Geographic Dependence and Diversification in House Price Returns: the Role of Leverage*

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Abstract

We analyze time variation in the average dependence within a set of regional monthly house price index returns in a regime switching multivariate copula model with a high and a low dependence regime. Using equidependent Gaussian copulas, we show that the dependence of house price returns varies across time, which reduces the gains from the geographic diversification of real estate and mortgage portfolios. More specifically, we show that a decrease in leverage, and to a lesser extent an increase in mortgage rates, is associated with a higher probability of moving to and staying in the high dependence regime.

Keywords: Time-varying dependence, copula, regime switching, diversification, mortgage, loan to value.
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1 Introduction

The collective collapse of house prices in the U.S. and the ensuing wave of mortgage defaults was at the center of the recent financial crisis. Securitized pools of subprime mortgages originated all over the U.S. and derivatives written on them were instrumental in the propagation of the crisis from a local to a global scale (see e.g. Brunnermeier 2009). The payoffs of such mortgage backed securities (MBSs) depend not only on the level of local house prices but also on their comovements. More specifically, house price returns are the main determinant of the decision to default,[1] and high levels of dependence in house price returns increase the probability of collective defaults, which in turn makes MBSs more risky. To limit risks, geographic diversification has been the fundamental tool in the construction of real estate portfolios by commercial banks, mortgage insurers, including the housing government sponsored enterprises (GSEs), and real estate investment trusts (REITs). This strategy has been followed also in the construction of pools of mortgages for the purpose of securitization, both on the prime and subprime segments. While such a strategy is based on the expectation that geographic dependence remains low, we find that in the period of strong deleveraging leading up to the subprime crisis it started increasing, causing the failure of geographic diversification. This gave rise to what Thakor (2015) refers to as a "diversification fallacy", whereby real estate investors overestimated the extent to which their portfolios were diversified.

In this paper, we provide evidence of time-variation in the average dependence among regional monthly house price returns, which measures the risk of a broadly held real estate portfolio. We show that there are two variables that exacerbate this risk, increases in mortgages rates, and especially decreases in leverage, whose effect on dependence is quantitatively much more important than that of mortgage rates. To that effect, we introduce a multivariate hidden Markov copula model, with a high and a low dependence regimes, and we allow the Markov transition probabilities to vary with changes

[1]Kau, Keenan, Muller III & Epperson (1992) propose a structural approach to default, based on option theory, where the house price plays the role of the underlying asset, whereas e.g. Schwartz & Torous (1993), Deng, Quigley & Van Order (1996) and Deng, Quigley & Van Order (2000) advocate a reduced form approach, and analyze the effect of house prices on the decision to default using hazard models.

in mortgage rates and leverage, measured by the loan to value ratio (LTV). We rely on equidependent Gaussian copulas to capture the average dependence within a large cross-section of Metropolitan Statistical Areas (MSAs), which is representative of the universe available to real estate investors. Our results provide evidence of a link between leverage and the risk of real estate portfolios, as measured by the geographic dependence among regional house price returns. We find that geographic dependence in regional house price returns oscillates between a low dependence regime with a copula equicorrelation coefficient of 11% and a 1% Value-at-Risk (VaR) of -1.7%, and a high dependence regime with an equicorrelation of 38% and a 1% VaR of -2.4%. Moreover, this dependence is particularly high during periods of deleveraging and increasing mortgage rates, which was the case in the period leading up to the crisis, with increasing mortgage rates from 2002 to 2006, and strong deleveraging starting in 2007. This shows that for a real estate investor, the benefits of geographic diversification disappear precisely in those times when they are most needed, which renders the strategy of geographic diversification ineffective. Our results about diversification are in line with those of Cotter, Gabriel & Roll (2015), who show that the extent to which local house price returns depend on aggregate factors varies over time.

Finally, we focus on a smaller set of four Southwestern MSAs in California and Nevada, two states that were particularly hard hit during the last financial crisis, and we show that decreases in leverage are associated not only with a high dependence regime, but also with asymmetry and tail dependence.[2] This asymmetric high dependence regime with tail dependence is particularly harmful for investors. First, asymmetric dependence, which refers to the fact that price decreases tend to be more dependent than price increases, exacerbates the downside risk in the portfolios of real estate investors. Moreover, tail dependence, which refers to the fact that this dependence is present for arbitrarily extreme events far out in the tails of the returns distribution, implies that even large price falls in different MSAs cannot be diversified away. Our findings are based on the multivariate Gaussian and canonical vine regime switching copula model of Chollete, Heinen

[2]Zimmer (2012) also finds evidence of asymmetry and tail dependence in an analysis of house price returns with bivariate and static copulas.

& Valdesogo (2009), where the canonical vine regime can accommodate asymmetric dependence, as well as tail dependence, which are commonly found in asset returns (for an application of canonical vines to house price returns, see Zimmer 2015*a*).

There is a large literature that discusses the link between our two main variables, mortgage rates and leverage ratios, and house prices and their returns. In the traditional user cost model of house prices of Poterba (1984), which assumes perfect capital markets, house prices depend on credit market conditions only through interest rates, see e.g. Himmelberg, Mayer & Sinai (2005), who find that house prices are particularly sensitive to interest rates, when interest rates are low. As real estate property is often purchased on credit, beyond the level of interest rates, house prices also vary with leverage or collateral rates. For instance, Stein (1995) develops a theoretical model with down payments, whose empirical prediction that house prices react more to economic shocks in highly leveraged cities is confirmed by Lamont & Stein (1999) in a cross-section of house prices and Benito (2006) in a time series of house price returns. Whereas Glaeser, Gottlieb & Gyourko (2013) find little support for the effect of easy credit either in the form of low interest rates or high leverage on house prices, Duca, Muellbauer & Murphy (2011) and Duca, Muellbauer & Murphy (2013) find that changes in credit standards that affect the loan to value (LTV) of first time home buyers are crucial determinants in explaining the boom and bust of the U.S. housing market. In particular they find that house prices and LTV form a stable long-term cointegrating relationship. Finally, Anundsen (2015) finds that, when LTV is not taken into account, the U.S. housing market shifts from a stable regime where prices are determined by fundamentals to a highly unstable regime. This suggests that there are regime shifts in the housing market that are related to LTV.

Our finding of an effect of leverage on the dependence in house price returns is consistent with the recent but fast-growing theoretical literature on the leverage cycle (for a model where interest and collateral rates are determined jointly, see e.g. Geanakoplos 1997, Fostel & Geanakoplos 2015). This literature emphasizes the impact of leverage on asset prices. For instance, in Geanakoplos (2010*a*), leverage fuels house price increases because it gives more optimistic buyers access to the market. In this model even a small bad news shock at the height of the leverage cycle can lead to a devastating deleveraging spiral, where optimistic investors either suffer losses or lose the ability to borrow and eventually withdraw from the market. This decreases the proportion of optimistic market participants with high expectations of future house prices and leads to a vicious circle of decreasing leverage and prices (see also Geanakoplos 2010*b*, Fostel & Geanakoplos 2013).[3] Our results capture this sort of non-linear dynamic interplay between leverage and regional house prices.

Our paper relates more generally to the literature about funding liquidity, which shows how a reduction in funding liquidity can increase dependence between asset prices. Funding liquidity refers to the ease with which financial intermediaries obtain the capital they need to purchase assets. When funding liquidity is abundant, capital can be borrowed with a small margin or haircut, and thus leverage, or LTV in the real estate context, is high. Brunnermeier & Pedersen (2009) provide a theoretical model of margin calls, in which a decrease in funding liquidity leads to comovements across assets, since changes in funding conditions affect speculators' market liquidity provision of all assets. In the same vein, Fostel & Geanakoplos (2008) build a pricing theory for emerging asset classes and show how bad news causes price comovement through leverage cycle in equilibrium. In a different context, Acharya, Schaefer & Zhang (2015) uses credit-default swap (CDS) data during the period around the downgrade of GM and Ford to show that when financial intermediaries with funding constraints are hit by an adverse liquidity shock on a given asset, this can also affect other assets for which they are providers of liquidity. Finally, Dudley & Nimalendran (2011) use dynamic copula models to analyze how the dependence and the risk of contagion between pairs of hedge fund style indices increase when funding liquidity dries up and futures margins increase.

Whereas there is little empirical evidence about time variation in the dependence between the returns of a large set of regional house price indices, there is a well-established

[3]Whereas, in this paper, we focus exclusively on borrower leverage, Fostel & Geanakoplos (2014) note that there is a "double leverage cycle", where the leverage of homeowners and that of the financial institutions that lend to them feed off each other. Goel, Song & Thakor (2014) provide a model in which more levered banks are less able to absorb a negative shock, leading them to restrict credit supply to mortgage borrowers. In turn, this leads to less borrowing and another round of house price decreases.

literature on time-varying dependence between returns of financial assets. Longin & Solnik (1995) use the constant conditional correlation (CCC) model of Bollerslev (1990) and provide evidence that correlations between stock markets are not constant, tend to increase over time, and vary with dividends and interest rates. Engle (2002) introduces the dynamic conditional correlations (DCC), which makes correlations among stock returns time-varying (for an application of the DCC to pairs of MSA house price index returns, see Zimmer 2015*b*). Since Hamilton (1989), Gaussian regime switching models have been widely used in economics and finance (see e.g Ang & Bekaert 2002*a*, Ang & Bekaert 2002*b*, Guidolin & Timmermann 2006*a*, Guidolin & Timmermann 2006*b*, Guidolin & Timmermann 2008). They have also been used to model dependence; see e.g. Pelletier (2006), who uses marginal GARCH models with regime switching correlations in a Gaussian framework. Another strand of the literature uses copulas to model time-variation in dependence (see e.g. Patton 2006*a*, Patton 2006*b*). Finally, there is a literature combining copulas and regime switching (in the context of bivariate copulas, see e.g. Rodriguez 2007, Okimoto 2008). Our econometric innovation in this paper is that we introduce a regime switching multivariate equidependent Gaussian copula model, and that we use time-varying transition probabilities in the Markov chain. Besides, we also use the multivariate regime switching canonical vine copula of Chollete et al. (2009).

The remainder of this paper is organized as follows. Section 2 introduces the econometric methodology, Section 3 describes the data and discusses the results, and Section 4 concludes.

2 The Model

In this section, we first provide a brief account of copula theory. We then present the marginal AR-GARCH model we fit to each regional house price return. We introduce the equidependent copulas that we use to capture the dependence structure among house price returns. We also discuss the canonical vine copula which delivers a flexible model of the dependence structure among regional house price returns. Finally, we discuss fixed and time-varying transition probability (FTP and TVTP) versions of the Markov regime switching copula model that we estimate.

2.1 Copulas

Copulas are a convenient tool to separate the dependence between variables from their marginal distributions in non-Gaussian contexts. They have become a standard tool in finance, to capture the dependence among financial asset returns, as well as in the context of credit risk analysis (see Embrechts, McNeil & Straumann 2001, Embrechts, Klüppelberg & Mikosch 1997). The use of copulas relies on the Sklar (1959) theorem, which states that a joint cumulative distribution function (CDF) F of n variables $(Y_1, \cdots, Y_n)$, where, in our context, Y_i denotes house price returns in MSA i, can be written in terms of a copula function C with dependence parameter θ, whose arguments are the n marginal distribution functions F_i of house price returns in MSAs $i = 1, \cdots, n$:

$$F(y_1, \cdots, y_n) = C(F_1(y_1), \cdots, F_n(y_n); \theta). \tag{1}$$

The joint probability density function (PDF), f obtains by differentiation, and can be written as a product of the marginal house price return distributions and of a copula density term, which captures all the dependence between them:

$$f(y_1, \cdots, y_n) = \prod_{i=1}^{n} f_i(y_i) c(F_1(y_1), \cdots, F_n(y_n); \theta), \tag{2}$$

where $c(F_1(y_1), \cdots, F_n(y_n); \theta) = \frac{\partial C(F_1(y_1), \cdots, F_n(y_n); \theta)}{\partial F_1(y_1) \cdots \partial F_n(y_n)}$. Equation (2) shows that when the copula density is equal to one, the joint density collapses to the product of the marginals, which is the case when all local house price returns are independent of each other.

The overall dependence captured by the copula can be quantified, regardless of the marginal distributions, by coefficients of rank correlation, such as Kendall's tau and Spearman's rho. These distribution-free measures of the association among variables range from -1 to 1, for perfect negative to positive dependence; see Appendix A for more details.

2.2 Marginal model

Before analyzing the dependence between regional house price returns with copulas, we need to correctly specify the marginal distributions of the house price return in each MSA. Since time series of monthly house prices are typically non-stationary, we model house price returns, defined as the difference in log house prices. To deal with the time variation in the mean and volatility of the house price return of MSA i at time t, $y_{i,t}$, we follow Zimmer (2015*b*) and use an autoregressive model for the mean and a GARCH(1,1) for the volatility.[4] The conditional mean of the house price return of each MSA can be expressed as follows:

$$y_{i,t} = \gamma_{i,0} + \sum_{j=1}^{3} \gamma_{i,j} y_{i,t-j} + \eta_{i,t}, \tag{3}$$

where $\gamma_{i,0}$ are the constants, $\gamma_{i,j}$, $j = 1, \cdots, 3$, are autoregressive coefficients, and $\eta_{i,t}$ is the residual. We further account for the dynamics in the volatility, using the following Student t GARCH model:

$$\begin{aligned} \eta_{i,t} &= \sqrt{h_{i,t}} \cdot \varepsilon_{i,t}, \\ h_{i,t} &= \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}, \\ \varepsilon_{i,t} &\sim \text{Student t}(\nu_i), \end{aligned} \tag{4}$$

where ω_i, α_i and β_i are the constant and the autoregressive coefficients of the GARCH, ν_i is the degrees of freedom parameter of the Student t and $h_{i,t}$ is the conditional variance of the house price return of MSA i at time t. The Student t distribution provides the best fit, over the Gaussian and the Skew-t, according to information criteria. We then filter out the effect of lagged house price returns and the dynamics of volatility to obtain the standardized innovations, $\hat{\varepsilon}_{i,t} = \frac{\hat{\eta}_{i,t}}{\sqrt{\hat{h}_{i,t}}}$, and compute the probability integral transforms (PITs), $z_{it} = T_{\nu_i}(\hat{\varepsilon}_{i,t})$, which are inputs of the geographic dependence model, where T_ν is the CDF of the Student t with degrees of freedom ν. Provided that the marginal distributions (the combination of mean and volatility models along with a distribution) are well specified, the PITs will be identically and independently uniformly distributed

[4] Since, according to the Bayesian information criterion (BIC), for most MSAs the optimal order of the AR is between 2 and 4, and the differences are very small, we use an AR(3) for all MSAs.

on $[0, 1]$.

2.3 Equidependent Gaussian copula

Our first objective is to analyze the average geographic dependence within our set of regional MSA house price returns. We focus on average geographic dependence, since this is most representative of the dependence of portfolios of real estate investors who seek a broad geographic diversification across the entire U.S. This dependence can be captured by the parameter of an equidependent elliptical copula, which imposes the same dependence between all pairs of MSAs. While equidependence is unlikely to strictly hold in practice, it is nonetheless an interesting approximation in terms of the trade-off it offers between bias and variance: while an equidependent copula delivers a slightly biased estimate of the dependence between any given pair, this estimate enjoys a low variance, since it pools information from all pairs into a single measure.

The assumption of equidependence is frequently made in the context of Gaussian copula portfolio models in credit risk (see e.g. Li 2000, Schoenbucher 2000, Schoenbucher 2003). A similar assumption underlies the Dynamic Equicorrelation (DECO) model of Engle & Kelly (2012), where the equicorrelation parameter is autoregressive. In our case, the equicorrelation copula parameter does not change continuously over time, but instead it switches discretely between a high and a low dependence regime. We consider either a Gaussian or a Student t version of an n-variate equicorrelated copula, whose correlation matrix $\mathbf{R}$ is restricted to have all of its off-diagonal elements equal to the equicorrelation copula parameter ρ, which controls the dependence between all $n(n-1)/2$ pairs of MSA house price returns:

$$R = (1 - \rho)\mathbf{I}_n + \rho\mathbf{J}_n, \tag{5}$$

where I_n denotes the n-dimensional identity matrix and J_n is the $n \times n$ matrix of ones. We further impose $\rho \in (\frac{-1}{n-1}, 1)$ to guarantee that R is positive definite.[5]

[5] See Lemma 2.1 of Engle & Kelly (2012).

2.4 Canonical vine copula

Whereas equidependent multivariate copulas restrict all pairwise dependence to be equal, at the other end of the spectrum, canonical vine copulas allow for maximal flexibility, but at the cost of a higher number of parameters (see e.g. Bedford & Cooke 2002, Berg & Aas 2009, Aas, Czado, Frigessi & Bakken 2009). These multivariate copulas are built hierarchically from bivariate copulas by iterative conditioning. When asymmetric copulas, such as the Gumbel, rotated Gumbel and Clayton, are used as building blocks, canonical vines can accommodate features frequently found in asset price returns, such as asymmetric dependence and tail dependence. Asymmetric dependence refers to the fact that negative returns tend to be more dependent than positive returns. Tail dependence, on the other hand, is a copula concept which characterizes the dependence in the tails of the distribution, i.e. during very large swings in house price returns. In particular, lower tail dependence measures the probability that house price returns in one MSA are at an extreme low, conditional on the observation of an extreme low return in the house price in another MSA. The presence of tail dependence increases the downside risk in the portfolios of real estate investors and can lead to very large losses. In contrast, the Gaussian copula does not allow for tail dependence, whereas the Student t imposes symmetric tail dependence. Note that the canonical vine nests the multivariate Gaussian, when all building block are Gaussian, and it nests the equidependent Gaussian, if in addition all pairwise copula correlation coefficients are equal. We refer to Appendix A for more details about the bivariate copulas we consider, as well as the concepts of upper and lower tail dependence.

The density of an n-dimensional canonical vine copula can be written as follows:

$$c(u_1, \cdots, u_n) = \prod_{j=1}^{n-1} \prod_{i=1}^{n-j} c_{j,j+i|1,\cdots,j-1}(F(u_j|u_1, \cdots, u_{j-1}), F(u_{j+i}|u_1, \cdots, u_{j-1})), \tag{6}$$

where $c_{j,j+i|1,2,\ldots j-1}$ denotes the conditional copula of u_j and u_{j+i}, given $u_1, \ldots, u_{j-1}$ and $F(.|.)$ is a cumulative conditional distribution, which can be evaluated, following Joe (1996), as:

$$F(y|\nu) = \frac{\partial C_{y,\nu_j|\nu_{-j}}(F(y|\nu_{-j}), F(\nu_j|\nu_{-j}))}{\partial F(\nu_j|\nu_{-j})}, \tag{7}$$

where ν_{-j} denotes the vector ν excluding the component ν_j. As can be seen in Equation (6), the construction of canonical vine copulas proceeds hierarchically along a tree; see Figure 5 for the tree structure we use to describe the dependence among four Southwestern MSAs. u_1 plays a pivotal role in the first level of the tree, which contains the bivariate copulas of u_1 with all other $n-1$ variables u_j, $j = 2, \ldots, n$. The next level of the tree consists of the bivariate conditional copulas $c_{2,j|1}$ of $u_2|u_1$ with all remaining variables $u_j|u_1$, for $j = 3, \ldots, n$. At each level of the tree, one conditions on the pivotal variable in the previous level. The n-dimensional canonical vine copula then obtains as the product of $n(n-1)/2$ bivariate conditional copulas. The specification of a canonical vine requires the choice of an ordering of variables, as well as the choice of all bivariate conditional copulas. We follow the standard practice in the literature and order the variables in such a way that the lowest levels of the tree capture most of the dependence; for more details on the construction of canonical vines, see Appendix A.3.

2.5 Multivariate regime switching copula

We assume that the n-variate vector $Y_t = (y_{1,t}, \ldots, y_{n,t})$ of monthly house price returns at time t depends on a latent binary variable $s_t = 1, 2$, which indicates the dependence regime the housing market is in. The density of the data conditional on being in regime $s_t = j$ is:

$$f(Y_t|Y_{t-1}, s_t = j) = c^{(j)}\big(F_1(y_{1,t}), \ldots, F_n(y_{n,t}); \theta_c^{(j)}\big) \prod_{i=1}^{n} f_i(y_{i,t}; \theta_{m,i}), \tag{8}$$

where $c^{(j)}(.)$ is the copula density of the marginal distribution of y_i with its parameter $\theta_{m,i}$, and F_i is the corresponding marginal distribution function. In order to describe time variation in dependence between house price returns, we switch between the two density functions conditionally on the underlying latent state s_t.

We entertain two assumptions about the evolution of the unobserved state of the economy s_t. The first is the classical homogeneous Markov chain assumption, where the transition probabilities $p_{jj} = P(s_t = j|s_{t-1} = j)$ are constant over time for regimes $j = 1, 2$ (see e.g. Hamilton 1989). Next we relax this assumption and follow the time-varying transition probability (TVTP) approach of Diebold, Lee & Weinbach (1994). More specifically, we allow for the effect of time-varying regressors such as changes in the interest rate, Δr_t and in the loan to value (LTV), ΔLTV_t on the transition probabilities:

$$p_{jj,t} = P(s_t = j|s_{t-1} = j) = \text{logit}^{-1}(\delta_{0,j} + \delta_{\Delta r,j}\Delta r_t + \delta_{\Delta LTV,j}\Delta LTV_t), \tag{9}$$

for $j = 1, 2$, where $\text{logit}^{-1}(x) = \frac{1}{1+\exp(-x)}$. This allows us to assess the effect of credit market conditions on the geographic dependence in house price returns. The TVTP model nests the homogeneous Markov chain approach, with $p_{jj} = \text{logit}^{-1}(\delta_{0,j})$, which obtains whenever $\delta_{\Delta r,j} = \delta_{\Delta LTV,j} = 0$, for $j = 1, 2$.

As shown in Equation (8), since the marginal distributions are not dependent on the regime, we can first estimate the parameters of the marginal AR(3)-Student t GARCH(1,1) models. We then estimate the parameters of the multivariate regime switching copula separately, taking as given the parameters of the marginals. This corresponds to the inference for the margins (IFM) method of Joe (2005), which is standard in copula applications; see Appendix B.1 for more details.

Since the regime s_t, which determines the state of the economy at each time, is not observable, the full copula likelihood cannot be evaluated directly. Instead, we rely on the EM algorithm: we first take expectations of the complete log likelihood conditional on the observable data (E-step). We then maximize the expected log likelihood with respect to the parameters of the copula and transition probabilities (M-step). We iterate these two steps until convergence. We rely on the Hamilton (1989) filter for the constant transition probabilities and on the filter proposed by Diebold et al. (1994) for the time-varying transition probability case; see Appendix B.2 for details.

3 Data and results

3.1 Data and descriptive statistics

We use monthly MSA level Case-Shiller house price index returns, based on repeat sale transactions, for 19 MSAs observed from May, 1991 to August, 2013, which corresponds to 279 monthly observations. For our main results we eliminate Boston, Chicago, Denver, Detroit, Minneapolis and New York, since these returns appear to be non-stationary according to an Augmented Dickey-fuller (ADF) test.[6] As show in Figure 1, house prices increased considerably from 2000 to 2006 and subsequently collapsed from the end of 2006 to 2008.

We let the transition probabilities of the regime switching copula be a function of changes in the average loan to value (ΔLTV) and mortgage interest rate (Δr) of a sample of conventional and single-family mortgages, compiled by the Federal Housing Finance Agency (FHFA). The FHFA computes average contract rates from the loans, reported by a sample of mortgage lenders (savings and loans associations, savings banks, commercial banks and mortgage companies), closed during the first 5 working days of the month up to October 1991 and for the last 5 working days of the month since.[7]

In addition to local economic and housing market conditions, both short term and long term mortgage rates depend also on credit markets and are significantly affected by U.S. monetary policy shocks (see e.g. Hamilton 2008, Xu, Han & Yang 2012). As shown in Figure 2a, over the 1991-2012 period mortgage rates decreased from about 10% to 3.5%, with rare episodes of stability or slight increases. Mortgage rates decreased after 2000, following a monetary expansion designed to attenuate the effects of the burst of the dot-com bubble. As a result of the policy reversal in 2003, mortgage rates stabilized until about 2005 and then started increasing until the crisis in 2007. Mortgage contract

[6] This leaves us with 13 MSAs covering Phoenix, Los Angeles, San Diego, San Francisco, Las Vegas, Miami, Tampa, Charlotte, Portland, Seattle, Washington, Atlanta and Detroit. The results for the full set of 19 MSAs are qualitatively similar. There is also data available for Dallas, but we exclude it, since it starts only in 2000.

[7] Our LTV series differs from the one of Duca et al. (2013), who build a quarterly LTV ratio on mortgages used by first time homebuyers, from biannual American Housing Survey (AHS) data. Unfortunately, it is not possible to construct such a series for the monthly frequency we need to estimate our regime switching model.

rates then decreased from 2007 to 2011 as a result of the Fed's attempt to rescue the U.S. housing market by cutting interest rates.

The time series of LTV ratios is displayed in Figure 2b. As shown in Fostel & Geanakoplos (2015), interest rates and average loan to value (LTV) are joint outcomes of an equilibrium process on the credit market. The increase in LTV in the early to mid-1990s followed the Federal Housing Enterprises Financial Safety and Soundness Act of 1992 (the GSE Act), which encouraged the GSEs to increase the credit supply by purchasing more low income and minority loans and allowed them to buy subprime MBSs.

LTV ratios experienced another period of strong increase from 2002 to 2006 that reflects both changes in the supply of credit induced by securitization and changes in the demand for credit. For instance, Mian & Sufi (2009) show that increased securitization into private-label MBSs is related to a relaxation of credit constraints and decreasing mortgage denial rates.[8] Over the same period, looser underwriting standards in the form of lower downpayments, and a reduced emphasis on proper documentation allowed previously constrained optimistic buyers, such as the ones in the model of Geanakoplos (2010*a*), to obtain more leverage and purchase additional housing, see e.g. Haughwout, Lee, Tracy & van der Klaauw (2011), who report an increase in the number of real estate investors who misreport their intention to occupy the property in order to secure a mortgage. Finally, Dell'Ariccia, Igan & Laeven (2012) argue that an increase in credit demand, evidenced by the number of loan applications, also contributed to the relaxation of lending standards.

This pattern began to reverse at the end of 2006. As subprime loans originated during the preceding periods proved worse than expected, with worrisome delinquency rates and decreases in the prices of MBSs, investment banks refrained from underwriting new MBSs,

[8]Gabriel & Rosenthal (2010) find that almost all of the capital used to finance conventional and conforming mortgages came from the secondary market in 2004, and remained at that high level through 2008, and that private second market loan purchases boomed relatively to those of the GSEs in 2004, peaking in 2006. Duca, Muellbauer & Murphy (2010) show that the behavior of house prices in 2003-2007 is significantly linked to financial innovations such as collateralized debt obligations (CDOs) that accelerated the financing of subprime mortgages, and in turn helped private subprime mortgages gain high market share by allowing much higher LTV ratios than before. For the effect of securization, see also Ashcraft, Goldsmith-Pinkham, Hull & Vickery (2011), Loutskina & Strahan (2009), Keys, Mukherjee, Seru & Vig (2010), and Demyanyk & Van Hemert (2011).

leading to higher required downpayments on new mortgages (see Geanakoplos 2010*b*).

Table 1 reports descriptive statistics for the residuals obtained from the mean model. The last column shows p-values from Jarque-Bera test. The results show that house price returns are not normally distributed at the 95% confidence level, except for San Diego. The distributions of the residuals have fat tails with a kurtosis larger than 3, which means that extreme movements in house prices are more likely than under the normal distribution. Table 2 reports unconditional Pearson correlations between price indices. The most strongly correlated pairs of MSA are San Diego-San Francisco (0.53), followed by Los Angeles-San Diego (0.50) and Miami-Tampa (0.45).

3.2 Marginal models

Table 3 shows results of the univariate Student t GARCH models we fit to every local house price return series. Most MSAs have fairly persistent volatility processes with $\alpha+\beta$ close to 1, with the exception of San Diego. Since misspecification of the marginal distributions can lead to severely biased copula parameter estimates (see e.g. Fermanian & Scaillet 2005), we apply several goodness of fit (GOF) tests to the probability integral transform (PIT) of the marginals obtained from the univariate Student t GARCH model. The tests include the Kolmogorov-Smirnov (KS) and Kuiper (KP), which check the correct specification of the marginal distribution by comparing the distribution of the PIT to the standard uniform. We also apply the Berkowitz (BK) test, a joint test of uniformity and lack of aucorrelation of the PIT, which is based on mapping the PIT to the normal and testing an AR(1) model against the null of an uncorrelated standard normal. The p-values of the tests, reported in Columns 5 to 7 of Table 3, show that all series pass the tests, which means that the marginals are well specified. In Columns 8 to 12, we present the p-values of the Ljung-Box test statistics which show that the squared residuals are no longer autocorrelated, and that the conditional variances are well modeled with the Student t-GARCH(1,1).

3.3 Dependence models

In this section, we first discuss the average dependence within MSA house price returns in the U.S. and then we analyze the dependence within a smaller subset of Southwestern MSAs.

A. Country-wide equidependent regime switching copula

Table 4 reports results of a regime switching model with two equidependent Gaussian copula regimes, using house price returns in 13 MSAs. The results show that in the fixed transition probability (FTP) model, the average dependence of regional house price returns varies across time between a high and a low dependence regime with equicorrelation coefficients of the Gaussian copula of nearly 0.4 and 0.11, which correspond to Kendall's tau rank correlation coefficients of 0.25 and 0.07, respectively. Moreover, the regimes are quite persistent, as shown by the transition probabilities. This means that the economy oscillates between fairly persistent episodes of high and low dependence in regional house price returns, which has strong implications for real estate investors seeking the benefits of regional diversification.

The second panel of Table 4 shows almost identical regimes when we consider the time-varying transition probability (TVTP) model instead. Since the TVTP and the FTP model are nested, we perform a likelihood ratio test, which strongly favors the TVTP model, with a p-value of 0.002.[9] Figure 3 shows the smoothed probabilities of the high dependence regime and the average dependence, measured as Spearman's rho rank correlation, under fixed transition probabilities (FTP) in Panels (a) and (c), and under time varying transition probabilities (TVTP) in Panels (b) and (d). Panel (d) shows that the TVTP model is able to capture strong dependence in house price returns during the moderate increase in house prices from 1994 to 1996, during some episodes in 2001, 2004 and 2005, and also during the housing market bust from 2007 to 2010, whereas this is not so clear with the FTP model in Panel (c), which is another reason to prefer the TVTP over the FTP model. To further measure the quality of our regimes, we rely on the regime classification measure put forward by Ang & Bekaert (2002*b*), which confirms

[9] In unreported results we also try equidependent Student t copulas, however the degrees of freedom are in most cases well above 10, which makes them virtually indistinguishable from the Gaussian ones.

the better performance of the TVTP model.[10]

The variables capturing credit market conditions, such as changes in mortgage rates, Δr, and in loan to value, ΔLTV, are significantly related to the transition probabilities, p_{11} and p_{22}, of the Markov chain. More specifically, a one standard deviation increase in mortgage rates leads on average to a 7% increase in the probability of staying in the high dependence regime, while a one standard deviation decrease in loan to value increases that probability on average by 40%.[11] A similar increase in mortgage rates and decrease in leverage would decrease the probability of staying in the low dependence regime by 9% and 7%, respectively.

The marginal effects implied by our results indicate that the impact of changes in mortgage rates and in leverage on the persistence of the low dependence regime, p_{22}, are similar in scale. In contrast, the effect of changes in leverage on the persistence of the high dependence regime, p_{11}, is much stronger than the effect of changes in mortgage rates. This shows that, whereas both increases in mortgage rates and decreases in leverage are associated with staying or moving to the high dependence regime, the effect of leverage dominates that of changes in mortgage rates in the probability of staying in the high dependence regime. Thus deleveraging is responsible for an increase in the duration of the high dependence regime. More generally, our results are consistent with the importance of leverage for house price returns, as documented also by Duca et al. (2013). Whereas they model the effect of leverage on house price returns, we provide evidence of a dependence channel through which leverage affects house price returns. More specifically, we show the importance of leverage as a determinant of the dependence in regional house price returns, which is an important dimension of the risk faced by real estate investors who seek to attain geographic diversification.

Our results show that the effect of leverage is quantitatively much more important

[10]The regime classification measure of Ang & Bekaert (2002*b*) is RCM $= 400\frac{1}{T}\sum_{t=1}^{T} p_t(1-p_t)$, where p_t denotes the smoothed probability of being in regime 1. If regimes are clearly identified, then the smoothed probability should either be 0 or 1 at all times, and the regime classification measure is zero, whereas in the worst case, the smoothed probability is always 1/2 and the measure is 100. In the FTP case, the regime classification measure is 59.44, whereas in the TVTP case, regimes are much clearer with a value of 32.04

[11]We calculate these effects by combining the marginal effects from Table 4 with the standard deviations of mortgage rates and LTV, which are, respectively equal to 0.8748%, and 0.4625%.

than the effect of mortgage rates. This is consistent with the findings of Ashcraft, Gârleanu & Pedersen (2011), that a reduction in the haircut on a financial asset has a much stronger impact on its price than a reduction in interest rates. They are also consistent with the simulations of Duca, Muellbauer & Murphy (2016), which show that leverage has a stronger effect on house prices than interest rates. Our results lend support to the idea that governments should not only monitor and adjust interest rates, but also monitor leverage and make sure it remains within reasonable bounds (see Geanakoplos 2010*b*, Lambertini, Mendicino & Punzi 2013).

We find that the average dependence within a wide set of regional house prices covering the entire U.S. becomes much higher during episodes of increases in mortgages rates and deleveraging. To illustrate the impact of such swings in dependence on a simple-minded strategy of geographic diversification, we compare the risk of an equally weighted portfolio of all MSAs in both regimes. As shown in Table 4, according to the TVTP model, the monthly standard deviation of such a portfolio changes from 0.76% to 1.02%, resulting in a 30% increase from the low to the high dependence regime. The results are more dramatic with Value-at-Risk (VaR)[12]: the 1% (5%) VaR decreases from −1.66% (−0.88%) to −2.44% (−1.37%), which corresponds to a 47% (56%) decrease. These results show that in the high dependence regime, the likelihood of experiencing extreme negative returns increases substantially, relative to the low dependence regime. However, whereas VaR is one of the most commonly used measures of risk, it suffers from the fact that it is not sub-additive (a risk measure is sub-additive, if the risk of a portfolio is no larger than the sum of the risks of its constituents; see Artzner, Delbaen, Eber & Heath 1999). In contrast, expected shortfall, which measures the average return in case of a VaR violation, does not suffer from this drawback.[13] The results show that expected shortfall changes from −2.49% (−1.41%) in the low dependence to −3.27% (−2.04%) in the high dependence regime for 1% (5%) expected shortfall. This implies that the average losses incurred in case of an extreme adverse outcome are much larger in the high

[12]Value-at-Risk (VaR) is defined as the quantile of the distribution of portfolio returns at level α: $\mathrm{VaR}_\alpha = \inf\{r \in \mathbb{R} : F_r(r) \geq \alpha\}$, where $F_r(.)$ is the cumulative density of the portfolio return r.

[13]Expected shortfall is the expected return, conditional on exceeding VaR: $\mathrm{ES}_\alpha = E[r|r < \mathrm{VaR}_\alpha]$.

dependence regime. Finally, like Cotter et al. (2015), we calculate the reduction in risk, which compares the average standard deviation of all MSA returns to that of the equally weighted portfolio. This measures the possible benefits of geographic diversification, and it shows an erosion in these benefits, which decrease from 1.22% in the low dependence to 0.89% in the high dependence regime, consistent with Cotter et al. (2015), who finds that they decrease during crisis periods. These results are qualitatively similar, yet slightly stronger if we consider instead the FTP model. Overall our results suggest that the benefits of diversification tend to disappear during periods of deleveraging, when they are most needed. This is bad news for real estate investors who seek to reduce the risk of their portfolios through geographic diversification across the U.S. A similar phenomenon has been documented by Ang & Bekaert (2002*a*) who find that high correlations between international equity market returns in highly volatile bear markets decrease the benefits of international diversification.

To check the robustness of our results, we also estimate the same models with all 19 MSAs, which include the returns of 6 MSAs that are not stationary according to an Augmented Dickey Fuller (ADF) test. The results in Table C.1 show that our main result is consistent, since the effect of leverage on the persistence of the high dependent regime is both qualitatively and quantitatively similar with an increase of 28.36% in the probability of staying in the high dependence regime after a one standard deviation increase in ΔLTV. The smoothed probabilities of the high dependence regime in Figure C.1 and the evolution of the Spearman's rho rank correlation are also very similar to those with 13 MSAs.

B. Dependence within Southwestern MSAs

So far we studied the average dependence within a large set of regional house price returns, representative of the whole U.S. We now focus attention on the dependence within a smaller set of MSAs in the Southwest of the U.S., that were particularly affected by the house price slump and the resulting wave of mortgage defaults. More specifically we analyze the joint dependence between house price returns in Los Angeles (LA), San Francisco (SF), San Diego (SD) and Las Vegas (LV). The dependence in such a more localized set of MSAs could be of interest to a regional bank, whose real estate portfolio is likely to be made up of mortgages originated from a more local region. The smaller dimension of this data set allows us also to offer a more sophisticated description of the dependence structure.

We first estimate a regime switching equidependent Gaussian copula model. As shown in Table 5, the dependence between house price returns varies across time and these variations can be described by a high and low dependence regime with Gaussian copula correlations of 0.55 and 0.13, which correspond to Kendall's tau rank correlation coefficients of 0.37 and 0.08 under the assumption of time varying transition probabilities (TVTP).[14] Compared to the results for the entire U.S., both the high and the low dependence regimes exhibit more dependence with a clearer differentiation between regimes. This is reflected also in the risk measures for an equally weighted portfolio in both regimes. As shown in Table 5, the standard deviation varies from 1.20% to 1.58% from the low to the high dependence regime, the 1% VaR varies from −2.84% to −3.88%, and the corresponding expected shortfall from −4.38% to −5.77%. Finally, the reduction in risk from an equally weighted portfolio decreases from 0.84% to 0.58% in the high dependence regime.

Although changes in mortgage rates, Δr, are no longer significantly associated with the probability of staying in the high dependence regime, a one standard deviation decrease in leverage, ΔLTV, leads to an 18% higher probability of moving to and a 17% higher probability of staying in the high dependence regime. Panel (d) of Figure 4 shows that on average, the house price returns of Southwestern MSAs are more dependent than house price returns in the entire U.S., given that they are strongly dependent not only during periods of housing bust but also during periods of housing boom. This might be due to the fact that the timing of the housing boom was more homogeneous within a local subset of Southwestern MSAs than it was for the whole of the U.S.

Next, we estimate a regime switching model with a canonical vine and a full multivariate Gaussian copula, where we relax equidependence to allow for different correlations for different pairs of MSAs. This richer but less parsimonious model allows us to see whether

[14] As in Section A, results with the equidependent Student t copula are virtually identical with degrees of freedom well above 10.

the dependence in house price returns within a smaller subset of regions exhibits features that could not be captured by an equidependent Gaussian copula, such as a different intensity and shape for the dependence between each pair of MSAs, and the possibility of tail dependence and asymmetric dependence. Asymmetric dependence refers to difference in the behavior of the upper and lower tail of the joint distribution, while tail dependence refers to dependence for extreme quantiles of the marginals. Figure 5 shows the structure of the canonical vine we estimate, and its caption discusses the choice of the ordering of the variables in the tree, as well as the selection of bivariate copulas. Los Angeles turns out to be the pivot of the canonical vine, since it is the most strongly correlated with all three other MSAs. While the dependence between Los Angeles and San Francisco are described by a Gaussian copula, the dependence between Los Angeles and San Diego is characterized by a Student t copula, which is symmetric like the Gaussian, but exhibits both upper and lower tail dependence, which reflects stronger dependence when returns are extreme (either positive or negative). In contrast, the Gumbel copula that describes the dependence between Los Angeles and Las Vegas captures upper, but not lower tail dependence, which means that there is more dependence when prices increase than when they decrease.

Table 6 first shows that the dependence between each pair of house price returns varies across time in magnitude as well as in shape. Specifically, time variation in the dependence can be described by a symmetric Gaussian regime with low dependence and an asymmetric canonical vine regime with high dependence, under the assumption of time-varying transition probabilities (TVTP). As shown in the left panel of Table 6, the approximate unconditional Kendall's tau rank correlation coefficients implied by the canonical vine copula are higher for all pairs of MSAs than those of the multivariate Gaussian copula. Note that one cannot directly compare the Kendall's tau of the bivariate building blocks of the canonical vine with those of the multivariate Gaussian or Student t copulas. Instead, we use the same approximation as Chollete et al. (2009) to compute the unconditional Kendall's tau of the canonical vine from those of the conditional copulas.[15]

[15] We use the fact that Kendall's tau is a known function of the copula, with closed-form solutions for many families of copulas. Using this information, we first compute the Kendall's tau of each bivariate

The estimation results of Table 6 also confirm that these variations are significantly associated with mortgages rates and loan to value (LTV). A one standard deviation increase in the change in mortgage rates, Δr, leads to a 5% increase in the probability of staying in the asymmetric high dependence regime, p_{11}, while a one standard deviation decrease in loan to value, ΔLTV, increases that persistence by 12%. Thus, a tightening credit market in the form of deleveraging and an increase in mortgage rates leads to a higher probability of staying in and moving to the asymmetric high dependence regime. The magnitude of the impact of credit market conditions on transition probabilities is lower than in the equidependent copula case. This is likely due to the fact that the high dependence canonical vine regime already captures more extreme dependence than the equidependent Gaussian copula.

Figure 6 shows the smoothed probabilities implied by the results above. Panel (a) shows that the housing market was in an asymmetric, high dependence regime from 1994 to 2000. During this period, house prices in the Southwest were recovering from the plunge of 1990. The figure also shows that the housing market was in an asymmetric dependence regime in the boom of 2005-2006, but also during the period of housing bust between 2007 and 2009.

Overall, our results suggest that a multivariate canonical vine copula is appropriate to capture the dependence of regional house price returns in a period with big swings in house prices. For the sake of comparison, we also estimate a regime-switching model with an unrestricted multivariate Gaussian copula in each regime. The results of Table 6 show that the canonical vine model fits observed dependence better and improves the loglikelihood by about 6.3 compared to the Gaussian model. Since the two models are not nested and the canonical vine model has one parameter more because one of its components is a Student t copula with an extra degrees of freedom parameter, we

conditional copula implied by the estimated parameter. Then we presume the data came from a Gaussian copula and we compute the conditional copula correlation that implies the same Kendall's tau, via the relation $\rho = \sin(\frac{\tau\pi}{2})$. We then compute the unconditional correlation matrix of the Gaussian copula from the conditional bivariate Gaussian copulas via the formula $R_{x|y} = R_x - R_{xy}R_y^{-1}R_{yx}$, which delivers the unconditional correlation matrix R_x from the unconditional correlations R_y, R_{xy} and the conditional correlation $R_{x|y}$. Finally, we report the unconditional Kendall's tau that corresponds to the unconditional correlation with the relation $\tau = 2\frac{\arcsin(\rho)}{\pi}$.

cannot strictly speaking compare them according to the value of the likelihood. However, according to both the Akaike and the Bayesian information criteria, the canonical vine copula is the preferred model. Thus, the results highlight the importance of considering asymmetry, fat-tailness and time variation when modeling the dependence between house price returns.

4 Conclusion

Using a multivariate regime switching copula model with two equidependent regimes, we analyze time variation in the average geographic dependence among regional house price returns in the US. An equidependent copula allows us to capture the average dependence between house price returns in a large cross-section of regions. We further let the Markov transition probabilities vary with credit market conditions, such as mortgage contract rates and loan to value ratios (LTV). More specifically we show that the average dependence in regional house prices varies over time, and high dependence is related to changes in mortgage rates, but even more strongly to changes in leverage. This has important consequences for real estate investors, who seek to reduce their risk through geographic diversification. We show that during periods of crisis, these gains from geographic diversification might be strongly reduced as dependence increases. As a result, real estate portfolios might turn out to be much more risky than investors initially thought, giving them a false sense of security.

Our results provide evidence of a new channel whereby leverage can affect the geographic dependence among regional house prices. We show that the effect of leverage is quantitatively much more important than that of mortgage rates. More generally, our results are consistent with the importance of leverage for house prices, as documented also by Duca et al. (2013) and Duca et al. (2016). Our results are consistent also with the effect of leverage on dependence found in the context of financial markets (see e.g. Ashcraft, Gârleanu & Pedersen 2011, Brunnermeier & Pedersen 2009, Dudley & Nimalendran 2011). In addition, our results lend support to the idea that governments should not only monitor and adjust interest rates, but also monitor leverage and make sure it remains within reasonable bounds (see Geanakoplos 2010*b*). Finally, we show in a small set of Southwestern MSAs, that deleveraging and increases in mortgage rates are associated with a high (low) probability of staying and moving to a high asymmetric (low symmetric) dependence regime.

Table 1: Summary Statistics

	Mean	Std. Dev.	Skewness	Kurtosis	Min	Max	Jarque-Bera (p-value)
Phoenix	0.0025	0.0142	-1.0139	6.9850	-0.0564	0.0477	0.0010
Los Angeles	0.0024	0.0126	-0.5216	4.0250	-0.0436	0.0351	0.0097
San Diego	0.0026	0.0121	-0.3875	3.9670	-0.0367	0.0362	0.1218
San Francisco	0.0028	0.0147	-0.5935	4.5511	-0.0517	0.0406	0.0010
Las Vegas	0.0009	0.0145	-0.2583	7.3972	-0.0524	0.0587	0.0010
Miami	0.0025	0.0123	-1.1273	5.1332	-0.0461	0.0274	0.0010
Tampa	0.0019	0.0109	-0.8240	5.1580	-0.0443	0.0285	0.0128
Charlotte	0.0017	0.0064	-0.6259	4.5328	-0.0261	0.0170	0.0010
Portland	0.0035	0.0090	-0.8123	4.8497	-0.0301	0.0274	0.0032
Seattle	0.0029	0.0092	-0.9636	5.3840	-0.0370	0.0260	0.0010
Washington	0.0028	0.0106	-0.1005	3.5785	-0.0276	0.0315	0.0010
Atlanta	0.0013	0.0075	-2.0676	11.7199	-0.0480	0.0189	0.0010
Detroit	0.0013	0.0129	-0.4005	7.9470	-0.0491	0.0558	0.0010

This table provides summary statistics of monthly regional house price returns, from May 1991 to August 2013, which correspond to a sample of 279 observations. The Jarque-Bera tests the null hypothesis of normality of the residuals from the AR(3) mean model for each MSA.

Table 2: Unconditional correlations of regional house price returns

	Phoenix	Los Angeles	SanDiego	San Francisco	Las Vegas	Miami	Tampa	Charlotte	Portland	Seattle	Washington	Atlanta
Los Angeles	0.3438	1.0000										
San Diego	0.3279	0.5019	1.0000									
San Francisco	0.3777	0.4133	0.5305	1.0000								
Las Vegas	0.1550	0.3088	0.1196	0.1352	1.0000							
Miami	0.1663	0.2980	0.2054	0.2065	0.0353	1.0000						
Tampa	0.2606	0.3072	0.2120	0.2579	0.1601	0.4528	1.0000					
Charlotte	0.2770	0.3049	0.1857	0.2085	0.0778	0.0305	0.0514	1.0000				
Portland	0.2883	0.2413	0.1910	0.3905	0.2019	0.1364	0.3376	0.1938	1.0000			
Seattle	0.4089	0.3581	0.3200	0.4176	0.2250	0.1651	0.2617	0.1972	0.3213	1.0000		
Washington	0.3275	0.4264	0.2820	0.2607	0.1674	0.2542	0.3066	0.3406	0.2186	0.3626	1.0000	
Atlanta	0.1925	0.2144	0.1019	0.0764	0.0836	0.0729	0.1971	0.1282	0.0753	0.0963	0.1993	1.0000
Detroit	0.0464	0.1598	0.0550	-0.0375	0.2271	0.2375	0.2058	0.1785	0.1731	-0.0269	0.2821	0.2521

This table provides unconditional Pearson correlations between the monthly house price index returns of the 13 MSAs.

Table 3: Univariate Student-t GARCH(1,1) estimates, goodness of fit statistics and Ljung-Box statistic

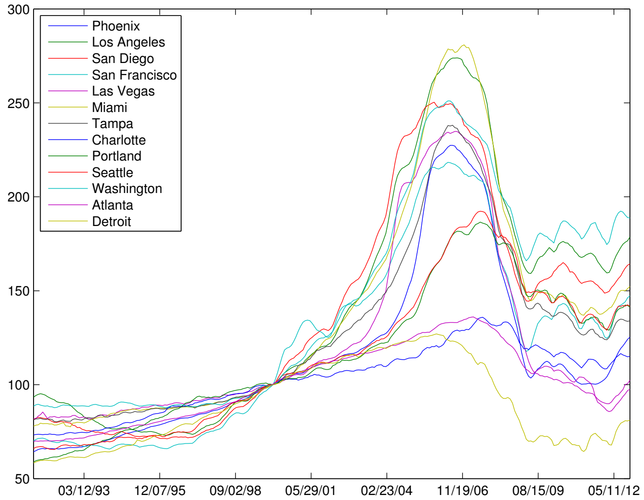
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ω	α	β	ν	KS	BK	KP	Ljung-Box				
								1	2	3	4	5
Phoenix	0.0000	0.1609***	0.8201***	11.2659*	0.9639	0.6504	0.8544	0.9022	0.9851	0.9857	0.9466	0.9807
Los Angeles	0.0000	0.0697	0.8260***	9.8368*	0.9671	0.9945	0.8857	0.9027	0.6970	0.8376	0.8680	0.9266
San Diego	0.0000	0.0740	0.6606***	24.6998	0.3018	0.9712	0.1525	0.7879	0.8726	0.8187	0.8226	0.8828
San Francisco	0.0000	0.0930**	0.8965***	5.9023***	0.4937	0.9326	0.2433	0.9832	0.6224	0.8032	0.3101	0.4033
Las Vegas	0.0000	0.1865*	0.7673***	4.9642***	0.8038	0.9405	0.4932	0.6921	0.8985	0.1005	0.1171	0.1932
Miami	0.0000	0.1571**	0.8199***	6.8495***	0.9089	0.5849	0.8568	0.6765	0.5186	0.2532	0.3904	0.3892
Tampa	0.0000	0.0913***	0.8638***	24.8978	0.9649	0.9986	0.9295	0.8773	0.1292	0.2407	0.2700	0.1428
Charlotte	0.0000	0.0488**	0.9510***	7.7613**	0.9430	0.8713	0.8210	0.8654	0.8779	0.9017	0.9655	0.9845
Portland	0.0000	0.0692***	0.9296***	7.2298**	0.5592	0.9398	0.6262	0.8631	0.9602	0.9721	0.9389	0.7440
Seattle	0.0000	0.1091	0.8398***	12.1797	0.9825	0.4760	0.9997	0.1747	0.3314	0.5289	0.3066	0.2718
Washington	0.0000	0.1011***	0.8613***	6.4190***	0.4630	0.8785	0.1103	0.4996	0.5598	0.6611	0.6977	0.7881
Atlanta	0.0000	0.1163***	0.8810***	5.1488***	0.5120	0.0020	0.7884	0.1724	0.3579	0.4497	0.3816	0.5087
Detroit	0.0000	0.2255	0.7743***	4.1196***	0.0778	0.4211	0.2262	0.4548	0.7563	0.6356	0.5713	0.2503

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table reports results of the univariate Student-t GARCH(1,1) models, as well as the outcomes of several goodness of fit tests and a Ljung-Box test. Columns 1 to 4 provide estimates of the parameters ω, α, β and the degree of freedom ν of the univariate Student t GARCH(1,1) given by:

$$\begin{aligned} \hat{\eta}_{i,t} &= \sqrt{h_{i,t}} \cdot \epsilon_t, \\ h_{i,t} &= \omega_i + \alpha_i \epsilon^2_{i,t-1} + \beta_i h_{i,t-1}, \\ \epsilon_{i,t} &\sim \text{Student-t}(\nu_i), \end{aligned} \tag{4}$$

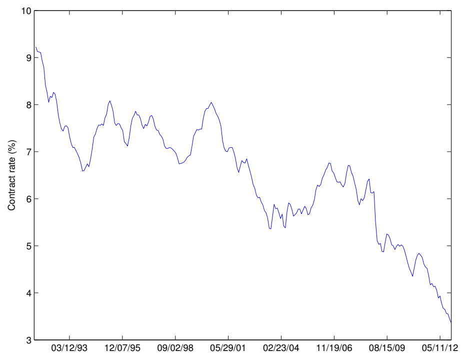
where for MSA i, the $\hat{\eta}_{it}$s are the residuals from the AR(3) model. Columns 5 to 7 contain p-values of the Goodness of Fit (GoF) statistics of the marginal distributions. The Kolmogorov-Smirnov (KS) evaluates departures from the null hypothesis that the cumulative density function (cdf) of the marginal models follow a Uniform [0,1]. BK is the Berkowitz test, which evaluates the null hypothesis of an uncorrelated and well-specified distribution of the marginal distributions. It is based on mapping the PIT of the data into a normal variate with the inverse cdf of the normal, Φ^{-1}, and to test uniformity and and lack of correlation, which corresponds to zero mean, variance one and zero correlation, against the alternative of an AR(1) model with unrestricted mean and variance. KP is Kuiper's test for uniformity, which puts more weight on the tails of the distribution. Columns 8 to 12 report the p-values of the Ljung-Box statistics for lack of autocorrelation in the squared standardized residuals of the Student t GARCH(1,1) models at orders 1, 2, 3, 4 and 5.

Figure 1: Regional house price indices

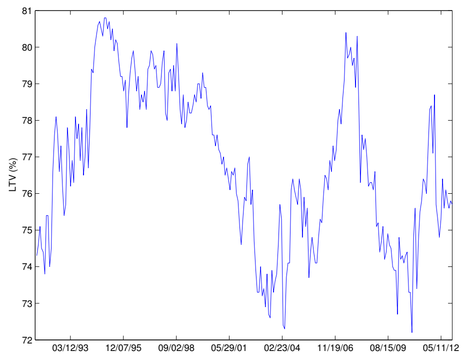


This figure shows the time series evolution of MSA level house price indices. The house prices are Case Shiller indices for 13 MSAs: Phoenix, Los Angeles, San Diego, San Francisco, Las Vegas, Miami, Tampa, Charlotte, Portland, Seattle, Washington, Atlanta and Detroit, observed from May, 1991 to August, 2013, which corresponds to 279 monthly observations.

Figure 2: Mortgage contract rate and loan to value ratio



(a) Mortgage contract rate (r)



(b) Loan to value ratio (LTV)

This figure shows the average mortgage contract rate in Panel (a) and the loan to value (LTV) ratio in Panel (b), from May, 1991 to August, 2013, which corresponds to 279 monthly observations. Average contract rate and loan to value ratio are from FHFA.

Table 4: Estimates of the regime switching equidependent Gaussian copula model, 13 MSAs

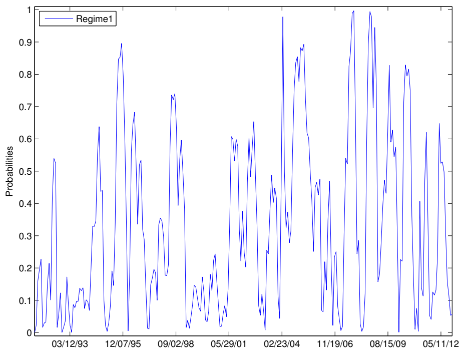
	(1)			(2)
	Fixed Transition Probability (FTP)			**Time-Varying Transition Probability (TVTP)**
	Regime 1: High dependence			
Equidependence ρ	0.3939***			0.3840***
P-value	(<0.0001)			(<0.0001)
Kendall's tau	0.2577***			0.2509***
Standard Dev	0.0103			0.0102
VaR (1%)	-0.0244			-0.0238
VaR (5%)	-0.0137			-0.0137
Expected Shortfall (1%)	-0.0331			-0.0327
Expected Shortfall (5%)	-0.0206			-0.0204
Reduction in Risk	0.0089			0.0091
	Regime 2: Low dependence			
Equidependence ρ	0.1058***			0.1143***
P-value	(<0.0001)			(<0.0001)
Kendall's tau	0.0675***			0.0729***
Standard Dev	0.0072			0.0076
VaR (1%)	-0.0151			-0.0166
VaR (5%)	-0.0082			-0.0088
Expected Shortfall (1%)	-0.0226			-0.0249
Expected Shortfall (5%)	-0.0130			-0.0141
Reduction in Risk	0.0122			0.0122
	Transition Probabilities	**Transition Probabilities**		
	p_{11}	δ_0	$\delta_{\Delta r}$	$\delta_{\Delta LTV}$
Coefficient	0.7067***	9.6430***	3.2390***	-30.3790***
Marginal Effect		0.2784	0.0935	-0.8770
P-value	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
	p_{22}	δ_0	$\delta_{\Delta r}$	$\delta_{\Delta LTV}$
Coefficient	0.8532***	2.7258***	-1.6124***	2.0339***
Marginal Effect		0.1828	-0.1082	0.1364
P-value	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
LogL	189.0692			197.5774

This table provides parameter estimates of the dependence structure in a Gaussian equidependent copula regime switching (RS) model for the 13 MSAs. The left panel shows the results of the Fixed Transition Probability (FTP) model, under the assumption that the transition probabilities p_{11} and p_{22} of the Markov chain are constant. The right panel shows the results of the Time-Varying Transition Probability (TVTP) model, where the probabilities $p_{jj,t}$, $j = 1, 2$, are functions of changes in mortgage rates, Δr_t and loan to value, ΔLTV_t, as follows:

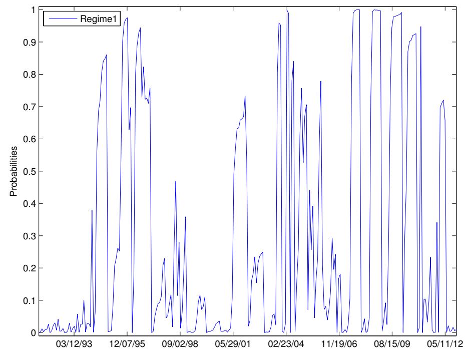
$$p_{jj,t} = P(s_t = j|s_{t-1} = j) = \text{logit}^{-1}(\delta_{0,j} + \delta_{\Delta r,j}\Delta r_t + \delta_{\Delta LTV,j}\Delta LTV_t), \tag{9}$$

where $\text{logit}^{-1}(x) = \frac{1}{1+\exp(-x)}$. We report p-values for all parameters and use house price returns of Phoenix, Los Angeles, San Francisco, San Diego, Las Vegas, Miami, Tampa, Charlotte, Portland, Seattle, Washington, Atlanta, Detroit from May 1991 to August 2013, which corresponds to a sample of 279 observations. The values of the log likelihood are reported in the last row. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

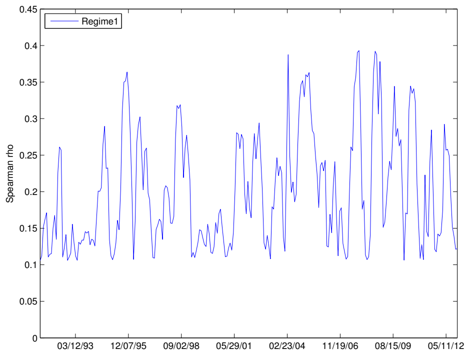
Figure 3: Smoothed probability of the high dependence regime and Spearman's rho: Equidependent Gaussian copula model with 13 MSAs



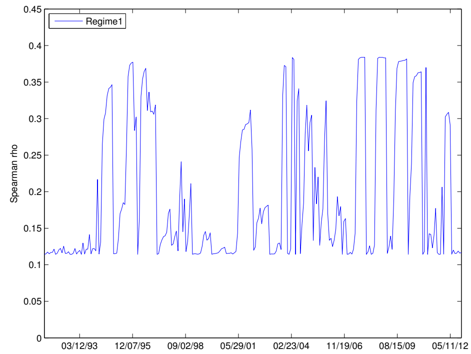
(a) Smoothed probability
Fixed
Transition Probability
(FTP)



(b) Smoothed probability
Time Varying
Transition Probability
(TVTP)



(c) Spearman's rho
Fixed
Transition Probability
(FTP)



(d) Spearman's rho
Time Varying
Transition Probability
(TVTP)

This figure is based on the equidependent Gaussian copula regime switching model estimated with 13 MSAs, whose results are shown in Table 4. Panels (a) and (c) respectively show smoothed probabilities of the high dependence regime and Spearman's rho for the fixed transition probability (FTP) case, whereas Panels (b) and (d) contains results for the time varying transition probability (TVTP) case.

Table 5: Estimates of the regime switching equidependent Gaussian copula model, four Southwestern MSAs

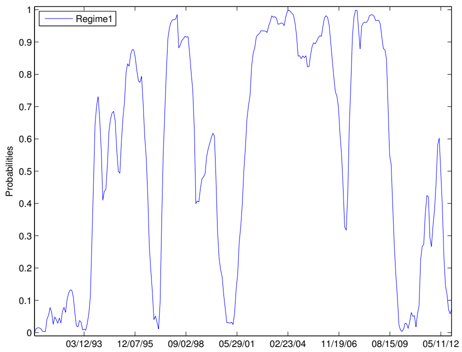
	(1)	(2)		
	Fixed Transition Probability (FTP)	**Time-varying Transition Probability (TVTP)**		
	Regime 1: High dependence			
Equidependence ρ	0.5139***	0.5543***		
P-value	(<0.0001)	(<0.0001)		
Kendall's tau	0.3436***	0.3740***		
Standard Dev	0.0149	0.0158		
VaR (1%)	-0.0355	-0.0388		
VaR (5%)	-0.0194	-0.0202		
Expected Shortfall (1%)	-0.0529	-0.0577		
Expected Shortfall (5%)	-0.0306	-0.0329		
Reduction in Risk	0.0055	0.0058		
	Regime 2: Low dependence			
Equidependence ρ	0.1287***	0.1312***		
P-value	(<0.0001)	(<0.0001)		
Kendall's tau	0.0822***	0.0838***		
Standard Dev	0.0132	0.0120		
VaR (1%)	-0.0299	-0.0284		
VaR (5%)	-0.0148	-0.0148		
Expected Shortfall (1%)	-0.0498	-0.0438		
Expected Shortfall (5%)	-0.0258	-0.0243		
Reduction in Risk	0.0090	0.0084		
	Transition Probabilities	**Transition Probabilities**		
	p_{11}	δ_0	$\delta_{\Delta r}$	$\delta_{\Delta LTV}$
Coefficient	0.9448***	2.9481**	0.2446	-4.6666***
Marginal Effect		0.2252	0.0187	-0.3564
P-value	(0.0042)	(0.0369)	(0.8684)	(0.0100)
	p_{22}	δ_0	$\delta_{\Delta r}$	$\delta_{\Delta LTV}$
Coefficient	0.9344***	2.4813**	-1.4948**	3.7933***
Marginal Effect		0.2066	-0.1245	0.3159
P-value	(0.0057)	(0.0206)	(0.0285)	(<0.0001)
LogL	80.4318	84.5903		

This table provides parameter estimates of the dependence structure in a Gaussian equidependent copula regime switching (RS) model for the 4 MSAs. The left panel shows the results of the Fixed Transition Probability (FTP) model, under the assumption that the transition probabilities p_{11} and p_{22} of the Markov chain are constant. The right panel shows the results of the Time-Varying Transition Probability (TVTP) model, where the probabilities $p_{jj,t}$, $j = 1, 2$, are functions of changes in mortgage rates, Δr_t and loan to value, ΔLTV_t, as follows:

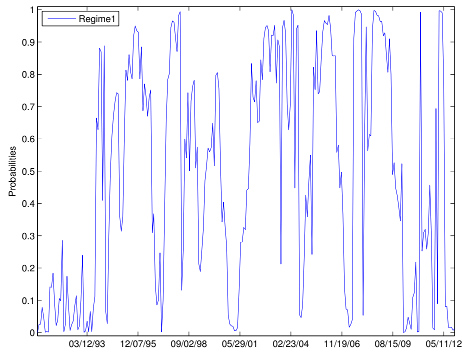
$$p_{jj,t} = P(s_t = j | s_{t-1} = j) = \text{logit}^{-1}(\delta_{0,j} + \delta_{\Delta r,j}\Delta r_t + \delta_{\Delta LTV,j}\Delta LTV_t), \tag{9}$$

where $\text{logit}^{-1}(x) = \frac{1}{1+\exp(-x)}$. We report p values for all parameters and use house price returns of Los Angeles, San Francisco, San Diego, Las Vegas from May, 1991 to August, 2013, which correspond to a sample of 279 observations. The value of log likelihood is reported in the last row.

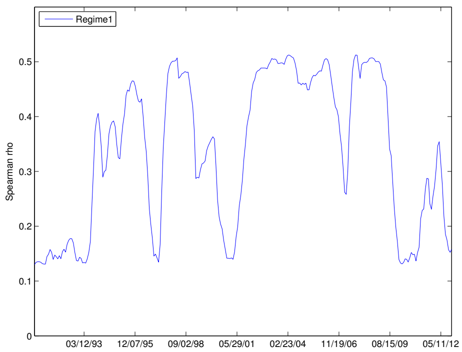
Figure 4: Smoothed probability of the high dependence regime and Spearman's rho: Equidependent Gaussian copula model with four Southwestern MSAs



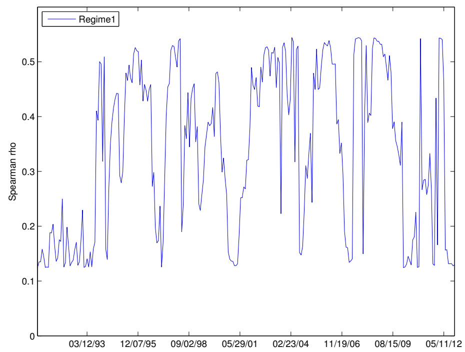
(a) Smoothed probability
Fixed
Transition Probability
(FTP)



(b) Smoothed probability
Time Varying
Transition Probability
(TVTP)



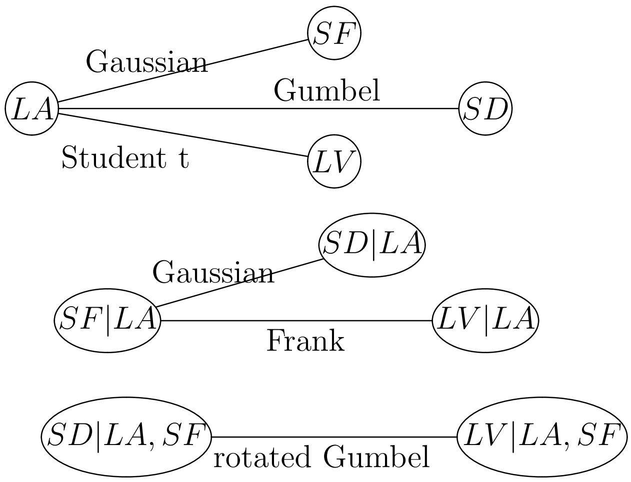
(c) Spearman's rho
Fixed
Transition Probability
(FTP)



(d) Spearman's rho
Time Varying
Transition Probability
(TVTP)

This figure is based on the equidependent Gaussian copula regime switching model estimated with four Southwestern MSAs, whose results are shown in Table 5. Panels (a) and (c) respectively show smoothed probabilities of the high dependence regime and Spearman's rho for the fixed transition probability (FTP) case, whereas Panels (b) and (d) contains results for the time varying transition probability (TVTP) case.

Figure 5: Dependence structure of the canonical vine copula for the Southwestern MSAs



This figure shows the structure of the canonical vine copula we use for the four Southwestern MSAs. We use the R function RVineStructureSelect to select the order of variables on the dependence tree. This is done by placing the variables that are most dependent in the lower levels of the trees. The optimal order of MSA returns places Los Angeles (LA) first, followed by San Francisco (SF), San Diego (SD) and Las Vegas (LV). Given the tree, we use R function VineCopula to select the bivariate copula for each pair. The pairs (LA,SF), (LA,SD) and (LA,LV) are modeled using a bivariate Gaussian, Student t and Gumbel copula, respectively. The dependence structures of (SF,SD) and (SF,LV), conditional on LA is captured by a Gaussian copula and a Franck copula, respectively. Finally, for (SD,LV) conditional on LA and SF, we use a rotated Gumbel copula. Thus, our canonical vine copula for the group of Southwestern MSAs is

$$\begin{aligned} c(F_{LA}, F_{SF}, F_{SD}, F_{LV}) \quad = \quad & c^{Ga}(F_{LA}, F_{SF})c^{Gu}(F_{LA}, F_{SD})c^{t}(F_{LA}, F_{LV}) \\ & c^{Ga}(F_{SF|LA}, F_{SD|LA})c^{F}(F_{SF|LA}, F_{LV|LA}) \\ & c^{RGu}(F_{SD|LA,SF}, F_{LV|LA,SF}), \end{aligned}$$

where c^{Ga}, c^{Gu}, c^{RGu}, c^{t}, c^{F} stand, respectively for the bivariate Gaussian, Gumbel, rotated Gumbel, Student t and Frank copula densities, F_A and $F_{A|B}$ denote the cumulative density function of A, and of A conditional on B, respectively.

Table 6: Estimates of the regime switching model with a canonical vine and a multivariate Gaussian copula, four Southwestern MSAs

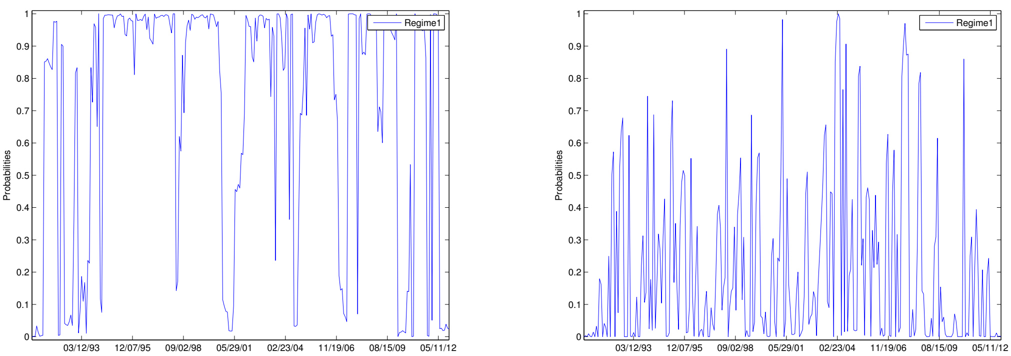
		(1)			(2)		
		Time-varying Transition Probability (TVTP)			**Time-varying Transition Probability (TVTP)**		
		Regime 1					
		Canonical vine			**Gaussian**		
		Coef	**P-value**	τ	**Coef**	**P-value**	τ
(LA, SF)	Gaussian	0.5905	<0.0001	0.4021	0.4524	0.05709	0.2989
(LA, SD)	Student t	0.5520	<0.0001	0.3723	0.7799	<0.0001	0.5694
	DoF	8.3724	0.0974				
(LA, LV)	Gumbel	1.2408	<0.0001	0.1941	0.7526	<0.0001	0.5424
(SF, SD)	Gaussian	0.3719	0.0114	0.3909	0.4282	<0.0001	0.2817
(SF, LV)	Frank	1.4203	0.0017	0.2361	0.4956	0.08646	0.3301
(SD, LV)	RGumbel	1.0996	<0.0001	0.2400	0.8699	0.0078	0.6717
		Regime 2					
		Gaussian			**Gaussian**		
		Coef	**P-value**	τ	**Coef**	**P-value**	τ
(LA, SF)		0.0058	0.4920	0.0037	0.4084	0.0038	0.2678
(LA, SD)		0.3256	0.0891	0.2112	0.3840	0.03235	0.2509
(LA, LV)		0.2667	0.0923	0.1719	0.1531	0.1845	0.0978
(SF, SD)		0.3281	0.1026	0.2128	0.5146	0.0016	0.3441
(SF, LV)		-0.2251	0.1215	-0.1446	0.0457	0.7797	0.0291
(SD, LV)		-0.1586	0.2361	-0.1014	-0.0661	0.6530	-0.0421
		Transition Probabilities			**Transition Probabilities**		
		δ_0	$\delta_{\Delta r}$	$\delta_{\Delta LTV}$	δ_0	$\delta_{\Delta r}$	$\delta_{\Delta LTV}$
	Coefficient	5.2534***	1.4319***	-6.9968***	-0.2485	-1.2665	-10.6414***
	Marginal Effect	0.1867	0.0509	-0.2487	-0.0200	-0.1020	-0.8566
	P-value	(<0.0001)	(0.0358)	(<0.0001)	(0.7761)	(0.2842)	(<0.0001)
		δ_0	$\delta_{\Delta r}$	$\delta_{\Delta LTV}$	δ_0	$\delta_{\Delta r}$	$\delta_{\Delta LTV}$
	Coefficient	3.8454***	-3.8421***	11.5419***	1.7386**	-0.4346	-0.9708
	Marginal Effect	0.2183	-0.2181	0.6553	0.2183	-0.0546	-0.1219
	P-value	(<0.0001)	(<0.0001)	(<0.0001)	(0.0248)	(0.4757)	(0.3231)
	LogL		115.2467			108.9665	

This table provides parameter estimates of the dependence structures in a regime switching (RS) models with a canonical vine copula (Regime 1) and a multivariate Gaussian copula (Regime 2) in the left panel and with multivariate Gaussian copulas (Regime 1 and Regime 2) in the right panel for the four Southwestern MSAs. The structure of the canonical vine copula is the following: Los Angeles-San Francisco, Los Angeles-San Diego and Los Angeles-Las Vegas are modeled using a bivariate Gaussian copula, Student t copula and Gumbel copula respectively. The dependence structures of San Francisco-San Diego and San Francisco-Las Vegas, conditional on Los Angeles is captured by a Gaussian copula and Franck copula, respectively. Finally, San Diego-Las Vegas conditional on Los Angeles and San Francisco is captured by a rotated Gumbel copula. The transition probabilities of the Markov chain are functions of changes in mortgage rates, Δr_t and loan to value, ΔLTV_t, as follows:

$$p_{jj,t} = P(s_t = j | s_{t-1} = j) = \text{logit}^{-1}(\delta_{0,j} + \delta_{\Delta r,j}\Delta r_t + \delta_{\Delta LTV,j}\Delta LTV_t), \tag{9}$$

for $j = 1, 2$, where $\text{logit}^{-1}(x) = \frac{1}{1+\exp(-x)}$. We report p values for all parameters. In order to compute the unconditional Kendall's tau, we transform each Kendall's tau into the parameter of the bivariate Gaussian copula with the same rank correlation. We then apply the rules of conditional variance-covariance to compute the corresponding unconditional correlations. Finally, we report the unconditional Kendall's tau corresponding to the unconditional Gaussian copula parameters, computed as $\tau = 2\text{arcsin}(\theta)/\pi$. We use house price returns of Los Angeles, San Francisco, San Diego, Las Vegas from May 1991 to August 2013, which corresponds to a sample of 279 observations. The values of the log likelihood are reported in the last row. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Figure 6: Smoothed probability of the high dependence regime from the time-varying transition probability (TVTP) canonical vine and Gaussian copula model, four Southwestern MSAs



(a) Smoothed probability Canonical vine-Gaussian

(b) Smoothed probability Gaussian-Gaussian

This figure shows smoothed probabilities of the high dependence regime for the time varying transition probability (TVTP) models, shown in Table 6, based on the canonical vine-Gaussian copula model in Panel (a), and the Gaussian-Gaussian copula model in Panel (b).

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On-line Appendix

A Copulas

In this Appendix, we first define copula-based measures of dependence, and then we introduce the copulas we work with. In the sequel, we denote the probability integral (PIT) of the i-th marginal y_i as $u_i = F_i(y_i)$, where F_i is the cumulative distribution of the marginal. When the marginal model is correctly specified the PIT follows a uniform distribution: $u_i \sim U_{[0,1]}$.

The dependence captured by a copula can be quantified by rank correlation coefficients such as Kendall's tau and Spearman's rho, which take values in the $[-1, 1]$ range and do not depend on the distributions, F_i, of the marginals. Kendall's tau can be expressed as a function of the copula, as follows:

$$\tau = 4 \int_{[0,1]^2} C(u_1, u_2) dC(u_1, u_2) - 1 \ , \tag{A.1}$$

and the expression for Spearman's rho is:

$$\rho = 12 \int_{[0,1]^2} C(u_1, u_2) du_1 du_2 - 3 \ . \tag{A.2}$$

While the Kendall's tau is the most commonly used measure, Spearman's rho is useful to examine smoothed dependence in the context of regime switching models, since, due to the linearity of Equation (A.2), the Spearman's rho of a linear combination of copulas, C_1 and C_2, with probability $0 \leq p \leq 1$ is just the linear combination of the Spearman's rhos:

$$\rho \left(pC_1(u_1, u_2) + (1-p)C_2(u_1, u_2) \right) = p\rho \left(C_1(u_1, u_2) \right) + (1-p)\rho \left(C_2(u_1, u_2) \right) .$$

Copulas also determine the dependence between two variables in the tails of the joint distribution, i.e. the dependence between extreme events. Mathematically, lower tail dependence can be defined as

$$\lambda_L = \lim_{\alpha \to 0} P(F_1(y_1) < \alpha | F_2(y_2) < \alpha). \tag{A.3}$$

If y_i is house price return in MSA i with cumulative distribution function $F_i(.)$, then y_1 and y_2 are lower tail dependent whenever the limit exists and is different from zero. Tail dependence is a copula concept, which means that it depends only on the copula C and not on the marginals $F_i(.)$. In the context of returns, the concern is usually about lower tail dependence, whose implications are particularly painful for investors:

$$\lambda_L = \lim_{\alpha \to 0} C(\alpha, \alpha)/\alpha. \tag{A.4}$$

Symmetrically, one can define upper tail dependence as $\lambda_U = \lim_{\alpha \to 1-} \bar{C}(\alpha, \alpha)/(1 - \alpha)$, where $\bar{C}(u_1, u_2) = 1 - u_1 - u_2 + C(1 - u_1, 1 - u_2)$ denotes the survivor function of copula C.

A.1 Bivariate copulas

For the following bivariate copulas, we show the cumulative distribution since they have nice functional forms. In estimation, we use their densities, which can be obtained by differentiation.

a. Gumbel The Gumbel copula has the form

$$C^{Gu}(u_i, u_j; \theta) = \exp -((-\log u_i)^\theta + (-\log u_j)^\theta)^{\frac{1}{\theta}}).$$

The Gumbel does not allow for negative dependence and it goes from independence to the Fréchet upper bound of perfect positive dependence, as its parameter θ moves in the range $[1, \infty)$. The Gumbel copula is asymmetric with upper tail dependence $\lambda_U = 2 - 2^{\frac{1}{\theta}}$, but no lower tail dependence. The Gumbel is often used in its rotated form, which obtains by interverting upper and lower tails, as follows: $C^{RGu}(u_i, u_j; \theta) = u_i + u_j - 1 + C^{Gu}(1 - u_i, 1 - u_j; \theta)$. The rotated Gumbel has only lower tail dependence, equal to the upper tail dependence, λ_U of the Gumbel. The Kendall's tau of the Gumbel or rotated Gumbel copula is $\frac{\theta-1}{\theta}$.

b. Frank The Frank copula has the form

$$C^F(u_i, u_j; \theta) = -\frac{1}{\theta} \log \left(1 + \frac{(\exp(-\theta u_i) - 1)(\exp(-\theta u_j) - 1)}{\exp(-\theta) - 1}\right),$$

where $\theta \in (-\infty, \infty) \setminus \{0\}$, and the dependence covers the full possible range, including both the Fréchet upper and lower bound, $\lambda_U = \lambda_L = 0$, except when $\theta \to \infty$. Its Kendall's tau is $1 - \frac{4(D_1(\alpha)-1)}{\alpha}$, where $D_1(\alpha) = \frac{1}{\alpha}\int_0^\alpha \frac{t}{\exp t - 1} dt$ is the Debye function.

c. Clayton The Clayton copula has the form

$$C^{Cl}(u_i, u_j; \theta) = (u_i{}^{-\theta} + u_j{}^{-\theta} - 1)^{-1/\theta},$$

where $\theta \in (0, \infty)$, and the dependence covers only postive dependence, including the Fréchet upper bound. The Clayton copula is asymmetric since the dependence is concentrated in the lower tail. The Clayton copula has only lower tail dependence $\lambda_L = 2^{\frac{-1}{\theta}}$. Its Kendall's tau is $\frac{\theta}{\theta+2}$.

d. Student t The density of the bivariate Student t copula is:

$$c^t(u_1, u_2; \rho, \nu) = \frac{\left(1 + \frac{x_1^2 + x_2^2 - 2\rho x_1 x_2}{\nu(1-\rho^2)}\right)^{\frac{-\nu+2}{2}}}{2\pi\sqrt{1-\rho^2}\prod_{i=1}^2 t_\nu(x_i)},$$

where $t_\nu(.)$ and $T_\nu(.)$ denote respectively the density and the cumulative density of the Student t distribution with $\nu > 2$ degrees of freedom, $x_i = T_\nu^{-1}(u_i)$, and ρ is the copula correlation parameter. The Student t copula has the same lower and upper tail dependence for every pair of variables: $\lambda_U = \lambda_L = 2t_{\nu+1}\left(-\sqrt{\nu+1}\sqrt{\frac{1-\rho}{1+\rho}}\right)$. Its Kendall's tau is $\frac{2\text{arcsin}(\theta)}{\pi}$.

A.2 Multivariate equidependent copulas

A.2.1 Equidependent Gaussian copula

The density of the n-dimensional equidependent Gaussian copula is:

$$c^{Ga}(u_1,\ldots,u_n;R) = |R|^{-1/2}\exp\left[-\frac{1}{2}\left(x'R^{-1}x - x'x\right)\right] ,$$

where $x = (x_1\ldots,x_n)$, $x_i = \Phi^{-1}(u_i)$ and $\Phi(.)$ denotes the cumulative density of the standard normal. The correlation matrix is $R = (1-\rho)\mathbf{I}_n + \rho\mathbf{J}_n$, with ρ, the copula equicorrelation parameter, I_n the n-dimensional identity matrix and J_n the $n \times n$ matrix of ones. R is positive definite if and only if $\rho \in (\frac{-1}{n-1}, 1)$. The bivariate version that we use as building block in the canonical vine copulas is:

$$c^{Ga}(u_1,u_2;\rho) = \frac{1}{\sqrt{1-\rho^2}}\exp\left[-\frac{x_1^2+x_2^2-2\rho x_1x_2}{2(1-\rho^2)} + \frac{x_1^2+x_2^2}{2}\right] ,$$

where ρ is a correlation coefficient that lies between -1 and 1. The Gaussian copula has zero upper and lower tail dependence, $\lambda_U = \lambda_L = 0$, except in the case of perfect correlation, $\rho = 1$. Its Kendall's tau is $\frac{2\arcsin(\theta)}{\pi}$.

A.3 Construction of canonical vine copulas

The idea underlying canonical vine copulas is the fact that a joint probability density function can be decomposed by iteratively conditioning as follows:

$$f(u_1,\cdots,u_n) = f(u_1)\cdot f(u_2|u_1)\cdot f(u_3|u_1,u_2)\cdots f(u_n|u_1,\cdots,u_{n-1}). \tag{A.5}$$

Each conditional density function can be represented as follows, where we use the fact that $f_i(u_i) = 1$, since $u_i \sim U_{[0,1]}$:

$$f(u_2|u_1) = f(u_1,u_2) = c_{12}(F_1(u_1),F_2(u_2)) \tag{A.6}$$

In the same way, a second conditional density can be represented as follows:

$$
\begin{aligned}
f(u_3|u_1,u_2) &= \tfrac{f(u_3,u_2|u_1)}{f(u_2|u_1)} \\
&= c_{23|1}(F_{2|1}(u_2|u_1),F_{3|1}(u_3|u_1))f(u_3|u_1) \\
&= c_{23|1}(F_{2|1}(u_2|u_1),F_{3|1}(u_3|u_1))c_{13}(F_1(u_1),F_3(u_3)),
\end{aligned} \tag{A.7}
$$

where $c_{23|1}$ is the conditional density copula of u_2 and u_3, given u_1. Now, by plugging Equations (A.6) and (A.7) into Equation (A.5), we obtain the joint density of the first three variables in the system as a function of bivariate conditional copulas, and further using the fact that $f(u_1,u_2,u_3)=c(u_1,u_2,u_3)$, we get:

$$
c(u_1,u_2,u_3)=c_{23|1}(F_{2|1}(u_2|u_1),F_{3|1}(u_3|u_1))c_{12}(F_1(u_1),F_2(u_2))c_{13}(F_1(u_1),F_3(u_3)). \tag{A.8}
$$

By continuing the same logic and iterating further, one obtains the expression for the n-dimensional canonical vine copula density function in Equation (6).

B Estimation

B.1 Two-step estimation

The log likelihood is composed of two parts, L_m that represents the marginal densities, and L_c that represents the dependence structure. For $\mathbf{Y}=(Y_1',\ldots,Y_T')$, the total log-likelihood is as follows (see Chollete et al. 2009).

$$
\begin{aligned}
L(\mathbf{Y};\theta,\alpha) &= L_m(Y;\theta_m)+L_c(\mathbf{Y};\theta_m,\theta_c) \\
L_m(\mathbf{Y};\theta_m) &= \sum_{t=1}^{T}\sum_{i=1}^{n}\log f_i(y_{i,t}|u_i^{t-1};\theta_{m,i}) \\
L_c(\mathbf{Y};\theta_m,\theta_c) &= \sum_{t=1}^{T}\log c(F_1(y_{1,t}|y_1^{t-1};\theta_{m,1}),\ldots,F_n(y_{n,t}|y_n^{t-1};\theta_{m,n});\theta_c),
\end{aligned} \tag{B.9}
$$

where $y_i^{t-1}=(y_{i,1},\ldots,y_{i,t-1})$ is the history of the variable i, and the vector $\theta_m=(\theta_{m,1},\ldots,\theta_{m,n})$ represents the parameters of each one of the n marginal densities f_i. The copula densities depend on $\theta_c=(\theta_c^{(1)},\theta_c^{(2)},\delta,\alpha)$ which is composed of copula parameters for each regime, transition probability parameters (δ) and initial probabilities (α) of being in each regime at $t=1$.

B.2 EM Algorithm

We estimate the parameters of the regime switching copula using the filter of Diebold et al. (1994), who adapt the EM algorithm to the TVTP case. Given starting values of the copula parameters in each regime, $\theta_c^{(j)}$, $j = 1, 2$, we can define a vector of regime-specific copula densities at time t

$$\eta_t = \begin{pmatrix} c^{(1)}\big(F_1(y_{1,t}|y_1^{t-1}), \ldots, F_n(y_{n,t}|y_n^{t-1}); \theta_c^{(1)}\big) \\ c^{(2)}\big(F_1(y_{1,t}|y_1^{t-1}), \ldots, F_n(y_{n,t}|y_n^{t-1}); \theta_c^{(2)}\big) \end{pmatrix}. \tag{B.10}$$

Given η_t, as well as starting values of the initial state probabilities α and of the transition probability parameters δ, and defining the transition matrix of the Markov Chain, which depends on regressors X_{t-1} as

$$P_{t-1} = \begin{pmatrix} p_{11,t-1} & 1 - p_{11,t-1} \\ 1 - p_{22,t-1} & p_{22,t-1} \end{pmatrix}, \tag{B.11}$$

where $p_{jj,t-1} = \text{logit}(X_{t-1}\delta_j)$, $j = 1, 2$, the E-step provides estimates of the filtered state probabilities at each time t, as follows:

$$S_{t|t} = \frac{S_{t|t-1} \odot \eta_t}{\mathbf{1}'(S_{t|t-1} \odot \eta_t)}, \tag{B.12}$$

$$S_{t|t-1} = P'_{t-1} S_{t-1|t-1}, \tag{B.13}$$

where $S_{t|t}$ is a vector whose elements denote the probabilities of being in each regime at time t, conditional on the observations up to time t, $\odot$ denotes the entry-wise product, $\mathbf{1}$ is a 2×1 vector whose components are $1s$, and $S_{t|t-1}$ denotes a vector of the probabilities of being in the regimes at time t conditional on the observations up to time $t-1$. Equation (B.12) is an application of Bayes theorem, and Equation (B.13) represents one forward iteration of the Markov chain. Having worked out $S_{t|t-1}$ for every period t, we obtain the log likelihood:

$$L_c(\mathbf{Y};\theta_m,\theta_c) \quad = \quad \sum_{t=1}^{T} \log(\mathbf{1}'(S_{t|t-1} \odot \eta_t)). \tag{B.14}$$

The M-step consists in maximizing this likelihood with respect to the copula parameters $\theta_c^{(j)}$, and to the parameters $\delta_j^{(i)}$, of the effect of regressors on the probability of staying in state j, in each regime $j = 1, 2$. The copula parameters need to be estimated numerically, whereas a first order Taylor approximation is available for $\delta_j^{(i)}$s in the ith iteration, which yields the following closed form:

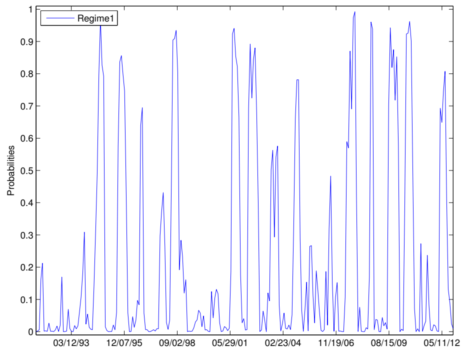
$$\begin{aligned} \delta_j^{(i)} \quad &= \quad \left(\sum_{t=2}^{T} P(s_{t-1} = j) X'_{t-1} \frac{\partial p_{jj,t-1}}{\partial X_{t-1}} \right)^{-1} \\ &\times \quad \sum_{t=2}^{T} X'_{t-1} \left[p_{jj,t-1} - P(s_{t-1} = j) \left(p_{jj,t-1} - \frac{\partial p_{jj,t-1}}{\partial X_{t-1}} \delta_j^{(i-1)} \right) \right], \end{aligned} \tag{B.15}$$

where $p_{jj,t-1}$ denotes the probability of staying in regime j from $t-1$ to t, Using these parameter values as new starting values, one starts again with the E-step and iterates until the algorithm converges.

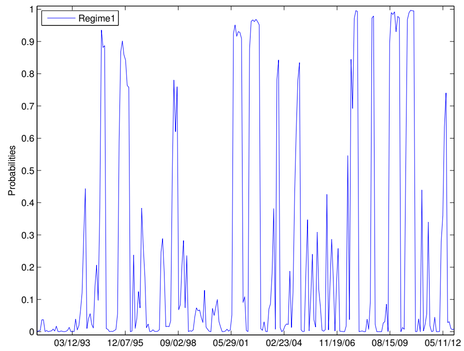
In the simpler homogeneous Markov chain case, the transition probabilities $p_{jj'}$ can be computed as sample averages of observed transitions from regime j to regime j'. Moreover in the E-step, in Equation (B.13), P_{t-1} is replaced by the constant P.

C Results with 19 MSAs

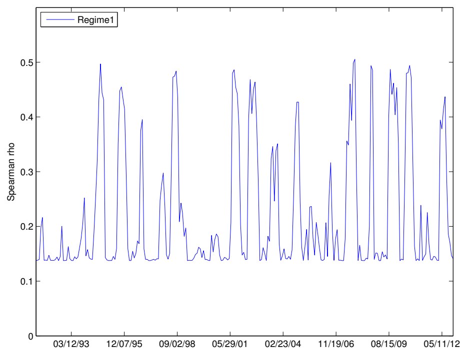
Figure C.1: Smoothed probability of the high dependence regime and Spearman's rho: Equidependent Gaussian copula model with 19 MSAs



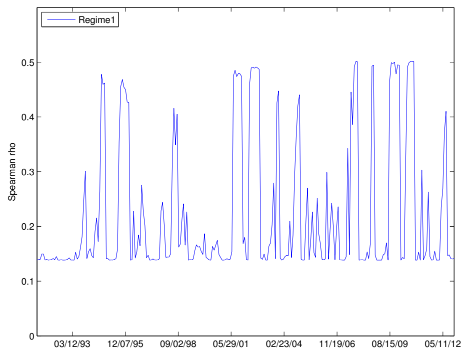
(a) Smoothed probability
Fixed
Transition Probability
(FTP)



(b) Smoothed probability
Time Varying
Transition Probability
(TVTP)



(c) Spearman's rho
Fixed
Transition Probability
(FTP)



(d) Spearmans' rho
Time Varying
Transition Probability
(TVTP)

This figure is based on the equidependent Gaussian copula regime-switching model estimated with 19 MSAs, whose results are shown in Table C.1. Panels (a) and (c) respectively show smoothed probabilities of the high dependence regime and Spearman's rho for the fixed transition probability (FTP) case, whereas Panels (b) and (d) contains results for the time varying transition probability (TVTP) case.

Table C.1: Estimates of the regime-switching equidependent Gaussian copula model, 19 MSAs

	Fixed Transition Probability (FTP)		Time-varying Transition Probability (TVTP)		
	Regime 1				
	Gaussian		**Gaussian**		
	ρ	τ		ρ	τ
Coefficient	0.5083***	0.3395***		0.5033***	0.3358***
P-value	(<0.0001)			(<0.0001)	
	Regime 2				
	Gaussian		**Gaussian**		
	ρ	τ		ρ	τ
Coefficient	0.1376***	0.0879***		0.1384***	0.0884***
P-value	(<0.0001)			(<0.0001)	
	Transition Probabilities		**Transition Probabilities**		
	p_{11}		δ_0	$\delta_{\Delta r}$	$\delta_{\Delta LTV}$
Coefficient	0.6765***		0.3147***	-2.9432***	-6.8499***
Marginal Effect			0.0282	-0.2635	-0.6133
P-value	(<0.0001)		(<0.0001)	(<0.0001)	(<0.0001)
	p_{22}		δ_0	$\delta_{\Delta r}$	$\delta_{\Delta LTV}$
Coefficient	0.9029***		2.2070***	-0.4751***	-0.4545***
Marginal Effect			0.1947	-0.0419	-0.0401
P-value	(<0.0001)		(<0.0001)	(<0.0001)	(<0.0001)
LogL	331.8590		335.3151		

This table provides parameter estimates of the dependence structure in a Gaussian equidependent copula regime-switching (RS) model for 19 MSAs. The left panel shows the results of the Fixed Transition Probability (FTP) model, under the assumption that the transition probabilities p_{11} and p_{22} of the Markov chain are constant. The right panel shows the results of the Time-Varying Transition Probability (TVTP) model, where the probabilities $p_{jj,t}$, $j = 1, 2$, are functions of changes in mortgage rates, Δr_t and loan to value, ΔLTV_t, as follows:

$$p_{jj,t} = P(s_t = j|s_{t-1} = j) = \text{logit}^{-1}(\delta_{0,j} + \delta_{\Delta r,j}\Delta r_t + \delta_{\Delta LTV,j}\Delta LTV_t), \tag{9}$$

where $\text{logit}^{-1}(x) = \frac{1}{1+\exp(-x)}$.We report p values for all parameters and use house price returns of Phoenix, Los Angeles, San Francisco, San Diego, Las Vegas, Miami, Tampa, Charlotte, Cleveland, Portland, Seattle, Washington, Atlanta, Boston, Chicage, Denver, Detroit, Minneapolis and New York from May 1991 to August 2013, which corresponds to a sample of 279 observations. The values of the log likelihood are reported in the last row. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.