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RESEARCH ARTICLE

Systematic and Liquidity Risk in Subprime-Mortgage Backed Securities

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Abstract The misevaluation of risk in securitized financial products is central to understanding the Financial Crisis of 2007–2008. This paper characterizes the evolution of factors affecting collateralized debt obligations (CDOs) based on subprime mortgages. A key feature of subprime-mortgage backed indices is that they are distinct in their vintage of issuance. Using a latent factor framework that incorporates this vintage effect, we show the increasing importance of a common factor on more senior tranches during the crisis. We examine this common factor and its relationship with spreads. We estimate the effects of the financial crisis on the common factor.

Keywords Asset backed securities · Subprime mortgages · Financial crisis · Factor models · Kalman filter

JEL Classification G12 · G01 · C32

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1 Introduction

Securities based on subprime mortgages played a central role in the Financial Crisis of 2007–2008. The shortcomings of models for pricing these securities became apparent when real estate prices started to fall and mortgages became delinquent. Difficulties valuing these securities led to widespread problems trading them, (Dwyer and Tkac 2011).

The period leading up to the crisis was one of dramatic growth in asset backed securities and structured financial products. These products were tranched and rated and acquired by investors across the world. Chiesa (2008) shows that pooled and tranched securities can generate optimal risk transfer, although one rationale for the issuance of pooled and tranched securities is an informational advantage about underlying asset quality enjoyed by informed sellers (DeMarzo 2005). Increased demand for structured securities led to an expansion in the range of underlying assets (Benmelech and Dlugosz 2009) and the creation of structured securities based on subprime mortgages increased dramatically. Mian and Sufi (2009) provide evidence that an increased demand for these products affected the market for subprime mortgages by resulting in less stringent lending criteria and contributing to their subsequent growth.

The spread of this crisis from a relatively small sector of the financial system across markets and international borders resulted in widespread financial distress.[1] Among other effects, banks in much of the world suffered substantial losses followed by serious retrenchment and restructuring. The turbulence and ensuing lack of confidence spread to other asset markets and the real economy. Brunnermeier (2009), Dwyer and Tkac (2009) and others document the evolution and spread of the crisis and the role of subprime-mortgage backed securities in it.

The misperception and misevaluation of risk in structured financial products is central to many explanations of the financial crisis. This may have arisen partly due to the failure of some market participants to differentiate between the risk of AAA-rated tranches of Collateralized Debt Obligations (CDOs) and AAA-rated corporate bonds (Brennan et al. 2009). In addition to possible mispricing, the valuation of CDO tranches is particularly problematic in the event of widespread defaults (Smithson 2009), a feature not apparent before defaults increased in 2007. Valuation models have four key inputs: default rates, prepayment risk, recovery rates and default correlations. Problems estimating the last two were important during the financial crisis. Default correlations inevitably are based on historical data and were underestimated based on a period of increasing house prices and economic expansion. As default correlations increase, the probability of observing large-scale defaults also increases, causing the prices of senior CDO tranches to fall. Estimates of recovery rates were also affected. Consequently, the risk priced in the different CDO tranches was underestimated. Coval et al. (2009) analyze the risk inherent in the securitization process and in particular how risk migrates to higher-rated tranches in the event of increasing importance of a large common shock such as falling house prices.

[1] Dwyer and Tkac (2009) estimate that subprime mortgages are no more than one percent of global bond values, stock values and bank deposits

A better understanding of the factors underlying price changes in these subprime-mortgage backed assets is important for understanding their role in the crisis. We characterize the driving forces behind the decreases in these securities' prices. In earlier work, Longstaff and Rajan (2008) show that a theoretical pricing model for CDOs can be represented as a three factor model, with common, credit rating and idiosyncratic shocks. An empirical application using tranches of corporate credit default swap indices (CDX) from 2003 to 2005 suggests that idiosyncratic default risk accounts for around 65 % of the risk premium, while common risk accounts for only 8 % of that premium. Extending the time period, Bhansali et al. (2008) show a substantial increase in common-event risk in 2007 and 2008.

An additional but potentially key feature of subprime-mortgage backed indices is variation in the quality of the underlying loans and collateral over time. Demyanyk and Van Hemert's (2011) analysis of subprime loans indicates a gradual and persistent deterioration of loan quality from 2001 to 2007. To reflect this deterioration, we extend Longstaff and Rajan's (2008) empirical model to include a fourth factor, a vintage factor. This vintage factor reflects risks associated with the dates the securities were created. The model is applied to asset tranches of mortgage backed securities using the Markit ABX.HE indices for three vintages over the period January 2006 to December 2009. An innovation of this paper is the exploitation of the unbalanced panel structure of the data to identify the vintage, credit, common and idiosyncratic effects. This allows us to assess the contribution of all factors to the asset prices and returns. We specify the model in state-space form and estimate it with a Kalman filter.

The ABX.HE data have been examined in several studies of the financial crisis. Fender and Scheicher (2009) use two vintages to track the crisis and find that increased liquidity risk and decreasing risk appetite were important factors in the price decreases of the higher-rated tranches. Our paper differs in many respects; we extract risk factors differently and focus on the level rather than the change of the common factor. Longstaff (2010) uses the ABX indices to test for contagion from the subprime-asset backed market to other parts of the financial system. He finds strong evidence of contagion and liquidity risk with revisions to risk premia identified as the most likely transmission channel. Longstaff also finds that ABX returns lead stock market returns and bond yield changes by up to 3 weeks, suggesting that significant information was uncovered in this market that led to subsequent price changes in other markets. Gorton (2009) finds that declines in the ABX indices and the repo market were highly correlated due to some combination of counterparty risk and lack of liquidity.

Our results summarize the behaviour of subprime-mortgage backed securities in terms of four factors. In 2006, all factors have a discernible role in asset returns. The common factor becomes more important when the financial turmoil begins and has a larger effect on AAA tranches than in the pre-crisis period. We examine the common factor's relationship with observable factors including real estate prices, the VIX index and interest rate spreads which reflect the financial crisis. We find that liquidity and counterparty risk, as represented by the spread between the London Interbank Borrowing Rate (LIBOR) and the Overnight Index Swap (OIS) rate, is sufficient to characterize the relationship between the common factor and the financial crisis as reflected in interest rate spreads. We undertake a counterfactual analysis of the evolution of the common factor if the LIBOR-OIS spread had remained at pre-

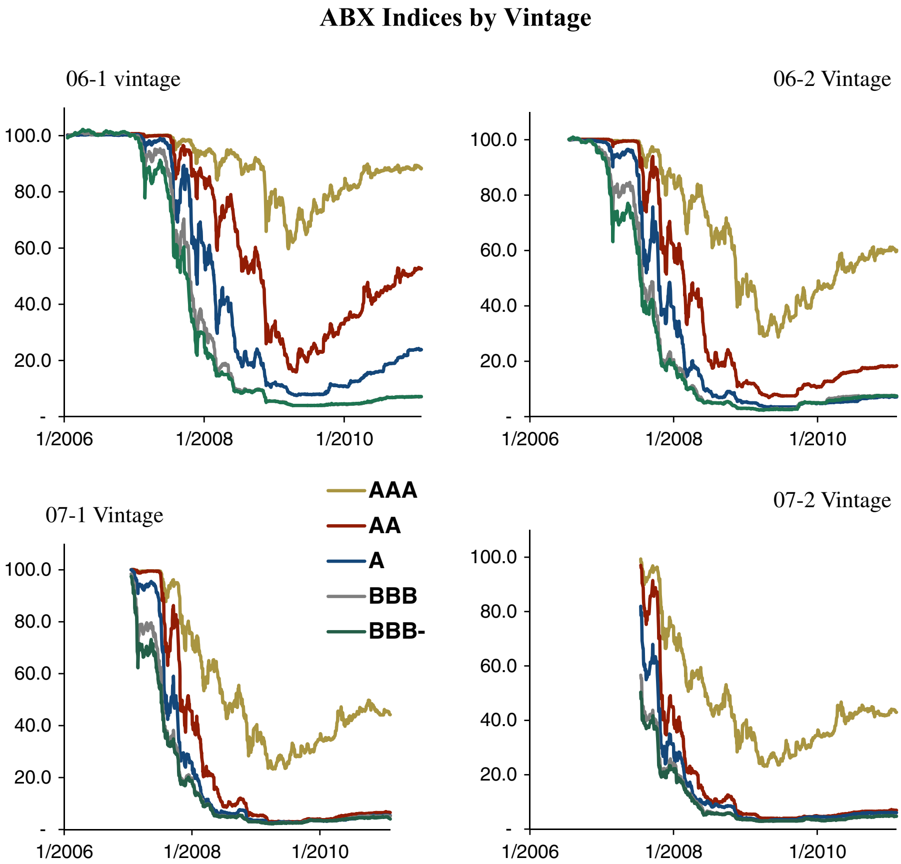


Fig. 1 ABX indices by vintage. This figure shows the levels of the Markit ABX indices of Collateralized Debt Obligations based on subprime mortgages. The data are from Haver Analytics. The vintages are January 2006 (06-1), July 2006 (06-2), January 2007 (07-1) and July 2007 (07-2). No indices have been created subsequently. The premium is set on the indices to have an initial value of 100 based on a survey of market participants, unless that premium is over 500 basis points in which case the premium is 500 basis points. The initial trading values were less than 100 for lower rated tranches in the January 2007 vintage and for the July 2007 vintages

crisis levels throughout. We estimate that the common factor is 20 % lower at the end of 2009 than it would have been if LIBOR-OIS had not been elevated during the financial crisis. Likewise we estimate that the actual value of the REIT index is about 40 % lower and VIX some 50 % higher than in the simulated model with a stable interest rate spread. The decreases in the common factor, decreases in the REIT index and increases of VIX are the estimated effects of the elevated values of LIBOR-OIS during the crisis, not effects of lower housing prices.[2]

The paper is structured as follows. Section 2 describes the ABX data and highlights its unique features which are reflected in the econometric model presented in

[2] A REIT index is included with the common factor in a cointegrating vector in order to reflect the stochastic trend in housing prices.

Section 3. The estimates of the factors are discussed in Section 4. Section 5 relates the common factor to observable short-term fixed-income spreads. Section 6 concludes.

2 Tracking the Market for Subprime Mortgages

The price decreases in asset backed securities during the financial difficulties of 2007 to 2009 were dramatic. They represent declines in the values of the underlying assets but probably also reassessments of the risks and liquidity of such assets. We analyze the risk factors inherent in these tranched pools by examining the relatively new indices of CDOs used as the basis for credit default swaps related to subprime-mortgage backed securities. These indices, entitled ABX.HE, were introduced in January 2006 by Markit and are widely used by market participants to track the market for subprime mortgages and to bet on it.

Figure 1 shows the evolution of the indices from January 2006 to December 31, 2009. Each issue is subdivided into five tranches, varying from AAA to BBB-, where the ratings are the lower of those issued by Moody's and S&P. The index values are derived from underlying credit default swaps with the insurance coupon fixed for the life of trading. The coupon is set so the index trades at par - 100 - at inception unless such a coupon exceeds 500 basis points, in which case the coupon is set at 500 basis points.

Each vintage of the index is based on twenty mortgage backed CDO deals created within the previous 6 months. For example, the ABX.HE 06-1 index is constructed from deals created in the second half of 2005. The issuers are the largest originators.[3] Strict requirements must be met to qualify for inclusion in the index. For example, the value of each deal must be at least \$500 million and each tranche must have an average life between 4 and 6 years, and the AAA tranche must have a weighted average life of more than 5 years. Furthermore, no security originator can have more than four deals included.

New indices were created every 6 months from January 2006 to July 2007. No indices have been created since then because there are too few new CDOs meeting the eligibility requirements.[4] New indices every 6 months with similar underlying securities might have created an index that could be spliced together as is done sometimes with on-the-run bonds and futures prices. Each vintage represents quite different risks though. At least part of the explanation for these vintage effects is an increase in the riskiness of the underlying mortgages (Demyanyk and Van Hemert 2011). This increase in risk is reflected in increased coupon rates for insurance on the ABX indices from 2006 to 2007. Figure 1 shows substantial heterogeneity in the index values across vintages from 2006 to the end of 2009 with later values declining more, which is consistent with the mortgages being riskier. These considerations suggest that successive rolls of the ABX are not suitable for splicing to create a continuous series, as Longstaff and Rajan (2008) do for CDX data. Instead, each new index is best viewed as a unique vintage with the risk of the underlying pool of assets different between vintages.

[3] Licensed dealers in the ABX.HE indices included ABN AMRO, Bank of America, Barclays Capital, Bear Stearns, BNP Paribas, Calyon, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, JPMorgan, Lehman Brothers, Merrill Lynch, Morgan Stanley, RBS Greenwich, UBS and Wachovia.

[4] As of this writing in 2012, there has been very little securitization since 2008.

Our initial analysis extracts a common factor from the behaviour of daily ABX returns. These "returns" on the ABX are the differences in the logarithms of the indices. Descriptive statistics for each tranche of each vintage are given in Table 1. The data set is unbalanced; all vintages exist at the end of the period but the vintages are created over time. Within each vintage, the standard deviation of returns is lowest for the AAA security. The first vintage has returns with the lowest volatility and there is some evidence of higher standard deviations of returns for later vintages. The distributions are negatively skewed with the exception of the AAA tranche of the final vintage. All assets display excess kurtosis. This is greatest for the first vintage, possibly reflecting the sustained low-variance period at the start of the period.

Tables 2 and 3 present correlations of the returns across credit ratings for given vintages and across vintages for given credit ratings. The correlations of the AAA tranches with other tranches decrease monotonically as ratings decline. The

Table 1 Summary statistics for asset returns by vintage

Rating	Mean	Standard deviation	Minimum	Maximum	Skewness	Excess kurtosis	Number of observations
Vintage 06-1							
AAA	−0.0002	0.0091	−0.082	0.076	−0.842	18.900	990
AA	−0.0011	0.0191	−0.140	0.143	−0.180	13.518	990
A	−0.0022	0.0213	−0.132	0.105	−0.421	7.575	990
BBB	−0.0031	0.0218	−0.206	0.107	−2.905	22.872	990
BBB-	−0.0031	0.0201	−0.187	0.112	−1.822	14.126	990
Vintage 06-2							
AAA	−0.0009	0.0168	−0.082	0.114	−0.397	6.924	865
AA	−0.0026	0.0222	−0.110	0.134	−0.324	6.256	865
A	−0.0035	0.0246	−0.172	0.105	−1.043	7.085	865
BBB	−0.0035	0.0241	−0.134	0.177	−0.261	7.573	865
BBB-	−0.0035	0.0237	−0.112	0.116	−0.059	4.074	865
Vintage 07-1							
AAA	−0.0014	0.0211	−0.114	0.139	−0.061	6.710	739
AA	−0.0043	0.0261	−0.156	0.101	−0.868	5.265	739
A	−0.0046	0.0282	−0.189	0.093	−0.893	5.269	739
BBB	−0.0045	0.0261	−0.185	0.105	−0.858	5.686	739
BBB-	−0.0045	0.0249	−0.181	0.092	−0.875	5.201	739
Vintage 07-2							
AAA	−0.0017	0.0227	−0.104	0.139	0.057	6.093	613
AA	−0.0049	0.0278	−0.140	0.148	−0.888	5.843	613
A	−0.0047	0.0260	−0.142	0.091	−0.623	3.517	613
BBB	−0.0046	0.0247	−0.199	0.086	−1.217	8.121	613
BBB-	−0.0044	0.0248	−0.156	0.090	−0.871	4.906	613

This table presents summary statistics for all vintages and all ratings of the ABX index for all dates from inception to December 31, 1999. The left-skewness and excess kurtosis of the returns for all vintages and ratings is evident

Table 2 Correlations of returns across credit ratings with vintages

Rating	AAA	AA	A	BBB	BBB-	AAA	AA	A	BBB	BBB-
	Vintage 06-1					Vintage 06-2				
AAA	1					1				
AA	.833	1				.599	1			
A	.492	.594	1			.396	.638	1		
BBB	.381	.415	.649	1		.220	.435	.581	1	
BBB-	.395	.428	.595	.837	1	.190	.402	.509	.740	1
	Vintage 07-1					Vintage 07-2				
AAA	1					1				
AA	.571	1				.605	1			
A	.300	.550	1			.399	.646	1		
BBB	.257	.412	.527	1		.287	.507	.481	1	
BBB-	.284	.398	.464	.827	1	.242	.455	.458	.841	1

Correlations include all vintages and ratings available. The data for each vintage uses all data available for computing the correlations across credit ratings

correlations across vintages are highest for the AAA tranches but this is not particularly surprising because they bear less idiosyncratic risk than lower-rated tranches.

Table 3 Correlations of returns across vintages within credit ratings

Vintage	06-1	06-2	07-1	07-2	06-1	06-2	07-1	07-2
	AAA credit rating				AA credit rating			
06-1	1				1			
06-2	.869	1			.604	1		
07-1	.815	.888	1		.506	.711	1	
07-2	.812	.865	.932	1	.503	.675	.785	1
	A credit rating				BBB credit rating			
06-1	1				1			
06-2	.631	1			.514	1		
07-1	.480	.584	1		.461	.601	1	
07-2	.549	.586	.561	1	.477	.497	.481	1
	BBB- credit rating							
06-1	1							
06-2	.508	1						
07-1	.523	.565	1					
07-2	.432	.418	.471	1				

This table shows the simple correlations of returns for all available vintages and ratings for the ABX indices. The tables use the maximum number of observations possible to compute each correlation. For example, the correlation of the AAA tranches of the January 2006 vintage and the July 2006 vintage uses all observations for which data are available for both vintages. Similarly, the correlation of the AAA tranches of the January 2006 vintage and the January 2007 vintage uses all observations for which data are available for both vintages

3 Modelling Framework for ABX Data

Financial market returns are frequently modelled with latent factor models, for example by Diebold and Nerlove (1989) and Dungey and Martin (2007). In this paper, we include four factors reflecting vintage effects in addition to the common, credit rating and idiosyncratic factors present in Longstaff and Rajan (2008). The explicit differences in ratings and vintages and the unbalanced nature of the data allow us to identify these four factors from the data rather than applying factor labels ex post. The model is

$$y_{i,j,t} = \beta_{i,j} w_t + \theta_{i,j} v_{i,t} + \varphi_{i,j} k_{j,t} + \phi_{i,j} f_{i,j,t} \tag{1}$$

where $y_{i,j,t}$ is the demeaned return on the ABX index of vintage i and credit rating j at time t. The vintage is the date of issuance of the security. The factors represent a common shock affecting all assets, w_t; a vintage shock unique to all assets of a particular index date, $v_{i,t}$; a ratings shock unique to assets of a specific rating across all vintages, $k_{j,t}$; and idiosyncratic shocks, $f_{i,j,t}$.

To capture serial correlation in the data, the common, ratings and vintage factors follow AR(1) processes. As in previous research on factor models (Dungey et al. 2000), we do not estimate persistence in the idiosyncratic shocks. The additional features of the model can be written

$$w_t = \rho_w w_{t-1} + \eta_{wt} \tag{2}$$

$$v_{i,t} = \rho_{v,i} v_{i,t-1} + \eta_{v,i,t} \tag{3}$$

$$k_{j,t} = \rho_{k,j} k_{j,t-1} + \eta_{k,j,t} \tag{4}$$

$$f_{i,j,t} = \eta_{i,j,t} \tag{5}$$

$$E(\eta_{w,t}) = 0, E(\eta_{w,t}\eta_{w,s}) = \sigma_w^2 \tag{6}$$

$$E(\eta_{z,t}) = 0, E(\eta_{z,t}\eta_{z,s}) = \sigma_z^2 \; for \; t = s \; for \; z = (v,i),(k,j),(i,j) \tag{7}$$

$$E(\eta_{z,t}\eta_{z,s}) = 0 \; for \; t \neq s \; for \; z = (v,i),(k,j),(f,i,j) \tag{8}$$

$$E(\eta_{z,t}\eta_{a,t}) = 0 \; for \; a, \; z = (v,i),(k,j),(f,i,j) \; and \; a \neq z \tag{9}$$

where equations (6) to (9) indicate that the shocks to each factor are independent with constant variances. There are no other restrictions on the variance-covariance matrix of the returns. The conditional variances of the returns vary over time and we account for this feature of the data. Our state space model is already heavily parameterized and it is impractical to include ARCH estimation directly into the estimation of the factor model. Instead, we pre-filter the returns by estimating an

Table 4 Estimates of IGARCH models

Estimated parameter	Rating				
	AAA	AA	A	BBB	BBB-
	Vintage 06-1				
Constant	−0.00004	0.00003	0.00015	−0.00154	0.00010
Standard error of constant	0.00001	0.00004	0.00006	0.00052	0.00020
IGARCH term (γ_1)	0.1829	0.1746	0.1835	0.1873	0.0988
Standard error of γ_1	0.0333	0.0311	0.0180	0.0455	0.0143
	Vintage 06-2				
Constant	−0.00042	0.00005	0.00002	−0.00190	0.00037
Standard error of constant	0.00064	0.00008	0.00006	0.00067	0.00118
IGARCH term (γ_1)	0.1438	0.1993	0.2000	0.1908	0.1029
Standard error of γ_1	0.0565	0.0423	0.0200	0.0406	0.0235
	Vintage 07-1				
Constant	0.00019	0.00018	−0.00080	−0.00280	−0.00240
Standard error of constant	0.00012	0.00017	0.00064	0.00097	0.00086
IGARCH term (γ_1)	0.1294	0.1650	0.1584	0.1472	0.1280
Standard error of γ_1	0.0178	0.0330	0.0286	0.0646	0.0356
	Vintage 07-2				
Constant	0.00077	−0.00090	−0.00218	−0.00299	0.00196
Standard error of constant	0.00100	0.00186	0.00149	0.00105	0.00063
IGARCH term (γ_1)	0.1044	0.0943	0.1370	0.1249	0.1528
Standard error of γ_1	0.0288	0.0879	0.0344	0.2062	0.0392

The parameters are estimates of the IGARCH equations for the returns $r_{i,j,t}$

$r_{i,j,t}=a_{i,j}+h_{i,j,t}\,y_{i,j,t}$

$h^2_{i,j,t}=\gamma_1\left(r_{i,j,t-1}-a_{i,j}\right)^2+(1-\gamma_1)h^2_{i,j,t-1}$

where $h_{i,j,t}$ is the conditional standard deviation of $r_{i,j,t}$ and $y_{i,j,t}$ is the innovation in the return with zero mean and unit standard deviation. The table presents estimate parameters for all vintages and ratings

IGARCH(1,1) model and use the standardized returns in the factor model.[5] If we let $y_{i,j,t}$ represent these standardized returns and $r_{i,j,t}$ represent the raw (unstandardized) returns, then

$$r_{i,j,t}=a_{i,j}+h_{i,j,t}y_{i,j,t} \tag{10}$$

$$h^2_{i,j,t}=\gamma_{1,i,j}\left(r_{i,j,t-1}-a_{i,j}\right)^2+\left(1-\gamma_{1,i,j}\right)h^2_{i,j,t-1}.$$

[5] Prefiltering the data may result in inefficiency in the second stage of estimation. The consistency of the estimates is unaffected by two-stage estimation if the estimators are orthogonal, which seems a strong assumption in our application. We do not focus on statistical significance of parameters and our analysis of the factors uses estimates of the factors with the filtering reversed.

Table 5 Summary statistics for standardized asset returns by vintage

Rating	Mean	Standard deviation	Minimum	Maximum	Skewness	Excess kurtosis	Number of 7observations
Vintage 06-1							
AAA	−0.0876	1.3641	−17.798	8.473	−3.154	36.585	990
AA	−0.1067	1.2440	−8.002	8.614	−0.390	8.506	990
A	−0.1400	1.1693	−5.923	8.292	0.157	7.038	990
BBB	−0.1622	1.1564	−7.056	12.827	0.628	21.347	990
BBB-	−0.1763	1.1378	−7.586	8.337	−0.342	8.594	990
Vintage 06-2							
AAA	−0.0914	1.2205	−14.639	6.579	−3.169	32.124	865
AA	−0.1318	1.2739	−7.652	9.679	−0.221	9.370	865
A	−0.1721	1.2027	−6.222	8.327	−0.196	5.180	865
BBB	−0.1919	1.1811	−7.203	10.417	−0.083	12.605	865
BBB-	−0.1968	1.1343	−7.596	8.413	−0.188	10.112	865
Vintage 07-1							
AAA	−0.0880	1.1743	−8.911	6.014	−1.204	8.870	739
AA	−0.1304	1.2057	−6.191	8.190	−0.038	7.982	739
A	−0.1799	1.1484	−5.534	7.661	−0.130	4.624	739
BBB	−0.2088	1.1617	−7.109	7.017	−0.847	7.442	739
BBB-	−0.2073	1.1368	−8.470	5.421	−0.998	6.931	739
Vintage 07-2							
AAA	−0.0699	1.1123	−7.825	4.898	−1.015	7.171	613
AA	−0.1178	1.1359	−5.960	8.358	0.071	8.795	613
A	−0.1693	1.1197	−5.268	6.843	−0.010	4.147	613
BBB	−0.1958	1.1379	−6.832	6.508	−1.024	8.218	613
BBB-	−0.1807	1.1287	−7.404	6.462	−0.535	7.060	613

This table shows summary statistics for the returns standardized for the IGARCH in the raw returns. There still is skewness and excess kurtosis, although generally quite a bit less than in the raw returns

Table 4 presents the parameter estimates of the IGARCH models estimated by Quasi Maximum Likelihood for all credit ratings and vintages (Lumsdaine 1996). Table 5 presents summary statistics for the adjusted returns and Fig. 2 shows the adjusted returns. The graphs suggest that the IGARCH model has stabilized the variances relative to the variances in the original series.

The factor model can be rewritten in state-space form as

$$Y_t = Z\alpha_t + S\varepsilon_t \tag{11}$$

$$\alpha_{t+1} = Y\alpha_t + Ru_t \tag{12}$$

where Y_t is the vector of the returns in each asset, $E[\varepsilon_t] = 0, E\left[\varepsilon_t\varepsilon_t^{'}\right] = H, E[u_t] = 0$,

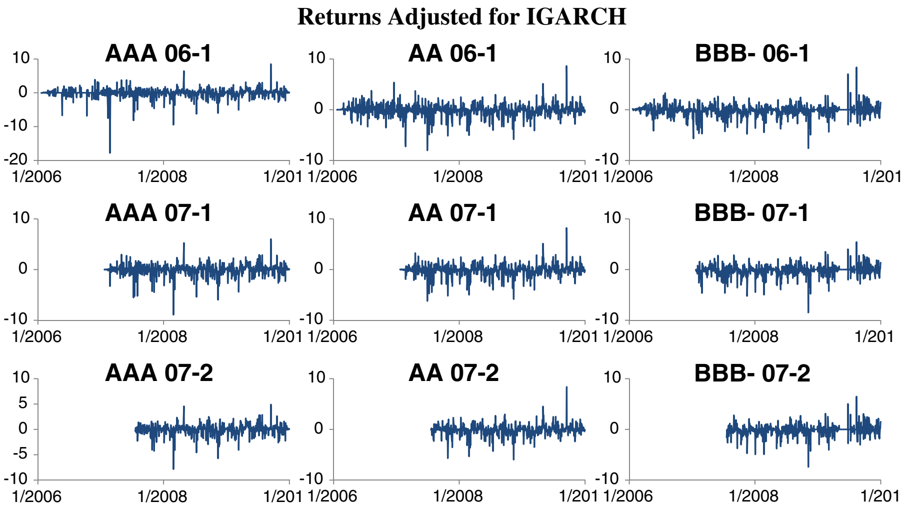


Fig. 2 Returns adjusted for IGARCH. These are the returns adjusted for IGARCH(1,1) based on the estimates in Table 4. The "06-1" vintage is the January 2006 vintage; the "07-1" vintage is the January vintage; the "07-2" vintage is the July 2007 vintage. The seemingly near-zero variances are periods of relatively low volatility

and $E\left[u_t u_t'\right] = Q$. The evolving latent factors are contained in the vector α_t and the idiosyncratic factors, $f_{i,j,t}$ are contained in the vector ε_t.

To reduce the dimensionality of the estimation problem and keep it tractable, our empirical estimation is based on a system of nine asset returns selected to span the range of ratings and vintages. We examine AAA, AA and BBB- rated securities from the January 2006, January 2007 and July 2007 vintages. The AAA and AA tranches have the largest share of the value of underlying subprime-mortgage bonds, and the BBB- tranche is included because it is the lowest rated tranche. We include the January 2006 and July 2007 vintages because they are the first and last issuances available. We prefer the January 2007 vintage to the July 2006 vintage mainly because the January 2007 vintage is based on later mortgages. These mortgages may have been less carefully vetted when created and may be affected more by the decline in housing prices and mortgages subsequently becoming upside down.

The following definitions of Z and α_t show the form of the restrictions in the model,

$$Z = \begin{bmatrix} \beta_{1,AAA} & \theta_{1,AAA} & 0 & 0 & \varphi_{1,AAA} & 0 & 0 \\ \beta_{1,AA} & \theta_{1,AA} & 0 & 0 & 0 & \varphi_{1,AA} & 0 \\ \beta_{1,BBB} & \theta_{1,BBB} & 0 & 0 & 0 & 0 & \varphi_{1,BBB} \\ \beta_{2,AAA} & 0 & \theta_{2,AAA} & 0 & \varphi_{2,AAA} & 0 & 0 \\ \beta_{2,AA} & 0 & \theta_{2,AA} & 0 & 0 & \varphi_{2,AA} & 0 \\ \beta_{2,BBB} & 0 & \theta_{2,BBB} & 0 & 0 & 0 & \varphi_{2,BBB} \\ \beta_{3,AAA} & 0 & 0 & \theta_{3,AAA} & \varphi_{3,AAA} & 0 & 0 \\ \beta_{3,AA} & 0 & 0 & \theta_{3,AA} & 0 & \varphi_{3,AA} & 0 \\ \beta_{3,BBB} & 0 & 0 & \theta_{3,BBB} & 0 & 0 & \varphi_{3,BBB} \end{bmatrix} \quad (13)$$

$$\alpha_t = \begin{bmatrix} w_t \\ v_{1,t} \\ v_{2,t} \\ v_{3,t} \\ k_{AAA,t} \\ k_{AA,t} \\ k_{BBB,t} \end{bmatrix} \tag{14}$$

Defining Υ as a 7×7 diagonal matrix of autoregressive parameters, $\rho=[\rho_w\ \rho_{v,i}\ \rho_{k,j}]$ for all i,j; S_t as a 9×9 matrix with parameters $\varphi_{i,j}$ on the main diagonal; and R as the appropriately sized identity matrix where the factor variances are standardized to unity, we can estimate the parameters by the standard Kalman filter procedure.[6] Its prediction equations are given by

$$\alpha_{t+1} = \Upsilon\alpha_{t|t} \tag{15}$$

$$P_{t+1|t} = \Upsilon P_{t|t}\Upsilon' + SQS' \tag{16}$$

where $P_{t+1|t}$ is the prediction vector. The updating equations are

$$\alpha_{t|t} = \alpha_t + P_t Z' F_t^{-1} v_t \tag{17}$$

$$P_{t|t} = P_t - P_t Z' F_t^{-1} Z P_t' \tag{18}$$

Where

$$v_t = Y_t - Z\alpha_t \tag{19}$$

$$F_t = ZP_t Z' + Z \tag{20}$$

Furthermore, we accommodate the unbalanced nature of our data by constructing a dummy matrix, D_t, as follows

$$D_t = \begin{bmatrix} 1 & 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 1 \\ d_{1t} & 0 & d_{1t} & 0 & d_{1t} & 0 & 0 \\ d_{1t} & 0 & d_{1t} & 0 & 0 & d_{1t} & 0 \\ d_{1t} & 0 & d_{1t} & 0 & 0 & 0 & d_{1t} \\ d_{2t} & 0 & 0 & d_{2t} & d_{2t} & 0 & 0 \\ d_{2t} & 0 & 0 & d_{2t} & 0 & d_{2t} & 0 \\ d_{2t} & 0 & 0 & d_{2t} & 0 & 0 & d_{2t} \end{bmatrix} \tag{21}$$

[6] Starting values are taken as the consistent estimates of the parameters of the factor model in equation (1) obtained from unconditional moments using GMM.

where d_{1t} takes the value of 1 from the initiation of the 07-1 vintage onwards and 0 otherwise and d_{2t} is similarly defined with respect to the vintage 07-2. The Kalman filter equations are then modified by replacing Z with $Z \circ D_t$ wherever it appears in the filter with the operator $\circ$ indicating element-by-element multiplication.

4 Results

A preliminary yet informative way to analyze the results is to perform an unconditional variance decomposition using equation (1) which implies

$$Var(y_{i,j}) = \beta_{i,j}^2 Var(w) + \theta_{i,j}^2 Var(v_i) + \varphi_{i,j}^2 Var(k_j) + \phi_{i,j}^2 Var(f_{i,j}) \tag{22}$$

so that, for example, the contribution of the vintage factor to variance in asset $y_{i,j}$ is expressed as

$$\frac{\theta_{i,j}^2 Var(v_i)}{\beta_{i,j}^2 Var(w) + \theta_{i,j}^2 Var(v_i) + \varphi_{i,j}^2 Var(k_j) + \phi_{i,j}^2 Var(f_{i,j})}$$

and similarly for other contributing factors.

Table 6 presents the unconditional variance decomposition for the full period of each vintage and for selected subperiods.[7] For the full period, the common factor is most important for the AAA and AA ratings for all vintages. Variability of the BBB-tranches is less closely related to the common factor and more closely related to the rating factor. The vintage factors are relatively unimportant for all assets. The ratings factors, on the other hand, affect all of the vintages and credit ratings, although they are less important for the AA tranches of the January and July 2007 vintages. The importance of idiosyncratic factors differs across vintages and across ratings. In particular, they exert a stronger influence on later vintages and we also observe an upward drift in terms of ratings over time. This likely reflects the losses and consequent collapse in prices for the lower-rated tranches of the later vintages, which decimated the protection for the higher-rated tranches. As a result of the large losses, idiosyncratic losses on mortgages migrate up to the AA and even the AAA tranches.

Table 6 also presents the unconditional variance decompositions for subperiods. In the non-crisis period of 2006, the variances of the AAA and AA tranches are dominated by the common factor and the credit rating factors. The idiosyncratic factor is easily the most important factor for the BBB- tranche and is quite unimportant for the higher-rated tranches. This is consistent with the role of the BBB- tranche as the absorber of the relatively small idiosyncratic losses. The common shock accounts for about half the variance of the AAA and AA tranches. This contrasts with Longstaff and Rajan's (2008) finding that a common factor is relatively unimportant in non-crisis periods. The first half of 2007 does not look markedly different for these securities. There are however differences in the relative importance of the factors for the January 2007 vintage. The AAA securities look little different, but the

[7] The parameter values themselves are estimated consistently, but are not very informative by themselves. The parameter values are available from the authors upon request.

Table 6 Average contribution of factors to variance in returns for subperiods

Factor/Vintage And rating	January 2006			January 2007			July 2007		
	AAA	AA	BBB-	AAA	AA	BBB-	AAA	AA	BBB-
	Start of each vintage to December 2009								
Common	.49	.62	.24	.58	.32	.29	.55	.47	.32
Vintage	.05	.02	.01	.00	.00	.00	.00	.00	.00
Credit rating	.43	.35	.39	.40	.11	.52	.33	.15	.63
Idiosyncratic	.03	.01	.37	.03	.57	.19	.38	.38	.05
	January 2006 to December 2006								
Common	.43	.50	.21						
Vintage	.08	.03	.00						
Credit rating	.45	.46	.29						
Idiosyncratic	.03	.01	.50						
	January 2007 to June 2007								
Common	.37	.50	.18	.47	.30	.24			
Vintage	.13	.09	.00	.00	.00	.00			
Credit rating	.46	.40	.41	.50	.22	.57			
Idiosyncratic	.04	.01	.41	.03	.48	.19			
	July 2007 to December 2008								
Common	.53	.71	.26	.59	.32	.30	.55	.46	.33
Vintage	.02	.01	.00	.00	.00	.00	.00	.00	.00
Credit rating	.42	.28	.43	.38	.08	.51	.33	.14	.62
Idiosyncratic	.03	.00	.32	.03	.60	.19	.12	.41	.05
	January 2009 to December 2009								
Common	.57	.70	.27	.62	.34	.30	.58	.48	.32
Vintage	.02	.01	.00	.00	.00	.00	.00	.00	.00
Credit rating	.39	.29	.45	.35	.10	.53	.31	.16	.64
Idiosyncratic	.02	.00	.28	.02	.56	.17	.11	.36	.04

The first panel of the table shows the variance decompositions for each of the vintages from the inception of each vintage until the end of 2009. The second panel shows the variance decompositions for a period clearly before the financial crisis, 2006. The second panel shows the variance decomposition for the first half of 2007. The third panel shows the variance decomposition for the period most evidently one of financial crisis and the fourth panel shows developments in 2009

idiosyncratic factor becomes quite a bit more important for the AA securities, roughly the same as for the BBB- tranche of the January 2006 vintage.

In the crisis from July 2007 to the end of 2008, the relative contributions of the factors change markedly. The common factor is most important for the AAA-rated tranches of all vintages. For the BBB- tranches, idiosyncratic factors remain prominent although the common factor exerts more influence and the ratings factors assume most importance. Idiosyncratic factors remain most important for the BBB- tranche in the January 2006 vintage, though, as well as for the AA tranches of the January and July 2007 vintages. Vintage factors, never especially important, all but disappear.

In 2009, there is little evidence of any return to pre-crisis factor contributions. The variance decompositions are hard to distinguish from those of the crisis period. This analysis reveals substantial time variation in the relative factor contributions to ABX returns.

Figure 3 shows daily variance decompositions for each vintage and credit rating. Each panel has 3 columns, representing AAA, AA and BBB- rated assets respectively. The first row in each panel presents the observed asset return volatility, and the following rows present the contributions of each factor to that volatility. Note that the common factor, shown in the second row, tends to be more important for the higher-rated tranches and the idiosyncratic factor tends to be more important for lower-rated assets. It is important to note that this is the variance decomposition for the standardized returns, not the raw returns. We discuss each of the factors in turn before delving more deeply into the relationship between the common factor with observables.

4.1 The Common Factor

The second row of Fig. 3 shows the common factor becoming increasingly important over time compared with other factors. Its influence is negligible during the relatively tranquil conditions that characterized the financial system before early 2007. This is consistent with relatively low default correlations during this period and the low credit default spreads demanded for protection against default of the pooled assets. For example, the spread for the AAA tranche of the first vintage was a mere 18 basis points, falling to 9 bps for the January 2007 vintage and finally increasing to 76 bps for the last vintage. The low realization of the common shock in the early period compared to the crisis period contributed to claims that credit rating agencies, and some market participants, under-estimated risk. Brennan et al. (2009) show that if investors rely exclusively on rating agencies to accurately assess creditworthiness, this can lead to mispricing of CDOs' (and similar products') tranches.[8]

As the crisis emerges in mid-2007, the contribution of the common shock to asset volatility increases noticeably. Its pervasive nature affects all assets in the underlying pool and thus heightens their pairwise correlations. These increased levels of comovement quickly eroded the buffer protecting the AAA tranche and in relative terms implies investors in these assets were worst hit by the common shock. This is consistent with the argument of Coval et al. (2009) that an amplified common shock effectively transfers risk from lower to more senior tranches. From mid-2007 onwards, the common factor swamps all other factors, suggesting that all AAA-rated assets behaved increasingly alike without any distinguishing vintage effects.

A number of other studies document a similar pattern for systematic shocks in different asset markets. Eichengreen et al. (2009) analyze CDS spreads of 45 international financial institutions and document an increasing role for a common factor as the financial crisis evolves, with its largest influence in the aftermath of the Lehman collapse. Similarly, Longstaff and Myers (2009) show that a common factor can explain a substantial proportion of bank and CDO equity return variation.

[8] Classens et al. (2010) argue that many investors actually did rely totally on credit ratings.

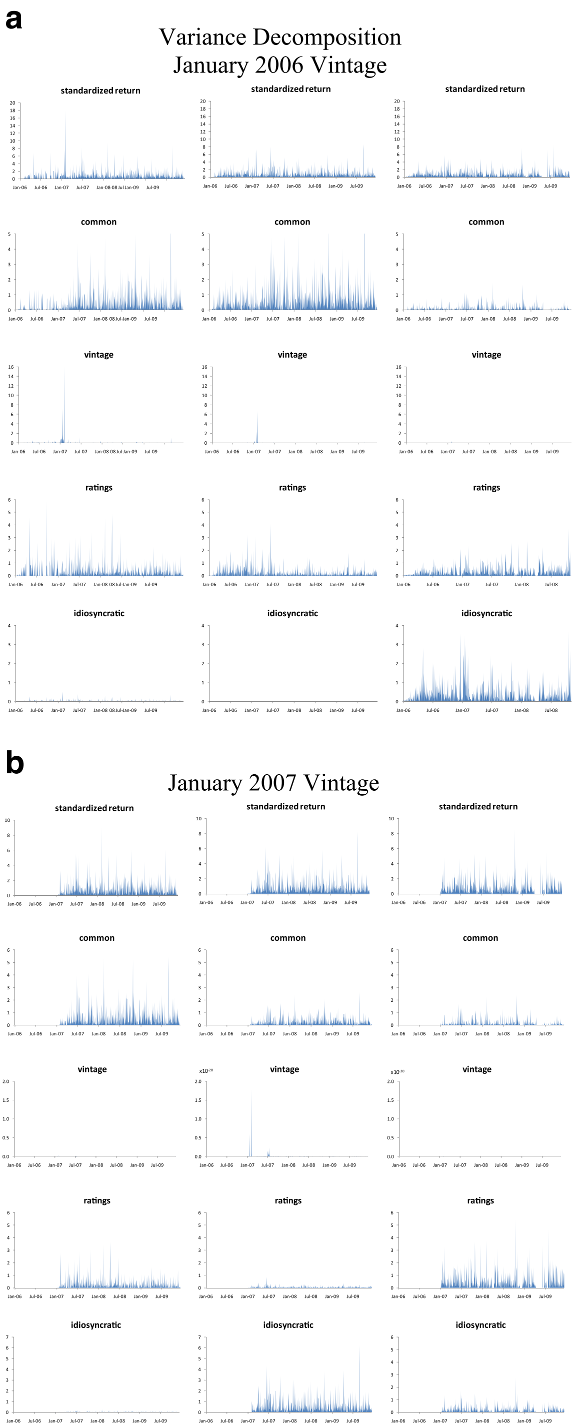
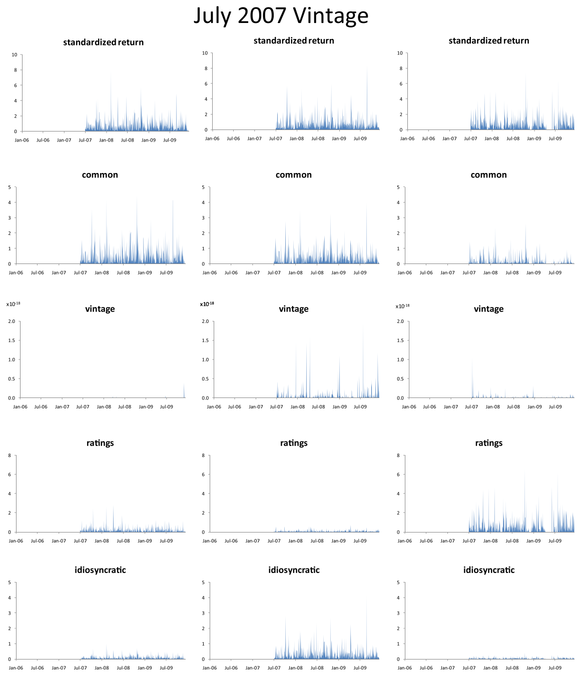


Fig. 3 Variance decomposition. This figure shows the daily variance decomposition for each vintage and credit rating within each vintage. The first row of each panel shows squared standardized returns. The following rows in the panel show the contributions by the common factor, the corresponding vintage factor, the corresponding ratings factor and the idiosyncratic factor. The vertical scales of the graphs differ vertically but not horizontally. The vertical scales differ too much to use the same scale for all graphs. Comparisons across credit ratings within a vintage are simpler with the same scale for all three credit ratings

Fig. 3 (continued)



4.2 Ratings and Vintage Factors

Both the rating and vintage factors exert a time-varying influence on asset return variability. At various times, the specific rating and vintage helped to differentiate between assets. For the earliest vintage, 06-1, ratings matter and this factor accounts for a non-trivial amount of asset return variability. For later vintages, ratings matter little for the two most senior tranches but continue to be an important determinant of returns for the equity tranche. In relative terms the contribution of the vintage factor is the smallest of all factors. However, in early 2007 as ABS markets become unsettled, the vintage factor has a pronounced effect. This suggests that market participants began to distinguish between ABX indices on the basis of the underlying asset quality. For all tranches the largest impact of the vintage factor occurs for the July 2007 issuance. The deals underlying this issue were struck in the first half of 2007, when US house price declines were already evident (previous issues were based on rising and then peak house prices).

The rating and vintage factors play an important role in distinguishing assets during non-crisis periods. However, during crisis, their influence is swamped by the common and idiosyncratic components.

4.3 The Idiosyncratic Factor

Just as the common factor exerts its greatest influence on the most senior claim, idiosyncratic shocks have their greatest effect at the other end of the rating spectrum. In the earliest vintage, idiosyncratic risk almost exclusively affects the BBB- tranche and were of little concern to holders of more senior claims because the lower-rated tranches absorbed these risks. In later vintages, there is a greater role for idiosyncratic shocks as mezzanine tranches also exhibit some vulnerability to them, most likely due to the inadequacy of the equity tranches to protect them. Interestingly, idiosyncratic shocks fall in importance for BBB- rated assets, which may be due to overwhelming influence of the common shock or may also reflect a lack of trades when the value of the BBB- tranche flattened out near zero.[9]

The behaviour of the idiosyncratic shock is consistent with the arguments outlined earlier. In normal market conditions, when assets in the underlying pool exhibited relatively low correlation, idiosyncratic risk resulted in a few random subprime mortgage defaults whose effects were absorbed by the equity tranche or other lower-rated tranches. The onset of the crisis in July 2007 led to this risk source being swamped by the common shock, limiting its impact on asset return volatility.

5 What Drives the Common Factor?

Initially, we recover the level of the common factor. The logarithm of the value of the underlying asset, $p_{i,j,t}$, for vintage i, credit rating j, in period t, from the adjusted return, $y_{i,j,t}$, accounting for GARCH is

$$p_{i,j,t} = a + h_{i,j,t} y_{i,j,t} + p_{i,j,t-1} \tag{23}$$

by the definition of the return and the equation for conditional heteroskedasticity (10). The relationship between this index value and the factors can be seen by substituting for $y_{i,j,t}$ to write

$$p_{i,j,t} = a + h_{i,j,t}\left(\beta_{i,j} w_t + \theta_{i,j} v_{i,t} + \varphi_{i,j} k_{j,t} + \phi_{i,j} f_{i,j,t}\right) + p_{i,j,t-1} \tag{24}$$

The contribution of the factors to the value of the assets can then be written as

$$p_{i,j,t} = a + \beta_{i,j} h_{i,j,t} w_t + \theta_{i,j} h_{i,j,t} v_{i,t} + \varphi_{i,j} h_{i,j,t} k_{j,t} + \phi_{i,j} h_{i,j,t} f_{i,j,t} + p_{i,j,t-1} \tag{25}$$

where $\beta_{i,j}\ h_{i,j,t}\ w_t$ is the contribution of the common factor to the value of the asset with vintage i and rating j in period t. Note that the common factor including heteroskedasticity is different for each tranche and vintage because different conditional standard deviations translate the adjusted returns into raw returns.

Section 4 showed that the common factor plays a major part in changes to the values of the most senior tranches of subprime-mortgage backed assets. We focus the rest of our analysis on the drivers of the common factor. We use the AAA tranche of the 06-1 vintage to construct the level of the common factor $h_{i,j,t}\ w_t$ because it represents the highest valued CDO tranche for the longest period.[10] Fig. 4 shows the integrated common factor with its level set to

[9] The buyer of insurance in the CDS on the CDO makes an initial payment to the insurance seller equal to the difference between 100 and the index value. When the index is near zero, this becomes a substantial unsecured loan.

[10] For example, Hu (2007) reports that for CDOs issued in 2006, AAA-rated assets accounted for 85 % of dollar value and 36 % of the number of tranches, while the figures for Baa and lower rated assets were 3.7 % and 24 % respectively. Many deals had more than one AAA tranche. The ABX index is based on the most subordinate AAA tranche.

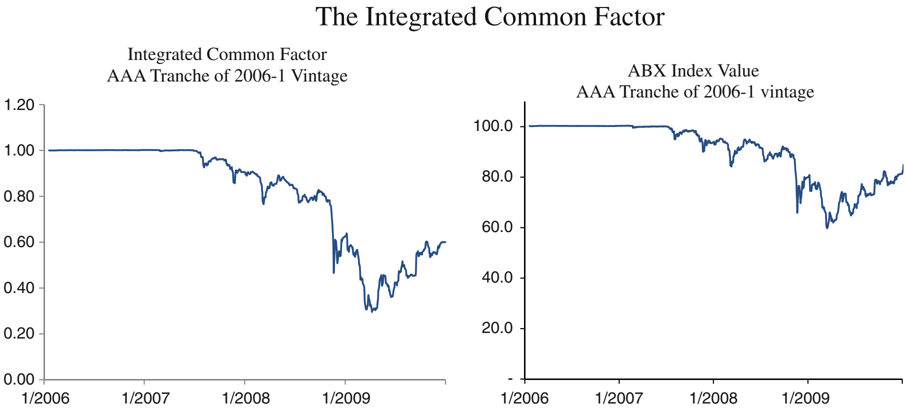


Fig. 4 The integrated common factor. The left panel shows the integrated common factor for the January 2006 AAA vintage with the initial value normalized to 1. This value reflects the conditionally heteroskedastic behavior of the common factor derived from the conditional heteroskedasticity in the original returns. The right panel shows the actual value of the AAA tranche of the January 2006 vintage of the ABX index. Many common features appear in both figures

unity at the start of the series.[11] The evolution of the common factor can be usefully compared to that of the AAA tranche of the ABX index for January 2006, both of which are shown in Fig. 4 for convenience. Consistent with the common factor's substantial importance in the evolution of the AAA tranches, the common factor reflects many of the characteristics of the AAA tranche.

Observable economic variables potentially related to the deterioration of the ABX are real estate prices, general financial market volatility and liquidity and counterparty risk. We use the logarithm of a daily price index for the U.S. real estate trusts (REITs) represented by the Dow Jones Equity All REIT Index to reflect news about housing prices; and the logarithm of the VIX index as a measure of general financial market volatility.

Liquidity and counterparty default risk are measured by three one-month interest rate spreads: the spread between the London Interbank Borrowing Rate (LIBOR) and the overnight index swap rate (OIS), LIBOR-OIS; the spread between LIBOR and the U.S. Treasury Bill rate, the TED spread; and the spread between the commercial paper rate and the U.S. Treasury Bill rate, CPR-TB.

LIBOR-OIS can be viewed as reflecting counterparty risk from the standpoint of a lender to another institution. Borrowers who believe the market is overstating their risk may also view this spread as reflecting liquidity. The TED spread is another common measure of liquidity and counterparty risk and would be partly redundant with the inclusion of LIBOR-OIS. The spread between OIS and the Treasury Bill rate (OIS-TB), which excludes the part of the TED spread already represented by LIBOR-OIS, provides a straightforward means of examining the informativeness of one spread relative to the other. OIS-TB is the clearest indicator of liquidity issues

[11] The contribution of the common factor to the measured return on the ABX is the common factor times its coefficient of 0.83. The contribution of the level of the factor to the level of ABX though depends on an unobserved initializing constant for the level of the common factor which cannot be recovered from first difference alone.

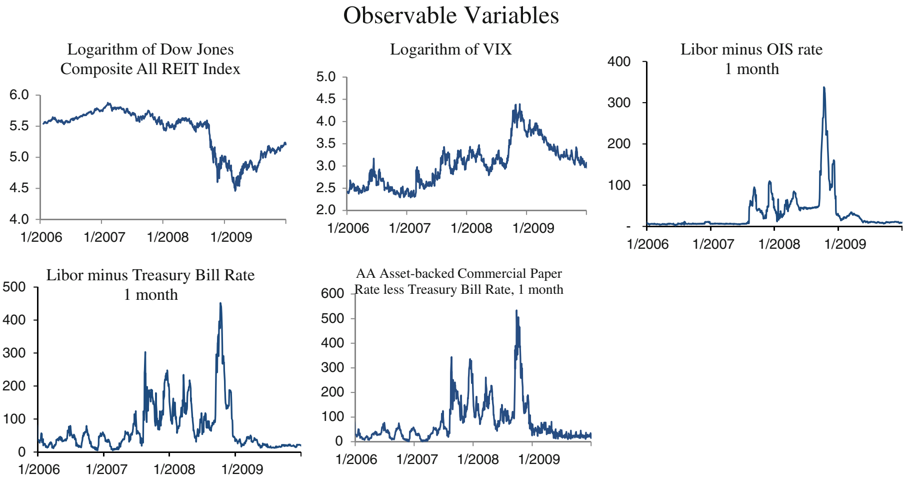


Fig. 5 Observable variables. This figure shows the values of the variables other than the ABX index which are included in the analysis of the variables' relationships. The figures suggest that the Dow-Jones Equity All REIT index and VIX have slow moving components, possibly unit roots, while the spreads do not. By the end of 2009, the spreads return to values similar to those before the crisis, although the behavior is not identical

because the OIS rate is the rate for almost fully collateralized private transactions and the Treasury Bill rate is a nominal risk-free rate. We also include the spread between the commercial paper rate on AA-rated asset-backed commercial paper and the U.S. Treasury bill rate, which can be interpreted as reflecting flights to quality during the crisis due to concerns about the value of the underlying assets.

Figure 5 shows the observable factors. The figures clearly show evidence of episodes with increasing and then decreasing spreads, most evidently for the CPR-TB spread but also for the spread of LIBOR over OIS.

Unit root tests indicate one unit root in each of the common factor, REIT and VIX. This unexpected outcome for the VIX is consistent with the results reported by Zhang

Table 7 Cointegration tests and cointegrating vector

Cointegration rank tests					
Number of cointegrating vectors	Eigenvalue	Trace statistic	p-value	Maximum eigenvalue statistic	p-value
None	0.0423	57.768	$<10^{-4}$	41.927	$<10^{-4}$
At most 1	0.0132	15.841	0.1819	12.934	0.1381
At most 2	0.0030	2.9071	0.5982	2.907	0.5982
Cointegration vector					
Variable	Level of Common factor		REIT index	VIX	Constant
Coefficient	1		−0.5138	0.1386	1.5652
Standard Error			0.0651	0.0477	0.4767

The p-values are based on MacKinnon, Haug and Michelis (1999). The trace test and maximum eigenvalue test lead to the same conclusion: one cointegrating vector among the three variables et al. (2010) for options prices. Johansen cointegration tests, reported in Table 7, are consistent with one cointegrating vector between the common factor and the logarithms of the Dow-Jones REIT index and VIX.

Table 8 presents a 3-variable Vector Error Correction Mechanism (VECM) for the common factor, the logarithm of the REIT index and the logarithm of VIX. All equations include two lags of all variables.[12] One month interest-rate spreads for LIBOR-OIS, OIS-TB, and CPR-TB are included as exogenous variables. The errors are specified as a diagonal GARCH(1,1), estimated using a diagonal vech structure. The zero restrictions on errors across variables reduce the number of parameters estimated.[13]

Table 9 presents tests to restrict this set of equations by deleting spreads. The results clearly indicate that LIBOR-OIS is very informative for these variables. The results also clearly indicate that the CPR-TB is not informative and can be dropped at little cost. The OIS-TB spread is somewhat informative, with a p-value of 10.3 % for dropping it from the equations with both other spreads but a *p*-value of only 20.5 % when the commercial paper rate spread is not included in the equations. Overall, the results are consistent with the informativeness of the spread of LIBOR - OIS but not the other spreads. Table 10 presents the estimated three-equation VECM with LIBOR-OIS as the only spread. While t-ratios might suggest that LIBOR-OIS is not uniformly important, likelihood ratio tests indicate that each of the variables reflects movements in LIBOR-OIS.[14]

The estimates in Table 10 can be used as the basis for comparing actual events with events estimated without the behaviour of LIBOR-OIS reflecting the financial crisis. We infer the no-financial-turmoil behaviour of LIBOR-OIS from its behaviour prior to the financial crisis. It is relatively simple to date the financial crisis in terms of LIBOR-OIS. It spiked from 9.65 basis points on August 8, 2007 to 38.18 basis points on August 9. This spike is extraordinary and not a random date. On August 9, 2007, BNP Paribus suspended redemptions in three funds holding securities based on subprime mortgages. Later that day, the European Central Bank and the Federal Reserve dramatically increased repurchase agreements with banks to provide additional reserves to banks. From the inception of the ABX indices on January 19, 2006 to August 8, 2007, the mean LIBOR-OIS spread is 6.32 basis points with a standard deviation of 1.38 basis points. The maximum spread is 11.95 basis points. For the rest of our time period, the mean spread is 64.38 basis points with a standard deviation of 58.88 basis points; the maximum spread is 337.75 basis points on October 10, 2008. As Fig. 5 shows, the LIBOR-OIS spread decreased from these extraordinary values. From June 1, 2009 to the end of 2009, the mean spread is 9.87 basis points with a standard deviation of 1.16 basis points, with a maximum of 12.95 basis points in

[12] The choice of lag length is based on F-tests and Akaike Information Criterion values, reported in Table 9, which support the reduction from 3 to 2 lags but not further. We also examined evidence for a VECM where spreads are treated as exogenous. For LIBOR less OIS in a four-equation system, the p-value is 13.4 %. For LIBOR less OIS in a five-equation system, the p-value is 13.7 %. These systems involve many parameters, so these results are at best indicative. Attempts to estimate a six-variable system with the AA asset-backed commercial paper rate were not successful.

[13] Bauwens et al. (2006) and Silvennoinen and Teräsvirta (2008) review multivariate GARCH models.

[14] The *p*-values for deleting the current and two lagged values of LIBOR-OIS are 0.01 %, 4.30 %, and 0.02 % for the common factor, the logarithm of the REIT index and for the logarithm of VIX equations respectively.

Table 8 Estimates of error correction mechanisms

Variable(lag)	Change in the logarithm of the common factor			Change in the logarithm of the REIT index			Change in the logarithm of VIX		
	Coefficient	Standard Deviation	*p*-value	Coefficient	Standard Deviation	*p*-value	Coefficient	Standard Deviation	*p*-value
Constant	$0.608{\cdot}10^{-4}$	$0.168{\cdot}10^{-4}$	0.0003	0.0017	0.0007	0.0261	−0.0023	0.0028	0.4170
Cointegrating vector(1)	$0.692{\cdot}10^{-4}$	$0.544{\cdot}10^{-4}$	0.2040	0.0129	0.0077	0.0917	−0.0719	0.0247	0.0036
LIBOR-OIS(1)	−0.0018	0.0004	$<10^{-4}$	0.0201	0.0126	0.1101	0.1013	0.0373	0.0066
LIBOR-OIS(2)	0.0009	0.0004	0.0164	−0.0316	0.0131	0.0156	−0.0909	0.0390	0.0198
OIS-TB(1)	−0.0007	0.0003	0.0280	0.0008	0.0072	0.9177	0.0325	0.0232	0.1611
OIS-TB(2)	0.0006	0.0003	0.0624	−0.0007	0.0073	0.3374	−0.0288	0.0258	0.2655
CPR-TB(1)	0.0007	0.0003	0.0317	0.0018	0.0057	0.7479	0.0034	0.0121	0.7797
CPR-TB(2)	−0.0006	0.0003	0.0734	0.0044	0.0057	0.4371	−0.0070	0.0148	0.6355
dlfw(1)	0.3000	0.0357	$<10^{-4}$	0.2057	0.1430	0.1502	−0.1009	0.3491	0.7726
dlfw(2)	−0.0178	0.0380	0.6400	−0.3146	0.1135	0.0056	0.0102	0.3453	0.9758
dlreit(1)	0.0003	0.0005	0.5474	−0.1467	0.0374	0.0001	−0.0461	0.0870	0.5957
dlreit(2)	0.0002	0.0004	0.6484	−0.0250	0.0383	0.5147	−0.0456	0.0830	0.5829
dlvix(1)	$0.260{\cdot}10^{-4}$	$0.800{\cdot}10^{-4}$	0.7371	−0.0206	0.0084	0.0139	−0.1422	0.0400	0.0004
dlvix(2)	$0.154{\cdot}10^{-5}$	$0.559{\cdot}10^{-4}$	0.9780	−0.0071	0.0090	0.4267	−0.0752	0.0398	0.0585
Diagonal VECH estimates of IGARCH(1,1) processes									
	Constant term			Squared-innovation term			Conditional-variance term		
Row 1	$0.160{\cdot}10^{-09}$	$-0.108{\cdot}10^{-7}$	$0.338{\cdot}10^{-7}$	0.7329	0.0499	0.0408	0.6431	0.8920	0.9011
Row 2		$0.295{\cdot}10^{-5}$	$-0.640{\cdot}10^{-5}$		0.0996	0.0613		0.8960	0.9279
Row 3			$0.193{\cdot}10^{-3}$			0.0684			0.8904
Log likelihood of system 8778.14									

This table shows estimates of the vector error correction mechanism with two lags of all variables. It also shows estimates of the GARCH(1,1) parameters estimated for each of the three equations. The variable dlfw is the change in the logarithm of the common facor for the AAA tranche of the January 2006 vintage, dlreit is the change in the logarithm of the REIT index, and dlvix is the change in the logarithm of VIX. All interest rate spreads are based on interest rates with 1 month to maturity. LIBOR-OIS is the spread of LIBOR over OIS. OIS-TB is the spread of OIS over the Treasury Bill rate. CPR-TB is the spread of the commercial paper rate on AA-rated asset-backed commercial paper over the Treasury bill rate

Table 9 Likelihood ratio tests of restrictions on error correction mechanism

Test	Test statistic	Degrees of freedom	*p*-value
Lag Length			
2 lags to 1 lag	32.118	18	0.0213
3 lags to 2 lags	11.906	18	0.8520
Conditional on other spreads in equations			
Drop Libor-OIS	40.292	6	$<10^{-4}$
Drop Libor-TB	10.568	6	0.1027
Drop CPR-TB	6.735	6	0.3461
Conditional on CPR-TB not in equations			
Drop Libor-OIS	34.776	6	$<10^{-4}$
Drop Libor-TB	8.478	6	0.2051
Conditional on CPR-TB and OIS-TB not in equations			
Drop Libor-OIS	37.318	12	0.0002
Current Libor-OIS helps to predict all three variables			
3-variable system	14.876	3	0.0019

In addition to the 3 underlying variables in the cointegrating vector error-correction mechanism – the common factor, the reit stock price index and VIX – the variables included are Libor minus the overnight index swap (OIS) rate, Libor minus the Treasury Bill rate (which can be represented by OIS minus the Treasury Bill rate if Libor-OIS is included in the equations) and the AA commercial paper rate minus the Treasury Bill rate. The tests for lag length are based on estimates of the VECM with lagged values of the three spreads. The Akaike Information Criterion values are −17.9322, −17.9386 and −17.9241 for lag lengths of three, two and one, leading to a choice of the same lag length as F-ratios. The last test examines whether current values of Libor-OIS included in each of the three equations in the 3-variable ECM help to predict the three variables

these 7 months. Even this slightly elevated level of LIBOR-OIS may well be a reflection of the financial crisis.

While there always is variation in LIBOR-OIS, we simplify our simulation by setting LIBOR-OIS to its average value before the financial crisis and impose that value for the crisis period. We then simulate the behaviour of the common factor, REIT and VIX using the same innovations to those three variables as derived from the estimates in Table 10. If LIBOR-OIS were exactly the same as its historical values, the actual values of the common factor, the REIT index and VIX would occur. The simulation is 'dynamic' in the sense that values of the common factor, the REIT index and VIX persist into subsequent periods, so that deviations of simulated from actual values persist. The estimated VECM, of course, will predict adjustment of the three variables in the cointegrating vector back to the stable long-run relationship. This need not mean adjustment of the levels of the variables back to their values before the financial crisis.

Figure 6 shows the actual and simulated values of the common factor, the REIT index and VIX. By the end of 2009, all of the variables still show effects of the financial crisis as reflected in LIBOR-OIS. None of the variables has returned to values similar to their values before the financial crisis. The percentage deviations between the actual values of the series – the common factor, the REIT stock price index and VIX – are shown in Fig. 7. The deviations are substantial. At the end of 2009, the simulation

Table 10 Estimates of error correction mechanisms

Variable(lag)	Change in the logarithm of the common factor			Change in the logarithm of the REIT index			Change in the logarithm of VIX		
	Coefficient	Standard Deviation	*p*-value	Coefficient	Standard Deviation	*p*-value	Coefficient	Standard Deviation	*p*-value
Constant	0.00012	$0.829 \cdot 10^{-4}$	0.1453	0.0209	0.0114	0.0662	−0.1152	0.0379	0.0023
Cointegrating vector(1)	$0.437 \cdot 10^{-4}$	$0.540 \cdot 10^{-4}$	0.4191	0.0126	0.0073	0.0841	−0.0723	0.0240	0.0026
LIBOR-OIS(0)	$0.922 \cdot 10^{-4}$	0.0004	0.8070	−0.0187	0.0101	0.0656	0.1456	0.0329	$<10^{-4}$
LIBOR-OIS(1)	−0.0012	0.0003	$<10^{-4}$	0.0420	0.0138	0.0024	−0.0792	0.0560	0.1718
LIBOR-OIS(2)	0.0003	0.0004	0.4633	−0.0271	0.0126	0.0321	−0.0578	0.0391	0.1396
dlfw(1)	0.3120	0.0345	$<10^{-4}$	0.1574	0.1406	0.2626	−0.0761	0.3403	0.8231
dlfw(2)	−0.0170	0.0363	0.6397	−0.2906	0.1090	0.0077	−0.0003	0.3331	0.9992
dlreit(1)	$0.713 \cdot 10^{-4}$	0.0004	0.8706	−0.1525	0.0368	$<10^{-4}$	−0.0393	0.0848	0.6428
dlreit(2)	0.0002	0.0004	0.5440	−0.0235	0.0376	0.5322	−0.0472	0.0818	0.5642
dlvix(1)	$0.628 \cdot 10^{-5}$	$0.773 \cdot 10^{-4}$	0.9352	−0.0224	0.0082	0.0062	−0.1342	0.0385	0.0005
dlvix(2)	$0.310 \cdot 10^{-5}$	$0.580 \cdot 10^{-4}$	0.9574	−0.0070	0.0087	0.4174	−0.0758	0.0389	0.0510
Diagonal VECH estimates of IGARCH(1,1) processes									
	Constant matrix			Squared innovation			Conditional variance		
Row 1	$0.154 \cdot 10^{-10}$	$-0.102 \cdot 10^{-7}$	$0.321 \cdot 10^{-7}$	0.7197	0.0532	0.0467	0.6474	0.8908	0.8955
Row 2		$0.292 \cdot 10^{-5}$	$-0.695 \cdot 10^{-5}$		0.1017	0.0645		0.8939	0.9235
Row 3			$0.188 \cdot 10^{-3}$			0.0694			0.8904
Log likelihood of system 8777.97									

This table shows estimates of the vector error correction mechanism with the current value and two lags of LIBOR minus OIS and two lags of the other variables. It also shows estimates of the GARCH(1,1) parameters estimated for each of the three equations. The definitions of variables are provided in the note to Table 8

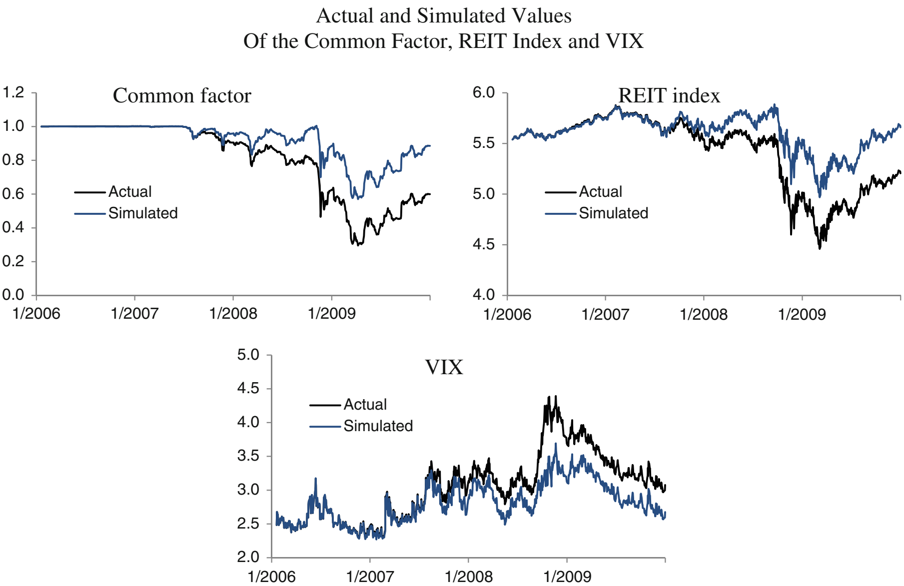


Fig. 6 Actual and simulated values of the common factor, REIT Index and VIX. This figure shows the actual values of the integrated logarithm of the common factor, the logarithm of the Dow-Jones Equity All REIT index and the logarithm of VIX. These actual values are shown on each graph with the simulated value from the estimated vector error correction mechanism in Table 10. The simulated values are from a dynamic simulation with LIBOR less OIS held to its mean value from January 19, 2006 to December 31, 2009

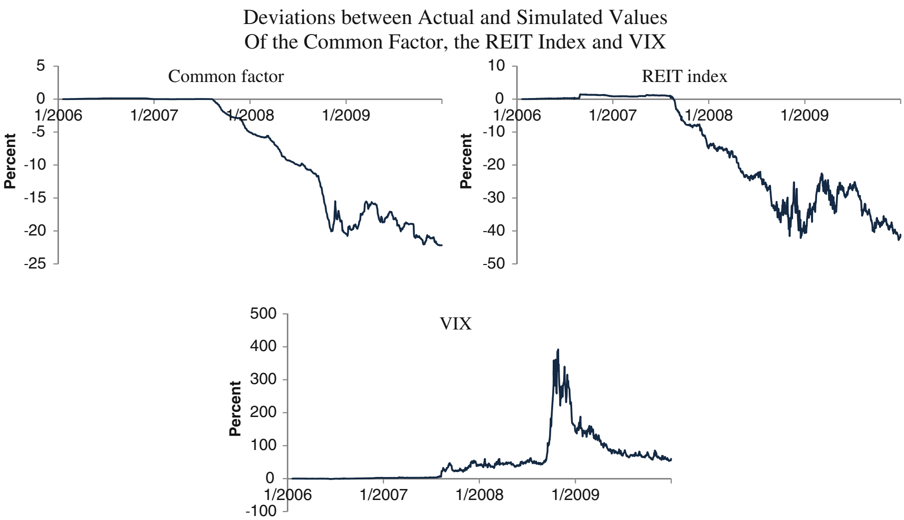


Fig. 7 Deviations between actual and simulated values of the common factor, the REIT index and VIX. This figure shows the percentage deviations between the actual and simulated values of the integrated common factor, the Dow-Jones Equity All REIT index and VIX. The percentage deviations are between the actual values and the exponentiated value of the logarithm of simulated values. The simulated values are from a dynamic simulation with LIBOR less OIS held to its mean value from September 19, 2006 to August 8, 2007. The deviation between the common factor and the simulated value shows a clear downward movement not reversed by the end of 2009. The deviation between the REIT index and the simulated value show a similar downward movement. The deviation between actual VIX and the simulated value shows a dramatic movement upward in 2008, much of which but not all is reversed by the last half of 2009

shows that the common factor would have been 20 % higher if the LIBOR-OIS had stayed close to its value before the financial crisis. Similarly, the REIT index is slightly more than 40 % lower than it would have been under the simulation. In contrast the VIX is over 50 % higher as a result of the LIBOR-OIS experiences than in the simulation where LIBOR-OIS remained around its pre-crisis values.

Even if LIBOR-OIS returns to pre-crisis values, the cointegrated values of the common factor, the REIT index and VIX need not return to their pre-crisis values even though they will return to the cointegrated relationship. The estimated cointegrating vector suggests that it will take a long time for the variables to return to equilibrium and that the shocks to LIBOR-OIS reflected in the common factor are likely to have permanently changed this factor in the wake of the crisis.

6 Conclusion

We characterize the behaviour of the ABX indices of subprime-mortgage backed assets during the Financial Crisis of 2007 and 2008. In the process, we gain a better understanding of the sources of the decline of this market, in particular the falls due to liquidity and counterparty risk. We apply a latent factor model to an unbalanced panel of returns by credit rating and vintage to obtain a measure of the common movement. The unbalanced nature of the data lends itself to identification of four factors from the returns: a common factor, a vintage factor relating to the issuance dates of the securities, a credit rating factor and an idiosyncratic factor.

All factors exert a time-varying influence on the volatility of asset returns. The factor common to all tranches and vintages shows the most important change in variation over time. The common factor's influence on the highly rated tranches increases with the financial crisis, although not dramatically. This is consistent with market participants underpricing, and credit agencies underestimating, the coming financial difficulties. This of course is easier to see now than before the crisis. Given the structure of CDOs, the most senior tranches are quite vulnerable to the miscalculation of common risk. The increasing magnitude of common undiversifiable shocks changes the return behaviour of AAA tranches dramatically as the crisis unfolds. As a result, the demarcation between tranches becomes blurred as assets within the underlying pool becoming increasingly correlated. Consequently, it is the common shock that is most closely associated with the main damage to the values of CDOs. As suggested by Coval et al. (2009), the securitization process led to more vulnerability to common risk that had been unimportant during the low volatility environment before 2007 but came to the fore with a vengeance during the subsequent downturn. At the other end of the spectrum, the role of idiosyncratic shocks in determining asset returns is predominantly associated with the lowest rated tranche, but even this is largely overwhelmed by the common factor after July 2007. Similarly, in the earlier tranquil market conditions, both the ratings and vintage factors are important for some tranches but again their influence is dwarfed by the common factor during the financial crisis.

To estimate the effects of counterparty risk and liquidity difficulties in financial markets, we delve deeper into the origins of the common factor. We relate the common factor to observable variables commonly mentioned as being crucial in the initiation and transmission of the crisis, capturing the real estate downturn, general financial market volatility, market liquidity decreases and increasing counterparty risk. The common factor, the REIT index and VIX are cointegrated and related to the LIBOR-OIS spread. The LIBOR-OIS spread played a critical role. Because the spread was elevated during the crisis, at the end of 2009, the common factor was 20 % lower, the REIT index was 40 % lower and the VIX was 50 higher than without the disruptions reflected in LIBOR-OIS. This of course does not imply that setting LIBOR-OIS to pre-crisis values would have reduced the effect on the other variables. Fixing a price cannot help. On the other hand, our results indicate that macroprudential supervision is an even more difficult task than commonly thought. A financial crisis has nontrivial effects that continue well after it is over.

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Appendix: Details on Data Series

The data series used in this paper are described below:

ABX Data, all from Bloomberg:

- ABX.HE-A 06-1: 0.54 % Coupon Closing Price, RED ID: 0A08AFAA7
- ABX.HE-A 07-1: 0.64 % Coupon Closing Price, RED ID: 0A08AFAC0
- ABX.HE-A 07-2: 3.69 % Coupon Closing Price, RED ID: 0A08AFAD8
- ABX.HE-AAA 06-1: 0.18 % Coupon Closing Price, RED ID:0A08AHAA1
- ABX.HE-AAA 07-1: 0.09 % Coupon Closing Price, RED ID:0A08AHAC6
- ABX.HE-AAA 07-2: 0.76 % Coupon Closing Price, RED ID:0A08AHAD4
- ABX.HE-BBB 06-1: 1.54 % Coupon Closing Price, RED ID:0A08AIAB6
- ABX.HE-BBB 07-1: 2.24 % Coupon Closing Price, RED ID: 0A08AIAC4
- ABX.HE-BBB 07-2: 5.00 % Coupon Closing Price, RED ID: 0A08AIAD2

Other series:

- US Real estate sector price index - Datastream code: DJAREIT
- VIX: CBOE Market volatility index – from Merrill Lynch and the Wall Street Journal.
- Interest rates: 1-month LIBOR; Overnight Index Swap (OIS) rate; 1-month Treasury bill rate; and 1-month Treasury bill rate. LIBOR and OIS rates are from Bloomberg. The Treasury bill rate and AA asset-backed 1-month commercial paper rate are from the Board of Governors of the Federal Reserve.

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