

Systematic and Liquidity Risk in Sub-prime Mortgage-backed Assets¹

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Abstract

The mis-evaluation of risk in securitized financial products is central to understanding the global financial crisis. This paper characterizes the evolution of risk 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 common factors on more senior tranches during the crisis. An innovation of the paper is that we use the unbalanced panel structure of the data to identify the vintage, credit, common and idiosyncratic effects from a state-space specification.

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1 Introduction

A consensus is emerging that securities based on subprime mortgages played a central role in the evolution of the Financial Crisis of 2008. Falling real estate prices and the resulting delinquencies on mortgages sparked turmoil in financial markets as participants began to realize the shortcomings of their pricing models. Financial market participants subsequently had difficulties estimating the values of securities relating to subprime mortgages and difficulties trading them. 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, banking 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) and Dwyer and Tkac (2009) among others document the evolution and spread of the crisis.

The crisis emerged after a period of unprecedented growth in structured financial products and the extensive creation of subprime-mortgage asset-backed securities. Figure 1 highlights the growth in this sector from 1995 to 2007.² These products were tranced and rated before being sold to investors in much of the world. Among others, DeMarzo (2005) provides a rationale for the issuance of pooled and tranced securities by informed sellers who enjoy an informational advantage regarding the quality of the asset. Although pooling alone may reduce value, the combination of pooling and trancing can be value enhancing due to the transformation of risk through trancing. Furthermore, this effect increases with the size of the underlying pool of assets. DeMarzo suggests that asymmetric information is the friction most consistent with the emergence and success of the CDO market. Whatever the underlying reason, as the creation of CDOs generated profits, there was an increased demand for underlying assets which could be included in a pool, a feature most clearly observed in growth in the market for subprime mortgages. Whether due to CDOs or increased demand for the related assets by the government-sponsored enterprises Fannie Mae and Freddie Mac, Mian and Sufi (2009) provide strong evidence that less stringent mortgage criteria and increased levels of securitization became increasingly important for subprime mortgages in less affluent geographical areas in the U.S. They also provide evidence consistent with the demand for securitized products contributing to the growth of such mortgages. Likewise, Benmelech and Dlugosz (2009) show that investor demand was important for the growth of CDOs and similar tranced products.

The mis-perception and mis-evaluation of risk in many of these structured financial products is central to explanations of the financial crisis. Some market participants equated the risk of AAA-rated tranches to the risk of AAA-rated corporate bonds and failed to take account of the very different risks of the

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

²Ashcraft and Schuermann (2008) document a range of potential explanations for the rapid expansion of subprime mortgage originations.

two assets. Such mis-evaluation may have affected valuations. 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 asset default correlations. Problems estimating the last two of these were important aspects of the financial crisis. Default correlations inevitably are based on historical data, which led to their underestimation based on data which reflected increasing house prices and economic expansion. As default correlations increase, the probability of observing large-scale defaults that affect senior tranches of CDOs increases and their prices fall. Estimates of recovery rates were also affected. Consequently, the risk priced in the different CDO tranches was under-estimated (Coval, Jurek and Stafford, 2009), and its realization amplified the downward pressure on tranche prices. Coval, Jubek and Stafford (2009) analyze the risk inherent in the securitization process and in particular how risk is transferred between tranches in the event of increasing importance of a large common factor such as falling housing prices.

A better understanding of the factors underlying price changes in these subprime-mortgage backed assets is important for understanding their role in the crisis. The aim of this paper is to characterize the driving forces behind the decreases in the prices of collateralized debt obligations (CDOs) based on subprime mortgages and the factors associated with these decreases. Our approach extends Longstaff and Rajan's (2008) empirical model. They show how a pricing model for CDOs can be represented as a three factor model, with the factors representing the credit rating of the asset, a global factor and an idiosyncratic factor. Their work is applied to pricing tranches of the CDX index, which is compiled from the credit derivatives of 125 single-name corporate entities. Using data for October 2003 to October 2005, they estimate that idiosyncratic default risk and common events account for roughly 65 percent and 8 percent of the CDX risk premium respectively. In an application to the more recent period, Bhansali, Gringrich and Longstaff (2008) show a substantial increase in common-event risk occurring in 2007 and 2008.

The CDOs used in this paper are credit derivatives based on subprime mortgages. The subprime mortgage-backed indices are distinct in their vintage of issuance as well as other dimensions. Thus, the empirical model of Longstaff and Rajan (2008) is extended to include an additional factor representing vintage effects.³ The model is applied to returns data for three different asset tranches (AAA, AA and BBB-) of mortgage backed securities using the Markit ABX.HE indices for three vintages of issuance over the period January 2006 to April 2009. Fender and Scheicher (2009) estimate the relationship between returns on these indices; Mizrach (2009) documents their jump behaviour.

Our results show the distinct characteristics of the tranches in terms of the four factors. First, in 2006, all factors have a discernible role in the returns of

³Loan level analysis of the subprime market in Demyanyk and Van Hemert (2009) also supports for the inclusion of a vintage factor. After controlling for a variety of borrower, lender and macroeconomic conditions, they find strong empirical support for a gradual and persistent deterioration of loan quality from 2001 to 2007.

the assets. Second, the common factor becomes important when the financial turmoil begins, with its effect on AAA tranches of various vintages increasing over time. The common factor overwhelms the vintage and ratings factors for all but the equity tranche during the high-volatility period of July 2007 onward. Third, the higher risk BBB- tranche is affected less by the common factor but shows a great deal of exposure to the idiosyncratic factor and, in later vintages, both credit rating and vintage factors. Finally, intermediate tranches display the greatest mixture of risk exposures, with all of the factors contributing to the variation of returns.

The paper is structured as follows. Section 2 describes the ABX data and highlights its unique features which are accommodated in our econometric model. Section 3 presents the econometric set up and describes our Kalman filter approach to estimating the factor model. Section 4 presents and discusses our results, while section 5 contains our concluding remarks.

2 Data

The price decreases in asset backed securities during the financial difficulties from 2007 to 2009 are dramatic. These declines are associated with declines in the values of the underlying assets but also seem to represent a significant reassessment of the risks of such assets. We analyze the risk factors inherent in these tranching pools by examining the relatively new indices of values of CDOs used as the basis for Credit Default Swaps (CDSs) related to subprime-mortgage-backed securities. These indices, entitled ABX.HE, are produced by Markit and were first introduced in January 2006.

Figure 1 shows the evolution of the indices from January 2006 to April 30, 2009. Financial market participants use ABX.HE indexes to track the subprime-mortgage market. Each index is represented by five different tranches, varying from AAA to BBB-, where the ratings are based on those from Moody's and S&P, with the lower of the two ratings taken when both are available and different. The index values are based on underlying credit default swaps, with the insurance coupon set so that the index trades at par - 100 - unless such a coupon would exceed 500 basis points. Fender and Scheicher (2008) represent each index's value as

$$100 + PV(\text{coupons}) - PV(\text{writedowns, shortfalls}).$$

In this representation, deviations below 100 indicate that the present value of the coupon payments for insurance are less than the expected value of losses.

Each vintage of the index is based on twenty mortgage-backed CDO deals with tranches covering all of the credit ratings over the prior six month period. 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.⁴ There are strict

⁴Licensed Dealers in the ABX.HE indices include the following: ABN AMRO; Bank of America; Barclays Capital; Bear Stearns; BNP Paribas; Calyon; Citigroup; Credit Suisse;

requirements that must be met by the deals to qualify for inclusion in the construction of the index. For example, the value of each deal must be at least \$500 million and each tranche must have an average life of between four and six years, except for the AAA tranche, which must have a weighted average life greater than five years. Furthermore, no loan originator can have more than four deals included.

These indices are ‘rolled’ every six months with indices commencing in January 2006, July 2006, January 2007 and July 2007. There have been no further rolls due to an insufficient number of new CDOs meeting the eligibility requirements.⁵ These rolls were designed to provide a current index reflecting securities recently created that are likely to be the most traded ones. However, these four indices are not suitable for splicing between issuances to create a continuous series on the most recent CDOs, as done in Longstaff and Rajan (2008) for CDX data. Figure 1 suggests substantial vintage effects that would distort any analysis based on a spliced series. Instead, each new roll is best viewed as a unique vintage with the risk of the reference portfolio of CDSs likely to change between rolls. The set of underlying loans for each vintage reflects mortgages created in market conditions in the preceding six months and represent quite different risks in this time period. The coupon rates for insurance on these ABX indices increased from 2006 to 2007. These increasing coupon rates for insurance are evidence of increases in the perceived risk even at origination.

Table 1 shows the weakening degree of comovement of the assets across vintages. These correlations show quite different relationships between the tranches over time and suggest that each vintage is better viewed as a unique asset, rather than the most recent vintage being the best indicator of the current value of the same security. Interestingly, the most senior (AAA & AA) and most junior claims (BBB & BBB-) exhibit the largest levels of comovement.

This paper explicitly analyzes tranches from three of the vintages across three credit ratings. We omit the vintage issued in June 2006 because it behaves similarly to the first vintage and leaving it out reduces dimensionality problems in our econometric model. The three credit ratings selected – AAA, AA and BBB- – span the range of ratings again without unnecessarily increasing the dimensionality of our estimation. We use daily “returns” of each series, where returns are computed as the difference in log index values. Our analysis covers the period from January 19, 2006 to April 30, 2009. Figure ?? plots the data. As explained above, the data set is unbalanced. All vintages exist at the end of the period, but the vintages arrive progressively. This feature is captured by the use of dummy variables in the modelling framework. Table 2 presents some summary statistics for the index values. Within each vintage, the standard deviation of return is inversely related to the credit rating of the

Deutsche Bank; Goldman Sachs; JPMorgan; Lehman Brothers; Merrill Lynch; Morgan Stanley; RBS Greenwich; UBS; and Wachovia.

⁵As of this writing in 2010, there has been very little securitization since 2008.

Table 1:
Correlation coefficients between assets of different credit ratings within
Vintages.

	06_1 Vintage	06_2 Vintage	07_1 Vintage	07_2 Vintage
Corr(AAA,AA)	0.842	0.695	0.644	0.683
Corr(AAA,A)	0.547	0.460	0.348	0.454
Corr(AAA,BBB)	0.426	0.294	0.312	0.326
Corr(AAA,BBB-)	0.443	0.258	0.323	0.273
Corr(AA,A)	0.684	0.658	0.580	0.664
Corr(AA,BBB)	0.482	0.463	0.436	0.492
Corr(AA,BBB-)	0.501	0.407	0.402	0.438
Corr(A,BBB)	0.678	0.635	0.538	0.480
Corr(A,BBB-)	0.638	0.532	0.492	0.454
Corr(BBB,BBB-)	0.852	0.787	0.861	0.824

asset. Across vintages, the standard deviation increases with the most recent vintage displaying the highest volatility. Consistent with most asset return data, the distributions are negatively skewed with the absolute value of the minimum return greater than its corresponding maximum. Within vintages, AAA-rated tranches exhibit the highest levels of excess kurtosis but kurtosis declines across vintages. This may suggest that AAA securities experienced the most serious revision in the crisis.

3 Modelling framework for ABX data

Longstaff and Rajan (2008) and Bhansali, Gringrich and Longstaff (2008) treat the asset backed securities data as a continuous stream from a homogenous asset. In particular, asset backed securities of this type are issued at regular time intervals, with the intent that there is a continuous market with positions rolled over from one contract to others, as well as a continued secondary market for older vintages of issue. In this way, these securities resemble on-the-run and off-the-run bonds markets as opposed to futures contracts which expire. These authors deal with the need for a continuous stream of data to represent prices or returns in this market by simply splicing the data together at a point in time. It seems to make little difference in the non-crisis period they cover. However, one of the defining features of the asset backed securities markets during our period is a perception that the underlying assets were declining in quality. From Figure 2, it is clear that the behavior of the price declines in these assets, as the financial difficulties from July 2007 to 2009 unfold, differs for each tranche. Much interesting information would be lost by splicing to form a single series for each tranche.

Table 2:
Summary statistics for assets by Vintage.

	Mean	Std Dev	Min	Max	Skewness	Kurtosis	No. obs
Vintage 06-1							
AAA	-0.00046	0.0088	-0.082	0.076	-1.137	24.426	822
AA	-0.00217	0.0175	-0.140	0.115	-1.237	16.157	822
BBB-	-0.00391	0.0212	-0.187	0.112	-1.818	13.247	822
Vintage 07-1							
AAA	-0.00066	0.0106	-0.082	0.076	-0.893	16.071	571
AA	-0.00313	0.0209	-0.140	0.115	-0.904	10.343	571
BBB-	-0.00563	0.0252	-0.187	0.112	-1.350	8.283	571
Vintage 07-2							
AAA	-0.00082	0.0120	-0.082	0.076	-0.751	11.928	445
AA	-0.00396	0.0236	-0.140	0.116	-0.702	7.446	445
BBB-	-0.00650	0.0276	-0.187	0.112	-1.208	6.826	445

In this paper, we extend the analysis on asset backed securities to exploit information on the credit rating of the asset, the common and idiosyncratic characteristics as in Longstaff and Rajan (2008) and also incorporate the information pertaining to the vintage of the issuance. The global, rating and vintage factors are all expected to be important in dealing with mortgage-backed securities, as these are more susceptible to economic conditions compared with single-name credit derivatives. The unbalanced nature of our dataset and the explicit differences in ratings allows us to identify these factors from the characteristics of the data rather than merely applying supposed labels to factors ex-post.

We propose a latent factor model for returns, such as for example in Dungey and Martin (2007), where, $y_{i,j,t}$ represents the return, at time t , of an asset-backed security of vintage i (with the vintage being the date of issuance of the security) and credit rating j . The returns are modelled as a linear combination of responses to shocks common to all assets in the dataset, w_t , a vintage factor representing the vintage to which a return belongs, $v_{i,t}$, a ratings factor representing the rating of the tranche, $k_{j,t}$, and idiosyncratic shocks, $f_{i,j,t}$. This linear model is similar to that resulting from the theoretical set up in Longstaff and Rajan (2008)⁶ and can be expressed as:

$$y_{i,j,t} = \alpha_0 + \beta_{i,j}w_t + \theta_{i,j}v_{i,t} + \varphi_{i,j}k_{j,t} + \phi_{i,j}f_{i,j,t}. \quad (1)$$

To capture serial correlation in the data, factors are modelled as autoregressive processes. We estimate AR(1) processes for the common, ratings and vintage factors. In line with evidence from previous research on factor models (Dungey et al. 2000), we do not estimate persistence in the idiosyncratic shocks.

⁶Note that although Longstaff and Rajan (2008) test their three factor model against reduction to a two or one factor model, they do not consider expansion to further factors.

The full specification of the model can be written

$$w_t = \rho_w w_{t-1} + \eta_{w,t} \quad (2)$$

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

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

$$f_{i,j,t} = \eta_{i,j,t} \quad (5)$$

$$\eta_{m,n,t} \sim N(0, 1) \text{ for all } m, n \quad (6)$$

It is clear from the data that the conditional variances of our asset returns vary over time and we account for this feature of the data. Since our model is already heavily parameterized, we cannot accommodate an ARCH specification directly into the setup. Instead, we pre-filter the returns by estimating an IGARCH(1,1) model and use the standardized returns in the factor model.⁷

This framework can be conveniently rewritten in state-space form as

$$Y_t = Z\alpha_t + S\varepsilon_t \quad (7)$$

$$\alpha_{t+1} = \Upsilon\alpha_t + Ru_t \quad (8)$$

where Y_t is the vector of the returns in each asset, $E[\varepsilon_t] = 0$, $E[\varepsilon_t \varepsilon_t'] = H$, $E[u_t] = 0$, and $E[u_t u_t'] = Q$. 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 . The identity of the Kalman filter and the factor model can be seen by the following definitions of the matrices for the 3 vintages and 3 asset ratings case:

$$Z = \begin{bmatrix} \beta_{1,AAA} & \theta_{1,AAA} & 0 & 0 & \varphi_{1,AAA} & 0 & 0 \\ \beta_{1,AA} & \theta_{1,AA} & 0 & 0 & 0 & \varphi_{1,AA} & 0 \\ \beta_{1,BBB} & \theta_{1,BBB} & 0 & 0 & 0 & 0 & \varphi_{1,BBB} \\ \beta_{2,AAA} & 0 & \theta_{2,AAA} & 0 & \varphi_{2,AAA} & 0 & 0 \\ \beta_{2,AA} & 0 & \theta_{2,AA} & 0 & 0 & \varphi_{2,AA} & 0 \\ \beta_{2,BBB} & 0 & \theta_{2,BBB} & 0 & 0 & 0 & \varphi_{2,BBB} \\ \beta_{3,AAA} & 0 & 0 & \theta_{3,AAA} & \varphi_{3,AAA} & 0 & 0 \\ \beta_{3,AA} & 0 & 0 & \theta_{3,AA} & 0 & \varphi_{3,AA} & 0 \\ \beta_{3,BBB} & 0 & 0 & \theta_{3,BBB} & 0 & 0 & \varphi_{3,BBB} \end{bmatrix} \quad (9)$$

$$\alpha_t = \begin{bmatrix} w_t \\ v_{1,t} \\ v_{2,t} \\ v_{3,t} \\ k_{AAA,t} \\ k_{AA,t} \\ k_{BBB,t} \end{bmatrix}. \quad (10)$$

Defining Υ as a 7×7 diagonal matrix of the autoregressive parameters, $\rho = [\rho_w \rho_{v,i} \rho_{k,j}]$ for all i, j , S_t as a 9×9 matrix with the parameters $\phi_{i,j}$ on the main

⁷Prefiltering the data may result in some inefficiencies in the second stage of estimation. However, the consistency of our estimates is unaffected. We adopt a univariate filtering approach in common with much of the existing literature.

diagonal, and R is the appropriately sized identity matrix where the variances of the factors are standardized to one, we can estimate the parameters by the standard Kalman filter procedure.⁸ The standard Kalman filter prediction equations are given by

$$a_{t+1} = \Upsilon a_{t|t} \quad (11)$$

$$P_{t|t+1} = \Upsilon P_{t|t} \Upsilon' + S Q S' \quad (12)$$

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

$$a_{t|t} = a_t + P_t Z' F_t^{-1} v_t \quad (13)$$

$$P_{t|t} = P_t - P_t Z' F_t^{-1} Z P_t' \quad (14)$$

where

$$v_t = Y_t - Z \alpha_t \quad (15)$$

$$F_t = Z P_t Z' + Z. \quad (16)$$

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

$$D_t = \begin{bmatrix} 1 & 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 1 \\ d_{1t} & 0 & d_{1t} & 0 & d_{1t} & 0 & 0 \\ d_{1t} & 0 & d_{1t} & 0 & 0 & d_{1t} & 0 \\ d_{1t} & 0 & d_{1t} & 0 & 0 & 0 & d_{1t} \\ d_{2t} & 0 & 0 & d_{2t} & d_{2t} & 0 & 0 \\ d_{2t} & 0 & 0 & d_{2t} & 0 & d_{2t} & 0 \\ d_{2t} & 0 & 0 & d_{2t} & 0 & 0 & d_{2t} \end{bmatrix} \quad (17)$$

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

Figures 3-5 succinctly summarize the results of estimating the model. The parameter values themselves are consistent, but not very informative.⁹ Instead, for each vintage, we present the squared standardized returns in the first panel and subsequent panels show how much of the movement in this return is due to

⁸Starting values are taken as the consistent estimates of the parameters of the factor model in equation (1) obtained from unconditional moments using GMM.

⁹Parameter values are available from the authors upon request.

a common factor, a vintage factor, a ratings factor and an idiosyncratic factor respectively. Thus, in the first column of Figure 3, the top panel presents the standardized returns. The panels underneath show that in the early part of the sample the ratings factor was an important contributor to the returns for this asset, but that from mid-2007 onwards the common factor plays a much larger role. Vintage and idiosyncratic factors are less important for the AAA:06_1 tranche; they play a more important role in lower ranked tranches. There is sufficient time variation and volatility in each factor to justify its inclusion in our estimated model. We discuss each of the factors in turn before delving more deeply into the sources of the common factor.

4.1 The common factor

Looking across the asset vintages in Figures 3 to 5, it is apparent that the role of the common factor is increasingly important over time. In all cases, the influence of the common factor is negligible during the relatively tranquil conditions that characterized the financial system before July 2007. The limited role for this risk source is consistent with default correlations being relatively low during this period as are the low credit default spreads demanded for protection against default of the pooled assets. For example, the spread for the AAA tranche of the 06-1 vintage was a mere 18 basis points, falling even further to 9 bps for the 07-1 vintage and finally increasing to 76 bps in the last vintage 07-2. It is plausible that the low realization of the common shock, more than anything else, contributed to the under-estimation of risk by credit rating agencies and some market participants. Brennan, Hein and Poon (2009) show that if investors relied exclusively on credit rating agencies to accurately assess creditworthiness, this can lead to mispricing of CDOs' (and similar products') tranches. Classens et al. (2010) argue that many investors actually did rely totally on credit ratings.

As the crisis emerges in mid-2007, the role of the common shock in contributing to asset volatility increases noticeably. The pervasive nature of the systematic downturn affects all assets in the underlying pool and thus heightens the pairwise correlation of those assets. The results show that the AAA-rated assets are the most vulnerable to common shocks, consistent with the argument of Coval, Jubek and Stafford (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 in determining the volatility of the most senior tranches. The other factors are unimportant, suggesting that all AAA-rated assets increasingly behaved similarly without any distinguishing vintage effects. The increasing levels of comovement in the underlying pool of assets quickly eroded the buffer protecting the AAA tranche and in relative terms implies investors in these assets were worst hit by the common shock.

A number of other studies document a similar pattern for systematic shocks in different asset markets. Eichengreen et al. (2009) use a principal components analysis on the 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.

4.2 Ratings and vintage factors

Both the rating and vintage factors exert a time-varying influence on asset return variability in the results. At various times in the life of these subprime-mortgage backed assets, 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, probably due to the increasing importance of the common shock. The vintage factor behaves in a less systematic manner. Its most striking role appears in the BBB- rated tranche of the July 2007 vintage, for which it exerts a large influence. Clearly, it is bad news to be a BBB- rated tranche of a CDO based on subprime mortgages that originated in the first half of 2007.

Overall, rating and vintage play a more limited role in determining asset returns than the common and idiosyncratic factors. There is sufficient evidence, however, to show that the rating and vintage factors affected returns and that the time-varying nature of their effects is captured by our modelling approach. These two factors are more important during the non-crisis period before July 2007, but their role from July 2007 on is overwhelmed by the common shock.

4.3 The idiosyncratic factor

Just as the common factor exerted the greatest influence upon the most senior claim, idiosyncratic shocks have their greatest effect at the other end of the rating spectrum. In the earliest vintage, idiosyncratic risk exclusively affects the BBB- rated tranche. Idiosyncratic shocks held little danger for holders of more senior claims of this vintage as the BBB- and equity tranches absorbed them. In later vintages, there is a greater role for idiosyncratic shocks as other mezzanine tranches also exhibit some vulnerability to it. In this case the equity buffer is not sufficient to prevent losses from moving into higher rated tranches. Finally, in the vintage initiated at almost the same time as the escalation of a subprime mess into the beginnings of a full-scale financial crisis, the effects of idiosyncratic risk are quite disparate and much less than on earlier CDO deals. Again this reflects the overwhelming influence of the common shock which left little scope for the idiosyncratic risk influence. It may also reflect a lack of trades when the value of the BBB- tranche flattened out near zero.¹⁰

The behavior 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

¹⁰The 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.

to this risk source being swamped by the common shock, limiting its impact on asset return volatility.

4.4 What drives the factors?

Although latent factors extract both observed and unobserved sources of commonality across the assets, it can be informative to examine how the factors correlate with a number of observed variables associated with the financial turmoil. The relationships with observed variables is likely to be informative about the driving forces behind the factors and possibly informative about the extent to which unobserved forces such as changes in investor perception are important. The weekly averages of the unobserved factors obtained from the Kalman filter estimation presented in Figure 6.¹¹

Section 4.1 showed that the common factor plays a major part in the increasing risk profile of the most senior tranches of subprime mortgage backed assets. Since AAA tranches constitute the majority of many CDOs, we examine the main drivers of this risk source.¹² The common factor exhibits a substantial increase in volatility when the financial turmoil begins. This reflects the deterioration in mortgages' credit quality as housing prices fell. For example, the houses underlying the mortgage pool in the 07-2 indices fell into negative equity sooner than earlier originated mortgages, which benefited from increases in real estate prices in 2005 and 2006.

Observable economic variables that are related to the deterioration of the ABX are proxies for real estate prices, liquidity, counterparty risk and general financial market volatility. We use a daily price index for the U.S. real estate trusts (REITs) to reflect news about housing prices. Liquidity and counterparty default risk are measured by two 3-month interest rate spreads: the spread between the London Interbank Borrowing Rate (LIBOR) and the overnight indexed swap rate (OIS); and the spread between the OIS rate and the U.S. Treasury Bill rate. The LIBOR-OIS spread can be viewed as representing counterparty risk from the standpoint of a lender to another institution. This spread also can be viewed as representing liquidity from the perspective of borrowers who believe they are not risky counterparties. The TED spread - the spread between LIBOR and the Treasury Bill rate - is the other common measure of liquidity and counterparty risk and would be partly redundant with the inclusion of the LIBOR-OIS spread. Instead of the TED spread, we include the spread between OIS and the Treasury Bill rate, thus excluding the section already represented by LIBOR-OIS. The spread between OIS and the Treasury Bill rate is the spread that is the clearest possible indicator of liquidity issues because the OIS rate is the rate for almost fully collateralized private transactions and the

¹¹Our results and conclusions are robust to other filtering techniques, such as the HP filter, 10- and 20-day moving averages etc.

¹²For 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.

Table 3:
Correlation coefficients for factors with observed variables.

factor		Libor-OIS	OIS-Tbill	VIX	REIT	Δ REIT
Panel A: Correlations						
common	w_t	-0.1916	-0.1004	-0.2149	0.1530	0.3625
vint 06-1	$v_{06-1,t}$	0.0544	-0.0106	0.0163	-0.0279	-0.0114
vint 07-1	$v_{07-1,t}$	0.1610	0.1483	0.2078	-0.1566	-0.1443
vint 07-2	$v_{07-2,t}$	-0.1690	-0.2399	-0.2265	0.2550	0.0606
AAA rated	$k_{AAA,t}$	-0.0984	-0.0900	-0.0932	0.0649	0.0598
AA rated	$k_{AA,t}$	-0.0419	0.0118	-0.0061	0.0302	0.0437
BBB rated	$k_{BBB,t}$	-0.0379	0.0295	0.0007	-0.1266	-0.0342

Treasury Bill rate is a nominal risk free rate. General financial market volatility is measured by the VIX index. The VIX index is a forward-looking variable which reflects expectations of stock market volatility over the next 30 days. Figure 7 presents the observed factors employed in our analysis.

The correlation coefficients for each of the factors with the observed variables are reported in Table 3.¹³

The common factor for the ABX index is most highly correlated with the value of housing. The correlation of the rate of change of the REIT index with the common factor is 36 percent, which we think is fairly substantial for daily data. The common factor is also correlated with the VIX, at 21 percent, suggesting a reflection of the general increase in financial turmoil through out the period. Both counterparty and liquidity risk are reflected in the common factor with around 20 percent correlations with each of the interest rate spreads. While each of these observed variables is somewhat correlated with the common factor, there is substantially more to be explained. The common factor is picking up other (possible unobservable) common influences such as changes in investor perception of asset quality, reassessment of the risk of these assets, as well as potentially changing weights on different variables over time. This latter points particularly to the lack of success of fixed weight regression analysis in this arena.

A similar analysis is applied to the vintage factors, which as they are orthogonal to the common factor, reflect developments common to particular vintages additional to the overall common effects. The vintage factors show a wide range of correlation behaviour with the observable variables. For example, the 06-1 vintage exhibits very little correlation with the observed variables. Interestingly, the degree of correlation with the observed variables increases with vintage.

¹³The strong correlations between all these indices effectively prohibits a meaningful multivariate regression analysis of these relationships.

This suggests that the tranches of later vintages have more common developments than the earliest vintage. All of the observed variables exert an ‘excess’ influence on the return behavior of these later-initiated assets. In particular, the REIT index is important, consistent with the argument that the underlying pool of mortgages was of changing quality over time. Likewise, tightening in liquidity, increasing counterparty risk and the expectation of persistent financial market volatility impact upon these assets. The main conclusion drawn from this analysis is that both observed and unobserved drivers imply that the vintages issued in 2007 were of poorer quality and more risky than the issue of 2006.

Finally, we focus on the ratings factors. The results show little or no ‘excess’ influence on the different tranches across vintages over and above that captured by the common factor. All ratings factors exhibit low correlation with the observable assets. This is consistent with the proposition that the common shock blurred the boundaries between different asset tranches, with common risk sources across all ratings.

In summary, the common shock incorporates observed factors, such as conditions in the underlying real estate market; general financial market volatility; and liquidity and counterparty risk in credit derivative markets. However, there is also a major component of the common factor attributable to other, potentially unobservable, factors including changes in the attitude of investors to subprime mortgage backed assets. The re-evaluation of these CDO instruments is an important feature of the return generating process, and its progress is evident in the factors. In general, the common factor subsumes all others and we find little differentiation by rating. All assets of a similar rating exhibit little excess reaction to the observable variables. Vintage factors matter more. These differentiate the issuances of assets and indicate that later vintages exhibit increased sensitivity to the level of real estate prices, volatility and liquidity. None of the factors other than the common factor has a high correlation with the observed variables, which demonstrates the difficulty of attributing the common changes in asset behaviour to individual observed indicators. The situation displays far more complexity than simple observed variables can replicate - and latent factors which can take into account observed and unobserved influences as well as potentially changing weights on those components provide a useful means of approaching this decomposition.

5 Conclusion

Our analysis focuses on the characterization of indices of subprime mortgage backed assets during the unfolding of the Financial Crisis of 2007-2008. In particular, we seek to gain a better understanding of the sources of the decline of this market, for example via liquidity and counterparty risk. To do so, we apply a latent factor model to an unbalanced panel of tranced asset returns. In this case, the unbalanced nature of the data allows identification of four factors from the returns; a common factor, a vintage factor relating to the is-

suance dates of the asset, 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 of indices exhibits the most important change in variation over time. Before July 2007, the common factor's influence is negligible. This is consistent with market participants underpricing, and credit agencies underestimating, the coming financial difficulties. (This of course is easier to see now.) Given the structure of CDOs, the most senior tranches are quite vulnerable to the miscalculation of asset risk. The increasing magnitude of common undiversifiable shocks changes the return behavior of AAA tranches dramatically as the crisis unfolds. In addition, 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, Jubek and Stafford (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.

Given its prevalence and its effects on the largest segment of the market – the AAA-rated tranches – we delve deeper into the origins of the common shock. Specifically, we relate the extracted common shock to a range of observable variables that are commonly cited as being crucial in the initiation and transmission of the crisis. Variables that capture the real estate downturn, general financial market volatility, market liquidity shortages and increasing counterparty risk are all related to the common factor responsible for the downturn in asset backed security performance. However, our latent factor approach captures two important features of the crisis. First, the relationship with ‘fundamental’ factors is likely to be time-varying. Second, unobserved sources of commonality, such as changes in investor perception of risk and appetite for these assets, were also important determinants of the demise of this market.

Further analysis of our latent factors reveals an important characteristic of CDOs. The structured product is only as good as the quality of the underlying asset. While the ratings factors are largely unrelated to our observed variables, the vintage factors reflect asset differentiation. As the quality of the underlying mortgages deteriorated due to conditions in the real estate sector and less stringent underwriting standards, the vintage factor becomes more correlated with observables.

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Appendix: Details on Data Series

The data series used in this paper are described below:

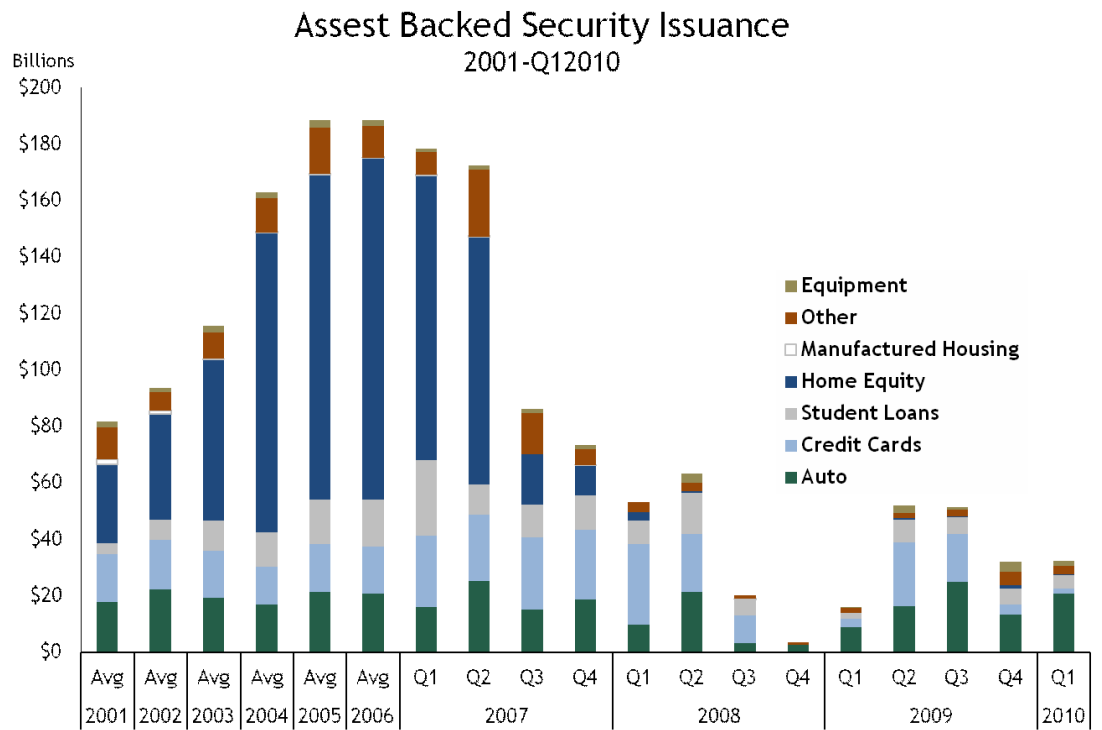
ABX Data:

- 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:

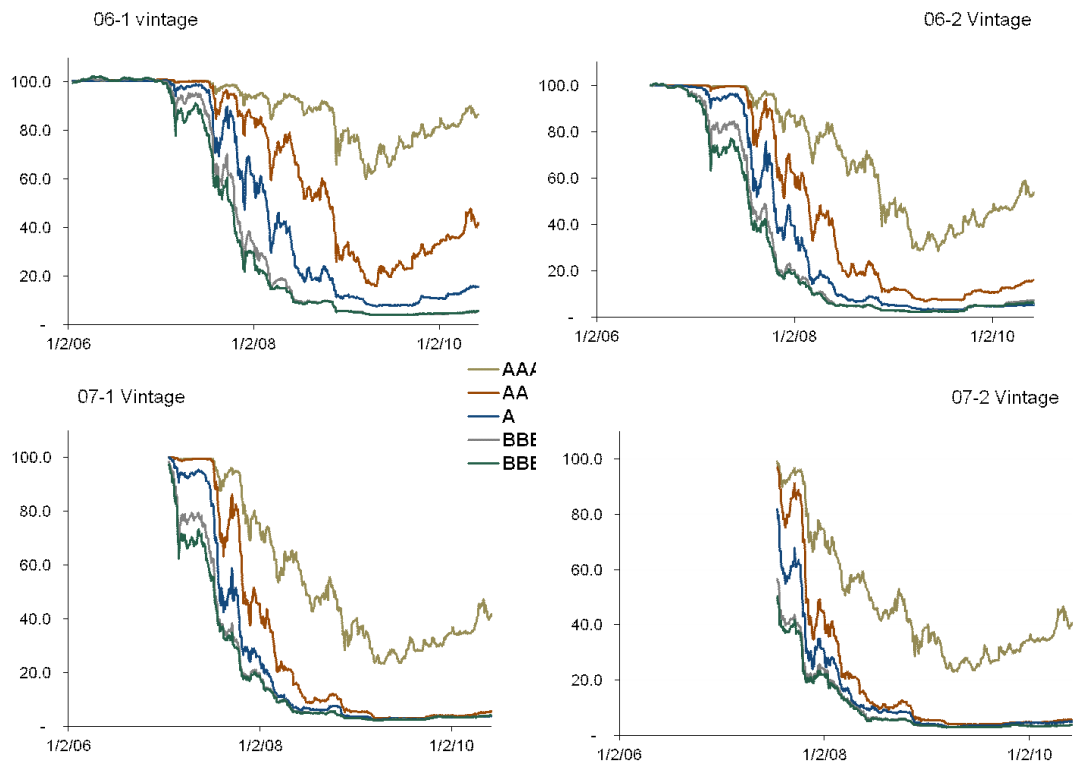
- US Real estate sector price index - Datastream code: DJAREIT
- VIX: CBOE Market volatility index
- Interest rates: 3-month LIBOR; OIS rate and 3-month Treasury bill rate

Figure 1: Growth of ABS market



Source: SIFMA

Figure 2: ABX price indices by vintage



Sources: Markit Group Limited/Haver Analytics

Figure 3. Results for ABX indices originated in Jan 06
AAA:06_1 AA:06_1 BBB:06_1

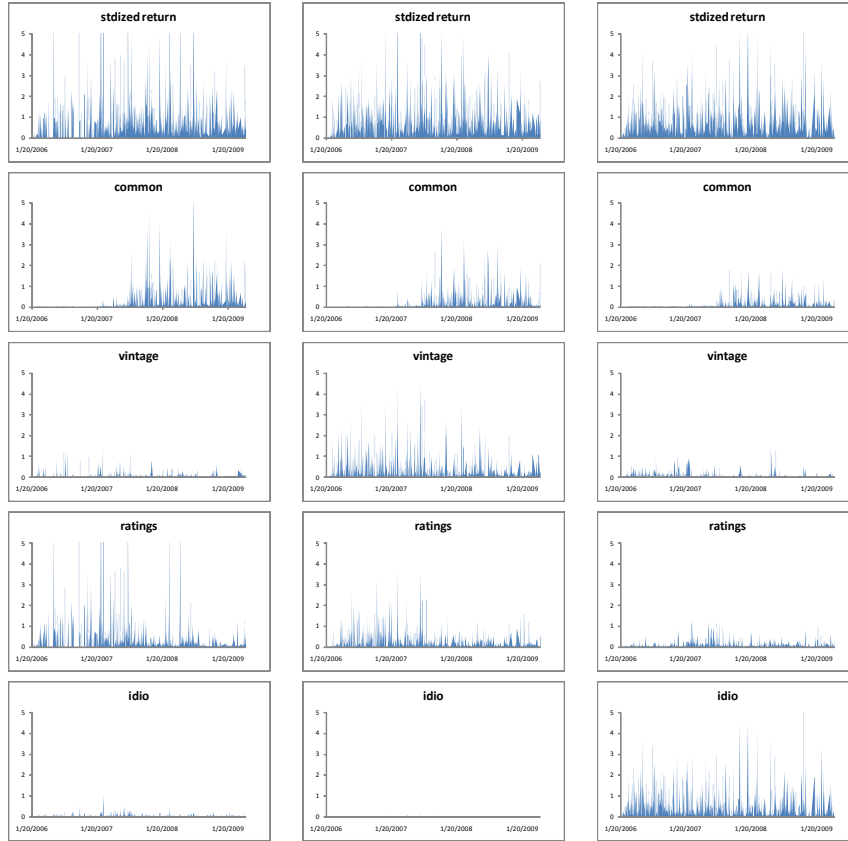


Figure 4. Results for ABX indices originated in Jan 07
AAA:07_1 AA:07_1 BBB:07_1

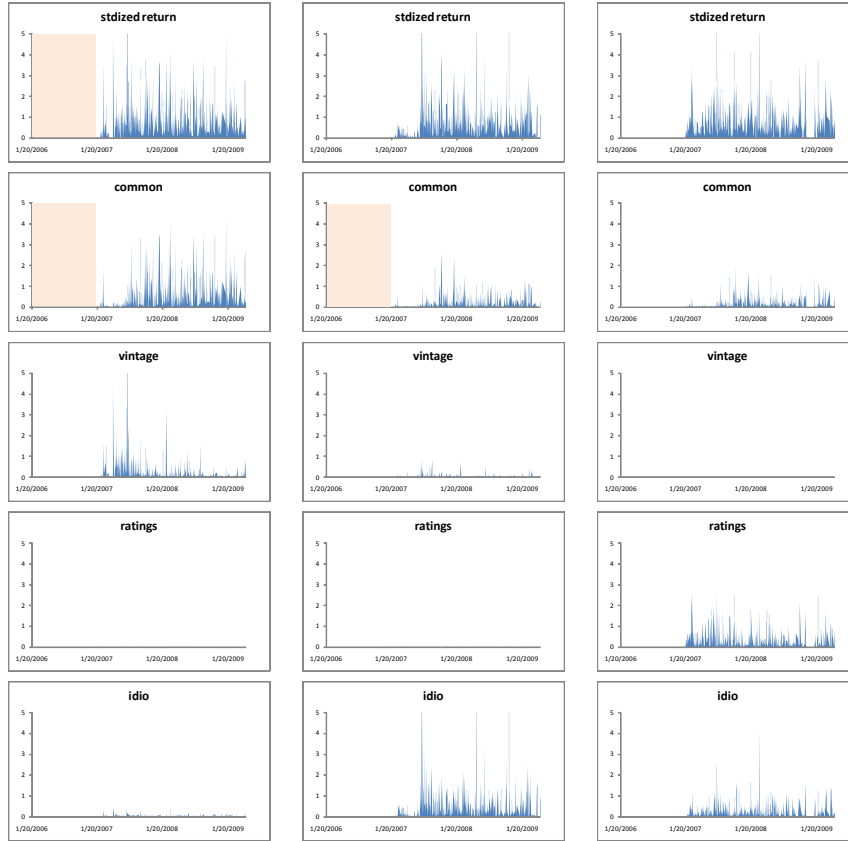


Figure 5. Results for ABX indices originated in July 07
AAA:07_2 AA:07_2 BBB:07_2



Figure 6. Extracted and filtered factors

Filtered Factors

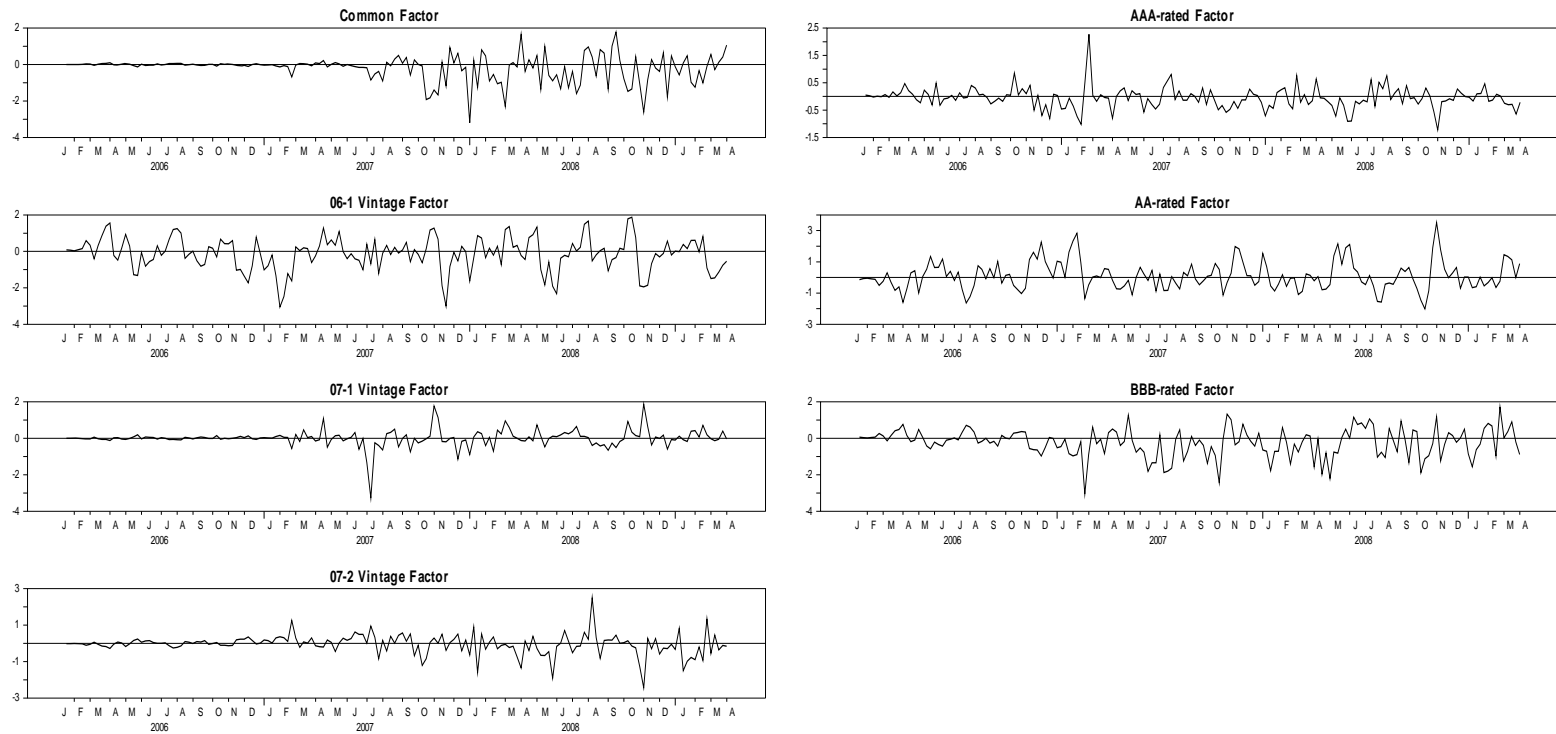


Figure 7. Observable economic variables used in analysis

Observable variables

