Co-movement of State's Mortgage Default Rates: A Dynamic Factor Analysis Approach

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Abstract

Underestimated default correlations of the underlying assets of Collateralized Debt Obligation (CDO) products have been partially blamed for the initial inaccurate ratings. Given the increasingly reliant on mortgage related assets in CDO products, a way to test the underestimation default correlation theory is to estimate how mortgage loan defaults have co-moved across states over time. In this paper, we use a dynamic factor model to estimate the co-movement of mortgage loan default rates across states. The results show that with only one latent factor about 62% of the variation in the states mortgage default rates could be explained when the full sample, 1979 to 2010, is used. However, limiting the sample from 1979 to 2003, the factor explains only 28% of the default variation. There was not much co-movement until the beginning of the 1st quarter of 2007 to 2009. This implies that the initial assigned default correlations were perhaps not inaccurate. An examined relationship between the latent factor and some national variables show a positive correlation between the factor and the St. Louis Fed's Financial Stress Index, and a negative correlation for percentage change in GDP, Retail and Food Services Sales and Consumer sentiments. The factor seems to be a leading indicator for Retail and Food Sales and the percentage change in the GDP.

JEL Classification: G01, G21, G24, C38

Key Words: Dynamic Factor Model, Mortgage, Default Correlation

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Introduction

How to measure the default correlation of the underlying assets of CDOs backed by real estate related assets have become a subject of importance after the collapse of CDO market. The underestimation of the default correlation of the underlying assets (which were mostly mortgage related assets) of CDOs by the rating agencies have been partially blamed for the initial rosy tranche ratings. The default correlation is an important factor in the ratings of the CDOs; a low default correlation assigned to the underlying assets would lead to a large fraction of the issued CDO tranches being assigned a higher rating than the average rating of the underlying pool of assets.

The share of real estate related assets as collateral in CDO deals increased significantly after 2001-2002 recession, primarily, due to the high housing appreciation from 2002 to 2006. The total percentage of subprime, alt and prime mortgage loan related assets which made up of only about 15% of the total assets in CDO products in 2000 has increased to over 80% by 2006. Mortgage loan related assets became the main collateral in the CDO deals during the securitization boom. These mortgage loans were initially issued in the states. A way to test the underestimation of the default correlation theory is to estimate how mortgage default loans have co-moved across the states over the years.

About 22[2] states accounted for 82% of the housing growth during the housing boom years of 2002 to 2006. It would not be a stretch to postulate that most of the mortgage related assets used as collateral for the CDOs were mortgage loans packaged from these states. The extent of the co-movement of the mortgage default rates across these 22 states would give us a sense of the default correlation of the underlying mortgage related assets in the CDO deals.

The mortgage default in each state can be decomposed into: a latent common factor that affects all the states and state specific shocks using dynamic factor analysis. The common factor—which represents an extraction of the common variations underlying the states default rates—not only captures common shocks, but also co-movements across the states. Dynamic factor analysis has become an important econometric tool in studying co-movements in macroeconomic time series. It is a dimension reduction technique that aims to reduce N dimension observed time series in terms of M common trends, where M is less than N. The aim

[2] Appendix A provides more information about the states and the total housing permit issued during this period.

of the technique is for M to be small as possible without losing too much information from the original time series.

The empirical results show that, when the full sample (1979 to 2010) is used there seem to be a single persistent latent common factor driving the state's mortgage default rates. This common factor explains on average about 62% of the variation in the state's mortgage default rates. However, when the sample is limited to 1979 to 2003, the common factor explains only 28% of the variation in the state's mortgage default rates. This implies that before 2003 there did not seem to have been a lot of co-movement between the states mortgage default rates, suggesting that, perhaps, the initial default correlation assigned to the underlying mortgage related asserts in the CDO deals were not inaccurate. The dynamics of the factor shows that between the 2nd quarters of 1979 to the 4th quarter of 2003 there was very little variation in the dynamics of the factor. From the beginning of the 1st quarter of 2004 there seem to be a slight decrease in the common factor till the 4th quarter of 2006. This period corresponds to a period of high home appreciation and huge investment in housing and low default rate. Form the 1st quarter of 2007 there was a significant increase in the common factor peaking at the 3th quarter of 2009. The revision of the initial default correlation by the credit rating agencies coincided with this period.

Because the latent factor is unobservable and we only have an estimate of it, it is not easy to emphatically state what it represents. But an examined relationship between the latent factor and the state's unemployment rates and house price indexes show a positive correlation between the factor and the unemployment rate (average of 0.44) and a negative correlation for the house price index (average of -0.34) . A second relationship between the factor and some national variables show a positive correlation between the factor and the St. Louis Fed's Financial Stress Index (0.61) and a negative correlation for percentage change in GDP (-0.67) , Retail and Food Services Sales (-0.51) and Consumer Sentiments (-0.55). The factor seems to be a leading indicator for Retail and Food Sales and the percentage change in the GDP

The paper proceeds as follows; Section 2 describes the methodology. Section 3 describes the data used. Section 4 provides the results and Section 5 concludes.

2. Econometric Methodology: Dynamic Factor Model

Dynamic factor model decomposes the dynamics of observables X_t (which denotes a measure of the mortgage default rate) into the sum of two unobservable components, one that affects all $X_t's$, the common factors (F_t) and the one that is idiosyncratic, u_t . The standard formulation of a factor model in matrix form is:

$$(1) \qquad X_t = \Lambda F_t + u_t$$

Where X_t is $N \times 1$ response variable, F_t is $M \times 1$ vector of common factors, whose loadings are grouped in the $N \times M$ matrix Λ, u_t is an $N \times 1$ vector of idiosyncratic disturbances and $t = 1, \dots, T$. These common factors not only capture common shocks, but also co-movement of default rates across the 22 states. F_t and u_t are assumed to be independent of each other. It is also assumed that u_t is normally distributed and is cross-sectionally and serially uncorrelated. It is also assumed that the factor components and the idiosyncratic disturbances follow an autoregressive process of order q and p respectively:

$$(2) \qquad F_t = \gamma_1 F_{t-1} + \cdots + \gamma_q F_{t-q} + v_t$$

Where $v_t \sim N(0, V_t)$

$$(3) \qquad u_t = \beta_1 u_{t-1} + \cdots + \beta_q u_{t-p} + \psi_t$$

Where $\psi_t \sim N(0, \Psi_t)$

$v_t \sim N(0, V_t)$ and $\psi_t \sim N(0, \Psi_t)$ are assumed to be independent of each other

For this paper q and p equals 1, F_t is a 1×1 and Λ is an $N \times 1$.

2.1 Estimation: Kalman Filter Algorithm

Following the usual approach for estimating dynamic factor models, equations (1), (2) and (3) are transformed into a state space form: (1) measurement and (2, 3) transition equations respectively. The state model can be set up by specifying a state vector

$$(4) \qquad Z_t \coloneqq \begin{bmatrix} F_t \\ u_t \end{bmatrix}$$

And the transition equation

$$(5) \qquad Z_t = \begin{bmatrix} \gamma_1 & \vdots & 0 \\ \cdots & \vdots & \cdots \\ 0 & \vdots & \beta_1 \end{bmatrix} Z_{t-1} + \begin{bmatrix} v_t \\ \psi_t \end{bmatrix}$$

The corresponding measurement

$$(6) \qquad X_t = \Lambda F_t + u_t = [\,\Lambda \colon \mathrm{I}_N] Z_t$$

Following De Jong (1988) and using Kalman filtering, and setting the initial to $Z_0 \sim N(\mu_0, \Sigma_0)$ and letting $KF(\mu, \Sigma)$ be the Kalman filter applied with the starting estimates γ_0 and Σ_0 , the minus twice the joint log likelihood function of the observations $X_1, \dots, X_T$, the factor components $F_0, \dots, F_T$ and the errors $u_0, \dots, u_T$ can be written can be written as:

$$(7)\; logL(X_1, \dots, X_T) = log|\Sigma| + \mu^{/}\Sigma^{-1}\mu + \textstyle\sum_{t=1}^{n}|D_t| + \sum_{t=1}^{n} e_t^{/} D_t^{-1} e_t$$
$$+ log|\Sigma^{-1} + S| - (\Sigma^{-1}\mu + s)^{/}(\Sigma^{-1} + S)(\Sigma^{-1}\mu + s).$$

Where e_t and D_t are the innovations and the innovations covariance matrices calculated with $KF(\mu_0, \Sigma_0)$. The vector s and matrix S are calculated in parallel with the e_t and D_t for $t = 1, \dots, T$ as follows:

$s = s + Y_{t-1}^{/}\Lambda^{/}D_t^{-1}e_t, \quad S = S + Y_{t-1}^{/}\Lambda^{/}D_t^{-1}\Lambda\Upsilon_{t-1}, \quad Y_t = \gamma(I - K_t\Lambda)\Upsilon_{t-1}$

With s and S initialized at 0, $Y_0 = I$ and K_t is the Kalman gain matrix from $KF(\mu_0, \Sigma_0)$.

2.2 Contribution of the Common Factor to the Total Variance

In this section we explain how to disentangle the contribution of the common factor and the state specific shock. Equations (1) and (3) represent a stacked vector of state individual equations:

$$(8) \qquad x_{it} = a_i + b_i f_t + \epsilon_{it}$$

$$(9) \qquad \epsilon_{it} = \rho_i \epsilon_{it-1} + \phi_{it}$$

Where $i = 1, \dots, 22$ indexes states, f_t represents the common factor, ϵ_{it} is an AR(1) idiosyncratic term which represents state specific shocks, and a_i is a time fixed-effect specific to each state. Since the common factor and the idiosyncratic term are assumed to be orthogonal, the variance of x_{it} can be decomposed into the sum of the variances.

$$(10) \qquad Var(x_{it}) = Var(b_i f_t) + Var(\epsilon_{it} + a_i)$$

The percentage of the variation of the mortgage default contributed by the common factor can be expressed as:

$$(11) \qquad \%\ factor = \frac{Var(b_i f_t)}{Var(x_{it})}$$

3. Data

The mortgage default rate is defined as loans that are 90+ delinquent each quarter. The data is obtained from Mortgage Bankers Association National Delinquent Survey. The data consist of quarterly default rates from the 2nd quarter of 1979 to the 3rd quarter of 2010 of the 22 states. Table 1 presents the summary statistics of the state's quarterly mortgage default rates.

Table 1

This table reports the summary statistics of the state's quarterly mortgage default rates from 2nd quarter 1979 to 3rd quarter 2010. The first values represent the mean and the standard value deviations are in the brackets.

State	**Default Rate**
Arizona	1.154(0.794)
California	0.959(1.323)
Colorado	0.824(0.591)
Florida	1.046(1.300)
Georgia	1.280(1.053)
Illinois	1.296(0.977)
Indiana	1.129(0.952)
Michigan	1.196(1.202)
Minnesota	0.695(0.603)
Missouri	0.933(0.681)
Nevada	1.320(1.711)
New Jersey	0.990(0.763)
New York	0.878(0.807)
Ohio	1.222(0.878)
North Carolina	0.935(0.724)
Pennsylvania	1.191(0.615)
South Carolina	1.070(0.701)
Tennessee	1.476(0.780)
Texas	1.259(0.734)
Virginia	0.733(0.628)
Washington	0.671(0.704)
Wisconsin	0.889(0.673)

4. Empirical Results

4.1 Estimation Results of Equation (1)

The dynamic factor model, equation (1), is estimated using the change in the mortgage default rate of the 22 states, i.e. X_t is the first difference of the default rate. Table 2 reports the parameter estimates of equation (1) and the contribution of the common factor to the total variance, equation (11) for the sample period 1979 to 2003. The common factor impacts all the states in the same direction. With the exception of Wisconsin, all the coefficients were statistically significant. The common factor explains on average about 28% of the variation in the states default rate. Table 3 reports the estimates for the sample period 1979 to 2010. For this period also the common factor impacts all the state default rates in the same direction. All the coefficients are statistically significant at 1%. The variance decomposition shows that the common factor explains on average about 62% of the variation in the states default rate.

This results show that there was not much co-movement of the default rates across the states from 1979 to 2003. All the co-movement occurred post 2003, especially, beginning of the 1st quarter of 2007 (Figure 1). This will imply that the initial default correlation assigned to the underlying assets of the real estate related assets backed CDO deals by the credit rating agencies were not inaccurate.

Table 2

This table reports the estimation results for equation (1). F_t Follows an AR (1) process and the default data is from 2nd quarter of 1979 to the 4rd quarter of 2003

State	Factor Coefficient (S. E.)	P-value	% of X_t explained by the common factor
Arizona	0.098 (0.012)	0.000	55
California	0.079 (0.017)	0.000	22
Colorado	0.077 (0.020)	0.000	14
Florida	0.081 (0.020)	0.000	29
Georgia	0.110 (0.012)	0.000	62
Illinois	0.152 (0.027)	0.000	29
Indiana	0.093 (0.013)	0.000	45
Michigan	0.085 (0.014)	0.000	27
Minnesota	0.047 (0.010)	0.000	22
Missouri	0.076 (0.012)	0.000	33
Nevada	0.097 (0.020)	0.000	15
New Jersey	0.069 (0.017)	0.000	16
New York	0.057 (0.015)	0.000	13
Ohio	0.096 (0.017)	0.000	28
North Carolina	0.061 (0.009)	0.000	34
Pennsylvania	0.120 (0.017)	0.000	35
South Carolina	0.098 (0.017)	0.000	25
Tennessee	0.092 (0.016)	0.000	25
Texas	0.104 (0.017)	0.000	32
Virginia	0.052 (0.010)	0.000	17
Washington	0.072 (0.010)	0.000	43
Wisconsin	0.025 (0.020)	0.213	0.7
Factor	**0.130 (0.106)**	**0.220**	

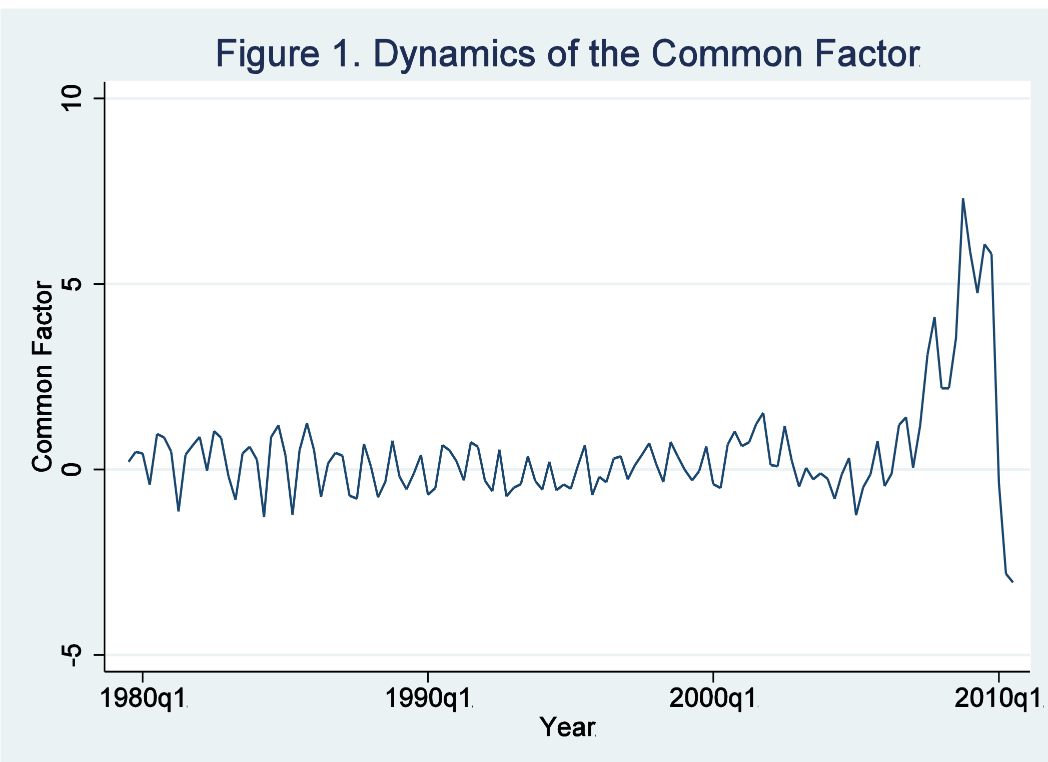
Table 3

This table reports the estimation results for equation (1). F_t follows an AR (1) process and the default data is from 2nd quarter of 1979 to the 3rd quarter of 2010

State	**Factor Coefficient (S. E.)**	**P-value**	**% of X_t explained by the common factor**
Arizona	0.209 (0.018)	0.000	81
California	0.190 (0.019)	0.000	69
Colorado	0.085 (0.012)	0.000	35
Florida	0.228 (0.023)	0.000	60
Georgia	0.162 (0.013)	0.000	86
Illinois	0.191 (0.018)	0.000	62
Indiana	0.118 (0.011)	0.000	71
Michigan	0.157 (0.014)	0.000	71
Minnesota	0.100 (0.010)	0.000	69
Missouri	0.097 (0.009)	0.000	63
Nevada	0.327 (0.026)	0.000	77
New Jersey	0.154 (0.016)	0.000	66
New York	0.128 (0.013)	0.000	64
Ohio	0.110 (0.011)	0.000	54
North Carolina	0.101 (0.009)	0.000	74
Pennsylvania	0.098 (0.010)	0.000	45
South Carolina	0.122 (0.012)	0.000	55
Tennessee	0.104 (0.010)	0.000	49
Texas	0.103 (0.014)	0.000	46
Virginia	0.099 (0.009)	0.000	66
Washington	0.103 (0.010)	0.000	70
Wisconsin	0.105 (0.012)	0.000	25
Factor	**0.759 (0.061)**	**0.000**	

4.2 Dynamics of the Latent Common Factor

Figure 1 is a graph of the plot of the common factor against time. From the graph between the 2nd quarter of 1979 and the 4th quarter 2003 the factor did not seem to have changed that much until the beginning of the 1st quarter of 2003 to the 4th quarter of 2006 where there seem to have been a slight decrease in the factor. This period corresponds to a period of high home appreciation and huge investment in housing and low default rate. Form the 1st quarter of 2007 there was a significant increase in the common factor peaking at the 3th quarter of 2009. Because the latent factor is unobservable and we only have an estimate of it explaining what it represents is not easy. Section 4.2.1 examines the relationship between the latent factor and the state's unemployment rates and house price indexes. Section 4.2.2 also examines the latent factor and some national variables: St. Louis Fed's Financial Stress Index Percentage in GDP, Retail and Food Services Sales and Consumer Sentiments.



4.2.1 Relationship between the Latent Factor and State Unemployment and Home Price Index

It is difficult to provide structural interpretations of the estimated factor because of identification issues. Nevertheless, it would be interesting to analyze the behavior of the factor in relation to other variables. An examination of the relationship between the latent factor and the state's unemployment rates and house price indexes showed a positive correlation between the factor and the unemployment rate (average of 0.44) and a negative correlation for the house price index (average of -0.34). Table 4 reports the correlation results.

For these states: California, Florida, New Jersey, Nevada and Washington the correlation between the common factor and their unemployment rate is 0.5 or bigger. The correlation between the home price index and the common factor is -0.51 for Illinois.

For North Carolina, South Carolina, Tennessee and Texas the correlation between the common factor and the state unemployment rate was much bigger than the correlation with the home price index.

Table 4

This table reports the correlation of the latent factor with the first differences of the state's unemployment rate and the Federal Housing Agency House Price Indices (HPI) of the states. The data is from 2nd quarter of 1979 to the 3rd quarter of 2010

State	Correlation of latent factor with states unemployment rate	Correlation of latent factor with states home price index
Arizona	0.33	-0.45
California	0.52	-0.43
Colorado	0.40	-0.21
Florida	0.59	-0.45
Georgia	0.42	-0.27
Illinois	0.47	-0.51
Indiana	0.38	-0.26
Michigan	0.43	-0.45
Minnesota	0.35	-0.40
Missouri	0.38	-0.32
Nevada	0.53	-0.48
New Jersey	0.52	-0.39
New York	0.45	-0.32
Ohio	0.33	-0.32
North Carolina	0.48	-0.25
Pennsylvania	0.39	-0.29
South Carolina	0.41	-0.18
Tennessee	0.47	-0.26
Texas	0.40	-0.02
Virginia	0.47	-0.36
Washington	0.50	-0.41
Wisconsin	0.40	-0.34

4.2.2 Relationship between the Latent Factor and National Variables.

Table 5 reports the correlation of the common factor with some national variables, the results show a positive correlation between the factor and the St. Louis Fed's Financial Stress Index (0.61) and a negative correlations for percentage change in GDP (-0.67) , Retail and Food Services Sales (-0.51) and Consumer Sentiments (-0.56). Figures 2, 3, 4 and 5 shows the graphs of the common factor with The St. Louis Fed's Financial Stress Index, Retail and Food Services Sales, percentage change in GDP, and Consumer Sentiments respectively. The graphs show that at the beginning of the first quarter of 2007 when the common factor starts to increase the financial stress index also start to increase and the consumer sentiments also start to decrease at the same time. There seem to be a few quarters delay before the GDP and Retain and Food sales start to fall. The factor seems to be a leading indicator for Retail and Food Sales and the Percentage change in the GDP.

Table 5

This table reports the correlation of the latent factor with some national variables. The data is from 2nd quarter of 1979 to the 3rd quarter of 2010

State	**Correlation of latent factor with some national variables**
The St. Louis Fed's Financial Stress Index	0.61
Percentage in GDP	-0.67
Retail and Food Services Sales	-0.51
Consumer Sentiments	-0.56

Figure 2. The St. Louis Fed's Financial Stress Index

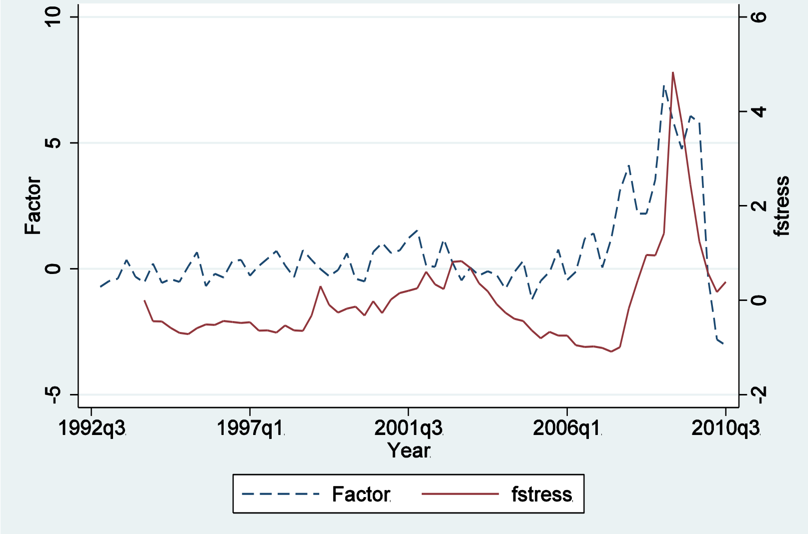


Figure 3. Retail and Food Services Sales

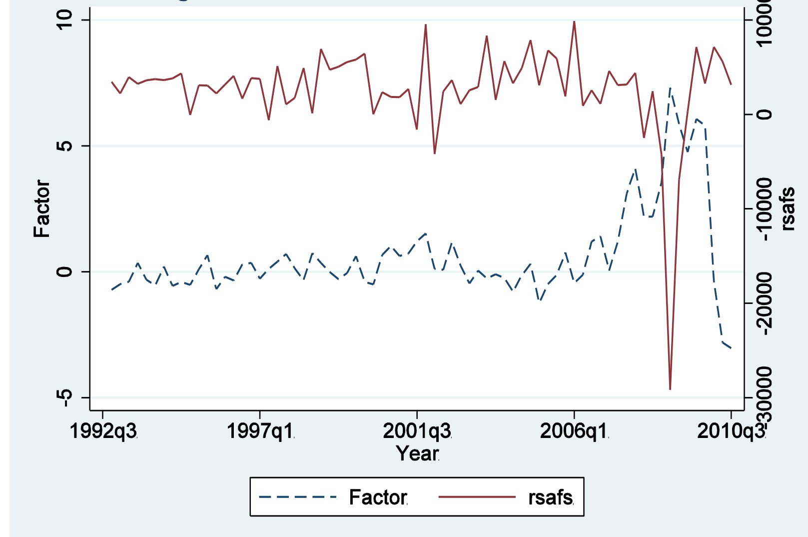


Figure 4. Percentage in GDP

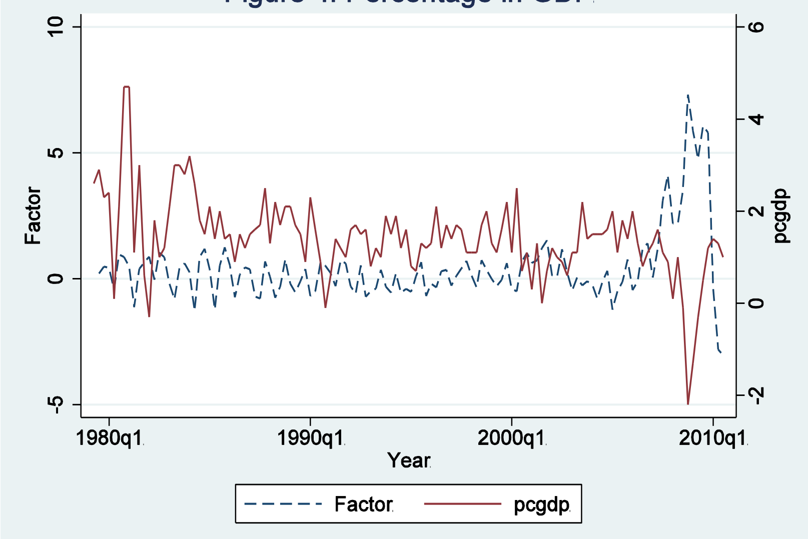
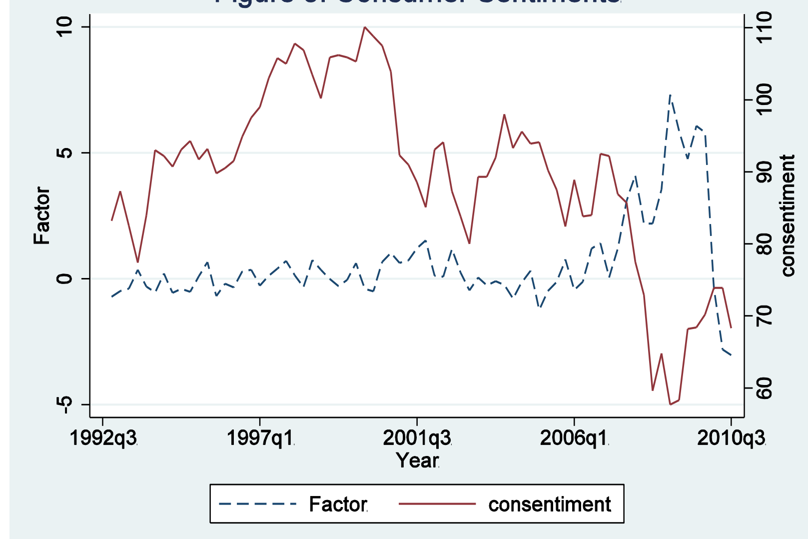


Figure 5. Consumer Sentiments



5. Conclusion

The estimated default correlations of the underlying assets of CDOs are one of the most important variables in the ratings of CDO products. Low default correlation assigned to the underlying assets would lead to a large fraction of the issued tranches being assigned a higher rating than the average rating of the underlying pool of assets. Rating agencies have been blamed for underestimating the default correlation of the underlying assets of real estate related asset backed CDOs which led to rosy tranche ratings.

Due to the increase in the reliant of mortgage loan related assets in CDO deals since 2002, we propose that an estimation of the co-movement of mortgage default rate across states over time can be used to test the default correlation underestimation theory. The empirical results show that there is a latent common factor driving the movement of the mortgagee default rates of the 22 states considered. This latent factor explains on average about 62% of the variation of the state mortgage default rates when the full sample 1979 to 2010 is used. However, when the sample is limited to 1979 to 2003 the factor only explains on average about 28% of the mortgage default variation. This shows that the mortgage default across the states did not co-move much until after 2003. Implying that the initial default correlation assigned to the CDO deals by the rating agencies might not be inaccurate.

A relationship between the factor and some national variables show a positive correlation between the factor and the St. Louis Fed's Financial Stress Index and a negative correlation for percentage change in GDP, Retail and Food Services Sales, and Consumer Sentiments.

As has been documented the ongoing turmoil in the financial markets was triggered by the problems in the housing market. The next step is to use the extracted states' default factor to explore the mechanism of the spillover effect of the increasing mortgage default rates on other financial markets during the recent crises.

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Appendix A
Table A

This table reports the total housing permits issued to the states from 2002 to 2006

State	Housing Permit
Arizona	387,885
California	984,433
Colorado	218,173
Florida	1,145,379
Georgia	516,119
Illinois	308,679
Indiana	185,795
Michigan	233,121
Minnesota	185,727
Missouri	152,641
Nevada	210,710
New Jersey	172,272
New York	268,685
North Carolina	450,016
Ohio	238,131
Pennsylvania	225,788
South Carolina	220,458
Tennessee	207,212
Texas	958,316
Virginia	287,823
Washington	236,135
Wisconsin	181,747

Appendix B

Table B.1

This table reports the estimation results for equation (3). $u_t = \beta_1 u_{t-1} + \psi_t$. u_t follows an AR (1) process and the default data is from 2nd quarter of 1979 to the 4th quarter of 2003

State	Factor Coefficient (S. E.)	P-value
Arizona	0.08 (0.115)	0.469
California	0.17 (0.108)	0.107
Colorado	0.05 (0.105)	0.619
Florida	-0.29 (0.101)	0.004
Georgia	-0.16 (0.123)	0.206
Illinois	-0.07 (0.104)	0.512
Indiana	0.15 (0.111)	0.171
Michigan	-0.31 (0.100)	0.002
Minnesota	-0.04 (0.104)	0.679
Missouri	-0.13 (0.105)	0.222
Nevada	-0.40 (0.094)	0.000
New Jersey	0.05 (0.103)	0.633
New York	-0.01 (0.102)	0.633
Ohio	-0.17 (0.104)	0.112
North Carolina	-0.25 (0.106)	0.017
Pennsylvania	-0.34 (0.100)	0.001
South Carolina	-0.28 (0.010)	0.005
Tennessee	-0.36 (0.097)	0.000
Texas	0.26 (0.104)	0.013
Virginia	-0.42 (0.093)	0.000
Washington	0.10 (0.111)	0.373
Wisconsin	-0.56 (0.083)	0.000

Table B.2

This table reports the estimation results for equation (3). $u_t = \beta_1 u_{t-1} + \psi_t$. u_t follows an AR (1) process and the default data is from 2nd quarter of 1979 to the 3rd quarter of 2010

State	Factor Coefficient (S. E.)	P-value
Arizona	0.70 (0.086)	0.000
California	0.51 (0.088)	0.000
Colorado	0.10 (0.090)	0.251
Florida	0.77 (0.064)	0.000
Georgia	-0.01 (0.106)	0.929
Illinois	-0.04 (0.092)	0.626
Indiana	0.10 (0.095)	0.288
Michigan	-0.03 (0.097)	0.728
Minnesota	0.28 (0.103)	0.007
Missouri	-0.09 (0.093)	0.358
Nevada	-0.11 (0.106)	0.289
New Jersey	0.26 (0.106)	0.013
New York	0.191(0.098)	0.050
Ohio	-0.16 (0.091)	0.075
North Carolina	-0.05 (0.099)	0.619
Pennsylvania	-0.26 (0.089)	0.004
South Carolina	-0.18 (0.091)	0.048
Tennessee	-0.31 (0.088)	0.000
Texas	0.19 (0.100)	0.054
Virginia	-0.20 (0.093)	0.034
Washington	0.40 (0.095)	0.000
Wisconsin	-0.49 (0.078)	0.000