CREDIT SPREAD DECOMPOSITION

Decomposing Bond-Level Credit OAS into Default and Liquidity Components[1]

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- We decompose a credit bond's OAS (over Treasuries) into three components: a market-wide risk premium, expected loss from default, and expected liquidity cost.
- We show that bond-level liquidity cost (as measured by Barclays Capital Liquidity Cost Scores – LCS℠) can help explain the OAS dispersion across bonds, even after accounting for differences in expected default losses. This holds for both investment grade and high yield bonds.
- Portfolio managers can use spread decomposition to help determine if a bond's spread has moved mainly because of liquidity or for default-related reasons. This information can potentially lead to better decisions regarding portfolio construction and positioning.
- Spread decomposition analysis indicates that, at the aggregate level, liquidity cost became an important determinant of OAS levels as early as mid-2007, during the early period of the mortgage crisis, before increases in expected default losses. Perhaps cash corporate market makers react more quickly to perceived corporate risk, by widening bid-ask spreads, than does the corporate default risk market.
- Although the September 2007 and April 2010 credit market OAS levels were similar, their compositions were very different. The OAS in September 2007 consisted mainly of risk premium unrelated to bond-level default or liquidity costs, whereas bond-level default cost was the main contributor to OAS in April 2010. However, during the intervening period (2008 to early 2009), bond-level liquidity cost was a particularly large component of OAS.
- We show that spread decomposition can also help forecast credit spread changes, as well as help identify undervalued bonds.
- Finally, results from spread decomposition can improve the hedging of credit bonds by allowing managers to focus on default and liquidity components separately.

[1] Many thanks to Arne Staal and Attakrit Asvanunt for their generous comments and access to the CDP/CRR database.

Spread Decomposition – Benefits and Challenges

Credit bonds are issued at a positive yield spread (i.e., a credit spread) over comparable maturity Treasury bonds to compensate credit investors for the chance that a bond may default with a recovery value less than par. However, many studies (e.g., Ng and Phelps, 2010 and Elton, Gruber, Agrawal, and Mann, 2001) have documented that the spreads on credit bonds are generally much larger than is justified by their subsequent default and recovery experience. Two explanations for the additional credit spread in excess of expected default losses are expected liquidity cost and risk premia.[2]

A portion of the credit spread may reflect an expected liquidity cost to execute a roundtrip trade in a credit bond as measured by the bond's bid-ask spread. The expected liquidity cost for a credit bond is typically greater than that for a comparable-maturity Treasury bond. A credit investor who anticipates selling the bond at some point wants compensation for this expected liquidity cost in the form of a wider spread at time of purchase. Another portion of the credit spread may reflect a risk premium demanded by risk-averse credit investors because of the uncertainty associated with the timing, magnitude, and recovery of defaults and liquidity costs.[3] Consequently, the greater the degree of uncertainty, the more the credit spread will diverge from the expected default and recovery rates. We propose to decompose a bond's spread into risk premium, expected default loss, and expected liquidity cost components.

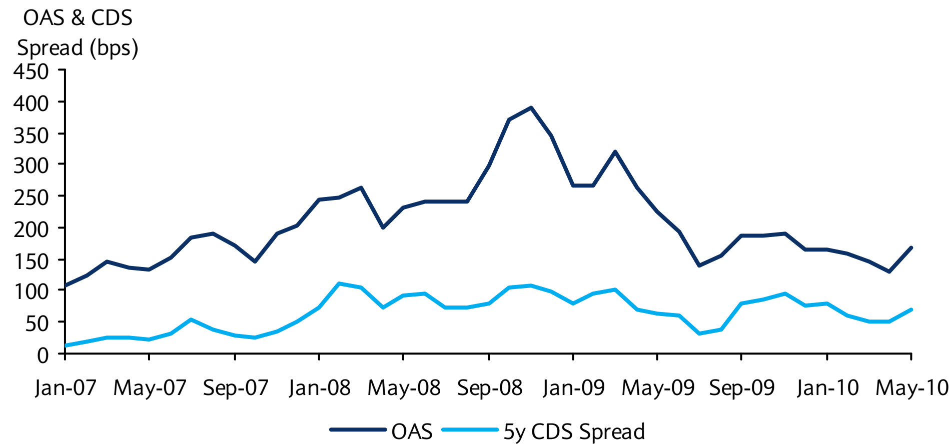
Credit spread decomposition can serve several purposes. For example, an insurance company may be holding a large portfolio of credit bonds currently at wide spreads. The company's portfolio strategy will likely depend on whether the source of the wide spreads is large expected default losses, high liquidity costs, or high risk premium. Presumably, the company can ride out periods of high liquidity cost and risk premium, as the firm is generally a buy-and-hold investor. However, if the wide spreads are from an increase in expected default losses, the company may need to re-position or hedge its portfolio. Active portfolio managers can also use spread decomposition to take specific exposures to bonds that have large liquidity or default components, depending on their views about how compensation for default or liquidity costs is likely to evolve. Finally, regulators can use spread decomposition to monitor separately the liquidity and credit risk of the institutions they supervise.

As a simple example of the value of spread decomposition, consider the spread behavior of the Kraft (KFT) 6.5% of 11/31 (cusip: 50075NAC) from January 2007 to April 2010. As shown in Figure 1, the bond's spread varied substantially over the period. Figure 1 also shows the level of KFT's 5y CDS spreads – a measure of the expected default losses from the issuer.

As seen in Figure 1, movements in the OAS for the KFT bond loosely track changes in the issuer's CDS. However, there is a wide, and variable, gap between the two spreads. The magnitude of the gap has ranged from a low of 82bp in April 2010 to a maximum of 282bp in November 2008. Presumably, this gap reflects risk premium and expected liquidity costs. To measure the expected liquidity costs, Figure 2 plots the bond's liquidity cost score (LCS[SM]) over the same period. As shown, much of the variability in the OAS-CDS spread gap tracks movements in the bond's LCS.

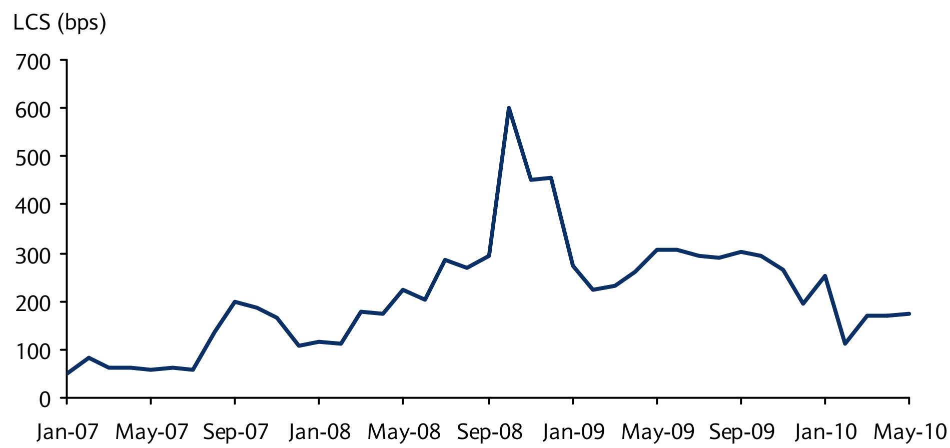
[2] Taxes are also cited as a cause of the credit spread premium. Since credit bonds are taxable at the state and federal level, whereas Treasury bonds are taxed only at the federal level, the credit spread premium may reflect this tax differential. Researchers are split regarding the magnitude of the tax effect in explaining the credit spread premium.
[3] Our work on Liquidity Cost Scores (LCS[SM]) indicates that a bond's liquidity cost can be highly variable. See *Introducing LCS: Liquidity Cost Scores for US Credit Bonds*, S. Dastidar and B. Phelps, Barclays Capital, October 6, 2009.

Figure 1: OAS and CDS Spread for KFT 6.5 of 11/31



Source: Moody's, Barclays Capital

Figure 2: LCS for KFT 6.5 of 11/31



Source: Barclays Capital

Figures 1 and 2 suggest that the rise in OAS in July 2007 was driven by both default and liquidity concerns (all three lines move up), whereas the spike in September 2008 was mainly a liquidity event (the line plotting the LCS moves much more than the CDS line). Understanding the source of such movements in OAS allows investors to better protect their portfolio from such moves or take advantage of them, as the case may be.

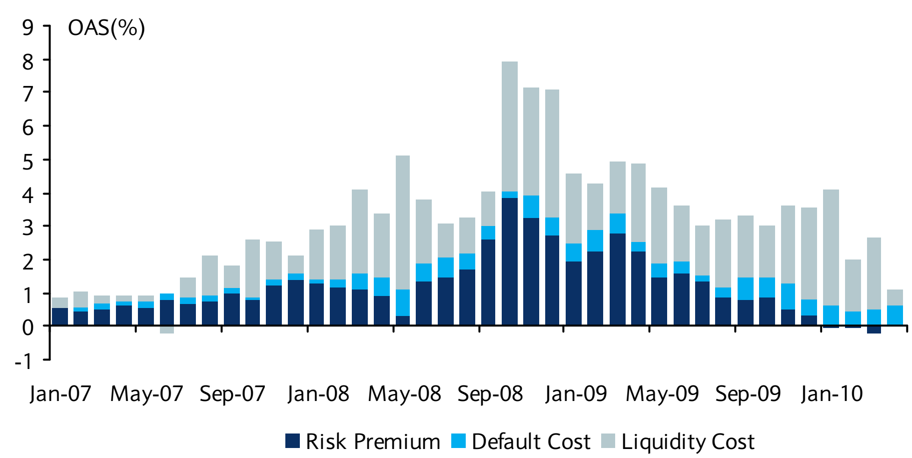
Conversely, investors may have a situation in which the OAS of a bond has been very stable or declining – suggesting improved creditworthiness. However, the bond's declining OAS may simply reflect improved liquidity and market-wide risk premium, while the CDS may be widening, reflecting deteriorating credit for this particular issuer. For instance, from July 2009 to October 2009, the OAS of the TWX 6.75s of 4/11 declined to 157bp from 199bp. Did this spread tightening reflect improving credit quality, or improved liquidity and/or a lower market risk premium? Over this period, TWX's CDS spread increased to 57 bp from 45bp, suggesting higher expected default losses. So why the reduction in OAS? The LCS for this bond fell to 21bp from 49bp. In addition, as we will show, there was a reduction in market-wide risk premium. In other words, despite an increase in expected default losses, the OAS for the bond declined because of lower liquidity costs and risk premium.

These two examples illustrate that to properly interpret OAS changes, we need to measure the components of OAS. So far, we have just shown how other variables (CDS and LCS) move in relation to OAS. Our goal, however, is to use regression techniques to rigorously decompose a bond's OAS into the three components. Researchers have struggled to perform credit spread decomposition (e.g., Collin-Dufresne, Goldstein and Martin, 2001). Although researchers can explain a large part of the excess spread using a broad market measure of liquidity cost, such as the spread between on- and off-the-run Treasury bonds, the lack of a bond-level liquidity cost measure has prevented spread decomposition across bonds. We will show how to use bond-level measures of default losses and liquidity costs to decompose a bond's OAS into risk premium, default, and liquidity components.

As a prelude to our spread decomposition model, Figure 3 shows output from the model using the KFT bond as an example. The figure shows that the effects of both default and liquidity on the bond's OAS were low in 2007. However, since late 2008, most of the increase in OAS has been liquidity related, while the default component has remained relatively stable. In other words, at the peak of the crisis, although the KFT bond's OAS shot up, investors didn't really believe that it was likely to default. The intercept term in the figure captures the effects of market-wide risk premium that was not specific to the liquidity and default characteristics of KFT.

This bond-level information can be invaluable to portfolio managers as they choose which bonds to hold, or which hedging instruments to employ for protection from certain market movements. Long-term investors, with minimal mark-to-market constraints, can choose to provide liquidity to the market if the contribution of liquidity is relatively high as long as they are comfortable with the idiosyncratic prospects of the issuer, whereas tactical mark-to-market investors would worry about short-term dislocations arising from any source of risk. To hedge default-related risks at the issuer level, investors can use the single-name CDS of the issuer. For systemic liquidity risks, VIX futures can serve as a hedging instrument. Our prior research documents a close relationship between LCS and VIX, across regimes. The correlation between LCS and VIX from January 2007 to April 2009 is 0.90.[3]

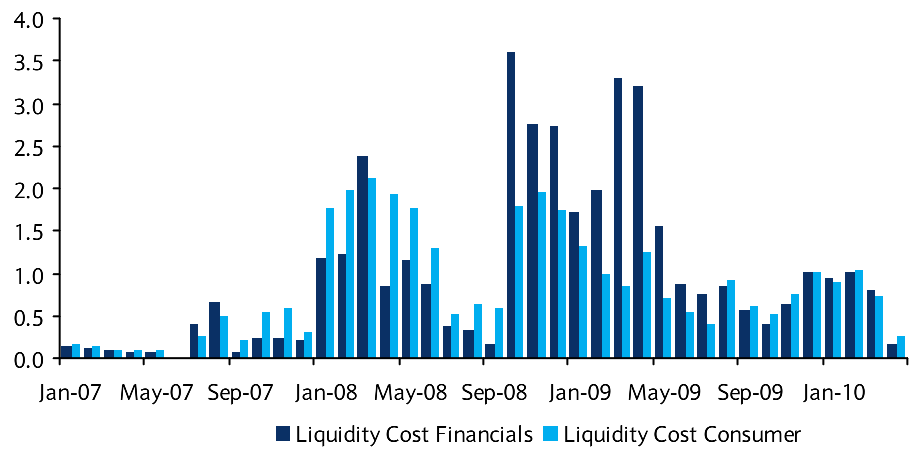
Figure 3: Spread Decomposition for KFT 6.5s of 11/31: Risk Premium, Expected Default Losses, and Liquidity Costs



Source: Barclays Capital

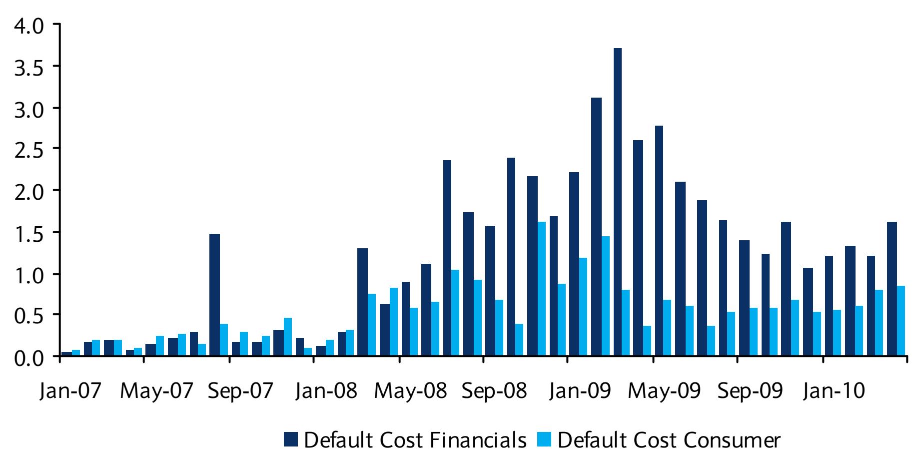
We can also aggregate the bond-level spread decomposition results to examine any differences in spread decomposition at the sector level. For example, in Figures 4 and 5, we apply the spread decomposition methodology to investment grade bonds in two sectors – consumer goods and financials – and examine the relative differences. In early 2007, in terms of both liquidity contribution and default contribution, there appears to be no difference between these two sectors. The rise in default contribution for financials in August 2007 was related to the first wave of financial sector difficulties (e.g., mortgage companies), and the liquidity contribution went up for both sectors, but clear differences in liquidity across the two sectors started appearing only after the Bear Stearns takeover in March 2008. Default contributions for the financials increased in the form of wider CDS spreads, but financials were still pretty liquid until the Lehman Brothers bankruptcy in September 2008. Thereafter, liquidity contributions to spreads for financials shot up and remained elevated until Q2 2009. The liquidity differences between the two sectors have since abated, but the default contribution differences that began during the crisis persist.

Figure 4: Liquidity Contribution – Consumer and Financial Sectors



Source: Barclays Capital

Figure 5: Default Contribution – Consumer and Financial Sectors



Source: Barclays Capital

We now present our spread decomposition framework.

Spread Decomposition Methodology

We assume that a bond's OAS (versus Treasuries) can be largely explained by three variables: a market-wide variable unrelated to the bond's attributes (such as a market-wide risk premium reflecting investors' demand for spread compensation for bearing risk), a variable reflecting expected default cost, and a variable reflect expected liquidity cost. Specifically, for every month t, we run the cross-sectional OLS regression presented in Equation (1).

$$OAS_{it} = \alpha_t + \beta\ ExpectedDefaultCost_{it} + \gamma\ ExpectedLiquidityCost_{it} + \eta_{it} \qquad (1)$$

The risk premium variable (the intercept term) represents a market-level risk premium, not a risk premium specific to each bond. We argue that any bond-level risk premium will likely be highly correlated with the bond's default cost or liquidity cost variable. In other words, a bond with a high LCS will also likely be a bond for which an investor will demand a higher spread premium as compensation for liquidity cost uncertainty. This would make it difficult to separate a bond's spread into a portion from expected liquidity cost and liquidity risk premium. If default risk or liquidity risk premia are highly correlated with default or liquidity costs, then the regression coefficient (β and γ) will be larger and/or more significant. Any part of risk premia that is unrelated to bond-level default and liquidity cost – in other words, a market-level risk premium – will show up in the constant term (α).[4]

To measure bond-level expected default cost, we are fortunate to have a choice of variables. First, as other researchers do, we use an issuer's market-quoted 5y CDS as a measure of its expected default cost (i.e., default probability and recovery). CDS, however, are not necessarily liquid and therefore cannot always be considered as a pure default proxy. To use CDS as a default loss variable, we confine ourselves to bonds close to the 5-year point on the curve, since 5y CDS are usually the most liquid. To identify issuers with liquid CDS, we restrict our analysis to names that are part of the CDX.

We also use another measure of expected default cost – the Corporate Default Probability (CDP) multiplied by one minus the Conditional Recovery Rate (CRR).[5] CDP and CRR are not market variables. Instead, they are output from a quantitative model that uses firm-specific fundamental information, equity prices, and macroeconomic data to estimate a 1y default probability and recovery rate for the issuer. Importantly, CDP and CRR are both computed independently of a bond's OAS.[6] Having two independent measures of expected default losses helps to assess the stability of the spread decomposition results.

[4] Our spread decomposition model assumes that any default and/or liquidity risk premia either do not vary across bonds in a given month or are highly correlated with expected default and liquidity costs. However, to try and capture any effect of risk aversion on cross-sectional OAS, we analyzed an alternative model in which we included the volatility of LCS over the past 12 months (i.e., a measure of liquidity risk) as an additional regressor. The results remain qualitatively the same. However, because of the relatively short history of LCS and the fact that we lose a year's data to construct this variable, these results are only a robustness exercise. We are ignoring tax effects.

[5] See *Corporate Default Probability Model in the Barclays Capital POINT Platform*, Barclays Capital, April 2009, and *The POINT Conditional Recovery Rate (CRR) Model*, Barclays Capital, August 2009.

[6] Both CDP and CDS (independent variables) vary at the ticker level, while LCS (another independent variable) and OAS (the dependent variable) vary at the bond level. Consequently, two 5y bonds from the same issuer will have the same CDP (and CRR) and corresponding 5y CDS values while having potentially different LCS. We have kept all bonds for every ticker (i.e., issuer) in the sample since the variation in OAS across bonds of similar duration by the same issuer can only be because of liquidity considerations. We have also done a robustness test using only one bond per ticker to avoid a situation in which the bond-level variability (rather than the incremental information in LCS) may be responsible for significant LCS coefficients. As discussed in the methodology section, to make sure that issue-level variation in OAS and LCS for a given issuer (along with the ticker-level variation in CDS/CDP) is not driving our results, we re-run Regression (2) using only one bond per ticker. We use this version of Regression (2) in the Applications section to avoid issuer concentration.

We measure a bond's expected liquidity cost using its LCS value. We use bonds only whose LCS are computed directly from a trader's bid-ask quotes rather than bonds whose LCS are estimated from our LCS model.[7]

We thus have two spread decomposition models depending on the variable chosen to represent expected default losses:

$$OAS_{it} = \alpha_t + \beta_t\, CDS_{it} + \gamma_t\, LCS_{it} + \eta_{it} \tag{2a}$$

$$OAS_{it} = \alpha_t + \beta_t\, CDP_{it}(1 - CRR_{it}) + \gamma_t\, LCS_{it} + \eta_{it} \tag{2b}$$

We refer to the first model (2a) as the "CDS model" and the second (2b) as the "CDP/CRR model." To get a sense of the value of incorporating a bond-level liquidity variable (LCS) to explain the cross-sectional distribution of spreads, we examine two versions of each model. First, we run both models without LCS as an explanatory variable. Then, we re-run both models with LCS added and compare the results with the first version. When comparing the results of the two versions, we check whether adding LCS improves the fit of the regression. In addition, we check to see if adding LCS detracts from CDS (or CDP/CRR) as an explanatory variable. If LCS is a useful explanatory variable, we would expect to see an improvement in the adjusted R^2 and a significant (and positive) LCS coefficient, with little disturbance to the significance and magnitude of the CDS coefficient.

We use monthly data from January 2007 to April 2010.[8] For a bond to be included in the sample set, it must satisfy the criteria discussed above (i.e., trader-quoted LCS and the issuer's CDS must be a member of the CDX universe for the month the regression is run). The number of bonds in our sample also varies depending on the regression model, as we have more bonds with CDP/CRR data than with liquid CDS. We also analyze both investment grade and high yield bonds, but report them in separate regressions. One drawback of our parsimonious spread decomposition models is that liquidity and default are unlikely to be completely independent of each other,, so multicollinearity may be a concern. However, our sample sizes are relatively large and we have only two explanatory variables, so multicollinearity is unlikely to be a serious problem.

What Drives Differences in OAS across Bonds?

Figure 6 presents the regression results for investment grade bonds for April 2010. The regression for first version of the CDS model (i.e., without LCS) produced an R^2 of 0.54 with a significant CDS coefficient and an intercept that was not significantly different from zero. When we run the second version by including LCS, the R^2 improves to 0.60. More importantly, the LCS coefficient is both positive and significant. In other words, in April 2010, bonds with higher LCS have higher OAS, holding expected loss from default constant. Bond-level LCS are important in explaining relative OAS levels across bonds.

Figure 6: Investment Grade Bonds – Regression of OAS on CDS Spreads and LCS (April 2010)

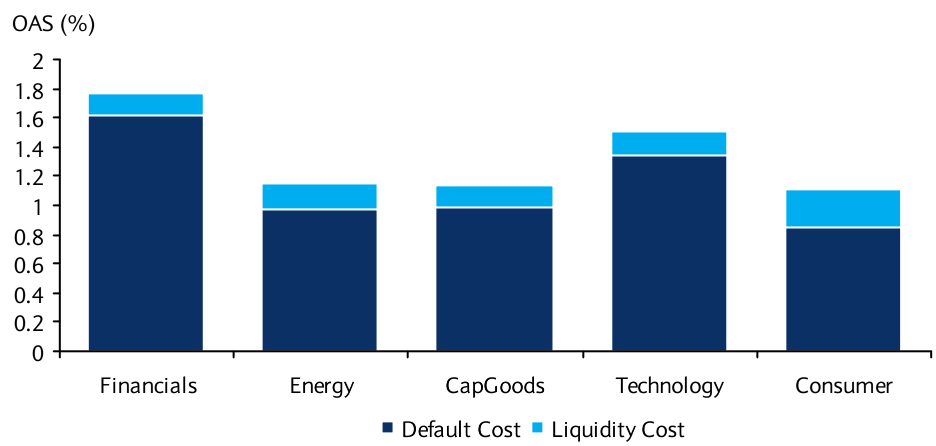
Same in Both Regs		Specification 1 - Only CDS			Specification 2 - Includes CDS and LCS			
Month	# obs	Intercept	CDS	R-sq	Intercept	CDS	LCS	R-sq
Apr-10	123	0.16	1.23	0.54	0.05	1.17	0.28	0.60
		1.31	*12.02*		*0.40*	*12.05*	*4.27*	

Source: Barclays Capital

[7] Since our LCS model uses a bond's OAS as an explanatory variable, regressing a bond's OAS on its LCS for spread decomposition could produce an artificial relationship between the two. To avoid this, we use only LCS values that are computed directly from trader quotes.
[8] LCS data begin in January 2007.

We can use the results above to look at the contribution of default and liquidity effects on OAS for various sectors, as shown in Figure 7. This chart is constructed by using the regression coefficients in the right panel of Figure 6 and multiplying them by the respective averages for each sector. We find that, in the current environment, liquidity effects are relatively small and uniform across sectors. In contrast, the default component varies more across sectors.

Figure 7: Sector-wise Spread Decomposition in April 2010 – Default Contribution and Liquidity Contribution



Source: Barclays Capital

How Has the Composition of OAS Changed?

We repeat the spread decomposition exercise for every month in the sample period to show how the relative effect of the three spread components has fluctuated. Figure 8 presents the monthly regression results for investment grade bonds for both versions of the CDS spread decomposition model for all 40 months. (Results for the CDP/CRR model are in Appendix 1).

In the first half of 2007, when liquidity was abundant, LCS might not have played an important role in explaining spread differences across bonds. In fact, we see that adding LCS to the regression did not meaningfully improve the R^2.[9] In contrast, when liquidity was poor from late 2007 through the first quarter of 2009, the R^2 increased significantly when LCS was added to the regression. This suggests a heightened role for LCS in explaining cross-sectional spreads. Note that the inclusion of LCS in the regression did not affect the size and significance of the CDS coefficient for most months. This confirms that LCS is providing new information.

The regression intercept captures the portion of (average) spread that is independent of CDS and/or LCS. As discussed earlier, the market risk premium is likely to be an important contributor to the level of OAS, and we use the time series of the intercept as an indicator of the variation of the market risk premium that is not already embedded in the bond-level default and liquidity variables.

For example, for the CDS model with LCS (the right panel of Figure 8), the intercept increases to 2.76 in March 2009 from about 0.5 in early 2007, before subsiding to near zero in recent months. Although part of this movement probably reflects the market's lack of liquidity

[9] This is also related to our prior LCS-related research, in which we show the very low dispersion of LCS across bonds in early 2007.

concerns in early 2007, the general movement in the intercept over time aligns well with investors' perception of fluctuations in the level of the market risk premium.

The regression coefficients for CDS and LCS are both positive and statistically significant for most months (except CDS from December 2007 to February 2008 and May 2008, and LCS in June 2007). In other words, LCS has a consistently large and significant effect on the distribution of OAS values across bonds. Since default risk for high grade bonds has been very low over time, a relatively large proportion of the OAS is potentially liquidity related. As shown in Figure 8, the relation of CDS with OAS is naturally tight, but maybe not as close as one might have thought.

The magnitudes of the CDS and LCS coefficients move broadly with the intercept value. This is not surprising because the CDS and LCS coefficients can be interpreted as the compensation (in spread space) that the market is currently paying, per unit of the corresponding cost. The prices of default and liquidity risk are likely to move similar to the market risk premium.

Figure 8: Investment Grade Bonds only Regression of OAS on CDS and LCS (January 2007-February 2010) ***(t-stats in italics)***

Same in Both Regs		Specification 1 - Only CDS			Specification 2 - Includes CDS and LCS			
Month	# obs	Intercept	CDS	R-sq	Intercept	CDS	LCS	R-sq
Jan-07	116	0.67 *25.45*	0.36 *6.32*	0.25	0.54 *11.56*	0.27 *4.47*	0.57 *3.16*	0.31
Feb-07	103	0.55 *28.00*	0.81 *15.42*	0.70	0.42 *14.63*	0.77 *16.45*	0.58 *5.75*	0.77
Mar-07	115	0.59 *36.04*	0.74 *19.26*	0.76	0.50 *16.56*	0.70 *18.45*	0.39 *3.47*	0.79
Apr-07	116	0.72 *26.64*	0.30 *7.39*	0.32	0.64 *12.56*	0.27 *6.08*	0.36 *1.89*	0.33
May-07	109	0.62 28.02	0.78 *14.46*	0.66	0.55 *16.04*	0.73 *13.00*	0.31 *2.52*	0.67
Jun-07	99	*0.70* 23.43	0.56 *12.60*	0.62	0.77 *19.90*	0.66 *11.46*	-0.37 *-2.59*	0.64
Jul-07	74	0.83 *14.80*	0.63 *12.53*	0.68	0.69 *12.75*	0.36 *5.26*	0.92 *5.30*	0.77
Aug-07	59	1.08 *11.41*	0.70 *20.06*	0.87	0.71 *5.76*	0.53 *10.16*	0.88 *4.07*	0.90
Sep-07	78	1.17 *18.90*	0.52 *9.51*	0.54	1.00 *10.94*	0.48 *8.47*	0.34 *2.47*	0.57
Oct-07	77	1.13 *15.94*	0.57 *9.03*	0.51	0.79 *9.37*	0.35 *5.38*	0.92 *5.60*	0.65
Nov-07	46	1.43 *11.39*	0.79 *7.33*	0.54	1.23 *8.70*	0.45 *2.78*	0.69 *2.61*	0.59
Dec-07	36	1.51 10.61	0.57 *4.35*	0.34	1.38 *9.07*	0.32 *1.74*	0.51 *1.95*	0.39
Jan-08	68	*1.63* 6.43	0.93 *5.70*	0.32	1.27 *7.00*	0.14 *0.92*	1.34 *8.37*	0.67
Feb-08	75	1.64 *6.06*	0.72 *5.35*	0.27	1.18 *6.42*	0.19 *1.81*	1.46 *9.82*	0.68
Mar-08	71	1.76 *5.34*	1.03 *9.06*	0.54	1.08 *5.11*	0.49 *5.76*	1.41 *10.85*	0.83
Apr-08	71	1.41 *7.01*	1.31 *9.38*	0.55	0.91 *5.87*	0.69 *5.58*	1.12 *8.20*	0.77
May-08	80	1.35 *6.25*	1.19 *7.67*	0.42	0.33 *1.55*	0.83 *6.41*	1.80 *7.34*	0.66
Jun-08	81	1.71 *8.12*	0.86 *8.55*	0.47	1.33 *7.35*	0.53 *5.61*	0.95 *6.47*	0.65
Jul-08	78	1.64 20.73	0.97 *32.56*	0.93	1.46 *17.67*	0.86 *22.56*	0.34 *4.20*	0.94
Aug-08	81	*1.84* 19.06	0.80 *22.21*	0.86	1.67 *17.65*	0.68 *16.43*	0.40 *4.51*	0.89
Sep-08	75	2.87 *17.96*	0.56 *7.64*	0.44	2.57 *13.82*	0.55 *7.89*	0.35 *2.86*	0.49
Oct-08	135	5.32 *24.37*	0.35 *15.80*	0.65	3.83 *22.15*	0.20 *11.46*	0.65 *14.23*	0.86
Nov-08	148	3.54 *11.13*	1.23 *12.36*	0.51	3.26 *16.80*	0.60 *8.30*	0.71 *15.82*	0.82
Dec-08	151	3.22 *9.72*	1.33 *10.19*	0.41	2.69 *12.59*	0.58 *5.99*	0.84 *14.94*	0.76
Jan-09	147	2.59 *9.88*	1.08 *11.85*	0.49	1.91 *9.37*	0.69 *9.11*	0.78 *10.98*	0.72
Feb-09	170	2.56 11.42	1.04 *17.70*	0.65	2.22 *12.61*	0.69 *12.27*	0.61 *10.65*	0.79
Mar-09	157	*3.45* 11.38	0.97 *16.96*	0.65	2.76 *12.41*	0.59 *11.64*	0.68 *12.47*	0.82
Apr-09	120	4.04 *12.21*	0.56 *14.32*	0.63	2.26 *7.35*	0.35 *9.81*	0.90 *9.77*	0.80
May-09	92	2.32 *9.74*	0.78 *16.36*	0.75	1.48 *7.03*	0.60 *14.38*	0.74 *8.08*	0.85
Jun-09	103	2.09 *8.78*	0.76 *12.22*	0.59	1.59 *7.01*	0.61 *9.99*	0.53 *5.63*	0.69
Jul-09	86	1.82 *7.91*	0.81 *13.56*	0.68	1.32 *5.91*	0.66 *10.86*	0.50 *5.18*	0.76
Aug-09	117	1.42 *7.29*	0.94 *11.78*	0.54	0.87 *4.70*	0.75 *10.02*	0.72 *6.70*	0.67
Sep-09	150	1.28 *10.38*	0.92 *14.05*	0.57	0.81 *6.60*	0.79 *13.52*	0.62 *7.36*	0.68
Oct-09	153	1.19 *10.50*	0.83 *13.39*	0.54	0.83 *7.25*	0.74 *13.10*	0.54 *6.49*	0.64
Nov-09	152	1.02 *7.49*	0.98 *14.03*	0.56	0.50 *3.76*	0.85 *13.89*	0.86 *7.95*	0.69
Dec-09	103	1.10 *7.01*	0.87 *8.96*	0.44	0.30 *2.03*	0.67 *8.74*	1.41 *8.88*	0.68
Jan-10	167	0.78 *6.93*	0.91 *11.91*	0.46	-0.02 *-0.17*	0.80 *12.73*	1.38 *9.67*	0.65
Feb-10	129	0.68 *5.13*	0.99 *11.52*	0.51	-0.05 *-0.35*	0.79 *11.02*	1.39 *8.82*	0.69
Mar-10	108	0.41 *2.72*	1.12 *8.96*	0.43	-0.24 *-1.82*	0.97 *10.23*	1.30 *9.21*	0.68
Apr-10	123	0.16 *1.31*	1.23 *12.02*	0.54	0.05 *0.40*	1.17 *12.05*	0.28 *4.27*	0.60

Source: Barclays Capital

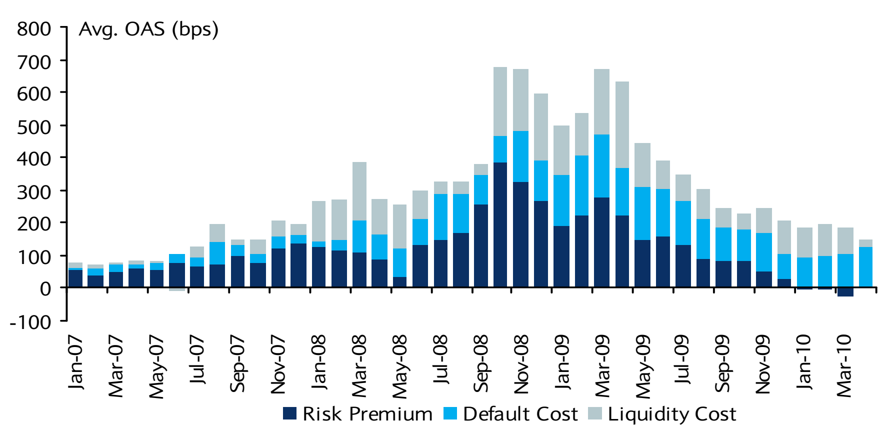
Whenever the intercept explains a relatively high proportion of OAS, this suggests that market factors rather than bond-specific factors are driving spreads. In periods when spreads are high, this may occur because of very high aggregate risk aversion (e.g., late 2008/early 2009). In periods when spreads are low (e.g., early 2007), this may be because the market was pricing bonds with little concern for issuer-specific information. For example, in September 2007, the OAS was similar to current levels but the intercept was a large component of total spreads. However, in the current period, the relative importance of the intercept is very small, suggesting that the market is possibly more discerning at present.

We can take the results in Figure 8 and break the OAS value down into the three components. In December 2009, for example, the average values of OAS, LCS, and CDS were 2.09%, 0.73%, and 1.14%. The coefficients of LCS and CDS were 1.41 and 0.67, respectively, and the intercept value was 0.3. As expected, 0.3 + 0.67 × 1.14% + 1.41 × 0.73% = 2.09%, which is the average OAS. We refer to the product of the average value of the variable and its coefficient (i.e., 0.67 × 1.14% and 1.41 × 0.73%) as the contribution of average CDS and LCS, respectively, to average OAS in December 2009.[10]

Figure 9 presents the contribution, in basis points, of the market risk premium, default cost, and liquidity cost to the market OAS every month since January 2007. The contribution pattern in Figure 9 diverges from the time series of coefficient values in Figure 8 during periods in which the mean value of the attribute and the OAS change a lot. For example, from September 2008 to October 2008, the average CDS spread jumped to 413bp from 166bp, but the coefficient of the CDS spread fell to 0.2 from 0.5, leading to a decline in the amount of OAS explained by CDS. This is because aggregate risk aversion, as measured by the intercept, shot up during this period. In October 2008, as Figure 9 shows, out of the average OAS of 6.76%, 383bp was explained by the intercept, 82bp by CDS, and 211bp by LCS.

Figure 10 shows the same information as Figure 9, but expresses the contributions of the three spread components as a percent of the average OAS value. This makes some earlier observations clearer. For instance, although the average OAS levels in April 2010 are similar to those in September 2007, the market in early 2007 was attributing OAS levels to overall market uncertainties, whereas in more recent times, this can be explained by larger variation in CDS spreads across bonds.

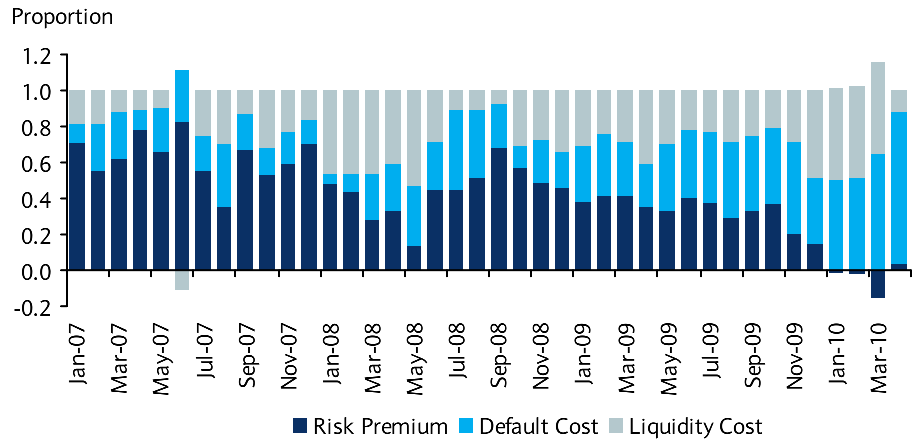
Figure 9: Contributions of Risk Premium, Default, and Liquidity Components to Market OAS Level (Equally Weighted Portfolio of the Bonds in Sample), January 2007-April 2010



Source: Barclays Capital

[10] Note: We used the results in Figure 8 to present the contributions of CDS and LCS to OAS for KFT in Figure 3 and the contributions for all sectors in Figure 7.

Figure 10: Share of OAS (as a % of OAS) of Market, Default, and Liquidity Components (Equally Weighted Portfolio of the Bonds in Our Sample), January 2007-April 2010

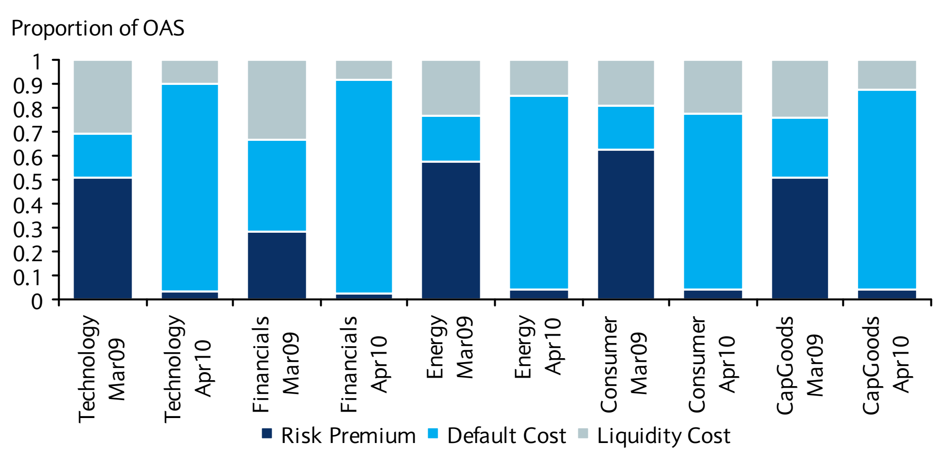


Source: Barclays Capital

If an investor is looking to hedge the default and/or liquidity component of the spread separately, then the contribution to OAS in basis points is the appropriate measure to look at. If an investor is analyzing current market compensation for taking on additional amounts of expected default/liquidity cost, the coefficient provides that information. Nevertheless, a view on liquidity or default should be based not just on the coefficients, but also on the expected future levels of these attributes.

Figure 11 compares data from April 2010 and March 2009 to provide a sense of how contributions to a sector's OAS can change over time. We observe that for every sector, a large proportion of the spread on March 2009 consisted of market risk aversion and liquidity components; these factors play a far smaller role in April 2010. Most of the OAS in April 2010 is attributed to CDS spreads. Of course, the OAS went down to 1.64% in April 2010 from 6.70% in March 2009, so the total contribution of CDS did not change nearly as much. Also, while there is a significant difference in cross-sectional contributions to spreads in March 2009, the market appears to be more homogeneous in April 2010.

Figure 11: Sector-wise Spread Decomposition in March 2009 and April 2010 – Default Contribution and Liquidity Contribution



Source: Barclays Capital

Spread Decomposition Using Alternative Measure of Expected Default Losses – CDP and CRR

So far, we have used an issuer's CDS to measure the expected default loss of one of its bonds. As expected, issuers' CDS spreads are significant in explaining the OAS variation across bonds. In addition, adding LCS to the regression significantly improves the regression's cross-sectional fit. However, both OAS and CDS are market spreads, and the good fit we observe may be the result of both spreads' being quoted in relationship to each other. In addition, we know that even though we measure LCS directly from trader quotes, a bond's liquidity cost is heavily influenced by the bond's spread volatility. To better test the model's fit, we would ideally like the expected default loss variable to be independent of market spreads. Fortunately, we have such expected default probability and loss given default measures: Conditional Default Probability (CDP) and Conditional Recovery Rate (CRR). Using CDP and CRR also provides us with a larger sample, because we have more tickers with CDP/CRR data than tickers in the CDX.

We run month-by-month regressions (i.e., model (2b)) using $CDP_{i,t}$×(1-$CRR_{i,\ t}$) as the expected default loss variable. These results, for investment grade and high yield indices, are reported in the Appendix. The regressions use a larger sample size and largely confirm the results presented earlier. The R^2 using CDP×(1-CRR) is lower than the R^2 using CDS spreads in many months, especially in 2007. This is not surprising, because market CDS spreads are more closely related to OAS compared with a modeled default probability estimate. The intercept is of a magnitude similar to before. The one notable difference is that the CDP×(1-CRR) coefficient changes more on including LCS as an additional variable than did the CDS spreads coefficient in Figure 8, suggesting that there is some collinearity between CDP×(1-CRR) and LCS. This is expected, as some modelling ingredients of CDP and LCS are likely to be correlated.

Spread Decomposition of High Yield Bonds

We perform the same analysis for high yield bonds, with CDS spreads and CDP×(1-RR) as alternative default measures. For economy, we present the results in the Appendix. Because high yield bonds have a higher expected default loss, it is only natural that default loss will be more important compared with investment grade bonds and play a more dominant role in explaining cross-sectional OAS. Until October 2008, LCS is insignificant in explaining cross-sectional high yield OAS. However, after October 2008 LCS consistently and significantly improves the regression fit until November 2009. These results suggest that liquidity cost provides additional explanatory power for the cross-sectional variation in high yield spreads only during periods of market stress. This may also be because CDS spreads of high yield issuers may be less liquid and contaminated with liquidity effects, which weakens the effect of adding LCS to the regression.

Overall, the CDS coefficient is similar in magnitude for both investment grade and high yield bonds, but the LCS coefficient is smaller for the high yield sector early in the sample period. The intercept is larger for high yield, suggesting that risk aversion, unrelated to the bond's default or liquidity characteristics, may drive a large proportion of the high yield spread. Despite the low importance of liquidity in the earlier part of the sample period, the adjusted R^2 is always high, pointing to the greater importance of default.

Applications of Spread Decomposition

Identifying Relative Value

So far, our analysis has used contemporaneous monthly data to attribute levels and changes in OAS to levels and changes in default and liquidity cost components ex-post. We now consider whether we can apply spread decomposition analysis to *ex-ante* investment.

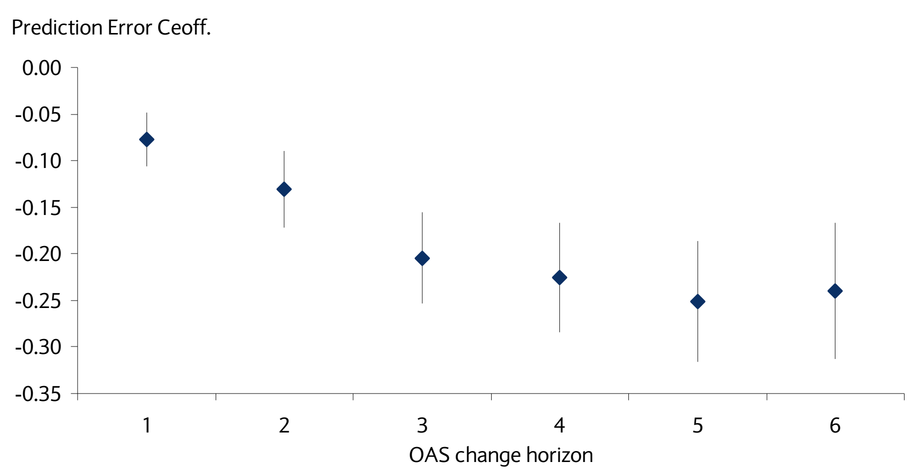
In principle, spread decomposition should help to identify relative value. To the extent that a bond's OAS is compensation for expected default and liquidity cost, a bond's market OAS can be compared with the estimated OAS using the parameters from the spread decomposition model. If the actual OAS is wider than the estimated OAS, it suggests that the bond is trading too wide, and vice versa. This may be a signal that the bond's OAS may change in the direction of reducing this "mispricing."

So as a first step, we examine whether the residuals ($Residual_{i,t}$) of Regression (2a) can help predict future OAS changes. Specifically, if the residual (observed OAS – estimated OAS) is large and positive in a given month, is it likely that the bond's OAS will tighten in the near future? We run this test for OAS changes for various horizons, ranging from one month to six months. In other words, we take the residual from the spread decomposition model for any bond this month and examine whether the bond's future OAS changes are of opposite sign to the sign of the residual. If so, in which future month does this reversal occur? We run the following Regression (6), where we expect β to be negative:

$$\Delta OAS_{it,t+j} = \alpha + \beta\, Residual_{it} + \delta\, MonthDummy_t + \eta_{it} \qquad (6)$$

Since we need six out-of-sample months for each in-sample monthly prediction error dataset, we can run this regression only through October 2009. Figure 12 shows that results for investment grade bonds are significant and strong at all horizons from one to six months, suggesting that even this simple model has some predictive power, on average. The values of the month dummy variables (not shown) are also as expected: they are large and positive in the second half of 2008 and consistently negative since Q2 2009. We now illustrate one possible method to create a portfolio for a simple relative value trading strategy that makes use of spread decomposition.

Figure 12: Investment Grade Bonds – Coefficient (β) of *Residual* and Confidence Intervals for Various OAS Change Horizons (Predictions from February 2007-October 2009)



Note: The graph above shows the coefficient (β) and the 95% confidence intervals of the independent variable (Residual) in Equation 5, estimated using various horizons (values of *j*)
Source: Barclays Capital

For our trading strategy, we use bonds with LCS between the 10th and 90th percentile in any month (to avoid outliers owing to data problems) and examine the largest and smallest residuals within that universe. We go long all bonds with residuals in the top 20% (of residuals), and short all bonds with negative residuals in the bottom 20%. For this exercise, we use a one-bond-per-ticker version of Regression (2a) because we do not want to inadvertently have high issuer concentration in our relative value trading portfolio.[11]

Once we select the bonds, we need to choose their weights in the long-short portfolio. We set the long and the short side to be $50mn each. To choose individual bond weights, we use the Barclays Capital Global Risk Model and Optimizer. From the spread decomposition residual analysis (above), we define the separate universes from which the Optimizer can go long and short. Then, using the POINT Optimizer, we minimize systematic and idiosyncratic exposures (i.e., TEV) of the target long-short portfolio relative to cash. Finally, we impose the requirement that the final long-short portfolio have no cash. The long-short portfolio as of September 30, 2009, is shown in Figure 13.

Figure 13: Portfolio Constituents and Weights Using the Spread Decomposition Regression and the Barclays Capital Risk Model

Short Portfolio		Long Portfolio	
Security	Mkt Val ($mn)	Security	Mkt Val ($mn)
UNH, 5.375% due 3/15/2016	(5.61)	XL, 6.5% due 4/15/2017	0.59
XTO, 5.3% due 6/30/2015	(5.54)	CB, 6.375% due 4/15/2017	1.11
VZ, 5.55% due 2/15/2016	(5.33)	COF, 6.15% due 9/1/2016	1.51
MET, 5% due 6/15/2015	(5.09)	TOL, 5.15% due 5/15/2015	1.59
CNQCN, 4.9% due 12/1/2014	(5.02)	RAI, 7.625% due 6/1/2016	2.51
EQR, 5.25% due 9/15/2014	(4.35)	DOW, 5.9% due 2/15/2015	2.65
NRUC, 3.875% due 9/16/2015	(3.96)	BAC, 6.5% due 8/1/2016	2.89
LOW, 5% due 10/15/2015	(4.15)	WFC, 4.75% due 2/9/2015	5.06
DD, 4.75% due 3/15/2015	(3.89)	HD, 5.4% due 3/1/2016	5.77
BAX, 4.625% due 3/15/2015	(3.58)	APC, 5.75% due 6/15/2014	11.65
WMT, 4.5% due 7/1/2015	(3.48)	CSX, 6.25% due 4/1/2015	14.68
	(50.00)		50.00

Source: Barclays Capital

Figure 14 presents the performance of this long-short portfolio over the next six months.

Figure 14: Long-Short Portfolio Performance using Spread Decomposition and Risk Model

	Oct-09	Nov-09	Dec-09	Jan-10	Feb-10	Mar-10
Strategy P&L	305,552	207,969	435,778	233,416	370,969	840,063

Source: Barclays Capital

We can suggest many modifications to this relative value strategy. For instance, the size of the exposure can be adjusted every month depending on how well the regression fits the data (e.g., using adjusted R^2). Transaction and funding costs can be incorporated to adjust the returns. These adjustments have not been highlighted here because the purpose is to illustrate an application of the spread decomposition exercise, rather than to robustly document the performance of an alpha strategy.

[11] For every ticker, we select the bond closest to the 5y point.

In addition to designing alpha strategies, investors may choose to take specific liquidity/default exposures. For example, as mentioned earlier, portfolio managers may decide to overweight or underweight liquidity-related compensation in their portfolios based on the investment horizon. The liquidity/default coefficients and contributions can assist investors in choosing securities.

Hedging a Credit Bond Portfolio

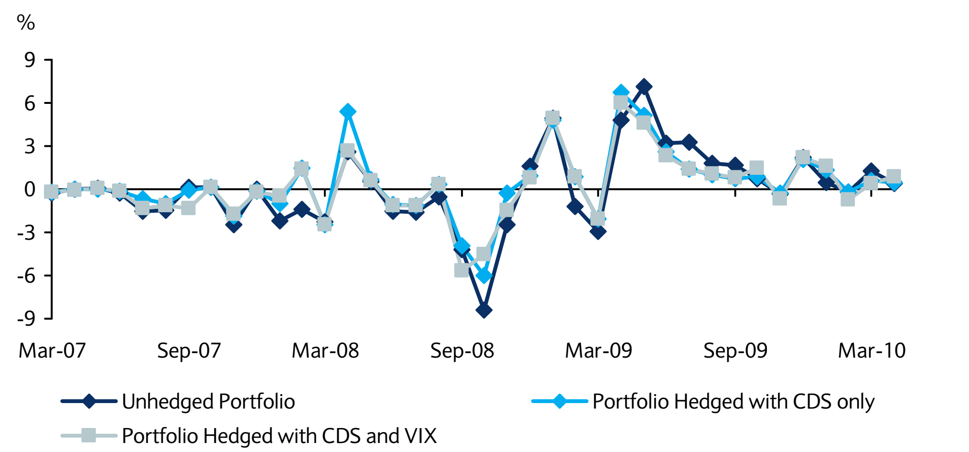
Investors who hedge credit bonds with CDS are exposed to fluctuations in the CDS-cash basis. One method to determine a hedge for a credit is to use regression to examine the historical relationship between the bond's OAS and potential hedge variables. As mentioned earlier, VIX has been closely related to both LCS and the intercept of the monthly regression. VIX futures can, therefore, potentially be used as a hedging instrument to counter spread changes related to changes in liquidity and aggregate risk aversion. The issuer's CDS may be an effective hedge against changes in expected default losses. If the relationship is stable and tight, then a hedge can be set up using the coefficients of the regression. However, the success of such a hedge depends on the goodness of fit and whether the historical relationship will hold in the future. Time series regressions are notoriously noisy, and the resulting hedge ratios are often unstable. To avoid these problems, investors can opt to set up a hedge against default or liquidity exposures using an alternative method that relies more directly on spread decomposition. This is discussed below.

Because a hedge is put on essentially to neutralize spread *changes*, we begin by repeating our month-by-month spread decomposition exercise using *changes* in OAS, CDS, and LCS. We estimate this cross-sectional regression every month. We use the regression coefficients at the end of each month to determine hedges for the next month for an equally weighted portfolio of all the bonds in our regression. The 5y CDS for each bond and the 1m VIX futures are the hedging instruments. VIX and LCS are highly correlated, even in changes, so we can use VIX to get exposure to LCS changes. Since VIX is far more volatile than LCS, we use the ratio of the volatilities of VIX returns and LCS changes as a scaling factor for the regression coefficient for LCS changes. The average hedge ratio for CDS is about 0.6. If one were to get direct exposure to LCS changes, the LCS hedge ratio would be 0.26, on average. If we use VIX futures instead, the allocation to VIX is usually about 0.02.

Figure 15 graphs the actual out-of-sample returns of the unhedged portfolio and the returns of the hedged portfolio over time. This is also compared with a hedge using only the CDS, using the cross-sectional univariate regression hedge ratios.[12] The summary statistics of the return time series are presented in Figure 16. The standard deviation is lowest in the portfolio hedged with CDS and VIX. The extreme values are also lower, because the VIX usually moves in a direction opposite to the OAS. Despite the improvement in hedged results, significant portfolio volatility unfortunately remains even after hedging with CDS and VIX.

[12] A time series analysis based on hedge ratios computed using rolling regressions has not been presented, since we have only 40 months of observations for both in-sample and out-of-sample analysis. However, it did not perform better than the cross-sectional hedge using VIX futures and CDS, for the few out-of-sample months we have data for, based on 18m rolling window regressions. Also, this short time series does not provide an insight into the crisis and pre-crisis months.

Figure 15: Returns of Hedged and Unhedged Portfolios



Source: Barclays Capital

Figure 16: Summary Statistics of Hedge Performance

	Monthly returns - March 2007-April 2010 (in %)		
	Unhedged Portfolio	Hedged with CDS Only	Hedged with CDS and VIX Futures
Average	0.04	0.40	0.21
Standard Deviation	2.72	2.39	2.25
Min	-8.38	-6.01	-5.68
Max	7.10	6.74	6.00

Source: Barclays Capital

Alternative Spread Decomposition Model Specifications

Aside from the month-by-month regressions described above, we also pool the data and run a single regression with month dummies and the default and liquidity proxies, as in Regression 2. This confirms the results presented above regarding the importance of expected default and liquidity cost variables to explain cross-sectional OAS variation.

As discussed earlier, the analysis so far has ignored bond-level risk premium variables. Instead, we assumed that either the risk premium would be highly related to the expected liquidity cost itself or it would be captured by the market factor term, the constant. Now we consider an alternative spread decomposition model that includes a term to represent bond-level liquidity risk premium. This is the additional spread investors demand as compensation for the risk that the actual liquidity cost may be different than the expected liquidity cost as measured by LCS. As a measure of liquidity risk, we calculate each bond's LCS volatility over the prior 12 months. So two bonds may have the same LCS today, but bond A may have had a much more volatile LCS history than bond B. An investor may then view bond A as having a riskier expected liquidity cost and would demand an OAS premium versus bond B, all else equal.

Regression (3) shows the spread decomposition model to incorporate a bond-level liquidity risk factor, $LCSVol_{i,t}$. The results, shown in Figure 17, indicate that $LCSVol_{i,t}$ is highly significant but absorbs part of the effect of LCS (the coefficient of LCS declines by more than 20%, from 0.98 to 0.80), thereby not improving the regression's adjusted R^2 substantially, despite the high significance.

$$OAS_{it} = \alpha + \beta CDS_{it} + \gamma LCS_{it} + \phi LCSVol_{it} + \delta MonthDummy_t + \eta_{ti} \quad (3)$$

Figure 17: Regression of OAS on CDS Spread, LCS and LCS Volatility – January 2008*-April 2010

	Intercept	CDS	LCS	LCS Volatility	Month Dummies	No of Obs	Adj R-sq
Coefficient	1.31	0.371	0.98		Yes	5715	0.77
t-stats	*(9.30)*	*(71.65)*	*(57.57)*				
Coefficient	1.016	0.333	0.803	0.789	Yes	5546	0.8
t-stats	*(7.51)*	*(64.11)*	*(44.54)*	(23.30)			

Note: * 12 months of data are lost because they are used to estimate LCS volatility
Source: Barclays Capital

We also run a regression in differences, to check if the changes in OAS are explained by changes in LCS and CDS spreads. The results hold in differences, too, suggesting that changes in liquidity and default proxies affect contemporaneous returns. Regression (4) details the specification, where ΔOAS_{it}, ΔCDS_{it} and ΔLCS_{it} refer to changes in a bond's characteristics in consecutive months. The results are shown below, in Figure 18, in which we can observe the significant coefficients of the explanatory variables.

$$\Delta OAS_{it} = \alpha + \beta \Delta CDS_{it} + \gamma \Delta LCS_{it} + \delta MonthDummy_t + \eta_{it} \quad (4)$$

Figure 18: Regression of ∆OAS on ∆CDS Spread and ∆LCS – January 2007-April 2010

	Intercept	∆CDS	∆LCS	Month Dummies	No of Obs	Adj R-sq
Coefficient	-0.184	0.097	0.406	Yes	7304	0.48
t-stats	*(2.59)*	*(29.97)*	*(35.44)*			

Source: Barclays Capital

One could also argue that the results above may be driven by outliers, especially since default and liquidity are arguably more important considerations for higher spread bonds. However, does this relationship hold as well for the bulk of the sample? To confirm this, we run log regressions using the variables above (e.g., the dependent variable is log (OAS) instead of OAS, similarly for the independent variables), as in Regression (5). The conclusions from Figure 19 are similar to those of Regression 2a, indicating that outliers are not driving the results.

$$\ln(OAS_{it}) = \alpha + \beta \ln(CDS_{it}) + \gamma \ln(LCS_{it}) + \eta_{it} \quad (5)$$

Figure 19: Regression of ln(OAS) on ln(CDS Spread) and ln(LCS) – January 2007-April 2010

	Intercept	ln(CDS)	ln(LCS)	Month Dummies	No of Obs	Adj R-sq
Coefficient	-1.30	0.425	0.26	Yes	7578	0.89
t-stats	*(45.56)*	*(107.33)*	*(44.67)*			

Source: Barclays Capital

Conclusion

We decompose credit bond (OAS) spreads into risk premium, default cost, and liquidity cost components. We find strong explanatory power for both investment grade and high yield bonds, using either CDS spreads or CDP/CRR as default proxies and LCS as a liquidity proxy. Liquidity is incrementally important (after considering default effects) throughout the sample period for investment grade bonds. However liquidity is generally important for high yield bonds only during stressful times. The results hold in a variety of specifications and datasets, including differences, logs, and additional controls. Spread decomposition can help portfolio managers understand spread movements better. Preliminary analysis suggests that this decomposition can be used for hedging, forecasting future OAS changes, and developing alpha strategies.

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Appendix

The Appendix includes month-by-month regression results for the spread decomposition model using CDP as a default proxy for both IG (Appendix 1) and the HY bonds (Appendix 3). We also include results for the HY bonds using CDS Spreads as the default proxy (Appendix 2).

Appendix 1: Investment Grade Bonds – Regression of OAS on CDP*(1-RR) and LCS (January 2007-April 2010)

Same in Both Regs		Specification 1 - Only CDS			Specification 2 - Includes CDS and LCS			
Month	# obs	Intercept	CDP*(1-RR)	Adj. R-sq	Intercept	CDP*(1-RR)	LCS	Adj. R-sq
Jan-07	132	0.80 32.16	-0.18 -0.78	0.00	0.65 18.19	-0.18 -0.88	0.47 5.51	0.18
Feb-07	107	0.79 27.43	-0.04 -0.16	-0.01	0.66 20.10	-0.03 -0.18	0.40 6.14	0.25
Mar-07	120	0.82 31.37	0.23 1.06	0.00	0.69 19.37	0.21 1.05	0.42 4.91	0.16
Apr-07	129	0.85 28.77	0.45 1.73	0.02	0.70 14.30	0.35 1.44	0.55 4.00	0.12
May-07	123	0.84 32.66	0.17 0.82	0.00	0.58 10.30	0.14 0.75	0.94 5.15	0.17
Jun-07	112	0.90 26.31	0.64 2.52	0.05	0.76 16.93	0.58 2.47	0.45 4.32	0.18
Jul-07	80	1.13 20.60	1.14 4.18	0.17	0.32 2.17	1.06 4.62	2.59 5.76	0.41
Aug-07	66	1.40 14.78	2.96 5.75	0.33	0.92 8.71	1.11 2.21	0.95 6.38	0.59
Sep-07	93	1.31 23.74	1.88 13.35	0.66	1.12 17.13	1.77 13.74	0.30 4.66	0.72
Oct-07	85	1.28 19.12	1.83 11.05	0.59	0.76 8.96	1.28 8.81	0.98 7.80	0.76
Nov-07	59	1.79 12.24	2.52 7.83	0.51	1.04 6.48	1.50 5.16	1.14 6.55	0.72
Dec-07	57	1.50 9.48	2.92 7.21	0.48	1.11 5.26	2.21 4.75	0.70 2.65	0.53
Jan-08	87	2.04 17.65	2.20 8.27	0.44	1.45 12.25	0.81 2.90	0.85 7.50	0.66
Feb-08	99	2.25 18.75	1.76 9.62	0.48	1.51 13.05	0.78 4.68	0.89 9.57	0.73
Mar-08	91	2.47 11.03	3.95 8.50	0.44	1.57 8.44	1.45 3.39	1.21 9.33	0.72
Apr-08	101	2.32 13.45	2.05 7.14	0.33	1.35 9.47	0.50 2.16	1.17 11.43	0.71
May-08	114	2.21 14.65	1.83 7.14	0.31	1.38 9.04	0.59 2.39	1.14 8.56	0.58
Jun-08	120	2.71 17.40	1.30 7.29	0.30	1.74 14.29	0.42 3.25	1.09 13.50	0.73
Jul-08	114	2.98 16.11	1.55 6.99	0.30	2.03 17.06	0.77 5.82	0.78 15.82	0.78
Aug-08	115	2.85 17.24	2.15 8.38	0.38	2.17 20.41	1.18 7.27	0.70 14.89	0.79
Sep-08	97	3.58 28.98	1.73 8.15	0.41	3.30 18.58	1.48 6.23	0.30 2.17	0.43
Oct-08	220	5.30 23.66	5.30 12.27	0.41	3.27 25.61	2.44 10.77	0.70 27.93	0.87
Nov-08	231	5.77 19.86	5.07 10.48	0.32	3.56 20.55	2.31 8.52	0.84 25.27	0.82
Dec-08	220	5.81 16.44	4.68 8.01	0.22	2.86 15.82	2.04 7.64	0.98 30.76	0.85
Jan-09	137	4.10 16.83	2.12 7.96	0.31	2.48 11.97	1.25 6.50	0.80 12.83	0.69
Feb-09	166	4.07 20.60	1.86 10.62	0.40	2.81 14.82	1.17 7.96	0.72 10.99	0.66
Mar-09	210	5.10 15.77	4.20 12.47	0.43	3.45 15.56	2.23 9.41	0.72 18.06	0.78
Apr-09	127	3.93 17.11	1.21 5.83	0.21	2.30 10.86	0.70 4.66	0.79 11.65	0.62
May-09	176	4.08 15.06	1.20 5.95	0.16	1.83 7.67	0.51 3.54	1.24 14.59	0.62
Jun-09	185	3.66 15.22	1.37 6.14	0.17	1.84 9.07	0.75 4.78	1.11 14.86	0.62
Jul-09	147	3.19 12.47	1.64 8.11	0.31	1.61 6.63	0.91 5.47	1.04 10.55	0.61
Aug-09	194	2.88 14.45	1.15 5.56	0.13	1.13 6.29	0.51 3.42	1.43 14.91	0.60
Sep-09	236	2.24 16.34	1.37 7.71	0.20	0.98 7.35	0.79 5.86	1.24 14.26	0.57
Oct-09	237	2.06 19.33	1.05 7.88	0.21	1.17 10.74	0.70 6.52	0.98 12.40	0.52
Nov-09	246	2.07 17.86	1.27 9.55	0.27	0.93 8.33	0.87 8.77	1.36 15.20	0.62
Dec-09	200	1.86 14.53	1.22 7.15	0.20	0.67 6.52	0.72 6.67	1.47 18.10	0.70
Jan-10	295	1.70 20.19	1.12 8.61	0.20	0.51 5.62	0.70 7.44	1.62 17.25	0.60
Feb-10	270	1.74 20.24	1.43 9.06	0.23	0.52 6.17	0.92 8.72	1.56 19.47	0.68
Mar-10	211	1.53 18.48	1.24 7.21	0.20	0.51 5.80	0.70 5.63	1.50 15.06	0.61
Apr-10	223	1.45 17.22	1.18 6.96	0.18	0.93 9.93	0.92 6.18	0.79 8.86	0.39

Source: Barclays Capital

Appendix 2: High Yield bonds – Regression of OAS on CDS Spreads and LCS (January 2007-April 2010)

Same in Both Regs		Specification 1 - Only CDS			Specification 2 - Includes CDS and LCS			
Month	# obs	Intercept	CDS	R-sq	Intercept	CDS	LCS	R-sq
Jan-07	45	1.21 7.50	0.51 7.85	0.58	1.18 5.22	0.50 7.65	0.04 0.23	0.57
Feb-07	50	1.37 7.95	0.50 7.27	0.51	1.24 5.46	0.48 6.91	0.17 0.87	0.51
Mar-07	42	1.37 5.53	0.44 5.93	0.45	1.46 4.55	0.45 5.61	-0.12 -0.43	0.44
Apr-07	97	1.17 7.81	0.59 10.91	0.55	1.27 6.44	0.60 10.88	-0.13 -0.75	0.55
May-07	99	1.05 6.94	0.56 10.11	0.51	1.11 5.18	0.56 10.04	-0.08 -0.41	0.50
Jun-07	87	1.48 6.46	0.48 7.84	0.41	1.74 5.78	0.49 7.98	-0.34 -1.33	0.42
Jul-07	63	1.17 3.67	0.63 10.85	0.65	0.67 1.88	0.55 8.85	0.69 2.75	0.69
Aug-07	57	1.66 8.59	0.60 14.96	0.80	1.28 4.96	0.54 11.51	0.31 2.11	0.81
Sep-07	64	1.25 5.46	0.69 14.79	0.78	1.29 4.36	0.69 13.51	-0.04 -0.21	0.77
Oct-07	72	1.40 6.51	0.65 16.61	0.79	1.58 6.10	0.68 14.27	-0.22 -1.23	0.80
Nov-07	95	2.39 12.51	0.55 18.38	0.78	2.48 9.60	0.56 14.87	-0.11 -0.55	0.78
Dec-07	108	2.60 13.92	0.52 19.39	0.78	2.72 11.09	0.54 16.32	-0.12 -0.74	0.78
Jan-08	103	2.72 10.17	0.58 16.80	0.73	1.94 5.33	0.52 13.44	0.73 3.03	0.75
Feb-08	96	2.40 9.60	0.66 19.31	0.80	1.84 5.67	0.62 17.25	0.52 2.63	0.81
Mar-08	96	3.56 14.13	0.53 20.06	0.81	3.26 7.81	0.51 15.96	0.27 0.91	0.81
Apr-08	83	2.85 10.31	0.50 10.70	0.58	2.29 5.59	0.47 9.29	0.49 1.85	0.59
May-08	97	3.01 11.65	0.46 14.50	0.69	2.62 5.77	0.45 12.79	0.28 1.03	0.69
Jun-08	82	4.27 12.74	0.33 8.66	0.48	4.29 7.84	0.33 8.08	-0.01 -0.04	0.47
Jul-08	89	3.48 12.25	0.51 15.19	0.72	3.10 8.40	0.49 13.57	0.28 1.56	0.73
Aug-08	85	3.67 10.15	0.52 12.80	0.66	2.81 6.78	0.44 9.78	0.73 3.55	0.70
Sep-08	50	3.13 8.10	0.71 15.70	0.83	3.49 8.18	0.81 11.78	-0.47 -1.80	0.84
Oct-08	60	6.21 7.94	0.57 9.18	0.59	4.46 4.75	0.48 7.26	0.76 2.99	0.64
Nov-08	59	8.94 13.08	0.40 11.02	0.67	7.24 12.50	0.19 4.49	1.15 6.57	0.81
Dec-08	48	7.56 6.77	0.54 10.74	0.71	6.18 6.24	0.32 4.90	0.89 4.47	0.79
Jan-09	84	7.26 7.82	0.50 9.85	0.54	4.67 6.34	0.33 7.83	1.05 8.66	0.76
Feb-09	67	7.70 10.80	0.28 7.30	0.44	5.94 8.40	0.19 5.04	0.88 4.96	0.59
Mar-09	65	8.32 12.00	0.29 8.12	0.50	5.21 10.66	0.23 11.02	0.93 11.20	0.83
Apr-09	59	3.88 5.11	0.65 11.54	0.69	2.50 4.30	0.47 9.99	0.78 7.24	0.84
May-09	73	4.18 9.14	0.53 11.89	0.66	3.35 10.43	0.34 9.47	0.80 9.25	0.85
Jun-09	79	4.13 8.26	0.49 9.70	0.54	3.34 6.74	0.40 7.77	0.72 4.04	0.62
Jul-09	75	5.88 9.69	0.21 5.98	0.32	3.14 7.48	0.13 6.29	1.39 12.01	0.77
Aug-09	88	4.23 8.87	0.47 9.00	0.48	2.69 5.86	0.36 7.73	1.05 6.48	0.65
Sep-09	96	2.33 5.33	0.72 11.57	0.58	1.19 2.59	0.64 11.13	0.80 4.80	0.66
Oct-09	94	2.70 5.88	0.65 10.81	0.55	1.26 2.97	0.51 9.78	1.29 7.08	0.71
Nov-09	94	2.93 6.03	0.69 11.17	0.57	1.62 3.83	0.53 10.05	1.28 7.43	0.73
Dec-09	89	1.66 4.57	0.85 15.58	0.73	1.23 3.13	0.76 12.30	0.53 2.54	0.75
Jan-10	88	5.67 21.16	0.03 2.15	0.04	4.05 8.90	0.03 2.32	1.03 4.21	0.20
Feb-10	99	2.28 5.64	0.68 12.29	0.60	1.76 4.48	0.56 9.48	0.75 4.14	0.66
Mar-10	96	2.30 7.02	0.59 12.01	0.60	1.74 3.91	0.56 11.32	0.51 1.80	0.61
Apr-10	107	2.29 7.59	0.61 12.74	0.60	1.64 4.43	0.58 12.31	0.58 2.83	0.63

Source: Barclays Capital

Appendix 3: High Yield Bonds – Regression of OAS on CDP*(1-RR) and LCS (January 2007-April 2010)

Same in Both Regs		Specification 1 - Only CDS			Specification 2 - Includes CDS and LCS			
Month	# obs	Intercept	CDP*(1-RR)	R-sq	Intercept	CDP*(1-RR)	LCS	R-sq
Jan-07	58	2.13 17.90	0.81 5.89	0.37	1.85 6.66	0.84 6.00	0.24 1.12	0.37
Feb-07	51	2.19 16.30	0.84 4.99	0.32	1.85 6.93	0.89 5.25	0.31 1.50	0.34
Mar-07	47	2.22 13.88	1.22 5.78	0.41	1.91 4.90	1.24 5.82	0.30 0.88	0.41
Apr-07	104	2.36 23.49	0.71 6.62	0.29	1.86 8.30	0.68 6.45	0.54 2.48	0.33
May-07	114	2.02 23.86	0.79 8.68	0.40	1.68 9.48	0.77 8.50	0.36 2.13	0.42
Jun-07	112	2.66 27.62	0.63 6.77	0.29	2.51 11.92	0.61 6.27	0.16 0.84	0.29
Jul-07	91	3.49 23.77	0.90 7.67	0.39	2.52 7.20	0.84 7.43	0.68 3.03	0.44
Aug-07	83	3.54 23.26	0.83 8.67	0.48	2.87 8.27	0.77 7.82	0.35 2.15	0.50
Sep-07	87	3.14 25.84	0.68 12.48	0.64	2.54 10.22	0.62 10.85	0.34 2.77	0.67
Oct-07	87	3.46 20.83	0.57 9.08	0.49	3.35 9.31	0.55 7.11	0.07 0.34	0.48
Nov-07	175	4.08 34.66	0.69 14.52	0.55	3.44 13.22	0.61 11.16	0.42 2.73	0.56
Dec-07	180	4.15 26.83	0.73 12.68	0.47	4.10 11.63	0.73 9.71	0.04 0.18	0.47
Jan-08	181	4.83 27.42	1.23 11.37	0.42	3.28 9.58	1.05 9.89	0.91 5.18	0.49
Feb-08	190	5.10 33.17	1.27 13.01	0.47	4.17 13.77	1.17 11.83	0.55 3.52	0.50
Mar-08	190	5.34 34.76	1.27 13.63	0.49	4.34 14.75	1.13 11.88	0.62 3.96	0.53
Apr-08	159	4.39 27.84	0.77 7.46	0.26	3.12 11.05	0.61 6.12	0.77 5.28	0.37
May-08	183	4.57 27.17	0.69 9.53	0.33	3.21 8.76	0.61 8.47	0.82 4.15	0.39
Jun-08	191	4.86 28.18	0.89 12.13	0.43	4.48 13.25	0.87 11.60	0.21 1.29	0.44
Jul-08	192	5.30 28.60	0.77 10.90	0.38	4.34 13.18	0.72 10.38	0.51 3.46	0.42
Aug-08	193	5.58 27.49	0.92 11.32	0.40	3.85 11.03	0.79 9.99	0.87 5.87	0.49
Sep-08	130	6.31 27.96	0.69 6.30	0.23	4.25 10.58	0.50 4.87	1.05 5.92	0.39
Oct-08	138	9.36 29.40	0.85 6.24	0.22	6.25 14.46	0.66 5.94	0.73 8.86	0.50
Nov-08	134	11.16 28.53	0.87 8.30	0.34	7.60 18.54	0.68 8.98	0.85 11.68	0.67
Dec-08	118	12.18 24.81	0.74 6.19	0.24	8.05 14.35	0.59 6.53	0.74 9.69	0.58
Jan-09	140	7.62 17.44	1.10 13.74	0.57	4.45 8.56	0.92 13.27	0.82 8.40	0.72
Feb-09	126	6.86 15.46	1.12 11.78	0.52	5.22 11.04	0.84 8.90	0.59 6.14	0.63
Mar-09	136	8.67 17.10	1.34 8.54	0.35	5.85 11.78	0.90 6.89	0.82 9.40	0.61
Apr-09	155	7.22 23.11	0.57 15.53	0.61	5.23 15.13	0.42 11.94	0.67 8.59	0.74
May-09	181	6.94 22.35	0.44 8.57	0.29	3.88 13.01	0.30 8.18	1.12 14.51	0.67
Jun-09	199	6.42 29.12	0.35 9.33	0.30	4.56 16.90	0.28 8.72	0.82 9.41	0.52
Jul-09	197	5.64 20.33	0.47 9.53	0.31	2.97 12.03	0.30 8.68	1.22 16.00	0.70
Aug-09	210	5.74 28.36	0.33 8.96	0.27	3.31 12.21	0.20 6.42	1.20 11.14	0.54
Sep-09	227	5.37 35.56	0.18 6.55	0.16	3.94 15.78	0.12 4.62	0.76 6.84	0.30
Oct-09	219	5.06 33.27	0.27 11.41	0.37	3.65 15.17	0.20 8.73	0.86 7.10	0.49
Nov-09	222	5.37 36.81	0.27 11.65	0.38	3.98 18.42	0.20 9.29	0.88 8.04	0.52
Dec-09	219	4.61 30.41	0.32 12.02	0.40	3.79 23.90	0.25 10.62	0.53 8.90	0.56
Jan-10	231	4.47 35.65	0.31 12.89	0.42	3.89 30.37	0.25 11.06	0.44 8.71	0.56
Feb-10	253	4.63 31.04	0.45 11.45	0.34	3.38 21.76	0.29 8.42	0.89 12.28	0.59
Mar-10	247	4.25 34.34	0.41 10.40	0.30	3.31 21.58	0.29 7.95	0.71 8.72	0.47
Apr-10	254	4.10 35.63	0.37 8.81	0.23	3.28 15.54	0.34 8.25	0.59 4.57	0.29

Source: Barclays Capital

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