Malkei and Xu (1997, 2002) all find the evidence of the positive tradeoff between idiosyncratic risk and the cross-section of expected stock returns. A key study supporting the CAPM theory is Fama and Macbeth (1973) who rejected the role of idiosyncratic risk in explaining the cross-sectional returns of common stocks. Recent papers by Campbell et al. (2001), Goyal and Santa-Calra (2003) and Ang et al. (2006) have rekindled the debate of whether idiosyncratic risk is priced in the equity market. Campbell et al. (2001) note that idiosyncratic risk has increased in U.S stock market in recent decades, and the similar trends in U.K market is also reported by Angelidis and Tessaromatis (2004). Goyal and Santa-Clara (2003) claimed that the average stock variance, which is demonstrated to be largely idiosyncratic risk, is significantly and positively related to subsequent capitalization weighted market returns, while no relation exists between market volatility and future market returns. Moreover, adopting the sophisticated generalized autoregressive conditional heteroskedasticity (GARCH) model to estimate the expected conditional idiosyncratic volatilities, Fu (2005), Brockman and Schutte (2007), Spiegel and Wang (2006) and Eliling (2006) all find a significantly positive relation between the estimated conditional idiosyncratic volatilities and expected returns. However, a puzzling negative relation found recently by Ang et al. (2006) shows that the US stocks with past high idiosyncratic volatility have low future risk-adjusted returns. Furthermore, Ang et al. (2008) also demonstrate this effect is individually significant in each G7 country and rule out the explanations based on trading frictions, information dissemination, and higher moments.

However, in this asset pricing literature strand, even though housing asset provides a unique and better opportunity to study the relationship between idiosyncratic risk and the cross-section of expected assets returns theoretically and empirically due to of its intrinsic difficulty to be diversified than financial assets (e.g. stocks), there is surprisingly little concerned with real estate housing market.

3. THE DATA

The empirical analysis of this study is based on the S&P/Case-Shiller® Home Price Index (CS HPI) from January 1987 to October 2008 instead of the OFHEO home price indices traditionally used in the previous literatures (See, for example, Deng and Quigley, 2008; Himmelberg, et al., 2005). Both OFHEO and CS housing price indices use the weighted repeated sales methodology. However, the OFHEO indexes have more limits compared to the CS housing price indexes. First, the CS housing price indexes use the real transaction home prices to establish the index while the OFHEO also includes refinance appraisals which will result in the "appraisal smoothing bias" for housing return measurement. This bias issue has been addressed in a substantial literature (see, e.g. Giliberto, 1988; Geltner, 1989a, 1989b, 1991; Ross and Zisler, 1991; Edelstein and Quan, 2005). Second, the OFHEO indexes are confined to Fannie Mae and Freddie Mac conforming mortgages, which are concentrated towards the lower end of the housing market. Third, the OFHEO index at MSAs level is quarterly issued while the CS index is monthly based, which provide a better opportunity to measure and model the housing price changes in a shorter time interval. Finally, the CS indexes are currently used for derivatives trading at the CME and the OTC market. Thus the study of CS home price indexes will have more important practical implications for the emerging housing price index derivatives market. However, one key concern for using home price indexes instead of house properties prices is that the volatility of aggregate local housing indices may underestimate the real risk exposure of a typical housing property in the submarket.

Recognized as one of the most authoritative and trustworthy home price change measures, Case-Shiller Home Price Index tracks changes in the value of the residential real estate market in 20 major metropolitan regions across the United States, and consisted of these 20 indices, there are also two composite indices as aggregates of the 10 regions and 20 regions, respectively. Figure 1 maps these 20 metropolitan regions in the S&P/Case-Shiller Home Price indices. The market value of housing stocks in these 20 major regions accounts for 42.5% of total value of the whole U.S housing market in terms of 2000 census. Table 1 gives the details about the housing market values of the covered metropolitans in the CS housing price indexes. To correct the effect of inflation, all nominal monthly housing price indexes have been deflated by the monthly CPI. Table 2 presents the summary statistics of the monthly housing returns for 20 major metropolitans. The Ljung-Box (1987) portmanteau test Q (6) at lag 6 is used to test the serial correlation in the monthly S&P Case-Shiller Home Price Indices. The significant positive first order and negative third order autocorrelation suggests the serial correlation exists in monthly returns. On the other side, the significant non-normality of return distribution was also found in most MSAs except for Boston and New York by utilizing Jarque-Bera Test (Jarque and Bera, 1987).

To capture the economic determinants of risk dynamics in the housing market, Plazzi et al. (2004) list some key macroeconomic variables widely used in finance literature (e.g. Campbell and Shiller, 1988; Fama and French, 1989; Torous, et al., 2005) which include the term spread (the difference between the yields on 10-year and 1-year Treasuries, TSPR), the credit spread (the difference between the yields on BAA-and AAA-rated corporate bond, CSPR), Consumer Price Index (CPI) inflation rate (INF) and 3 month Treasure bill rate (TB3M). The term spread is used to proxy for business cycle effects. As noted by Fama and French (1989), the term spread is closely related to short-term business cycle as identified by the NBER (Plazzi, et al. 2004). Given housing investment is highly leveraged by mortgage financing, the widening of credit spread, consistent with tightening conditions in credit markets and more expensive external mortgage financing, is expected to lead to the lower the housing returns. Therefore, this study uses the credit spread as the proxy for availability of credit with narrow credit spreads corresponding to an abundance of mortgage financing. The term spread (TSPR) is closely related to short-term economic cycle with the term spread being wider in a business cycle downturn and narrower in a business expansion, while the credit spread (CSPR) tends to be widening in a business downturn cycle since negative economic shocks amplify asymmetric information and the costly enforcement of contracts which will significantly raise the external debt financing (Bernanke and Gertler, 1995). CPI inflation rate captures the current economic activity while the 3 month Treasury bill serves as a proxy for future economic activity (Plazzi, et al. 2004). This paper also uses these economic variables. Except the 3-month Treasury bill rate, all data are taken from the FRED database. The 3-month Treasury bill rate is obtained from Ibboston Associates.

The panel A of Table 3 contains corresponding summary statistics of macroeconomic variables. For all macroeconomic variables the AR (1) model coefficients are higher than 0.9 which suggests that the fluctuations in economic variables are highly persistent in the sample period. The unconditional correlations between economic variables are presented in the Panel B of Table 3. The unconditional correlation between the credit spread and the term spread is negative, which reflects the different reactions of the term spread and the credit spread to the economic cycle.

4. MEASURING RISKS IN HOUSING MARKET

Although the concepts of idiosyncratic and systematic risk[7] are quite simple and widely accepted and employed in the finance literature, how to measure them correctly is not an easy thing and much more complex than what previous research assumed them would be. The idiosyncratic and systematic risks are unobservable, and are generally estimated using a return generating process based on the variance decomposition (see, e.g Campbell, et al., 2001; Xu and Malkiel 2003) or using the residuals from the one-factor capital asset pricing model (CAPM) or three-factor mode of Fama and French (1993). Early asset-pricing studies define the total risk of an individual asset i as follows:

$$\sigma_i^2 = f\left(M\right) + \zeta\left(\varepsilon_i\right) \tag{1}$$

where $f\left(M\right)$ is the portion of total variance explained by the factor model M, and $\zeta\left(\varepsilon_i\right)$ measures the idiosyncratic risk that is unique to the asset i and irrelevant to the overall market. However, there are various models M_1, M_2, M_3 measuring the systematic risk, which will end up with different measures of idiosyncratic risk for the same individual asset i. Unless the model M is correct, the calculated idiosyncratic risk $\zeta\left(\varepsilon_i\right)$ can not be accurate and unique (Bali and Cakici, 2008). There has been

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[7] Where there is no scope for confusion, I refer to standard deviation as “volatility” and “risk” in this paper.

plenty of literature addressing the problems in CAPM model and three-factor model, so the model-dependent measures of idiosyncratic risk maybe inconsistent and inaccurate. This study will introduce model-independent measures of idiosyncratic risk to overcome above problems in previous studies.

It is worth noting that not focusing on measuring idiosyncratic risk of individual housing submarket; this study pays more attention to the average systematic/idiosyncratic risk of the whole housing market since the key research question is about the dynamic risk for the overall housing market. Some financial studies like Bali et al. (2005), Brown and Ferreria (2004), Angelidis and Tessaromatis (2007) have noted that the weighting scheme used to compute the average aggregate idiosyncratic risk play a critical role in determining the existence and significance of a relation between idiosyncratic risk and the cross-section of expected returns. Goyal and Santa-Clara (2003) use the cross-sectional average stock variance of all the stocks traded in the market as the indirect measurement for the average idiosyncratic risk. This paper will measure the average idiosyncratic risk in the housing market by employing (1) Principal Component Analysis (PCA) approach; (2) the Portfolio approach; and (3) the dispersion of housing returns which are different to previous studies.

The PCA Approach

The variance decomposition will be the starting point for the PCA approach. Considering a multi-factor model derivation of Equation (1), for each metropolitan housing submarket MSA i:

$$R_i = \sum_{j=1}^{m} \beta_{ij} F_j + \tilde{\varepsilon}_i \tag{2}$$

This simple regression model decomposes stock returns into a systematic components $\sum_{j=1}^{m} \beta_{ij} F_j$ and an (uncorrelated) idiosyncratic component $\tilde{\varepsilon}_i$. The terms F_j, $j = 1, ...m$ represent returns of risk-factors associated with the market under consideration, which can be thought of as the returns of “benchmark” portfolios representing systematic factors. The traditional CAPM model in finance literature uses “market portfolio” as one systematic factor F (e.g. the return on a capitalization-weighed index, such as the

S&P 500) while Fama and French (1993) suggest three systematic risk factors F_j, and Miller and Pandher (2008) use two market factors F_j, the overall housing market return and the aggregate stock market return to calculate the idiosyncratic risk in the housing market. Therefore, this leads to the interesting question of how to define the "factors" correctly in practice.

Instead of using explicit market variables *in priori* as proxies for systematic factors, the PCA approach in this paper uses the Principal Component Analysis to extract underlying "systematic risk factors" that affect all MSAs directly from data itself. This approach uses the historical housing price index data on a cross-section of N MSAs going back, say, M months for the estimation window and T months for the whole sample period. Denote the returns of the N MSAs at time t by $\{R_i\}_{i=1}^{N}$, since different metropolitan housing markets have varying levels of volatility, it is convenient to work with a normalized return $\{Y_i\}_{i=1}^{N}$,

$$Y_{ik} = \frac{R_{ik} - \overline{R}_i}{\overline{\sigma}_i}, \qquad k = 1,\dots,M\ ,\ i = 1,\dots,N \tag{3}$$

where $$\overline{R}_i = \frac{1}{M}\sum_{k=1}^{M} R_{ik}$$

and $$\overline{\sigma}_i^2 = \frac{1}{M-1}\sum_{k=1}^{M}(R_{ik} - \overline{R}_i)^2 .$$

The $N \times N$ empirical correlation matrix C with element is defined by

$$\rho_{ij} = \frac{1}{M-1}\sum_{k=1}^{M} Y_{ik}Y_{jk}$$

which is symmetric and non-negative definite. By solving the eigenvalues and eigenvectors problem $CX_i = \lambda_i X_i$, $i = 1,\dots,N$ the correlation matrix C can be diagonalized into

$$C = XDX' \tag{4}$$

where D is the diagonal matrix with eigenvalues as the diagonal elements in a decreasing order :

$$D = \{\lambda_1, \lambda_2, \dots, \lambda_N\},\ N \ge \lambda_1 \ge \lambda_2 \ge \dots \ge \lambda_N \ge 0$$

and X is composed by the corresponding eigenvectors:

$$X = \{\vec{x}_1, \vec{x}_2, ..., \vec{x}_N\}$$

From the point of view of investment theories, each eigenvector $\vec{x}$ can be considered as a realization of an N - submarkets portfolio P_i (so-called eigenportfolio) with the weights equal to the eigenvector components $x_i^{(m)}$, $m = 1,..., N$, $i = 1,..., N$.

There are some important properties of eigenportfolios. Firstly, for a non-degenerate correlation matrix C, the eigenvectors are orthogonal to each other, that means any pair of eigenportfolios P_i and P_j are independent whose risk is independent of others. Secondly, the risk of these eigenportfolios can be easily related to the corresponding eigenvalues:

$$R(P_i) = \sigma^2(P_i) = \vec{x}_i^T C \vec{x}_i = \lambda_i \quad (5)$$

Thus, the eigenvalue size is a risk measure and, as a consequence, the larger the λ_i, the larger the risk of the corresponding eigen-portfolio P_i. In this way, if first m eigenportfolios are used to proxy the market factors, in equation (2), the residual part $\tilde{\varepsilon}$ will not be correlated with those "market" factors. Then its volatility can be regarded as a measurement of the idiosyncratic risk in housing market. As noted by Meucci (2005), it is easy to prove that the risk of market portfolio equals the sum of risks of these m eigenalues $Var(\sum_{i=1}^{m} P_i) = \sum_{i=1}^{m} \lambda_i$ and the aggregate idiosyncratic volatility $Var(\tilde{\varepsilon}) = \sum_{i=m+1}^{N} \lambda_i$. Furthermore, $E\left(\tilde{\varepsilon}\right) = 0$ and $Corr(\sum_{i=1}^{m} P_i, \tilde{\varepsilon}) = 0$. Finally and most importantly, applying the Random Matrix Theory (RMT) to analyze the properties of C, recent studies have found that the largest eigenvalue and its corresponding eigenvector of C represent the influence of the entire housing market on all metropolitan housing submarkets[8]. Therefore, the largest eigenvalue λ_1

[8] The logic behind applying Radom Matrix Theory (RMT) is that if the properties of *C* conform to those of a random correlation matrix, then it follows that the contents of the empirically measured *C* are random. Conversely, deviations of the properties of *C* from those of a random correlation matrix convey information about ''genuine'' correlations. Thus, by comparing the properties of *C* with those of a random correlation matrix and separate the content of C into two groups: (1) the part of *C* that conforms to the properties of random correlation matrices (''noise'') and (2) the part of *C* that deviates (''information''). Refer to Plerou et al. (2002), Laloux et al. (2000) for details.

corresponding eigenportfolio $\vec{x}_1$ is a good proxy for the systematic factor F, which reflects the genuine underlying "interactions" for all housing submarkets

So this study adapts one factor model in equation (2) by taking the eigenvector corresponding to the largest eigenvalue as the only systematic factor and the residual part as the source of the idiosyncratic risk. The estimation window for calculating the covariance matrix is 12 months. It is worth noting that sometimes it is possible that other eigenvalues also contain the "market information", in that situation, one-factor model maybe underestimate the systematic risk and overestimate the idiosyncratic risk. However, my estimates suggest that generally the largest eigenvalue and its corresponding eigenvector can reflect the market systematic information. Figure 2 presents the time-varying values of three largest eigenvalues of the correlation matrix. One can find that the largest eigenvalue become to dominate the system after 1991 and is well separated from other eigenvalues. This feature confirms the result of Plerou et al. (2002) that the largest eigenvalue represents the market portfolio. Moreover, Figure 3 shows the components of the largest three eigenvlues corresponding eigenvectors at the end of the sample period (October, 2008), which indicates the weights on REITs in the sample correspondingly. Since all components in the eigenvector corresponding to the largest eigenvalue are positive and almost equal cross different MSAs, it represents an influence that is common to all metropolitan areas, while most components of the remaining eigenvectors usually are near zero and only few are positive, which indicates their effects only concentrate on several individual metropolitan submarkets.

The Portfolio Approach

The portfolio approach measuring average idiosyncratic risk in housing market is based on the definition of idiosyncratic risk itself. Since idiosyncratic risk is local housing market specific and not attributable to overall housing market volatility, theoretically which can be eliminated by complete diversification, this means a fully diversified portfolio will not contain any idiosyncratic risk (fully diversified portfolio), on the other hand, when the correlations among housing returns across metropolitans equal one, there is no gain from diversification (non-diversified portfolio). Therefore, the portfolio approach's measure of average idiosyncratic volatility in housing market is defined as the difference between the variance of the non-diversified housing portfolio and the variance of the fully diversified housing assets portfolio.

Based on the mean-variance portfolio theory and the concept of gain from portfolio diversification introduced by Markowitz (1952, 1959), the portfolio approach for average idiosyncratic risk in the housing market is to calculate the difference of variances between two constructed housing assets portfolios. The return of the portfolio which is consisted of n representative housing assets across different metropolitan areas measured by the local housing price index can be defined as:

$$R_{p,t} = \sum_{i=1}^{n} w_{i,t} R_{i,t} \tag{6}$$

The risk of the portfolio measured by the variance is given as:

$$\sigma_{p,t}^2 = \sum_{i=1}^{n} w_{i,t}^2 \sigma_{i,t}^2 + 2\sum_{i=1}^{n}\sum_{j>i}^{n} w_{i,t} w_{j,t} \rho_{ij,t} \sigma_{i,t} \sigma_{j,t} \tag{7}$$

where $\sigma_{i,t}^2$ is the variance of excess return in submarket MSA i at time t, $\rho_{ij,t}$ is the correlation of excess returns in submarkets MSA i and MSA j, and $w_{i,t}$, $w_{j,t}$ represent the weights of housing submarket i and j.

It is well known that for a given weights, the lower the correlations ρ_{ij}, the smaller the portfolio variance, hence the larger the gain from diversification. For the non-diversified portfolio, the representative housing assets across metropolitan areas are perfectly correlated ($\rho_{ij} = 1$), no diversification gains are achieved. When $\rho_{ij} = 1$ in equation (7), the variance of non-diversified housing portfolio which contains both systematic risk and idiosyncratic risk is written as:

$$\sigma_{p,t}^2 = \left(\sum_{i=1}^{n} w_{i,t} \sigma_{i,t} \right)^2 \tag{8}$$

An equally-weighted portfolio of n housing assets in n MSAs when n is large can be viewed as a fully diversified portfolio which does not contain any idiosyncratic risk. When $w_{i,t} = \frac{1}{n}$, the variance of the portfolio return in equation (7) changes to:

$$\sigma_{p,t}^2 = \frac{1}{n^2}\sum_{i=1}^{n}\sigma_{i,t}^2 + \frac{2}{n^2}\sum_{i=1}^{n}\sum_{j>i}^{n}\rho_{ij,t}\sigma_{i,t}\sigma_{j,t}$$

$$\sigma_{p,t}^2 = \frac{1}{n}\left(\frac{1}{n}\sum_{i=1}^{n}\sigma_{i,t}^2\right) + \left(1-\frac{1}{n}\right)\left(\frac{1}{n(n-1)/2}\sum_{i=1}^{n}\sum_{j>i}^{n}\text{cov}(R_i, R_j)\right) \quad (9)$$

$$\sigma_{p,t}^2 = \frac{1}{n}\begin{pmatrix} average \\ \text{var}\,iance \end{pmatrix} + \left(1-\frac{1}{n}\right)\begin{pmatrix} average \\ \text{cov}\,ariance \end{pmatrix}$$

when n is going to infinity, the first part in equation (9) will be eliminated to zero, and the risk (variance) of portfolio return will be reduced to average of covariance of returns in the portfolio. Since idiosyncratic risk is unique to a local housing market because it is only related to the return of local housing market that does not vary with returns of other housing submarkets or overall market, the $\frac{1}{n}$ portfolio contains no idiosyncratic risk any more, and only the non-diversifiable (systematic) risk contributes to the total risk of the housing portfolio. Hence, with a large number of different MSAs, the equally-weighted portfolio can be treated theoretically as a well-diversified portfolio, the risk of which is due solely to the systematic risk in the housing portfolio.

Following Bali and Cakici (2008), the concept of gain from portfolio diversification yields a model-independent measure of aggregate idiosyncratic risk which does not require the estimation of market beta or correlations:

$$\sigma_{\varepsilon,t}^2 = \left(\sum_{i=1}^{n} w_{i,t}\sigma_{i,t}\right)^2 - Var(R_{1/n,t})$$

$$\sigma_{\varepsilon,t}^2 = \left(\frac{1}{n}\sum_{i=1}^{n}\sigma_{i,t}\right)^2 - \left[\frac{1}{n}\left(\frac{1}{n}\sum_{i=1}^{n}\sigma_{i,t}^2\right) + \left(1-\frac{1}{n}\right)\left(\frac{1}{n(n-1)/2}\sum_{i=1}^{n}\sum_{j>i}^{n}\text{cov}(R_i, R_j)\right)\right] \quad (10)$$

$$\sigma_{\varepsilon,t}^2 = \left(\frac{1}{n}\sum_{i=1}^{n}\sigma_{i,t}\right)^2 - \begin{pmatrix} average \\ \text{cov}\,ariance \end{pmatrix}$$

where $\frac{1}{n}\sum_{i=1}^{n}\sigma_{i,t}$ is the equally weighted average standard deviation of individual housing submarket. The difference between the variance of the non-diversified housing portfolio, $\left(\frac{1}{n}\sum_{i=1}^{n}\sigma_{i,t}\right)^2$, and the variance of the completely diversified portfolio, $Var(R_{1/n,t})$, yields the average idiosyncratic variance $\sigma_{\varepsilon,t}^2$ in equation (10).

It is worth noting that despite the sophisticated theoretical optimization models developed in the last fifty years and the advances in methods for reducing the variance of portfolio, there are other three reasons choosing the $\frac{1}{n}$ rule to build up the fully diversified portfolio. First, it is easy to implement because it does not rely either on estimation of the moments of housing returns or on optimization. Second, such simple allocation rule are widely used by investors continue to use for diversification[9]. Third, recently DeMiguel, et al. (2008) find that of the fourteen models across seven empirical dataset, none is consistently better than the naive portfolio diversification $\frac{1}{n}$ rule in terms of Sharpe ratio, certainty-equivalent return, or turnover. In addition, this paper also uses the composite housing market index and Minimum-variance portfolio as the fully diversified portfolio to calculate the aggregate housing market idiosyncratic risk. There are no significant differences to the following economic analysis.

For month t in metropolitan local housing market i, I estimate the monthly variance(volatility) $\sigma_{i,t}^2$, using m -months estimation time window (including the current month t) in the equation (11) as:

$$Var(R_{i,t}) = \sigma_{i,t}^2 = \frac{1}{m}\sum_{j=t-m}^{t}(R_{i,j} - \overline{R}_i)^2 \qquad (11)$$

$$\overline{R}_i = \frac{1}{m}\sum_{k=1}^{m} R_{ik} \qquad (12)$$

where m is the number of months in the estimation period. $Var(R_{i,t})$ is the monthly variance of housing submarket metropolitan i in the month t, $R_{i,j}$ is the return in local housing market i at month j. It's worth noting that the estimation window m for estimating monthly variance needs to be chosen carefully. This paper has tested the different estimation window values of m and takes $m = 12$, because the test results

[9] For instance, Benartzi and Thaler (2001) document that investors allocate their wealth across using the equally weighed portfolio rule. Huberman and Jiang (2006) find that participants tend to invest in only a small number of funds offered to them, and that they tend to allocate their contributions evenly across the funds that they use, with this tendency weakening with the number of funds used.

indicate that for monthly housing returns, a value of lag value twelve tends to render the devolatized returns, nearly Gaussian.

The Cross-sectional of Housing Returns

The average variance approach introduced by Goyal and Santa-Clara (2003), is computed as the arithmetic average of the monthly variance of each asset's returns. Goyal and Santa-Clara (2003) illustrate that the effect of idiosyncratic risk constitutes almost 85 percent of the average variance measure by decomposing the total risk into systematic risk and idiosyncratic risk. Based on the average variance approach, Plazzi, et al. (2004) denote the cross-sectional dispersion of housing returns as

$$S_{t+1} = \sqrt{\sum_{i=1}^{N_{t+1}} (R_{i,t+1} - \overline{R}_{t+1})^2 / N_{t+1}} \tag{13}$$

where $R_{i,t+1}$ is the housing price appreciation rate in metropolitan i at time $t+1$. If there are N_{t+1} metropolitans areas included in the sample at time $t+1$, the average return across metropolitan is $\overline{R}_{t+1} = \frac{1}{N_{t+1}} \sum_{i=1}^{N_{t+1}} R_{i,t+1}$. Following Plazzi, et al. (2004), I also calculate the cross-sectional dispersion of housing returns as equation (13). This is a measure of heterogeneity across the metropolitan areas in housing market. The heterogeneity of housing returns is driven by their idiosyncratic shocks. The cross-sectional variation of housing return is conditional on the cross-sectional mean of housing market return, whereas the time-series of housing return volatility considers the deviations of the local housing market from its long-term means (Solnik and Roulet, 2000). For housing market, Plazzi, et al., (2004) have proved that the cross-sectional dispersion of housing returns is a more appropriate measure of the risk in housing market than the time-series volatility of housing returns because it can reflects market-wide and local-specific fluctuations across metropolitan housing markets. As housing submarket tends to affected by geographic, demographic, economic and other local socioeconomic factors, the dispersion of housing return across metropolitan areas can capture fluctuations due to common aggregate factors as well as idiosyncratic fluctuations arising from local shocks (Redfearn, 2001; Carlino and DeFina, 2003; Plazzi, et al., 2004).

After taking square of equation (13) and simplification we can get the equation (14), which is the cross-sectional measure of idiosyncratic risk:

$$\sigma_{\varepsilon,t}^2 = \left(\sum_{i=1}^{n} w_{i,t} \sigma_{i,t}^2 \right) - Var(R_{1/n,t}) \tag{14}$$

where $w_{i,t} = \frac{1}{N_t}$. Compared with the portfolio measure of idiosyncratic risk:

$$\sigma_{\varepsilon,t}^2 = \left(\sum_{i=1}^{n} w_{i,t} \sigma_{i,t} \right)^2 - Var(R_{1/n,t}) \tag{15}$$

It is clear that the difference between the cross-sectional dispersion measure of idiosyncratic risk and the portfolio measures of idiosyncratic risk actually is the difference between $\left(\sum_{i=1}^{n} w_{i,t} \sigma_{i,t}^2 \right)$ and $\left(\sum_{i=1}^{n} w_{i,t} \sigma_{i,t} \right)^2$. Recently Bali et al. (2007) has demonstrated that under the condition $0 \le w_{i,t} \le 1$ and $\sum_{i=1}^{N} w_{i,t} = 1$, $\left(\sum_{i=1}^{n} w_{i,t} \sigma_{i,t}^2 \right)$ is greater than $\left(\sum_{i=1}^{n} w_{i,t} \sigma_{i,t} \right)^2$ as long as the standard deviations (or variances) of individual asset are different from each other. Therefore, the idiosyncratic risk measured by the cross-sectional dispersion measure should be higher than the one measured by the portfolio measure.

5. TIME-SERIES PROPERTIES OF RISKS IN HOUSING MARKET

Although some literature has documented the temporal aspects of housing price volatility, there is surprisingly little empirical research specialized on the time series and the cross-sectional characteristics of idiosyncratic and systematic risks in housing market.

Figure 4 shows the historic monthly idiosyncratic volatility pattern in the US housing market between 1988 and 2008 measured by three model-independent measures: the PCA approach, the portfolio approach as well as the cross-sectional dispersion approach. Whilst monthly idiosyncratic volatility of the housing market fluctuates over time, some discernable patterns still can be observed with regard to the behavior of aggregate idiosyncratic volatility for the housing market. Firstly, different to Campbell et al. (2001) who find a noticeable increase in idiosyncratic volatility at firm level in the stock market over the period from 1962 to 1997, my findings here show that there is a decrease trend for aggregate idiosyncratic volatility in housing market from 1988 to 1997 while there is a increase trend after 1997 but accompanying with a significant cyclical pattern. However, the historical patterns estimated in different model-independent approaches in this paper show the similar trend and cyclical time-series patterns except that the cross-sectional dispersion of housing returns is much more volatile than other two measures. The estimated idiosyncratic risk series by the PCA and the Portfolio measures are smoother mainly because these two approaches use the estimated window and continue to roll over for the whole sample period. Secondly, the idiosyncratic risk of housing market is time varying but especially low between 1995 and 1998 and spikes quickly during the bad economic conditions such as April 2004 and Jan 2008. Campbell et al. (2001) suggest that this characteristic of idiosyncratic volatility has important implications for portfolio diversification at different stages of the economic cycle. Since idiosyncratic risk in housing market increases fast during the bad market time, diversification will be more difficult.

Following the Anderson et al. (2005), furthermore, I employ a “variance decomposition” approach to examine the significance of the systematic/idiosyncratic component of housing return volatility. Specifically, its relative contribution to total housing return volatility is inferred by calculating the proportion of the variance of housing returns due to the idiosyncratic component, as follows: $\sigma^2_{\varepsilon,t} / \sigma^2_{p,t}$. The results over the sample period are reported in Figure 5.

Essentially the ratio of housing idiosyncratic volatility to the total volatility is quite time-varying and volatile between 0.85 and 0.3; however, it is obvious that since 2007 systematic volatility begins to account for most of the total volatility exhibited in the housing market. The ratio of housing idiosyncratic volatility to the total volatility decreases from 0.85 at the middle of 2007 to 0.19 at the beginning of 2008, which shows the significant effects of subprime mortgage crisis on systematic risks commonly across different metropolitan housing markets. This finding is inconsistent with Goyal and Stata-Clara (2003) and Ooi et al. (2007) [10] who observe that the total volatility of stock returns is largely idiosyncratic volatility. In particular, Figure 6 and Figure 7 present the decomposition of monthly total volatility into systematic risk and idiosyncratic risk estimated by the PCA approach and the Portfolio approach, respectively. The similar trends are also found at quarterly frequency. The quarterly risk pattern is not as volatile as the monthly one no matter systematic or idiosyncratic risks. The quarterly dynamic risk tends are clearer as shown in Figure 8. While Figure 9 presents the ratio of quarterly idiosyncratic risk to total risk in the sample period, Figure 10 and Figure 11 present the decomposition of quarterly total volatility into systematic risk and idiosyncratic risk estimated by the PCA approach and the Portfolio approach, respectively.

Table 4 presents the time-series property of housing monthly idiosyncratic volatility time series. The time series mean, median and standard deviation of idiosyncratic risk measured by the portfolio approach are the lowest among three approaches. This is consistent with what has documented in the previous section that as long as the standard deviations (or variances) of local housing market return are different from each other, the idiosyncratic risks measured by the cross-sectional dispersion measure should be higher than the ones measured by the portfolio measure; While for the PCA approach, this study only uses the largest eigenvector as one market factor, and the possible other key systematic information contained by the rest eigenvectors may be neglected. With the above considerations, both average approach and the PCA approach may overestimate the true idiosyncratic volatility. Although the aggregate idiosyncratic volatilities vary substantially over time, quite different to Fu (2005), who find that the mean autocorrelation of idiosyncratic risk estimated by the FF-three factor model is only 0.33 at the first lag, this paper shows a more consistent time series pattern in the model-independent estimated idiosyncratic volatilities: the first lag auto-correlation coefficients are all above 0.97 for three different approaches. Furthermore, they have a slow decay rate.

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[10] Goyal and Santa-Clara (2003) find that over the period 1926-1999, idiosyncratic volatility is on average *80%* of total volatility of common stocks. While, Anderson, et al. (2005) observe that *62%* of the monthly return volatility of the NAREIT index is unrelated to any of the capital market factors in their asset pricing model. Ooi et al. (2007) find that during 1990 to 2005, *78.3%* of the monthly return volatility can not explained by the three risk factors in Fama-French (1993) model.

High autocorrelation coefficient and slow decay rate imply the possibility of existence of unit root and non-stationarity of idiosyncratic volatility in the housing market. I carry out the Augmented Dickey-Fuller (ADF) unit root test and the KPSS test to determine whether the idiosyncratic risk series in housing market is non-stationary and follows a random walk process or not. This question is especially important for measuring the expected idiosyncratic risk. Whilst some previous studies such as Fama and French (1993) and Ang et al. (2006) have employed the lagged values of idiosyncratic risk as the best estimates of its expected value, Fu (2005) argues that such approximation is only valid of the conditional volatility follows a random walk process. In absence of evidences about the random walk process existing in idiosyncratic risk, some researchers like Fu (2005), Brockman and Schutte (2007), Spiegel and Wang (2006) use EGARCH model to estimate the conditional idiosyncratic volatility. Table 5 reports the results of unit root tests. The optimal lag lengths for those tests are chosen based on the Akaike's Information Criterion (AIC). For each estimated idiosyncratic volatility time series, I have done the best-known ADF (see, e.g. Fuller, 1976; Dickey and Fuller, 1979) and KPSS (see, Kwiatkowski et al., 1992) econometric models with and without time-trend being included. For all three idiosyncratic volatilities time series, according to the ADF critical values of t-statistics, the null hypothesis of a random walk process can not be rejected; while for the KPSS test, the null hypothesis that the idiosyncratic volatility is stationary are all rejected. However, after taking first difference on these three time series, the time series exhibit the stationary and non-existence of unit root, which are also reported in Table 5. My results thus suggest that it is appropriate to describe the aggregate housing market idiosyncratic volatility process as a random walk. Put differently to Fu (2005) etc, using this month's idiosyncratic volatility to approximate the value in the next month should not introduce severe measurement errors.

Table 6 reports the statistics summary of housing monthly systematic volatility time series measured by the PCA approach and the portfolio approach, since the cross-sectional dispersion of housing returns can only estimate the idiosyncratic risk of the housing market. The statistics of systematic risk in housing market is similar to the ones of idiosyncratic risk. Interestingly the volatility of systematic risk is 0.0014 (measured by PCA approach) which is higher than that of idiosyncratic risk 0.0009. It suggests that the systematic risk is much more volatile. Similarly the systematic risk is also highly autocorrelated and decay slowly. The coefficients of first autocorrelation are both above 0.99 measured by the PCA and portfolio approaches. Table 7 presents the results of the Augmented Dickey-Fuller (ADF) unit root test and the KPSS test. For two systematic volatilities time series, according to the ADF critical values of t-statistics, and the KPSS test, the null hypothesis that the idiosyncratic volatility is stationary are all rejected. The results suggest that the aggregate housing market systematic volatility also follows as a random walk.

6. LINKS BETEEN RISKS DYNAMICS IN HOUSING MAREKT AND ECONOMIC FLUCTUATIONS

There are a growing number of literatures which have addressed the close relationship between housing price volatilities and the macro-economic variables. However, due to the intrinsic heterogeneity of housing properties, the effects of macroeconomic fluctuations and their speed of propagation differ across the different housing assets as well as the various metropolitan local housing markets. The differences depend on several factors, including the demographics, the hedonic characteristics of housing, as well as the composition of local economy. Thus the variance that is not attributable to overall market volatility, but related to the property's specific volatility will also reflect the overall economic fluctuations. Another link between risk of housing market and the economy operates through the leverage mortgage finance structure of local housing market. One important characteristic for housing investment is high-leverage with high Loan to Value (LTV) ratio. Different leverage ratios of local housing markets will lead to different volatility pattern of returns even under the same changes of external mortgage financing condition. In this way, the idiosyncratic risk in housing market will be related to the conditions of credit markets and external debt financing, which are inherently linked to the macro economy. Actually, recent research by Miller and Pandher (2008) has already confirmed this claim with strong empirical evidences. Therefore, both the systematic and idiosyncratic risks of housing markets (securitized real estate) are expected to be related to the economic conditions.

To investigate whether changes in economic conditions systematically affect the systematic and idiosyncratic volatilities in the housing market, I firstly run the following regressions for each estimated idiosyncratic volatility series, respectively.

$$R_t = \alpha + \gamma R_{t-1} + \sum_{k=1}^{n} \beta_k X_{t-k} + \varepsilon_{i,t} \qquad (16)$$

where R_t denotes the conditional systematic/idiosyncratic volatility at time t, the parameter γ is the auto-regression parameter which reflect how R_{t-1} at time t-1 affect the idiosyncratic volatility value R_t at time t; the parameters β_k are vector parameters which measure the sensitivities of the risk dynamics in housing markets to the current and k-lagged macroeconomic variable vector X_{t-k}. Here I include an autoregressive term to capture any time-series variation in R_t attributed to factors other than prevailing macroeconomic conditions. These factors include the liquidity, the momentum effects, as well as idiosyncratic shocks.

Table 8A shows the results of regression estimations using idiosyncratic volatility in the housing market as dependent variable and the cotemporaneous economic variables as regressors. The autoregressive term is excluded as well as included. With including one-lagged idiosyncratic volatility, both the credit spread (CSPR) and the CPI inflation rates (CPI) have a positive effect on the idiosyncratic volatility. Moreover, they are statistically significant at least 5% level for all three different model-independent measures of idiosyncratic volatility. The term spread (TSPR) and the three-month treasury bill rate (TB3M) are not statistically significant at 5% level in the regression of the idiosyncratic risks measured by the PCA and the portfolio approaches but the three-month treasury rate (TB3M) enters into the regression of idiosyncratic risk measured by the cross-sectional dispersion approach negatively with significance at 5% level. When lagged idiosyncratic volatility is excluded, the regression estimates of Table 8A displays the marginal economic significance of all the economic variables. Again both the credit spread (CSPR) and the CPI inflation rates (CPI) enter each regression with a positive sign at 1% significance level. The term spread (TSPR) is found to be positively significant at the 1% level for the portfolio measure as well as at the 10% level for PCA measure of idiosyncratic risk, but negatively significant at 1% level for the cross-sectional dispersion measure. The three-month treasury rate (TB3M) is statistically significant at 1% level for three different measures of idiosyncratic risk but positive for the PCA and portfolio measures and negative for the cross-sectional dispersion measure. In addition, the high adjusted R-square in Table 8A also shows that the economic variables capture most of variations in aggregate housing idiosyncratic volatility measured by different approaches.

Table 8B checks the significance of only the credit spread (CSPR) and the CPI inflation rates (CPI) with one auto-regression term of idiosyncratic risk being included. Both CSPR and CPI are still statistically significant at 1% level with a positive sign for all three different measures of aggregate housing idiosyncratic volatilities. This findings suggest that economic variables, the credit spread (CSPR) and the CPI inflation rates (CPI) do have strong positive effect on the fluctuations of aggregate housing idiosyncratic risk dynamics.

As previously conjectured, the observed effects of the economic variables on the housing idiosyncratic volatility are consistent with the differences in the propagations of economic shocks across metropolitan areas. The positive signs of the credit spread coefficient in these regressions imply that idiosyncratic volatility is high (low) in periods when the term spread is wide (narrow). Since the credit spread is a proxy of external mortgage financing to the housing investment with narrow credit spreads corresponding to an abundance of credit financing (e.g. Fama and French, 1989, Campbell, et al., 1997), my findings indicate that the aggregate housing idiosyncratic volatility is significantly affected by the external financing and the underlying credit channel of monetary policy transmission to housing market. Due to the importance of mortgage and credit markets to the housing market, the widening of the credit spread, consistent with the tightening conditions in credit markets and more expensive mortgage financing, results not only in the lower return of housing returns but also increase the idiosyncratic volatility in the housing market. This is also consistent with the observation in the historical performance of idiosyncratic volatility in Figure 4. Furthermore, the idiosyncratic is also positively related to the inflation rates (CPI). The idiosyncratic risk tends to be high (low) when the inflation rate is high (low).

Table 9A reports the regression results of economic determinants of systematic risk in housing market. After including the lagged systematic volatility as the regressor, only the credit spread (CSPR) is statistically significant at 5% for both the PCA and the portfolio measures. Without the lagged systematic risk, the marginal economic significance of all the economic variables on the systematic volatility in housing market show that all economic variables are statistically significant at 1% level in the regression of systematic volatility. However the signs of coefficients on CSPR and

CPI are positive while the signs on TSPR and TB3M are negative. The results suggest that the credit spread also has significant and positive effect on the systematic risk. A narrower (wider) credit spread is correlated to the lower (higher) systematic risk in housing market. To the contrary, the systematic risk is negatively related to the term spread. When the term spread is wider (narrower), the systematic risk in housing market is lower (higher). It is worth noting that because the term spread is closely related to shorter-term economic cycle with the term spread being wider in an economic downturn and narrower in an economic expansion, my findings suggest that the idiosyncratic risk dynamics behave counter-cyclically while the systematic risk in housing market behave cyclically.

Table 9B checks the significance of only the credit spread (CSPR) with one auto-regression term of idiosyncratic risk being included. TSPR keeps being statistically significant at 5% level with a positive sign for all three different measures of aggregate housing idiosyncratic volatilities. This result again emphasizes the importance of credit market to the risk dynamics housing market.

7. DOES IDIOSYNCRATIC RISK REALLY MATTER?

I now explore the linkage between the cross-sectional expected housing returns and idiosyncratic volatility. From the theory perspective, the risk and return tradeoff should be contemporaneous. Investors earn returns for bearing the risk in the same period. A conventional practice is to use the realized return as the unbiased estimate of expected returns[11]. However, it is crucial to have a quality estimate of the expected idiosyncratic volatility.

Recently using the portfolio sorting method, Ang et al. (2006, 2008) find a negative relationship between the lagged idiosyncratic risk and the cross-section of expected stock returns. The negative relation is quite puzzling because it suggests that stocks with lower idiosyncratic risk earned higher average returns. Fu (2005) refutes this argument by indicating that the lagged idiosyncratic volatility values can not properly proxy for the expected idiosyncratic volatility. Fu (2005) uses the EGARCH model to estimate the expected idiosyncratic volatility and a positive relation between the

[11] See, for example, Fama and French (1992), Chordia, et al. (2001), Easley, et al. (2002) among others.

expected idiosyncratic volatility and the expected stock returns is still found significant by employing the same portfolio sorting methodology.

The key question here is whether the lagged value is a proper proxy of the expected idiosyncratic volatility. Most of previous studies including both Fu (2005) and Ang et al. (2006, 2008) use the three factor model of Fama and French (1993) to measure the idiosyncratic volatility at firm level. The estimated idiosyncratic volatilities, unlike some firm characteristics, are very volatile and not very persistent over time. More importantly, a growing literature studies since Fu (2005) have demonstrated that the time-series idiosyncratic volatility at firm level by the three-factor model can not be approximated by a random walk process. Hence using the lagged idiosyncratic volatility to proxy the expected value will introduce severe measurement errors. That's why Fu (2005), Brockman and Schutte (2007), Spiegel and Wang (2006) and Eliling (2006) all adopt the sophisticated GARCH models to estimate the expected conditional idiosyncratic volatilities. However, as discussed in Section 5, the time-series idiosyncratic volatility in housing market measured by the model-independent approaches instead of the three-factor model exhibits a highly persistent pattern that does follow a random walk process. Therefore, this paper uses the lagged idiosyncratic volatility as a proxy for the expectation of the current period's idiosyncratic volatility[12].

The procedure of the portfolio sorting methodology is similar to Ang et al. (2006, 2008). In their study, every month stocks are formed into five equal size portfolios according to their corresponding idiosyncratic risk in the previous month; they compared the risk-adjusted returns between the highest risk and lowest risk portfolios and found the return difference is significantly negative. Here based on the monthly idiosyncratic volatility of housing returns at metropolitan level estimated by the PCA model, at the beginning of each month, I sort the expected idiosyncratic volatility to form two portfolios with equal number of metropolitan areas. One portfolio contains five local housing markets that have the lowest idiosyncratic volatilities in the last month and another portfolio consists of five local housing markets that have the highest idiosyncratic volatilities. The portfolios are updated monthly. Table 10 presents the descriptive statistics for these two portfolios. The equally weighted mean

[12] The results are essentially the same if one replaces idiosyncratic volatilities by the fitted values from an ARMA model (see, Schwert, 1989, 1990).

return of portfolio with highest lagged idiosyncratic volatility is 0.436% per month, while the portfolio return for the lowest lagged idiosyncratic volatility is 0.293% per month. So the highest-minus-lowest idiosyncratic risk portfolio which is zero-cost can generate an average annual return 1.72%. Although the return is not significantly high since the transaction costs, etc have not been considered, it is still provide some evidences that the idiosyncratic risk is priced in by the housing market. In addition, for comparison purpose, I also sort the current month idiosyncratic risk to establish high and low idiosyncratic risk housing portfolios. The average monthly return for the high idiosyncratic risk portfolio is 0.434% while the mean return of portfolio with the lowest idiosyncratic risk is only 0.3%. Figure 12 give the total return of these two portfolios for the sample period. The total return for the highest idiosyncratic volatility housing portfolio is much higher (maximum total return is 400%) than the lowest idiosyncratic risk housing portfolio (maximum total return is 250%). My findings reaffirm that it is rewarding to follow a trading strategy of constructing portfolios based on the idiosyncratic volatility of housing market.

8. CONCLUSION

This article investigates the risk dynamics in the U.S housing market and its relationship to the economic fluctuations. First of all, this paper decomposes the total risk into the systematic and the idiosyncratic risks by introducing new approaches for the measuring of risk: (1) the PCA approach which is based on random matrix theory and the procedure of principal component analysis; (2) the portfolio approach which is based on mean-variance portfolio theory and the concept of gain from portfolio diversification; (3) the cross-sectional dispersion of housing returns which is a measure of the heterogeneity in housing market determined by the idiosyncratic risk in the housing market. The measure of systematic/idiosyncratic risk by the PCA approach mainly relies on the estimation of the largest eigenvalue of the covariance return matrix for all local housing markets. The measure of idiosyncratic risk by the portfolio approach is defined as the difference between the variances of the non-diversified and fully diversified housing portfolios. The cross-sectional dispersion of housing returns is to calculate the cross-sectional variance of housing markets. The crucial difference between the new and the existing systematic/idiosyncratic volatility measures is that the new measure does not depend on any parametric specifications of the return generating process such as the CAPM model or three-factor capital asset pricing model.

Second, relying on data over the 1987-2008 sample period, this paper analyzes the time-series properties of risks (systematic and non-systematic). The systematic /idiosyncratic volatility in housing market is found to be time varying and highly persistent as following a random walk process, and more importantly, the fluctuations of idiosyncratic risk in housing market can be explained by the economic variables such as the credit spread and the inflation rate. In addition, the housing idiosyncratic volatility is counter-cyclical, being high (low) in periods when the term spread is wide (narrow), and the idiosyncratic risk is increasing (decreasing) when the credit spread increases (decreases). While the variations of systematic risk are positively related to the credit spread. A narrower (wider) credit spread is correlated to the lower (higher) systematic risk in housing market. However, different to the idiosyncratic risk, the systematic risk in housing market is negatively related to the term spread. When the term spread is wider (narrower), the systematic risk in housing market is lower (higher).

Third, the results show that idiosyncratic risk is positively and significantly priced in the U.S metropolitan housing market. I analyze the return differences of portfolios sorted by idiosyncratic risk using portfolio sorting methods and find that the return of the portfolio with the highest idiosyncratic risk is higher than one with lowest idiosyncratic risk. Since the housing investment is more difficult to be fully-diversified, the results actually support Merton's (1987) proposition that idiosyncratic volatility should be positively related to the cross-section of expected returns if investors demand compensation for imperfect diversification in presence of incomplete information.

This article raises several additional issues. First, this paper analyzes the time variations as well as the economic determinants of risk dynamics in the aggregate housing market. While the economic variables used in this study are the national level, some important local social-economic variables at the MSA level are omitted. Another limit is that the Case & Shiller housing price indexes only cover very limited MSA housing markets. So using disaggregate local economic data and including more metropolitan areas data may further enhance the understanding for the risk dynamic pattern in the housing market.

Another interesting question is regarding the factors that influence housing risk dynamics. While this research actually originates within the asset pricing literature, another tradition derives from the market microstructure literature and looks at the relationship between the liquidity and the risk. I do not consider the liquidity effect in this study. An interesting direct for future research would be to design direct tests to empirically disentangle the roles played by liquidity (e.g. housing transaction volume) and risk (systematic and idiosyncratic) in the housing market.

Finally, the results presented in this article underscore the importance of short-sale constraints in housing market. One overlooked assumption in Merton (1987) is frictionless market, in particular an absence of short-sale constraints. With controlling for short-sale constraint, Miller (1977) and Boehme et al. (2005) show that when short-sale constraint are absent, idiosyncratic risk is positively correlated with future excess returns, a result consistent with Merton (1987); However, when short-sale constraints are present the correlation becomes negative: increased idiosyncratic volatility produce negative abnormal returns. To date there has not been an attempt to empirically examine the relation between risk and the housing return with a special consideration on this short-sale constraint effect. I hope the findings in this article will stimulate future work on this important issue.

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Figure 1 Metropolitan Regions in the S&P/Case-Shiller Home Price Indices

Source: MacroMarkets LLC.

Figure 2 Time-varying Top 3 Eigenvalues of PCA Analysis

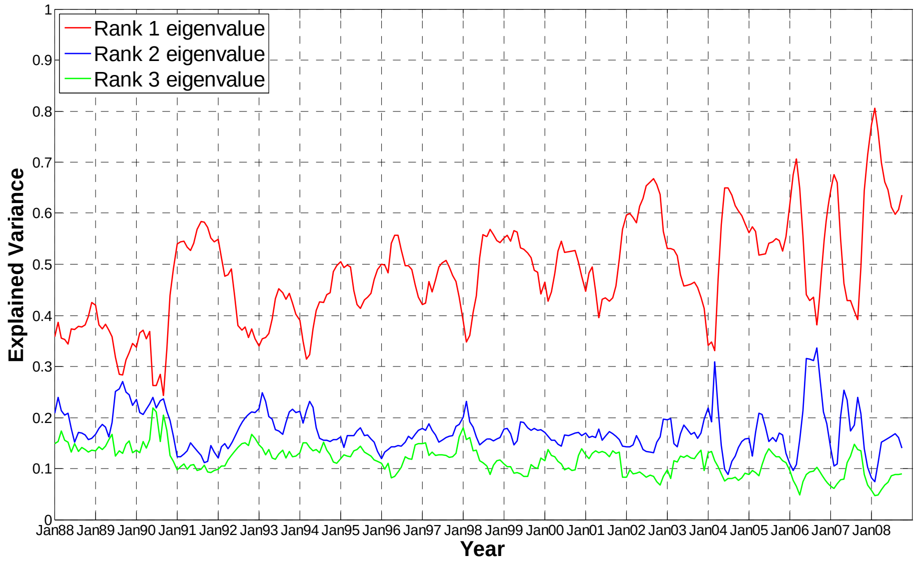

Figure 3 Weights for First Three Eigenvectors
(At the end of the sample period)

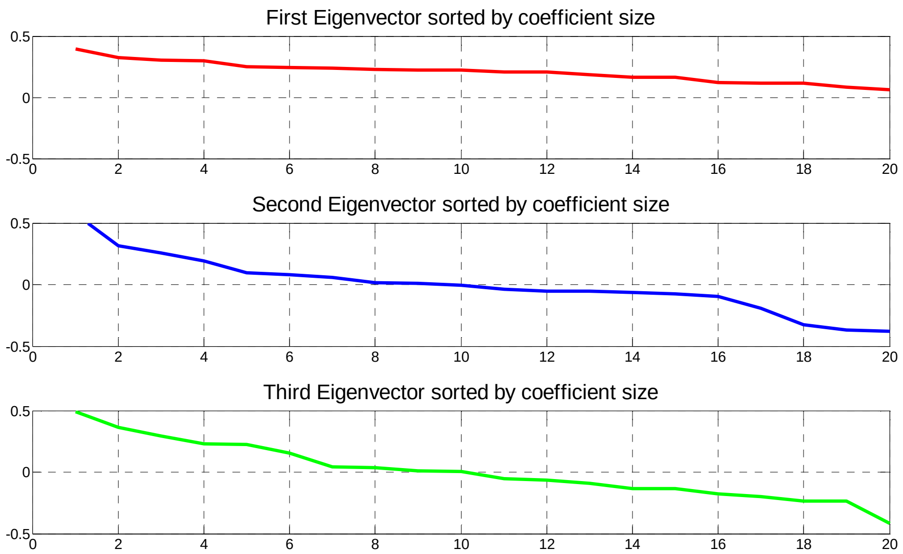

Figure 4 Monthly Idiosyncratic Risk (IR) Dynamics in Housing Market:
PCA, Portfolio, and Cross-Section Measures
(Jan 1988 – Oct 2008)

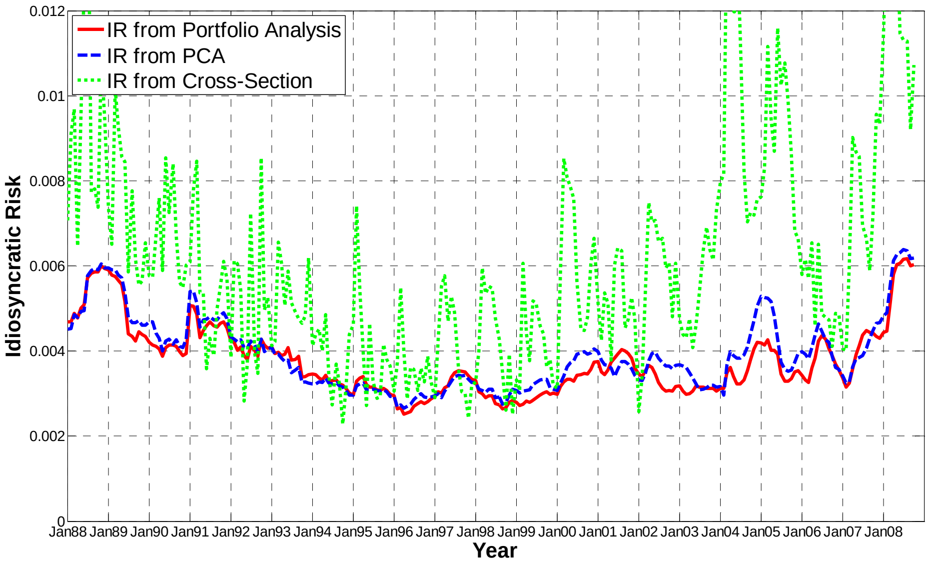

Figure 5 Ratio of Monthly Idiosyncratic Risk to Total Risk in Housing Market:
PCA and Portfolio Measures
(Jan 1988 – Oct 2008)

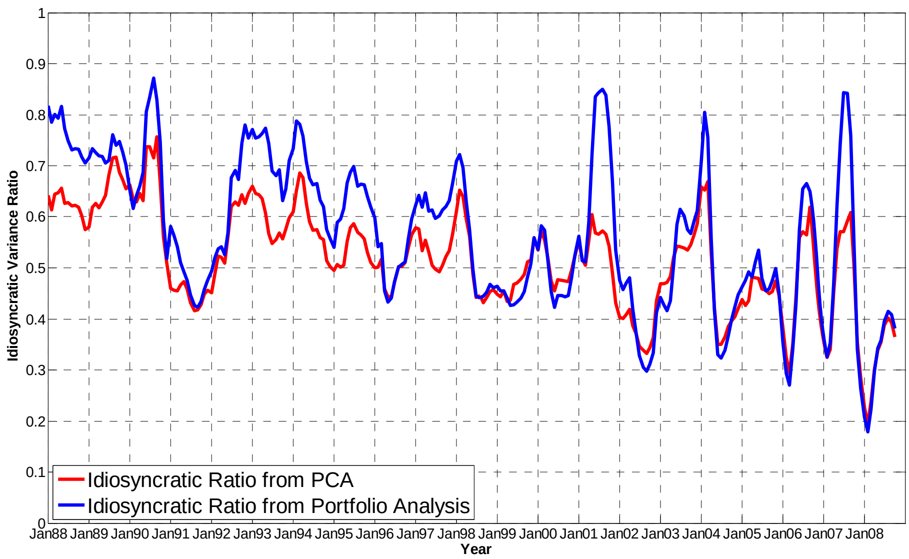

Figure 6 Decomposition of Monthly Total Risk in Housing Market:
PCA Approach
(Jan 1988 – Oct 2008)

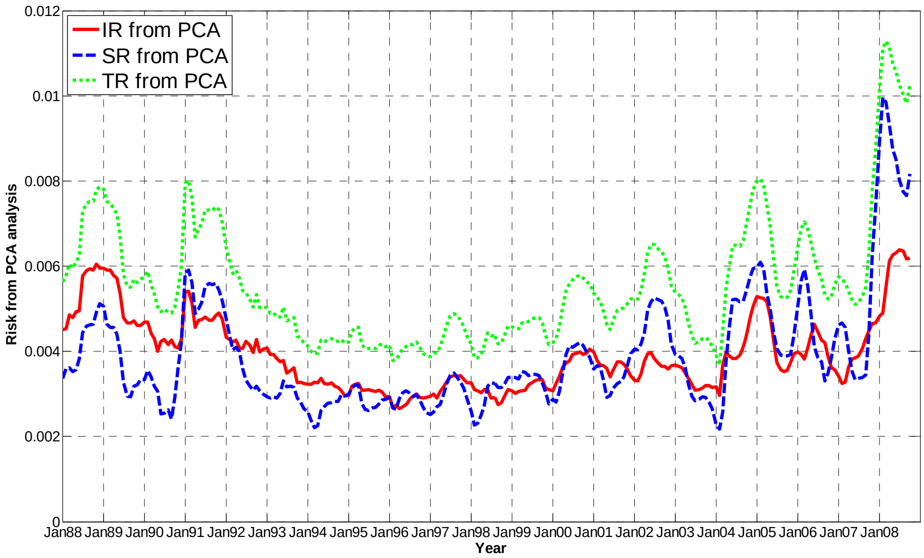

Figure 7 Decomposition of Monthly Total Risk in Housing Market:
Portfolio Approach
(Jan 1988 – Oct 2008)

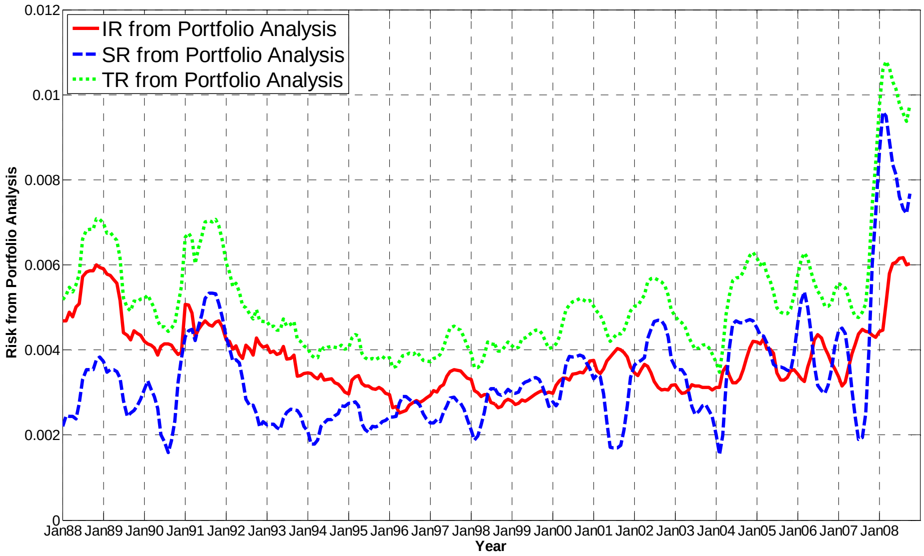

Figure 8 Quarterly Idiosyncratic Risk (IR) Dynamics in Housing Market: PCA, Portfolio and Cross-Section Measures
(Q1 1988- Q3 2008)

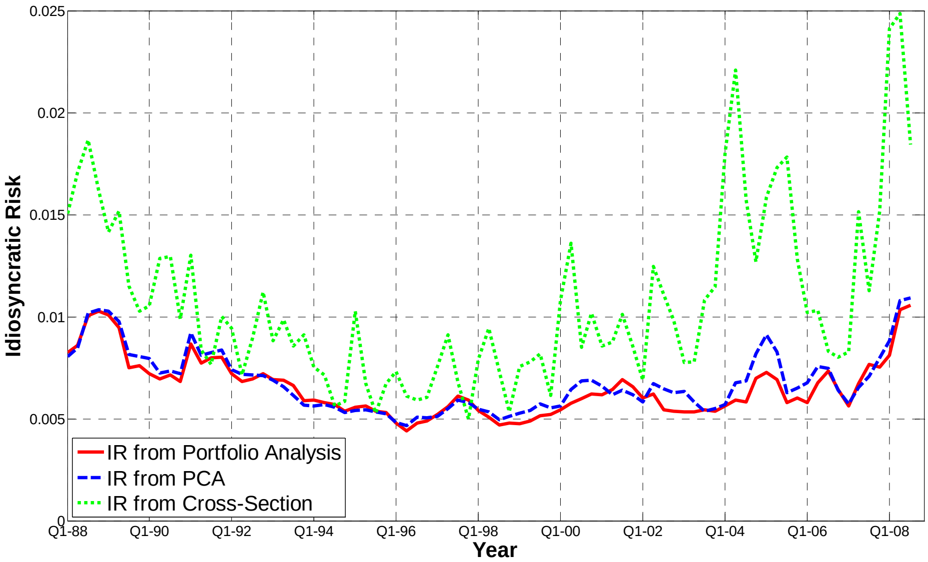

Figure 9 Ratio of Quarterly Idiosyncratic Risk to Total Risk in Housing Market: PCA Measures
(Q1 1988- Q3 2008)

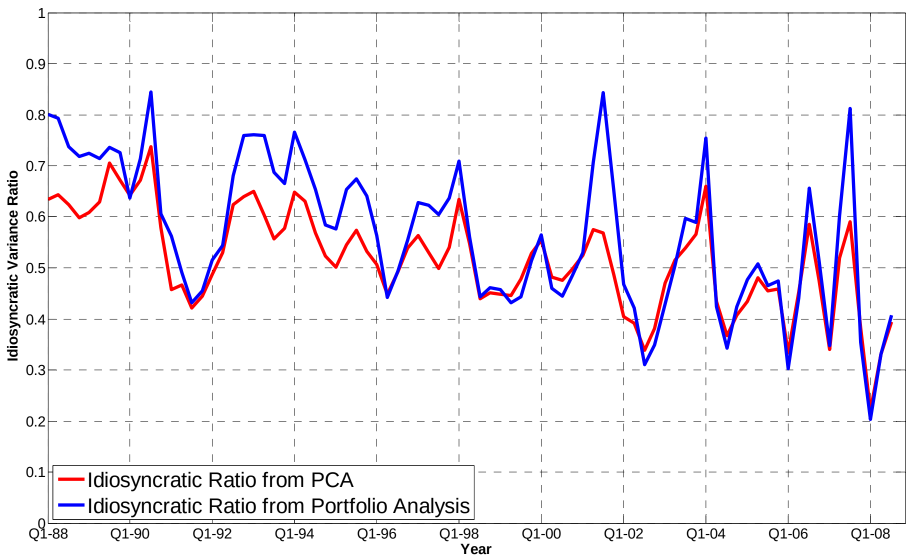

Figure 10 Decomposition of Quarterly Total Risk in Housing Market:
PCA Approach
(Q1 1988- Q3 2008)

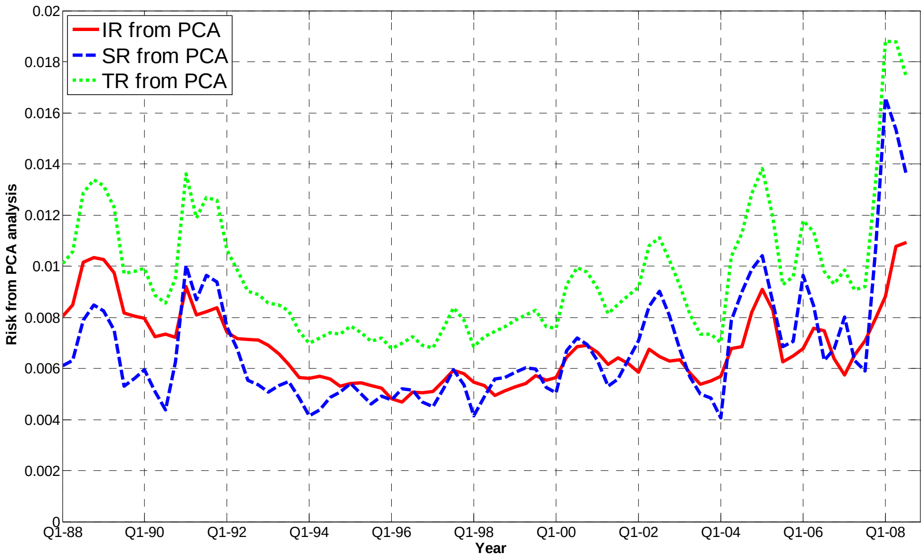

Figure 11 Decomposition of Quarterly Total Risk in Housing Market:
Portfolio Approach
(Q1 1988- Q3 2008)

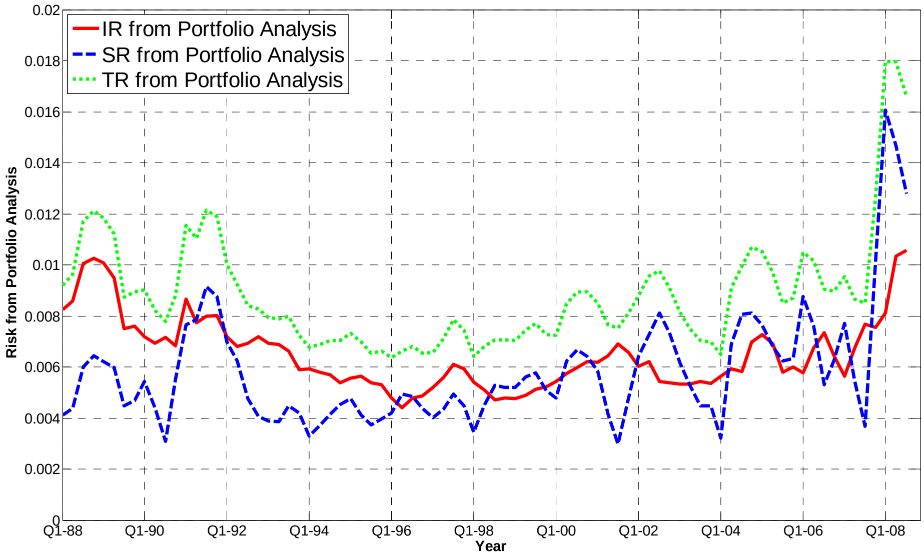

Figure 12 Total Return: Sorting Portfolio based on Idiosyncratic Risk in Housing Market
(Jan 88- Oct 2008)

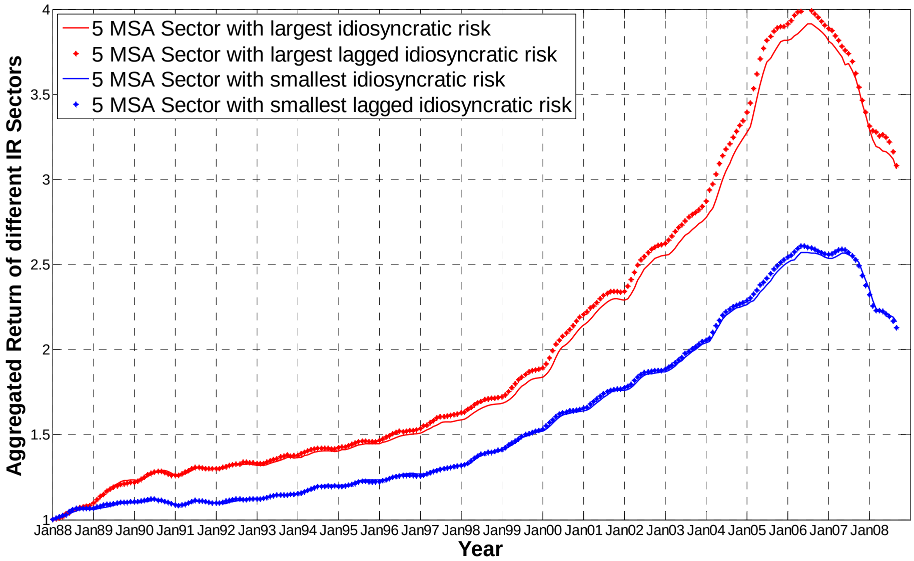

Table 1 S&P/Case-Shiller Home Price Indexes: MSA Coverage

Census Division	MSA	Housing Value* ($mm)	% of U.S	% of Div	Composite 10 weight	Composite 20 weight
New England	Boston	$220,448	2.3%	35.7%	7.4%	5.3%
Middle Atlantic	New York	$826,909	8.5%	62.5%	27.2%	19.4%
East North Central	Chicago	$325,954	3.4%	21.3%	8.9%	6.3%
	Detroit	$189,917	2.0%	12.4%	n/a	4.8%
	Cleveland	$80,009	0.8%	5.2%	n/a	1.7%
West North Central	Minneapolis	$126,237	1.3%	21.8%	n/a	2.8%
South Atlantic	Miami	$154,650	1.6%	9.1%	5.0%	3.6%
	Tampa	$69,455	0.7%	4.1%	n/a	1.5%
	Atlanta	$158,706	1.6%	9.4%	n/a	3.9%
	Charlotte	$49,954	0.5%	3.0%	n/a	1.3%
	Washington,DC	$237,472	2.5%	14.0%	7.8%	5.6%
West South Central	Dallas	$143,355	1.5%	20.5%	n/a	4.0%
Mountain	Phoenix	$117,756	1.2%	17.9%	n/a	2.9%
	Denver	$108,884	1.1%	16.5%	3.7%	2.6%
	Las Vegas	$43,695	0.5%	6.6%	1.5%	1.1%
Pacific	Los Angeles	$549,808	5.7%	25.7%	21.2%	15.1%
	San Diego	$136,719	1.4%	6.4%	5.5%	3.9%
	San Francisco	$320,763	3.3%	15.0%	11.8%	8.4%
	Portland	$88,465	0.9%	4.1%	n/a	1.9%
	Seattle	$165,144	1.7%	7.7%	n/a	3.9%
Composite 20 Index		$4,114,301	42.50%			
Composite 10 Index		$2,925,302	30.20%			

* Aggregate Value for all Owner-Occupied Housing Units, 2000 Census

Table 2 Summary Statistics of Monthly S&P/Case-Shiller Home Price Indexes (Jan 1987-Oct 2008)

MSA	Mean	Max	Min	SD	P_1	P_2	P_3	P_4	P_5	P_6	Q(6)	JB
Atlanta	0.07%	1.24%	-2.67%	0.51%	0.634	0.083	-0.335	0.315	-0.084	0.133	74.27	439.67
Boston	0.08%	2.53%	-2.37%	0.86%	0.896	0.010	-0.374	0.215	0.032	-0.030	318.83	0.20
Charlotte - NC	0.03%	1.56%	-1.57%	0.49%	0.395	0.058	-0.365	0.192	0.011	-0.057	31.73	10.78
Chicago	0.17%	2.29%	-3.09%	0.72%	0.723	-0.021	-0.299	0.253	0.057	-0.030	97.46	28.21
Cleveland - OH	0.02%	1.47%	-4.09%	0.64%	0.557	0.242	-0.418	0.198	0.087	-0.111	35.54	699.70
Dallas - TX	-0.06%	1.21%	-2.69%	0.67%	0.492	0.069	-0.177	0.185	-0.185	0.113	24.77	29.58
Denver	0.12%	1.99%	-2.61%	0.68%	0.908	-0.053	-0.309	0.289	-0.235	0.184	59.42	20.89
Detroit - MI	0.04%	2.12%	-3.92%	0.80%	0.792	-0.146	-0.008	0.094	0.109	0.006	42.84	53.42
Las Vegas	0.15%	5.55%	-6.08%	1.16%	0.969	0.052	-0.017	-0.042	-0.087	0.069	92.25	60.32
Los Angeles	0.27%	3.36%	-4.61%	1.16%	0.899	0.141	-0.267	0.132	-0.030	0.056	616.09	26.72
Miami	0.22%	2.69%	-3.60%	0.94%	0.588	0.289	-0.357	0.316	0.188	-0.067	609.24	59.36
Minneapolis - MN	0.14%	2.04%	-3.87%	0.75%	0.683	0.102	-0.244	0.171	0.072	-0.022	134.98	86.59
New York	0.14%	2.12%	-1.94%	0.79%	0.889	-0.084	-0.143	0.161	0.014	0.034	81.48	0.99
Phoenix	0.18%	4.72%	-4.98%	1.03%	0.836	0.236	-0.227	0.196	-0.068	-0.012	602.92	475.01
Portland - OR	0.33%	2.69%	-2.87%	0.67%	0.486	0.262	-0.300	0.146	0.112	-0.067	108.71	57.11
San Diego	0.25%	4.75%	-4.07%	1.11%	0.631	0.193	-0.104	0.195	-0.050	0.027	507.41	38.06
San Francisco	0.29%	4.00%	-3.88%	1.11%	1.072	-0.167	-0.240	0.185	0.006	0.011	374.07	19.14
Seattle - WA	0.29%	4.24%	-2.62%	0.82%	0.786	0.134	-0.343	0.225	-0.102	-0.035	166.38	98.33
Tampa	0.11%	2.92%	-3.62%	0.85%	0.486	0.177	-0.258	0.364	0.232	-0.055	456.81	24.93
Washington	0.22%	2.83%	-3.41%	0.89%	0.825	0.032	-0.182	0.149	0.058	0.027	515.48	10.69
Composite10	0.20%	1.95%	-3.19%	0.79%	1.043	-0.203	-0.064	0.110	-0.076	0.133	118.85	125.26
Composite20	0.38%	1.73%	-3.22%	0.90%	0.946	-0.195	0.034	0.133	-0.091	0.135	37.70	61.28

Note: $Mean$, Max, Min and SD are the sample mean, maximum, minimum, and standard deviation of the variable. P_t is the sample autocorrelation at lag t and $Q(6)$ is the Ljung-Box (1978) portmanteau test statistic for 6 autocorrelations, distributed chi-squared with 6 degrees of freedom, and JB is the Jarque-Bera (1987) test for non-normality based on the skewness and kurtosis of a distribution. If the distribution is normal, *JB* has an asymptotic chi-square with 2 degrees of freedom. All returns are taken into ln base. The real monthly housing index returns are created by deducting inflation provided by the Bureau of Labor Statistics monthly inflation series from the nominal ones.

Table 3 Descriptive Statistics of Macroeconomic Variables in the Sample

	Period: Dec 1989 to Jun 2008			
	TSPR	CSPR	TB3M	INF
Panel A: Descriptive Statistics				
Mean	1.28%	0.85%	4.06%	0.74%
Median	0.97%	0.83%	4.50%	0.72%
Standard Deviation	1.08%	0.22%	1.72%	0.60%
Minimum	-0.41%	0.55%	0.88%	-1.18%
Maximum	3.29%	1.42%	7.90%	2.48%
Skewness	0.2892	0.8805	-0.1725	0.2331
Kurtosis	1.7619	3.0849	2.4695	4.1453
AR(1)	0.996	0.998	0.992	0.902
Panel B: Correlation Matrix				
TSPR	1	0.2986	-0.6872	-0.042
CSPR		1	-0.3335	0.1108
TB3M			1	0.145
INF				1

Note: The table repots descriptive statistics of economic variables. The economic variables are defined as follows: *TSPR* is the difference between the yield on 10-year and 1-year Treasuries, *CSPR* is the difference between the yields on BAA- and AAA-rated corporate bonds, *INF* is inflation computed as the growth of the CPI index and *TB3M* is the 3-month Treasury bill rate. All variables are measured on a month basis. Panel A reports the mean, the standard deviation (denoted by Std), the *AR(1)* coefficient, the coefficients of skewness (*Skew*) and kurtosis (*Kurt*), the minimum (*Min*) and maximum (*Max*) value in the sample. Panel B shows the correlation matrix. The sample is 261 monthly observations from 1987:01 to 2008:10.

Table 4 Descriptive Statistics of Idiosyncratic Volatility in Housing Market

IR	Mean	Median	StdDev	Min	Max	Skew	Kurt	AR1	AR1:12
Cross-section	0.0061	0.0055	0.0027	0.0023	0.0173	1.3295	5.0509	0.9741	0.9899
PCA	0.0039	0.0037	0.0009	0.0027	0.0064	0.9754	3.3339	0.9989	0.9985
Portfolio	0.0038	0.0035	0.0008	0.0025	0.0062	1.0994	3.8151	0.9989	-0.9993

Note: This table presents descriptive statistics on returns and measures of idiosyncratic volatility in housing market. The sample period is Jan 1988 to Oct 2008 (249 monthly observations). The variable "*IR*" represents the idiosyncratic risks under different measure approaches. Cross-section approach, PCA approach and portfolio approach, respectively. "*Skew*" is the skewness, "*Kurt*" is the kurtosis, "*AR1*" is the first-order autocorrelation, and "*AR1:12*" is the sum of the first 12 autocorrelation coefficients.

Table 5 Do Monthly Idiosyncratic Volatilities Follow a Random Walk Process?
(Unit Root Test and Stationary Test for Idiosyncratic Volatility)

Idiosyncratic Risk	ADF Test t-statistics			KPSS Test		
	Levels	Trends	First Difference	Levels	Trends	First Difference
Cross-section	-1.5480(7)	-2.1040(7)	-9.8068**(6)	0.7140*(7)	0.4714**(7)	-9.9823(6)
PCA	-1.8960(1)	-1.7043(1)	-11.3938**(0)	2.1358**(1)	2.0287**(1)	0.2595(1)
Portfolio	-1.7228(1)	-1.3642(1)	-12.3315** (0)	2.4959**(1)	2.0154**(1)	0.3235(1)

Note: **indicate the statistical test is significant at 1% level. * indicate the statistical test is significant at 5% level. This table presents the results of unit root test for the idiosyncratic volatility measured by three different approaches: cross-sectional variance approach (Goyal and Santa-Clara,2003), PCA approaches, and Portfolio approach, respectively. The number in brackets means the optimal lag lengths for the ADF test and KPSS test based on the Akaike's Information Criterion (AIC).

(1) ADF Test is based on the model: $\Delta y_t = \Phi y_{t-1} + \sum_{j=1}^{p-1} \alpha_j^* \Delta y_{t-j} + u_t$, in the model the pair of hypotheses $H_0 : \Phi = 0$ versus $H_1 : \Phi < 0$ is tested based on the t-statistics of the coefficient Φ. H_0 is rejected if the t-statistics is smaller than the relevant critical value*. If $\Phi = 0$ (that is, under H_0) the series has a unit root and is non-stationary.

(2) KPSS test the hypothesis that $H_0 : y_t \sim I(0)$ versus $H_1 : y_t \sim I(1)$, the null hypothesis of stationary is rejected for larger values of KPSS than critical values.

* Dicker-Fuller and KPSS Test Critical Value

		1%	5%	10%
ADF	Level Test	-3.43	-2.86	-2.57
	Time Trend Test	-3.96	-3.41	-3.13
KPSS	Level Test	0.739	0.463	0.347
	Time Trend Test	0.216	0.146	0.119

Table 6 Descriptive Statistics of Systematic Volatility in Housing Market

SR	Mean	Median	StdDev	Min	Max	Skew	Kurt	AR1	AR1:12
PCA	0.0039	0.0034	0.0014	0.0022	0.01	1.8973	7.3827	0.9965	0.9973
Portfolio	0.0034	0.0030	0.0014	0.0015	0.0096	2.0506	8.4581	0.9953	0.9976

Note: This table presents descriptive statistics on returns and measures of systematic volatility in housing market. The sample period is Jan 1988 to Oct 2008 (249 monthly observations). The variable "*SR*" represents the systematic risks under different measure approaches. PCA approach and portfolio approach, respectively. "*Skew*" is the skewness, "*Kurt*" is the kurtosis, "*AR1*" is the first-order autocorrelation, and "*AR1:12*" is the sum of the first 12 autocorrelation coefficients.

Table 7 Do Monthly Systematic Volatilities Follow a Random Walk Process?
(Unit Root Test and Stationary Test for Systematic Volatility)

Idiosyncratic Risk	ADF Test t-statistics			KPSS Test		
	Levels	Trends	First Difference	Levels	Trends	First Difference
PCA	-2.3210(3)	-2.9168(3)	-8.1114**(2)	1.4103**(3)	0.5847**(5)	0.0972(2)
Portfolio	-1.1038(5)	-1.9111(5)	-8.5034**(4)	1.0600**(5)	0.3314**(5)	0.0630(4)

Note: **indicate the statistical test is significant at 1% level. * indicate the statistical test is significant at 5% level. This table presents the results of unit root test for the systematic volatility measured by two different approaches: PCA approaches, and Portfolio approach, respectively. The number in brackets means the optimal lag lengths for the ADF test and KPSS test based on the Akaike's Information Criterion (AIC).

(1) ADF Test is based on the model: $\Delta y_t = \Phi y_{t-1} + \sum_{j=1}^{p-1} \alpha_j^* \Delta y_{t-j} + u_t$, in the model the pair of hypotheses $H_0 : \Phi = 0$ versus $H_1 : \Phi < 0$ is tested based on the t-statistics of the coefficient Φ. H_0 is rejected if the t-statistics is smaller than the relevant critical value*. If $\Phi = 0$ (that is, under H_0) the series has a unit root and is non-stationary.

(2) KPSS test the hypothesis that $H_0 : y_t \sim I(0)$ versus $H_1 : y_t \sim I(1)$, the null hypothesis of stationary is rejected for larger values of KPSS than critical values.

* Dicker-Fuller and KPSS Test Critical Value

		1%	5%	10%
ADF	Level Test	-3.43	-2.86	-2.57
	Time Trend Test	-3.96	-3.41	-3.13
KPSS	Level Test	0.739	0.463	0.347
	Time Trend Test	0.216	0.146	0.119

Table 8A Economic Determinants of Idiosyncratic Volatility in Housing Market

Idiosyncratic	PCA		Portfolio		Cross-sectional	
Risk	(1)	(2)	(1)	(2)	(1)	(2)
Constant	0.001	0.000	0.001	0.000	0.003	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
TSPR	0.010	-0.001	0.019	-0.001	-0.048	-0.016
	(0.006)*	(0.002)	(0.005)***	(0.002)	(0.018)***	(0.012)
CSPR	0.202	0.015	0.183	0.014	0.424	0.109
	(0.018)***	(0.006)**	(0.017)***	(0.006)**	(0.056) ***	(0.042)***
TB3M	0.015	-0.001	0.021	-0.001	-0.040	-0.015
	(0.003)***	(0.001)	(0.003)***	(0.001)	(0.010)***	(0.007)**
CPI	0.033	0.007	0.023	0.008	0.189	0.061
	(0.007)***	(0.002)***	(0.007)***	(0.002)***	(0.023)***	(0.017)***
LAG	--	0.954	--	0.956	--	0.731
		(0.018)***		(0.018)***		(0.042)***
R^2_{adj}	0.4251	0.9549	0.4244	0.9525	0.3666	0.7169

Note: This table reports the results from the regression by model-independent measures of idiosyncratic volatility at time t on economic variables at time t with and without lagged idiosyncratic volatility at time *t-1*for the PCA approach, the portfolio approach and average variance approach, respectively. The economic variables are defined as in Section 3, and LAG is the time *t-1* idiosyncratic volatility. The standard deviation values are in parentheses. Significance at 90%, 95% and 99% level is denoted with one, two and three asterisks, respectively. The R^2_{adj} is goodness of fit measure. The sample is 249 monthly observations from 1988:01 to 2008:10.

Table 8B Economic Determinants of Idiosyncratic Volatility in Housing Market

Idiosyncratic Risk	PCA	Portfolio	Cross-sectional
Constant	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
CSPR	0.007	0.007	0.112
	(0.002)***	(0.002)***	(0.040)***
CPI	0.016	0.015	0.050
	(0.006) ***	(0.005)***	(0.016)***
LAG 1	0.950	0.951	0.751
	(0.017)***	(0.016)***	(0.041)***
R^2_{adj}	0.9548	0.9528	0.7138

Note: This table reports the results from the regression by model-independent measures of idiosyncratic volatility at time t on economic variables at time t with and without lagged idiosyncratic volatility at time $t-1$ for the PCA approach, the portfolio approach and average variance approach, respectively. The economic variables are only CSPR and CPI as defined in Section 3, and LAG (1) is the time *t-1* idiosyncratic volatility. The standard deviation values are in parentheses. Significance at 10%, 5% and 1% level is denoted with one, two and three asterisks, respectively. The R^2_{adj} is goodness of fit measure. The sample is 249 monthly observations from 1988:01 to 2008:10.

Table 9A Economic Determinants of Systematic Volatility in Housing Market

Systematic Risk	PCA (1)	PCA (2)	Portfolio (1)	Portfolio (2)
Constant	0.002	0.000	0.002	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
TSPR	-0.039	-0.003	-0.030	-0.004
	(0.009)***	(0.003)	(0.005)***	(0.003)
CSPR	0.317	0.028	0.302	0.028
	(0.028)***	(0.011)**	(0.027)***	(0.011)**
TB3M	-0.026	-0.001	-0.045	-0.001
	(0.005)***	(0.002)	(0.009)***	(0.002)
CPI	0.047	-0.005	0.047	-0.006
	(0.011)***	(0.004)	(0.011)***	(0.004)
LAG	---	0.960	---	0.959
		(0.022)***		(0.022)***
R^2_{adj}	0.4310	0.9378	0.4336	0.9349

Note: This table reports the results from the regression by model-independent measures of systematci volatility at time t on economic variables at time t with and without lagged systematic volatility at time $t-1$ for the PCA approach and the portfolio approach, respectively. The economic variables are defined as in Section 3, and LAG is the time $t-1$ systematic volatility. The standard deviation values are in parentheses. Significance at 90%, 95% and 99% level is denoted with one, two and three asterisks, respectively. The R^2_{adj} goodness of fit measure. The sample is 249 monthly observations from 1988:01 to 2008:10.

Table 9B Economic Determinants of Systematic Volatility in Housing Market

Systematic Risk	PCA	Portfolio
Constant	0.000	0.000
	(0.000)	(0.000)
CSPR	0.027	0.026
	(0.011)**	(0.011)**
LAG 1	0.959	0.958
	(0.022)***	(0.020)***
R^2_{adj}	0.9377	0.9344

Note: This table reports the results from the regression by model-independent measures of systematic volatility at time t on economic variables at time t with and without lagged idiosyncratic volatility at time $t-1$ for the PCA approach, the portfolio approach and average variance approach, respectively. The economic variables are only CSPR as defined in Section 3, and LAG (k) is the time $t-k$ idiosyncratic volatility. The standard deviation values are in parentheses. Significance at 10%, 5% and 1% level is denoted with one, two and three asterisks, respectively. The R^2_{adj} goodness of fit measure. The sample is 249 monthly observations from 1988:01 to 2008:10.

Table 10 Summary Statistics for Monthly Returns of Portfolios Formed on the Conditional Idiosyncratic Volatility

Port. Return	Mean	Median	StdDev	Min	Max	Skew	Kurt
High Lagged IR	0.00436	0.00456	0.00769	-0.0254	0.0245	-0.6379	5.5513
Low Lagged IR	0.00293	0.00327	0.00608	-0.0269	0.0191	-1.4805	8.7324
High IR	0.00434	0.00457	0.00757	-0.0251	0.0247	-0.4774	5.0810
Low IR	0.00300	0.00302	0.00573	-0.0275	0.0173	-1.5849	9.4354

Note: At the beginning of each month two portfolios are sorted based on the conditional idiosyncratic risk estimated using the PCA model, which equals to the idiosyncratic volatility for the last month/current month. The first portfolio (Low) consists of the five metropolitans with the lowest idiosyncratic volatility and the second portfolio (High) consists of the five metropolitans with the highest idiosyncratic risk. Portfolios are updated monthly. The "*Port. Return*" represents the equally weighted portfolio (monthly) return. The "*High Lagged IR*" and "Low Lagged IR" means the portfolios are sorted on the lagged highest and lowest idiosyncratic risk respectively. The "*High IR*" and "*Low IR*" mean the portfolios are sorted on current month highest and lowest idiosyncratic risk respectively. The sample is 249 monthly observations from 1988:01 to 2008:10.