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Liquidity and Market Efficiency: Cash Corporates, ETFs, and CDX

Vadim Konstantinovsky, CFA
+1 212 526 8290
vkonstan@barclays.com

Bruce Phelps, CFA
+1 212 526 9205
bruce.phelps@barclays.com

www.barclays.com

- We look at an alternative way to measure liquidity. Portfolio managers may consider a market to be liquid if it adjusts rapidly to news and changes in portfolio preferences. In such a market, excess returns quickly and fully reflect new information, so yesterday's returns do not help explain today's returns. In a less liquid market, it takes time for excess returns to fully adjust. Consequently, another possible way to assess liquidity objectively is to check for persistence in returns.

- We examine corporate bond index excess returns to measure the degree of persistence. Unlike the Treasury, equity and MBS markets, the corporate market displays considerable return persistence, indicating that it is relatively less liquid.

- We also measure relative liquidity *within* the corporate market. To that end, we segment the market into liquidity buckets based on our published measure of *relative* liquidity – Trade Efficiency Scores (TES) – a bond-level metric that combines our absolute liquidity measure, Liquidity Cost Scores (LCS), and trading volume.

- Looking at both daily and monthly excess returns since February 2007, we find that TES rank and return persistence are highly positively correlated, which corroborates the validity of our LCS liquidity measure. TES1 bonds display little return persistence, suggesting that these bonds are the most liquid portion of the cash corporate market.

- Lately, the growth of trading in CDX and corporate bond ETFs has provided investors with realistic alternatives to express views on corporate excess returns. Perhaps security design and market microstructure for CDX and ETFs are more conducive to better liquidity? We find that these alternative markets display lower return persistence than the cash market.

- The conclusions of this study have several implications for portfolio managers. If cash corporate returns are persistent, it becomes more difficult to interpret the observed excess returns. Correlations of corporate returns with other asset classes depend on the corporate portfolio's liquidity profile, which may affect a manager's asset allocation decisions. In addition, a corporate portfolio's relative liquidity profile may determine whether its performance leads or lags a broad benchmark index. Finally, alternative corporate markets (ETFs and CDX) contain information useful for cash corporate investors.

Introduction

Liquidity is difficult to measure objectively because there is no common, well-specified definition. The meaning of liquidity can vary by individual and by the market environment. For some, liquidity is the expense of trading a standard lot in the market. When defined like this, we can measure liquidity using our Liquidity Cost Scores (LCS), which are based on bid-ask spreads. For others, liquidity is the relative market impact of trading small lots versus trading large lots. In a liquid market, even large trades have little market impact. Given the large number of bonds and the infrequent trading of most of them, it is very difficult to reliably measure market impact.

Another possible way to assess liquidity objectively is to check for persistence in returns between periods. In other words, do past returns help explain current-period returns? Portfolio managers might consider a market to be liquid if prices adjust rapidly to news and changes in portfolio preferences. For a market with many potential buyers and sellers constantly interacting (inquiring, quoting and trading), it is reasonable to expect prices (and, hence, excess returns) to quickly reflect an equilibrium incorporating many viewpoints. In such a market, past returns would show little correlation (i.e., no persistence) with current-period returns.

Investors would probably agree that last month's returns in either the cash Treasury or equity (e.g., as represented by SPX) markets do not provide useful information about current-month returns. Given the heavy quoting and trading activity, which is widely disseminated, information flows pretty quickly in these markets. Consequently, prices rapidly and fully adjust to new information. Investors characterize these markets as "liquid".

In contrast, in a market (or sub-market) with more limited quoting and trading activity, the propagation and evaluation of news, or changed preferences, may affect returns more gradually. Theoretically, new information flows to all investors simultaneously, and they instantaneously adjust their prices and portfolios. However, in reality, this process may take some time. For example, news about a small company or an old bond issue of a larger company may not prompt immediate inquiry or trading activity. Or, such activity may be limited to just a few potential sellers and buyers. Also, while any subsequent trade (not the inquiry) would probably be publicly reported, it may take some time for the next interested party to notice and properly evaluate the news and take action. In other words, prices will not adjust rapidly. Consequently, excess returns would exhibit some degree of persistence, and would be positively correlated over time.[1] We consider such a market less liquid than one without return persistence.

In this study, we use the estimated degree of return persistence in a market (or sub-market) as an objective measure of the market's liquidity.

Some consider the corporate bond market less liquid than other markets. The USD IG Corporate Index has more than 750 unique issuers and more than 5,100 issues (September 2014). There is also a constant inflow of new issuers/issues. As market participants know, while some corporate bonds trade very actively, many others rarely trade at all. In addition, unlike the public equity market, there are few central trading locations for corporate bonds. Corporate bonds trade mostly over-the-counter on a bilateral negotiated basis, although transaction prices (but not spreads) and trade sizes (capped) are reported publicly *via* TRACE.

[1] Informational inefficiency does not necessarily create profit opportunities (i.e., economic inefficiency). Even if a bond's excess returns are persistent (i.e., somewhat predictable), structuring trades to take advantage of this may not be economical after transaction costs.

This report examines three questions:

1. What is the degree of return persistence in corporate bond excess returns?
2. Does return persistence vary within segments of the market?
3. How does return persistence in the cash corporate market compare with that of alternative markets that provide corporate exposure (e.g., ETFs and CDX)?

We can use standard statistical techniques to answer the first question. The second question requires that we specify a way to segment the corporate market. We partition the Corporate Index into various TES buckets and examine the time series properties of excess returns of these buckets. Trade Efficiency Scores (TES) are our published measure of *relative* liquidity, which combines our bond-level absolute liquidity measure, LCS, and market trading volume. Do lower-TES (i.e., better relative liquidity) buckets display less persistence than higher-TES buckets? If so, we would argue that lower-TES buckets are, in fact, more liquid than higher buckets. An additional advantage of segmenting the corporate market by TES is that finding positive correlation between the TES bucket and return persistence (i.e., higher TES buckets having higher return persistence)provides independent corroboration of our LCS methodology.

The growth of trading in IG corporate bond ETFs and IG CDX has created realistic alternative venues for investors to express their views on corporate excess returns. Are the security design and market microstructure for ETFs and CDX more conducive to rapid market adjustment? In other words, does the cash market display more, or less, return persistence than these newer markets? If so, this suggests that the newer markets might provide useful information to cash corporate bond investors.

Conclusions of this study may have several other implications for portfolio managers. If cash corporate returns are persistent, it becomes more difficult to interpret the observed excess returns. It is also possible that a corporate bond portfolio's correlations with other asset classes depend on the liquidity profile of that portfolio. If so, this may influence a manager's asset allocation decisions. Also, a portfolio's relative liquidity profile may determine whether its performance leads or lags a broad benchmark index. This information may assist managers with the construction and performance evaluation of their portfolios.

Return Persistence as a Measure of Liquidity

To measure persistence in the USD investment grade corporate market, we regress the Barclays IG Corporate Index[2] current-month excess returns (ER) on its prior months' excess returns. For this study we use the corporate excess returns reported by the Barclays Indices.[3]

[2] In this study, "Corporate Index" refers to the Barclays USD IG Corporate Index ex 144A bonds. We exclude144A bonds because we do not have TRACE trading volume for them and, because of that, are unable to compute TES (described later).

[3] We also examined bond-level corporate excess returns generated by the POINT Risk Model that removes the carry (*i.e.*, "deterministic") component. The autoregressive structure of these returns is very similar to that of reported index returns, even though the latter include the net carry difference between a corporate bond and its matched-KRD Treasury portfolio. The conclusions of this study are virtually the same regardless of whether we use Risk Model returns or reported Index returns.

We estimate the following autoregressive model:

$$ER_t = \alpha + \beta_1 \times ER_{t-1} + \beta_2 \times ER_{t-2} + \ldots + \varepsilon_t$$

For a market with no return persistence, the estimated regression coefficient on the lagged excess return terms would be statistically indistinguishable from zero. Figure 1 presents the estimated OLS coefficients and adjusted R^2 using returns over the 92-month period from February 2007 through September 2014. For comparison, we also apply the same model to the Barclays Treasury and Mortgage indices, as well as to the S&P500 Index (SPX). For the Treasury and SPX, we use total returns, not excess returns.

FIGURE 1

Estimated Autoregression Coefficients. Monthly Returns. February 2007 – September 2014

	Intercept	Lag(-1)	Adj R^2
Corp ER	0.05	**0.34**	0.11
	(0.26)	*(2.58)*	
Tsy TR	**0.34**	0.09	0.00
	(2.71)	*(0.99)*	
MBS ER	0.04	**0.21**	0.03
	(0.95)	*(2.43)*	
SPX TR	0.53	0.20	0.03
	(0.98)	*(1.54)*	

Based on the AIC, we estimate the model using one lag. Standard errors are Newey-West with a truncation parameter of 3. t-statistics are in parentheses. Coefficients in bold are statistically significant at the 5% confidence level.
Source: Bloomberg, Barclays Research

As Figure 1 shows, for the Treasury and SPX indices, the lagged (total) return coefficient is not significant. This means that prior-month returns do not help explain this month's returns, which is consistent with the conventional view that these are very liquid markets. In other words, prices (and returns) quickly adjust to new equilibrium levels.

We see a different pattern for the Corporate Index excess returns. The one-month (from now on, "first") lag coefficient (0.34) is statistically significant, meaning that this month's excess returns have a 0.34 correlation with last month's returns.[4] In addition, the regression R^2 is 11% (healthy for a regression of historical financial returns), meaning that 11% of the variation in this month's Corporate Index excess return is explained by its previous month's excess return.

Mortgage excess returns also display correlated excess returns. The first lag coefficient (0.21) is statistically significant. However, it is only about two-thirds the size of the corresponding coefficient for corporates, and its R^2 is only 3%, which suggests that prior month's returns explain much less of the variation in this month's returns. This lower degree of price persistence for the Mortgage Index is not unexpected given its greater homogeneity, as well as the existence of the very popular and active TBA market that is often the basis for pricing MBS Index generics. As far as return persistence is concerned, the IG corporate market seems to be in a class of its own.

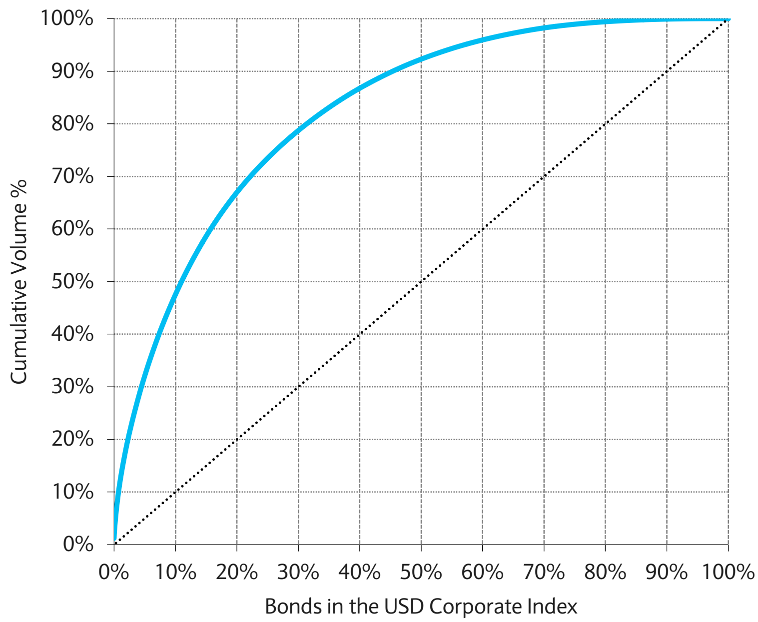
What could explain this persistence pattern for the Corporate Index? Unlike Treasury bonds and stocks in the S&P500, many corporate bonds trade rarely or not at all in a particular month.[5]

[4] A first lag coefficient of 0.34 implies that this month's return has a 0.12 correlation with returns two months ago and a 0.04 correlation with returns three months ago.
[5] V. Konstantinovsky, K Y Ng, and B. Phelps, "LCS Report – July 2014," Barclays Research, August 2014.

Hence, while changes in investors' views quickly affect bid and ask prices of actively traded corporate bonds, their influence on infrequently-traded bonds is probably more gradual. Eventually, the news becomes fully reflected in their prices as well, but this slow adjustment can cause lagged returns to be positively correlated with the current period's returns. Figure 2 attests to this.

FIGURE 2

Cumulative Corporate Trading Volume. Index Bonds Sorted by Monthly Trading Volume. May 2010 – September 2014



Source: Barclays Research.

The highly non-linear shape of the cumulative volume shows that the bulk of the overall market activity happens in a relatively small group of bonds. In fact, 20% of the issues account for about two-thirds of the total market trading volume.

We note that while many bonds may not trade during a particular month, at month-end every bond in the Barclays IG Index is hand-marked by Barclays traders and reviewed by the Index Group. So, any observed persistence in corporate returns should not be the result of a technical issue of stale pricing. However, given the lack of investor inquiries and trading for many bonds in the index, traders may need more time to learn the full extent of any change in the equilibrium price for such bonds. The prices of actively traded bonds, with substantial investor interest, may adjust almost instantaneously, so returns will show little persistence. It is the prices and returns of bonds with limited investor interest that display persistence, even though the prices are manually updated each month.

The speed with which bond prices adjust may depend on the overall liquidity environment. For example, in benign market conditions with ample trading and client inquires across a wide spectrum of bonds, traders may have sufficient information to quickly update prices for most bonds in the index, thereby reducing return persistence. In contrast, in difficult market conditions, when, perhaps, most market participants are focused on a limited set of actively traded bonds, traders may have insufficient information on a large segment of the corporate market. It seems reasonable to suppose that corporate bonds differ cross-sectionally in their return persistence, and that this difference fluctuates with the market environment.

Relative Liquidity: Trade Efficiency Scores (TES)

In this study, we segment the USD IG corporate market by our objective LCS-based measure of relative liquidity and investigate whether it is correlated with excess return persistence.

How do we segment the corporate market by relative liquidity? LCS is an absolute liquidity measure.[6] It reflects the cost of trading a bond at a particular moment and fluctuates over time as not only the bond's liquidity, but also the overall market's liquidity ebbs and flows. For example, a bond may have an LCS of 2.200 in December 2008, 1.563 in May 2009, and 1.235 in December 2009. These numbers do not tell us where the bond stood relative to its peers in each of these months.

Along with LCS, we also compute and publish Trade Efficiency Scores (TES)[7] for all bonds in the USD IG Corporate Index.[8] TES is a *relative* bond-level liquidity ranking ranging from 1 (best) to 10 (worst). The motivation behind TES is to help investors quickly judge a bond's liquidity relative to other bonds in its market/index, both currently and over time.

Although LCS captures liquidity cost, it does not directly measure a bond's actual trading flow. As shown, many bonds in broad credit indices rarely trade. A bond with a low trading volume generally has a higher LCS, reflecting a higher cost of executing a regular-size trade. However, LCS may not adequately reflect the difficulty of implementing large or numerous trades. Investors interested in immediate execution, or traders who need to commit to making a market in a bond, may prefer a bond with higher current trading volume to another with a similar LCS but lower volume. TES blends LCS and monthly trading volume into a single score that reflects a bond's relative trade *efficiency* (i.e., trading cost and trading flow). Within a market, bond-level TES are comparable both over time and among bonds, and may come close to a trader's intuitive sense of liquidity in terms of both transactions cost and market impact.[9]

To compute TES, each bond in the corporate universe is first assigned to an LCS (OASD-adjusted)[10] quintile and to a monthly trading volume decile. Then, these two quantiles are added, and the sum (which ranges from 2 to 15) is mapped to a TES ranking from 1 to 10. Figure 3 provides the details.

[6] Dastidar, S. and B. Phelps. "Introducing LCS – Liquidity Cost Scores for US Credit Bonds." Barclays Research. October 2009.
[7] The TES methodology is described in "Liquidity Cost Scores (LCS) for Pan-European Credit Bonds," S. Dastidar, A. Edelstein and B. Phelps, Barclays Research, September 2010.
[8] We generate TES for other indices as well: EUR IG Corporate, USD EM and Global Covered.
[9] Portfolio managers can use TES as a filter when back-testing alpha strategies to get a realistic measure of the strategy's performance.
[10] A bond's LCS has a strong positive dependence on its spread duration. Investors generally select bonds for a given duration exposure, so before plugging LCS in the TES calculation, we divide it by OASD. A ranking based on LCS adjusted by OASD (i.e., "round-trip cost per unit of duration") allows a portfolio manager to construct a liquid portfolio by simply filtering on bonds with, say, TES less than 3, knowing that these will be very liquid bonds for a given spread duration at the time when the analysis is done.

FIGURE 3

TES Mapping Scheme and TES Breakdown of the USD IG Corporate Index. September 30, 2014

Trading Vol Decile plus LCS Quintile	Trade Efficiency Score (TES)	Number of Bonds	% of Bonds in the Index	%MV of the Index	Avg Age	Avg Issue Size, ($'000)	Avg OAS (bp)	Avg OASD	Avg LCS	Avg Trading Volume ($'000)
2 and 3	1	715	14.0%	26.9%	2.49	1,411,691	116	7.78	0.414	286,922
4 and 5	2	513	10.1%	14.4%	3.41	1,037,239	101	6.41	0.555	80,426
6	3	350	6.9%	7.6%	3.78	793,059	103	6.49	0.722	59,741
7	4	424	8.3%	8.0%	3.55	703,766	98	6.08	0.757	41,749
8	5	416	8.2%	7.7%	4.40	670,173	105	6.66	0.889	29,118
9	6	437	8.6%	7.2%	4.52	596,395	104	6.55	0.935	18,544
10	7	515	10.1%	7.5%	5.06	520,806	112	7.36	1.082	10,942
11	8	467	9.2%	6.1%	5.75	458,974	118	7.32	1.104	5,722
12	9	462	9.1%	5.7%	6.80	427,653	122	7.42	1.144	2,736
13-15	10	801	15.7%	8.8%	7.85	375,249	130	6.27	1.275	749

Source: Barclays Research.

The TES buckets do not necessarily contain the same number of bonds or have the same market value. For example, the TES1 bucket comprises approximately 14% of the corporate index by number of bonds and 27% by market value, while the TES3 bucket comprises 7% by number and 8% by market value.

The composition of the TES buckets varies substantially. By construction, low-TES buckets have bonds with low LCS and high average trading volume. As Figure 3 shows, the average LCS for the TES1 bucket is approximately a third of that for the TES10, while its average trading volume is $287mn per bond versus $0.7mn per bond. There are other differences among TES buckets. Not surprisingly, low-TES buckets tend to be populated by large, recent issues. The issue size column in Figure 3 shows a dramatic decrease as we move to the high-TES buckets, while the average bucket age increases. Interestingly, there is no comparable OAS or OASD trend.

We use end-of-month, bond-level TES to segment the Corporate Index each month.[11] We then generate historical time series of excess returns for the 10 TES buckets and examine the autocorrelation structure of each bucket's returns. Specifically, we regress the current month's ER of each TES bucket on its own prior-months ER. For the lower TES buckets, we expect lagged excess returns to have little explanatory power, *i.e.,* statistically insignificant coefficients and low R^2. For the higher-TES buckets, the coefficients – at least the first lag coefficient – should be significant and explain a meaningful percentage of the TES bucket's excess return volatility.

Return Persistence and Relative Liquidity – Monthly Returns

Figure 4 presents the autoregressive model results by TES bucket. It shows clearly a large variation in excess return persistence within the corporate market.

For the most liquid bucket, TES1, the lagged ER coefficient is statistically zero, and the regression adjusted R^2 is also zero. TES1 bonds are relatively cheap to trade and have relatively high trading volumes, so it is not surprising that new information is quickly and fully reflected in their prices and, hence, excess returns.

[11] A bond's end-of-month (say, March) TES reflects its LCS and trading volume in March. We align the bond's March excess returns with its end-of-month March TES.

FIGURE 4

Estimated Autoregression Coefficients by TES Bucket. Monthly Returns. February 2007 – September 2014

	Intercept	Lag(-1)	Adj R^2
TES1 ER	0.02	0.17	0.02
	(0.11)	*(1.32)*	
TES2 ER	0.07	**0.28**	0.07
	(0.34)	*(2.14)*	
TES3 ER	0.08	**0.34**	0.10
	(0.41)	*(2.75)*	
TES4 ER	0.06	**0.37**	0.13
	(0.34)	*(2.87)*	
TES5 ER	0.07	**0.39**	0.14
	(0.40)	*(2.98)*	
TES6 ER	0.05	**0.43**	0.18
	(0.29)	*(3.27)*	
TES7 ER	0.05	**0.43**	0.17
	(0.27)	*(3.17)*	
TES8 ER	0.03	**0.44**	0.19
	(0.17)	*(3.40)*	
TES9 ER	0.03	**0.50**	0.24
	(0.14)	*(3.89)*	
TES10 ER	0.06	**0.48**	0.22
	(0.38)	*(3.67)*	
Corp ER	0.05	**0.34**	0.11
	(0.26)	*(2.58)*	

Based on the AIC, we estimate the model using one lag. Standard errors are Newey-West with a truncation parameter of 3. t-statistics are in parentheses. Coefficients in bold are statistically significant at the 5% confidence level.
Source: Barclays Research.

Beyond TES1, the picture changes. For TES2, the coefficient for the lagged ER term is positive (0.28) and statistically significant. The R^2 is a modest 7%. Moving from TES1 to TES2 produces a noticeable change in the persistence of excess returns, suggesting a reduction in liquidity. The LCS and trading volume levels for the two buckets confirm that. The average LCS over the study period is 0.627 for TES1 and 0.929 for TES2, while the September 2014 average volume is $287mn for TES1 and $80mn for TES2.

As we move to higher and higher TES buckets, both the coefficient of the first lagged ER term and the regression R^2 increase almost monotonically. For TES9 and TES10, the first lag coefficient reaches 0.50, and the R^2 is high at 24%.[12]

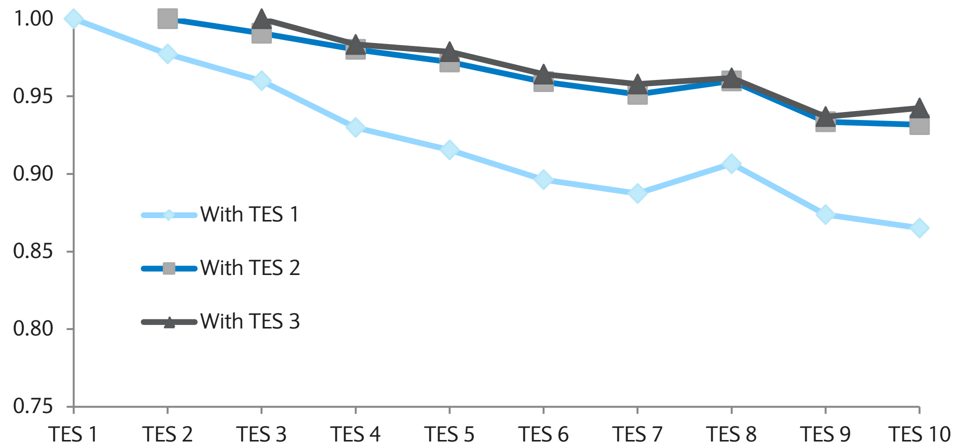
Figure 4 also shows that the autoregressive properties of the Corporate Index as a whole is about the same as TES3. The takeaway from Figure 4 is that TES1 is the most liquid portion of the corporate market, with significantly better liquidity compared with the other TES buckets and the index itself.

[12] The magnitude of the first lag coefficient implies that the correlation of this month's returns with returns three months prior is 0.22!

Another way to see the difference in excess return behavior is by looking at contemporaneous cross correlations. Figure 5 shows the cross correlations of all TES buckets with the three most liquid ones, TES1, TES2 and TES3.

FIGURE 5

Contemporaneous Cross Correlations by TES. %. Monthly Returns. February 2007 – September 2014

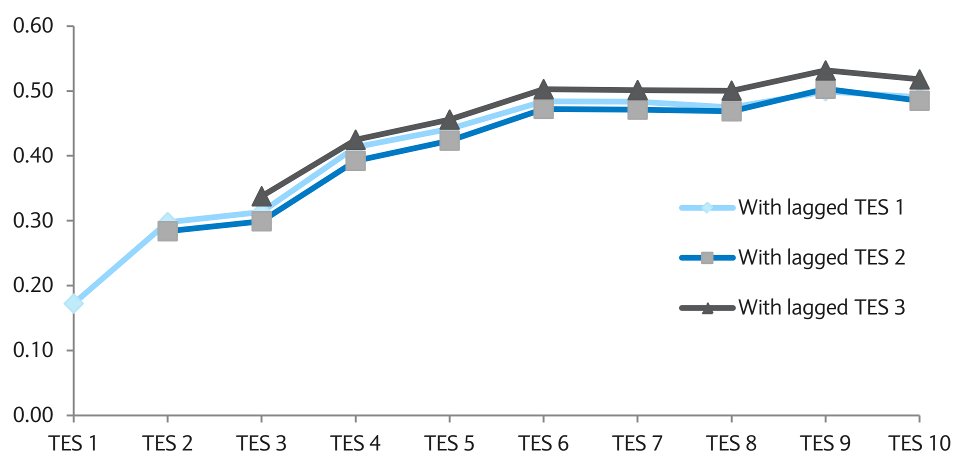


Source: Barclays Research

For all three liquid buckets (i.e., TES1, 2, and 3) the correlation coefficient declines as we move to higher TES (there is, however, a small blip for TES8). Over the sample period, the correlation between TES1 and TES2 was 0.98, but the correlation between TES1 and TES10 was only 0.87. While the pattern is the same for TES2 and TES3, it is strongest for TES1.

FIGURE 6

1mo-Lag Cross Correlations by TES. %. Monthly Returns. February 2007 – September 2014



Source: Barclays Research.

We see this pattern because higher-TES buckets react to news slower than TES1 – progressively so. As a result, the correlation declines as we move to higher and higher TES. This suggests that today's TES1 bucket return probably helps explain next month's returns for higher-TES buckets. This is exactly what we observe. Figure 6 shows that, as we move to higher-TES buckets, correlation coefficients with lagged low-TES bucket returns increase steadily. While the correlation between lagged TES1 and TES2 is 0.30, that between lagged TES1 and TES10 is 0.49 (compare with the non-lagged 0.98 and 0.87, respectively). This is a clear visual illustration of the autoregression results in Figure 4.

Yet another way to quantify the differences in return persistence among the TES buckets is to regress the excess returns of one TES bucket on those of another, and vice versa. For example, given their relative liquidity properties, we expect previous month's TES1 returns to partially explain this month's TES10 excess returns, but not vice versa. To verify this, we regress TES1 excess returns on TES10 ER(-1), and then, TES10 excess returns on TES1 ER(-1). Figure 7 shows the results.

FIGURE 7

Relative Informational Efficiency: TES1 vs. TES10. Monthly Returns. February 2007 – September 2014

	Intercept	TES10 ER(-1)	TES1 ER(-1)	Adj R^2
TES10 ER	0.11		0.40	0.23
	(0.62)		*(3.33)*	
TES1 ER	0.00	0.21		0.02
	(0.02)	*(1.36)*		

Based on the AIC, we estimate the model using one lag. Standard errors are Newey-West with a truncation parameter of 3. t-statistics are in parentheses. Coefficients in bold are statistically significant at the 5% confidence level.
Source: Barclays Research.

Not surprisingly, TES1 contains information that helps explain the current-month's TES10 excess returns. The coefficient on the lagged TES1 term is positive and significant, and the model R^2 is 23%. In contrast, the lagged TES10 term does not provide statistically significant information for this period's TES1 returns.[13]

Given the varying autoregressive nature of the TES buckets, we might expect differences in contemporaneous correlations with other markets (e.g., Treasuries and equities). Figure 8 shows the average monthly excess return, volatility, and the annualized Sharpe ratio by TES bucket. We notice that the TES1 bucket has earned a significantly lower average excess return compared with the other TES buckets. The highest-TES bucket, TES10, has the highest monthly excess return. This return difference may be the opportunity cost for holding bonds with lower transaction costs and lower liquidity risk (discussed next). Not unexpectedly, TES1 has the highest monthly excess return volatility. The lower excess return volatility of the non-TES1 buckets does not necessarily mean they have lower risk. It is their slower adjustment of excess returns that likely explains their lower volatility. Overall, TES1 has, by far, the worst Sharpe ratio, while TES10 has the highest. Does this mean that a buy & hold investor can rely on Sharpe ratios to justify holding less-liquid bonds? Perhaps not, if the low volatility of the less-liquid buckets means that the bid prices are slow to adjust and may not be executable.

All 10 TES buckets have similar OAS and OASD. They are large portfolios of bonds, so each TES bucket has relatively small idiosyncratic risk. Overall, the buckets have similar risk.[14] However, one type of risk is not the same at all and varies systematically across the TES buckets. It is liquidity risk, as measured by the volatility of LCS. Any bond's bid-ask spread can change, sometimes dramatically. So an investor holding a bond cannot be sure what it will cost him to sell it at some point in the future. This is what is meant by liquidity risk. As

[13] It is far from clear that these results hold promise for profitable trading strategies. There is still considerable variation in TES10 excess returns beyond the influence of lagged TES1 excess returns. Also, trading cost (LCS) for TES10 bonds is quite high (Figure 3).
[14] We verified this using the Barclays Global Risk Model, as of 9/30/2014.

FIGURE 8

Excess Return Statistics and Correlations with Other Markets, by TES bucket. Monthly Returns. February 2007 – September 2014

	Index	TES1	TES2	TES3	TES4	TES5	TES6	TES7	TES8	TES9	TES10
Avg ER	0.08	0.03	0.10	0.12	0.11	0.12	0.10	0.09	0.06	0.06	0.13
StDev ER	1.92	2.13	1.95	1.98	1.94	1.85	1.84	1.84	1.90	1.93	1.74
Annual SR	0.14	0.05	0.17	0.21	0.19	0.22	0.18	0.17	0.11	0.10	0.25
StDev LCS	0.52	0.25	0.39	0.57	0.64	0.67	0.73	0.72	0.68	0.76	0.93
Correl MBS ER	0.51	0.48	0.50	0.49	0.51	0.52	0.54	0.53	0.52	0.52	0.50
Correl Tsy TR	-0.43	-0.39	-0.43	-0.40	-0.43	-0.44	-0.45	-0.43	-0.44	-0.44	-0.47
Correl SPX TR	0.63	0.64	0.62	0.61	0.59	0.58	0.58	0.59	0.58	0.61	0.58

Source: Bloomberg, Barclays Research

Figure 8 shows, the liquidity risk, measured by the historical LCS volatility of each TES bucket, rises almost monotonically as we move to higher-TES buckets. In an earlier study, we looked at the relationship between liquidity level and short-term liquidity uncertainty, and found it to be strong and almost perfectly linear.[15]

A question relevant for asset allocation is whether the different monthly excess return behavior of different TES buckets affects their correlations with other markets. Figure 8 shows the monthly correlation of various TES buckets with the total returns of Barclays Treasury Index and the SPX. The well-known negative correlation of corporate excess returns with Treasury returns is less pronounced for TES1 (-0.39) than for higher-TES buckets (e.g., -0.47 for TES10). The correlation between corporate excess returns and the SPX is highest for the TES1 bucket (0.64) and lowest for the TES10 bucket (0.58).

Comparing Different Liquidity Environments

Portfolio managers often remark that a market "is liquid until it is not." In other words, a market seems to have only two liquidity states: either most bonds trade easily and cheaply, or it is difficult to trade just about any bond. We see evidence of this in the LCS data. Figure 9 shows the historical time series of the Corporate Index LCS and the LCS spread between TES10 and TES1. Liquidity in the USD IG corporate market experienced a significant shock during the financial crisis of 2008. Not only did the Corporate Index LCS shoot up during the crisis, but also, and even more relevant for our analysis, so did the liquidity differential between high- and low-TES buckets. In fact, the dynamics of both are remarkably similar. Since 2009, LCS has gradually declined, although there have been a couple of bumps along the road: the European sovereign crisis in 2011 and the "taper tantrum" in 2013.

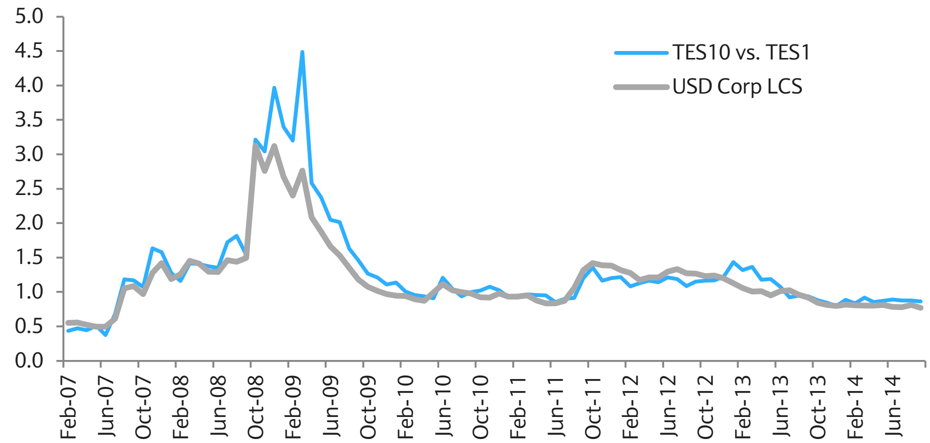
In stressed markets, liquidity deteriorates not only in absolute terms. Its intra-market distribution also undergoes significant change. Figure 10 shows the cross-sectional frequency distribution of bond-level LCS within the Corporate Index for several representative months, including a good-liquidity month of July 2007 (Index LCS = 0.609), and a liquidity squeeze month of November 2008 (Index LCS = 2.757). The July 2007 LCS distribution is highly clustered at low LCS values. In November 2008, however, the distribution not only shifts to the right, but also flattens out considerably. Looking at this example of two dramatically different market environments, we might expect a commensurate difference in the autoregressive structure of excess returns across TES buckets.

[15] Konstantinovsky, V., K Y Ng, and B. Phelps. "A Case Study: The Relationship between LCS Level and LCS Volatility" in "LCS Report – June 2013." Barclays Research. July 2013.

Accordingly, we repeat our analysis for two roughly equal sub-periods, February 2007 through December 2010, and January 2011 through September 2014. These two periods represent different liquidity regimes, with the average LCS of the USD IG Corporate Index 1.330 and 1.034 respectively. However, the LCS in the first period experienced significant volatility, whereas in the second period, it was more stable.

FIGURE 9

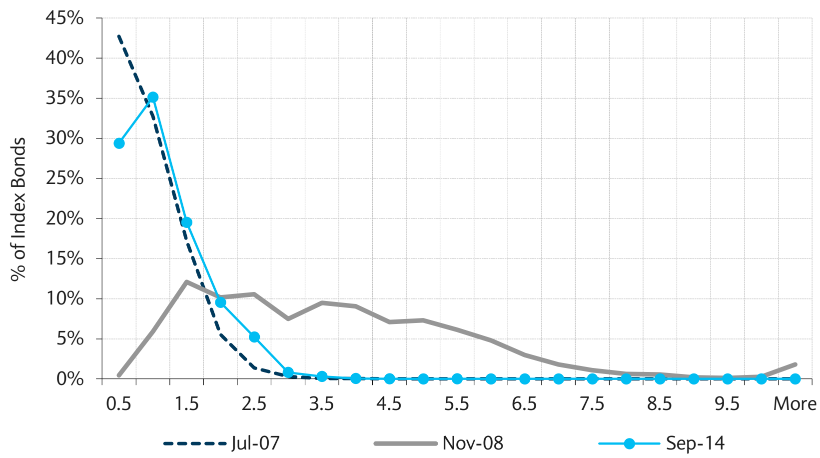
Corporate Index LCS and LCS Difference between TES10 and TES1. Monthly. February 2007 – September 2014



Source: Barclays Research.

FIGURE 10

LCS Distribution in Different Liquidity Environments. USD IG Corporate Index. Various Months



Source: Barclays Research

For the two sub-periods, we repeat the autoregression analysis of the set of indices in Figure 1. Figure 11 shows that the full-period results do not hold uniformly for the sub-periods, especially for the Corporate Index. During the first sub-period, with the higher average LCS, we see a stronger autoregressive structure of excess returns for the index, compared with the entire period. The magnitudes and t-statistics for the first lag coefficients of excess returns are considerably higher, as is the R^2 (16% vs. 11%).

In contrast, the second sub-period, uneventful from the liquidity standpoint, shows no explanatory power of lagged returns. The coefficients are insignificant, and the R^2 is essentially zero.

Why is there such a large difference in the autoregressive structure of corporate excess returns in the two sub-periods? Periods of market stress, and high liquidity costs, are also associated with markets with high market excess return volatility. In such environments, bonds that normally generate few inquiries and trades may become even more neglected compared with more actively quoted and traded bonds. In addition, firm-level news may only slowly be reflected in prices, as attention is more focused on systematic market movements. As a result, prices and returns for such less actively traded bonds will display heightened return persistence in volatile markets. In contrast, during quiet markets, participants can spend less time monitoring market-wide movements and focus more on how firm-level news affect firms' bond prices. This may explain the reduction in return persistence during quiet market environments.

FIGURE 11

Estimated Autoregression Coefficients. Various Indices. Monthly Returns. Sub-Periods

Feb 07 - Dec 10				Jan 11 - Sep 14			
	Intercept	Lag(-1)	Adj R^2		Intercept	Lag(-1)	Adj R^2
Corp ER	-0.02	**0.43**	0.16	Corp ER	0.20	-0.10	-0.01
	(-0.06)	*(3.65)*			*(1.15)*	*(-0.55)*	
Tsy TR	**0.53**	0.03	-0.02	Tsy TR	0.24	0.17	0.01
	(2.54)	*(0.25)*			*(1.95)*	*(1.49)*	
MBS ER	0.05	**0.25**	0.04	MBS ER	0.02	0.13	-0.01
	(0.67)	*(2.27)*			*(0.28)*	*(0.94)*	
SPX TR	-0.02	**0.29**	0.06	SPX TR	**1.43**	-0.10	-0.01
	(-0.02)	*(2.18)*			*(2.21)*	*(-0.59)*	

Based on the AIC, we estimate the model using one lag. Standard errors are Newey-West with a truncation parameter of 3. t-statistics are in parentheses. Coefficients in bold are statistically significant at the 5% confidence level.
Source: Bloomberg, Barclays Research

In the first sub-period, the autoregressive structure of the Treasury and MBS markets was not very different from the full period. During this time, which included the financial crisis, these two markets showed remarkable resiliency. Noticeably, the SPX exhibited some significant autocorrelation, but the model R^2 was relatively modest (6%).

Next, we examine TES bucket returns for the two sub-periods (Figure 12). The full-period results (Figure 4) showed that the TES1 bucket demonstrated no persistence in returns compared with the others, with a model R^2 close to zero, whereas the first lag coefficient for all the non-TES1 buckets was large and significant, with relatively large model R^2s. In addition, the magnitude of the coefficient and the R^2 were increasing with the TES bucket. For the first, less liquid, sub-period, we see the same pattern, but it is accentuated. For the first sub-period, even the TES1 bucket has a statistically significant first lag coefficient. However it is considerably smaller than the coefficients for the other TES buckets, and the TES1 model's R^2 was modest (6%). In contrast, all the other TES buckets had large first lag coefficients that increased in magnitude as the TES rank increased. The R^2s were generally increasing as well. There is a very good correspondence between the degree of return persistence and TES.

However, for the second, more liquid, period, there is no evidence of excess return persistence across the TES buckets. In liquid markets, prices (and, excess returns) tend to reflect available information irrespective of the TES bucket – at least at a monthly frequency. In the next section we examine whether this absence of persistence in quiet markets also holds for daily returns.

FIGURE 12

Estimated Autoregression Coefficients by TES Buckets. Monthly Returns. Sub-Periods

Feb 07 - Dec 10	Intercept	Lag(-1)	Adj R^2	Jan 11 - Sep 14	Intercept	Lag(-1)	Adj R^2
TES1 ER	-0.08	**0.28**	0.06	TES1 ER	0.20	-0.18	0.01
	(-0.23)	*(2.73)*			*(0.88)*	*(-1.00)*	
TES2 ER	0.01	**0.39**	0.13	TES2 ER	0.19	-0.12	-0.01
	(0.03)	*(3.57)*			*(1.01)*	*(-0.61)*	
TES3 ER	0.05	**0.42**	0.16	TES3 ER	0.16	-0.09	-0.02
	(0.16)	*(3.90)*			*(0.89)*	*(-0.47)*	
TES4 ER	0.01	**0.44**	0.17	TES4 ER	0.19	-0.03	-0.02
	(0.03)	*(3.46)*			*(1.20)*	*(-0.20)*	
TES5 ER	0.04	**0.46**	0.19	TES5 ER	0.19	-0.05	-0.02
	(0.11)	*(3.53)*			*(1.25)*	*(-0.30)*	
TES6 ER	0.01	**0.49**	0.22	TES6 ER	0.18	-0.02	-0.02
	(0.02)	*(3.75)*			*(1.27)*	*(-0.12)*	
TES7 ER	-0.01	**0.48**	0.21	TES7 ER	0.21	-0.06	-0.02
	(-0.03)	*(3.59)*			*(1.63)*	*(-0.40)*	
TES8 ER	-0.04	**0.49**	0.22	TES8 ER	0.20	-0.03	-0.02
	(-0.13)	*(3.94)*			*(1.41)*	*(-0.19)*	
TES9 ER	-0.05	**0.55**	0.29	TES9 ER	0.23	-0.07	-0.02
	(-0.14)	*(4.60)*			*(1.82)*	*(-0.49)*	
TES10 ER	0.00	**0.52**	0.25	TES10 ER	0.25	0.04	-0.02
	(-0.01)	*(3.91)*			*(1.97)*	*(0.27)*	
Corp ER	-0.02	**0.43**	0.16	Corp ER	0.20	-0.10	-0.01
	(-0.06)	*(3.65)*			*(1.15)*	*(-0.55)*	

Source: Barclays Research.

Return Persistence and Relative Liquidity – Daily Returns

We might reasonably expect stronger return persistence when using daily data. On a given day traders may not receive inquiries or observe quotes, much less engage in trades, for a large number of bonds in the Corporate Index. It is difficult, if not impossible, for any index provider to manually price all index bonds at a transactable level on a daily basis. New information about many bonds/issuers is likely to take a while, maybe a day or two (or three) to spread throughout the marketplace. In addition, although all bonds are priced for the index, not all bonds receive an end-of-day trader mark. Instead, some bonds are model-priced, and such prices are unlikely to fully reflect issuer-specific information.

In this section we analyze the daily autocorrelation properties of the TES buckets and the corporate market as a whole. Does TES continue to sort bonds by their relative efficiency?

Figure 13 presents the estimated daily return autocorrelation coefficients using three daily lags. The Treasury and SPX markets demonstrate daily efficiency as the autocorrelation coefficients are either statistically indistinguishable from zero or, if significant, very small (and negative). In addition, the R^2s are practically zero. Even the MBS Index shows good efficiency at daily frequency, probably a testament to the high degree of homogeneity in that market.

FIGURE 13

Estimated Autoregression Coefficients. Various Indices. Daily Returns. February 2007 – September 2014

	Intercept	Lag(-1)	Lag(-2)	Lag(-3)	Adj R^2
Corp ER	0.00	**0.36**	0.15	**0.06**	0.22
	(0.37)	*(7.67)*	*(1.87)*	*(2.07)*	
Tsy TR	**0.02**	-0.04	**-0.05**	0.01	0.00
	(3.06)	*(-1.53)*	*(-2.30)*	*(0.35)*	
MBS ER	0.00	0.11	-0.01	-0.06	0.01
	(0.71)	*(1.83)*	*(-0.37)*	*(-1.61)*	
SPX TR	0.04	**-0.15**	-0.04	0.05	0.02
	(1.30)	*(-4.39)*	*(-0.87)*	*(1.11)*	

Based on the AIC, we estimate the model using three lags. Standard errors are Newey-West with a truncation parameter of 9. Coefficients in bold are statistically significant at the 5% confidence level. Source: Barclays Research, Bloomberg.

With daily returns, the Corporate Index also stands out, even more so than with monthly returns. Its first lag coefficient is positive and significant. While the second is positive but not quite significant, the third lag is also positive and significant. In addition, the R^2 is large at 22% – double that of the model with monthly returns (Figure 1). As relatively few corporate bonds trade daily, the heavy positive autocorrelation may reflect a slow-to-adjust pricing methodology, or show that corporate bond information is slow to diffuse throughout the decentralized and privately negotiated corporate market.

We look at the two sub-periods again as well, this time using daily returns. For monthly returns we saw a stark difference in persistence at the index level between the two sub-periods. In the first, less liquid, sub-period, monthly returns reflected a slower flow-through of information and showed substantial persistence. In the second, more liquid, sub-period, we saw little persistence, implying much faster propagation of news. However, during quiet market environments, a month may be more than sufficient for any new information to get fully reflected in bond prices. But a few days may not be enough, irrespective of the market environment. The results (Figure A1 in the Appendix) bear this out: for the Corporate Index, both sub-periods reflect persistence, with a positive and significant first lag coefficient and R^2s of approximately 20%. Compared with the Treasury, Mortgage and SPX markets, only the corporate market demonstrates daily return persistence irrespective of the sub-period.

Figure 14 illustrates the autocorrelation structure of the daily excess returns for the 10 TES buckets. In contrast to monthly returns, we see that even TES1 has a positive and significant first lag coefficient that explains a significant fraction of the bucket's daily return variance (R^2 of 18%). For the TES1 bucket, however, return persistence stops at the first lag. In contrast, as we move to higher-TES buckets, we see positive, and mostly significant, second and third lag coefficients. In addition, while the R^2 does not increase monotonically with the TES bucket rank, the R^2s are generally lowest for the lowest TES buckets.

FIGURE 14

Estimated Autoregression Coefficients by TES Index. Daily Returns. February 2007 – September 2014

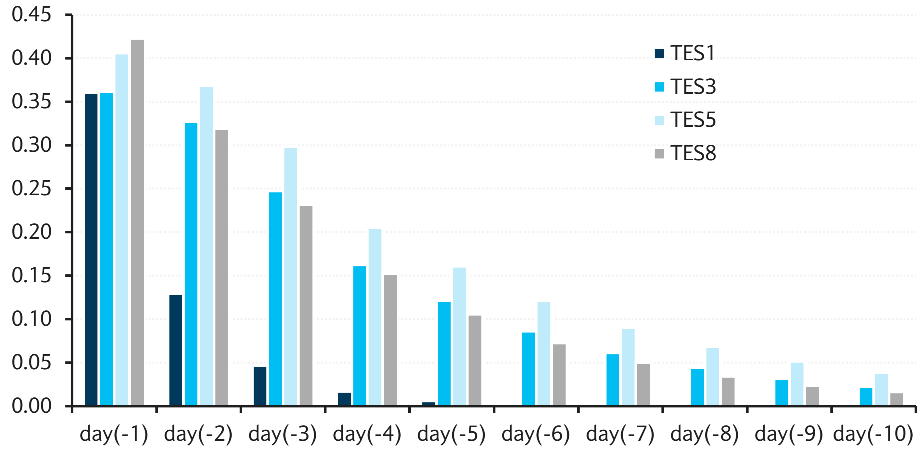
	Intercept	Lag(-1)	Lag(-2)	Lag(-3)	Adj R^2
TES1 ER	0.00	**0.36**	0.11	0.03	0.18
	(0.09)	*(7.31)*	*(1.31)*	*(0.80)*	
TES2 ER	0.00	**0.27**	**0.22**	0.03	0.17
	(0.47)	*(3.16)*	*(2.25)*	*(0.63)*	
TES3 ER	0.00	**0.26**	**0.20**	**0.09**	0.18
	(0.61)	*(3.65)*	*(3.31)*	*(3.59)*	
TES4 ER	0.00	**0.27**	**0.19**	**0.13**	0.21
	(0.48)	*(4.65)*	*(3.20)*	*(4.25)*	
TES5 ER	0.00	**0.28**	**0.21**	**0.11**	0.22
	(0.60)	*(5.81)*	*(2.93)*	*(3.01)*	
TES6 ER	0.00	**0.35**	**0.18**	0.07	0.24
	(0.55)	*(8.83)*	*(2.22)*	*(1.97)*	
TES7 ER	0.00	**0.32**	**0.16**	**0.12**	0.23
	(0.47)	*(8.27)*	*(2.38)*	*(3.61)*	
TES8 ER	0.00	**0.34**	**0.15**	**0.06**	0.20
	(0.32)	*(6.78)*	*(2.12)*	*(2.12)*	
TES9 ER	0.00	**0.33**	**0.14**	**0.09**	0.20
	(0.27)	*(7.04)*	*(2.56)*	*(2.74)*	
TES10 ER	0.00	**0.30**	**0.13**	**0.08**	0.15
	(0.79)	*(6.87)*	*(2.38)*	*(1.98)*	
Corp ER	0.00	**0.36**	0.15	**0.06**	0.22
	(0.37)	*(7.67)*	*(1.87)*	*(2.07)*	

Based on the AIC, we estimate the model using three lags. Standard errors are Newey-West with a truncation parameter of 9. Coefficients in bold are statistically significant at the 5% confidence level.
Source: Barclays Research.

For the non-TES1 buckets, the positive, and significant, second and third lag coefficients indicate substantially more persistence compared with TES1. Figure 15 plots the autocorrelation function (ACF) for several TES buckets, using daily data. The ACF shows correlation of today's excess return with returns for each of the 10 preceding days. For the TES1 bucket, with only one significantly positive lag coefficient, the correlation of today's return with yesterday's return is 0.36. However, the correlation with returns for earlier days drops off rather quickly. The pattern for other TES buckets is noticeably different. For TES3, with its three significant positive lag coefficients, today's return also has a correlation of 0.36 with yesterday's return. However, the correlation declines slowly to 0.33, 0.25, and 0.16, respectively, for returns two, three and four days ago. The pattern of decline for the TES5 bucket is even slower, with the correlation of today's return with returns five days ago still 0.16. While all TES buckets show some persistence in daily returns, the pattern for the TES1 bucket is quite different from the rest.

FIGURE 15

Autocorrelation Function (ACF). USD IG Corporates. Various TES Buckets. Daily Returns. February 2007 – September 2014



Source: Barclays Research.

What is the pattern of TES bucket returns for the two sub-periods? For the less liquid sub-period we see (Figure A2 in the Appendix) results similar to those with monthly returns: for TES1, only the first lag coefficient is positive and significant, whereas for the others, non-TES1 buckets, almost all coefficients for the first three lags are positive and significant. For the second, more liquid, sub-period, all TES buckets continue to exhibit some persistence, as the first lag coefficients are all positive and significant. Importantly, however, several higher-TES buckets have some positive and significant higher-order lags coefficients, whereas for lower-TES buckets, only the first lag coefficient is significant. Overall, the TES ranking and persistence are correlated in both sub-periods, but more so in the first one.

Figure 16 shows returns, volatility and correlations with other markets for the 10 TES buckets. The patterns here are similar to those based on monthly data (Figure 8). The TES1 bucket still has the lowest average excess return and the lowest Sharpe ratio. The excess return volatility generally declines as we move to higher-TES buckets. In contrast to the results for monthly returns, the correlation with Treasury daily returns is most negative for the low-TES buckets. As with monthly returns, correlation of daily TES returns with daily SPX returns remains highest for the low-TES buckets compared with the high-TES buckets.

FIGURE 16

Excess Return Statistics and Correlations with Other Markets, by TES bucket. Daily Returns. February 2007 – September 2014

	Index	TES1	TES2	TES3	TES4	TES5	TES6	TES7	TES8	TES9	TES10
Avg ER	0.003	0.001	0.004	0.006	0.005	0.005	0.005	0.004	0.003	0.002	0.006
StDev ER	0.19	0.24	0.20	0.19	0.19	0.17	0.16	0.16	0.18	0.18	0.17
Annual SR	0.29	0.07	0.34	0.46	0.39	0.49	0.45	0.38	0.24	0.21	0.54
Correl MBS ER	0.27	0.30	0.25	0.22	0.24	0.23	0.23	0.23	0.24	0.23	0.24
Correl Tsy TR	-0.25	-0.24	-0.26	-0.24	-0.22	-0.22	-0.21	-0.20	-0.20	-0.20	-0.22
Correl SPX TR	0.25	0.25	0.28	0.25	0.22	0.22	0.20	0.20	0.20	0.21	0.20

Source: Bloomberg, Barclays Research

Cash Bonds, ETFs, and CDX

In recent years, there has been strong growth in corporate bond ETFs. A corporate index ETF is a single security that represents a *pro rata* share of a portfolio of cash bonds held against this ETF. In a single transaction, investors obtain long or short exposure to that portfolio (sometimes called the “NAV” portfolio). However, the market ETF price does not necessarily equal the NAV price. Unlike a closed-end fund, an ETF allows the creation/redemption of ETF shares, which enables arbitrage with the underlying cash market and helps keep the ETF and NAV prices close to each other. Nevertheless, various factors make the two prices diverge. Mostly, these are liquidity-related, such as bid-ask spreads on the underlying cash bonds, and the volatility and depth of both the cash and ETF markets, which may make authorized participants more or less willing to engage in arbitrage.

For IG Corporates, one of the more active ETFs is the iShares “LQD”. This ETF is benchmarked against the Markit iBoxx USD Liquid Investment Grade Index (“IBOX”) of corporate bonds. There are differences between the IBOX and the Barclays Corporate Index.[16] In the context of a liquidity study, the most important one is the different minimum-outstanding thresholds ($750mn for IBOX vs. $250mn for the Barclays index). At the overall index level, IBOX is likely to be more liquid by construction.[17]

Might the ETF display a quicker adjustment of returns, i.e., less persistence, than the cash corporate market? Unlike a portfolio of bonds, the ETF is a single security and trades on a central (electronic) exchange. The underlying index, on the other hand, has approximately 1,300 bonds that trade over-the-counter on a bi-lateral negotiated basis. Many of these bonds may not trade on a given day. News affecting the systematic component of corporate bond returns might be reflected more quickly in the ETF market compared with the cash market which would have to wait for all 1,300 prices to be updated. We examine the autocorrelation structure of both the ETF and cash IBOX index returns.

Figure 17 shows the autoregression coefficients for the IBOX cash index, using both monthly and daily data. For monthly excess returns, IBOX has a positive and significant first lag, although its coefficient (0.24) is smaller than that for the Corporate Index (0.34 – Figure 13). In addition, the R^2 for the IBOX autoregressive model is smaller than that of the Corporate Index (5% vs. 11%), again suggesting less persistence in IBOX cash index returns. For daily ETF excess returns, the model produces no positive and significant lag coefficients, quite unlike that for the Corporate Index. The R^2 for LQD excess returns is 0% compared with 22% for the Corporate Index.

This is not surprising, perhaps, considering the different characteristics of the two indices. IBOX is a smaller index of larger cash bonds, so this may not be a fair comparison. A more interesting question would be: is the ETF market more informationally efficient than the most efficient part of the cash corporate market (i.e., TES1)? In Figure 17, we see that, for monthly excess returns, TES1 shows less return persistence. However, while the IBOX first lag coefficient is positive and significant, the R^2 is low.

Figure 17 shows a much bigger difference between the two cash indices when we look at daily returns. As mentioned, IBOX excess returns display no persistence, while TES1 shows some meaningful persistence, if only for a day or two.

[16] A Markit index factsheet can be found at *http://www.markit.com/assets/en/docs/fact-sheets/MKT_iBoxx_USD_Liquid_Investment_Grade_Index_factsheet.pdf*
[17] Approximately 70% of bonds in the iBoxx Liquid IG Corporate Index are either TES1, TES2 or TES3. This compares with 31% for the Barclays IG Corporate Index.

FIGURE 17

Estimated Autoregression Coefficients. IBOX, LQD, CDX, and TES1. Monthly and Daily Returns. February 2007 – September 2014

Monthly returns

	Intercept	Lag(-1)	Adj R^2
IBOX ER	-0.06	**0.24**	0.05
	(-0.24)	*(2.52)*	
IBOX TR	**0.44**	0.19	0.02
	(2.16)	*(1.83)*	
LQD ER	-0.09	0.12	0.00
	(-0.35)	*(1.22)*	
LQD TR	**0.48**	0.07	-0.01
	(2.12)	*(0.91)*	
CDX	**0.19**	0.04	-0.01
	(2.63)	*(0.44)*	
TES1 ER	**0.02**	0.17	0.02
	(0.11)	*(1.32)*	

Daily returns

	Intercept	Lag(-1)	Lag(-2)	Lag(-3)	Adj R^2
IBOX ER	-0.01	-0.09	0.00	0.04	0.01
	(-0.44)	*(-1.79)*	*(0.10)*	*(1.21)*	
IBOX TR	**0.02**	0.11	0.02	**0.07**	0.02
	(2.41)	*(1.24)*	*(0.33)*	*(2.06)*	
LQD ER	-0.01	-0.15	-0.13	-0.01	0.03
	(-0.48)	*(-0.95)*	*(-1.59)*	*(-0.22)*	
LQD TR	**0.03**	-0.07	-0.12	0.00	0.02
	(2.13)	*(-0.63)*	*(-1.75)*	*(0.14)*	
CDX	0.01	-0.04	-0.02	-0.06	0.00
	(1.65)	*(-0.31)*	*(-0.71)*	*(-1.08)*	
TES1 ER	0.00	**0.36**	**0.11**	0.03	0.18
	(0.09)	*(7.31)*	*(1.31)*	*(0.80)*	

For monthly returns, we estimate a one lag model (based on the AIC). Standard errors are Newey-West with a truncation parameter of 3. For daily returns, we estimate a three lag model. Standard errors are Newey-West with a truncation parameter of 9. t-statistics are in parentheses. Coefficients in bold are statistically significant at the 5% confidence level. For CDX daily returns, the estimation period is 1/7/2008 to 9/30/2014.
Source: Bloomberg, Barclays Research

What about the LQD ETF? In terms of monthly excess returns,[18] LQD shows no persistence (Figure 17), based on the significance of the first lag coefficient and the model R^2, which is somewhat better than IBOX itself and about the same as TES1. For daily excess returns, we see that LQD behaves similarly to its underlying index and shows no persistence in returns, unlike TES1.

Finally, we examine the autoregressive properties of CDX monthly and daily returns, namely the returns of the Barclays funded 5y CDX Index. Figure 17 shows that, just like LQD, CDX returns, whether monthly or daily, do not exhibit any persistence.

Relative Informational Efficiency: Cash Bonds, ETFs, and CDX

We now turn to the relative informational efficiency of these four markets where investors can express and act on their views on corporate excess returns. If, for example, past IBOX returns help explain this period's TES1 returns but not vice-versa, we would argue that IBOX is more informationally efficient than TES1. If we use return persistence as an objective measure of liquidity, we would conclude that IBOX is relatively more liquid than TES1. We can use this framework to answer other questions. For example, does LQD show any lead or lag behavior compared with its underlying IBOX cash index? Does the derivatives market (CDX) demonstrate an informational advantage versus the cash indices and the ETF?

We start by comparing the two cash indices: IBOX and TES1. Figure 18 shows that when regressing TES1 excess returns on lagged IBOX excess returns, the three lagged daily IBOX excess returns (lags 1, 2, and 3) are all positive and significant. In addition, the R^2 is a healthy 13%. In other words, lagged IBOX excess returns significantly help explain today's TES1's returns. In contrast, even though two of the three lagged daily TES1 returns are

[18] The only public data available for LQD are total returns. However, we saw that the autoregressive properties of excess and total returns can be very different. To facilitate a proper comparison, we construct an LQD excess return series as follows: we assume that the difference between IBOX total and excess returns approximates the Treasury component of returns. We then subtract this component from the LQD total return to obtain its excess return. The rationale behind this methodology is that, because LQD tracks IBOX, an interest rate hedge would be the same for both.

positive and significant for explaining today's IBOX returns, the R^2 is only 3%. This difference in informational efficiency could reflect several factors. First, IBOX could contain a more liquid subset of bonds. Or, IBOX may use a more comprehensive daily pricing methodology than bonds in TES1.

How does the informational efficiency of IBOX compare with that of its ETF? Figure 19 shows that lagged LQD monthly excess returns do not help explain today's IBOX returns. However, the reverse is also true. Lagged IBOX excess returns provide no information for today's LQD return. Apparently, the ETF and its underlying cash index absorb new information equally quickly.

These results imply that LQD is more informationally efficient than TES1. The bottom half of Figure 19 supports this. It shows that the two prior days' LQD excess returns help predict today's TES1 return, with a meaningful R^2 of 15%. In contrast, the first lagged TES1 returns explain only 4% of the LQD return variance. Although LQD trading volume is low, the centralized nature of the market and pricing transparency help information spread faster than even within the most liquid subset of the cash market, represented by TES1.

FIGURE 18

Relative Informational Efficiency: IBOX vs. TES1. Daily Returns. February 2007 – September 2014

	Intercept	TES1 ER(-1)	TES1 ER(-2)	TES1 ER(-3)	IBOX ER(-1)	IBOX ER(-2)	IBOX ER(-3)	Adj R^2
TES1 ER	0.00				**0.14**	**0.11**	**0.05**	0.13
	(0.37)				*(7.35)*	*(4.36)*	*(2.75)*	
IBOX ER	-0.01	**0.33**	-0.05	**0.17**				0.03
	(-0.64)	*(4.19)*	*(-0.39)*	*(2.69)*				

For daily returns, we estimate the model using three lags. Standard errors are Newey-West with a truncation parameter of 9. Coefficients in bold are statistically significant at the 5% confidence level.
Source: Bloomberg, Barclays Research

FIGURE 19

Relative Informational Efficiency: LQD vs. IBOX and TES1. Daily Returns. February 2007 – September 2014

	Intercept	IBOX ER(-1)	IBOX ER(-2)	IBOX ER(-3)	LQD ER(-1)	LQD ER(-2)	LQD ER(-3)	Adj R^2
IBOX ER	0.00				-0.01	0.00	0.00	0.00
	(-0.44)				*(-0.30)*	*(0.01)*	*(0.10)*	
LQD ER	-0.01	0.14	-0.02	-0.02				0.01
	(-0.45)	*(1.51)*	*(-0.25)*	*(-0.40)*				

	Intercept	LQD ER(-1)	LQD ER(-2)	LQD ER(-3)	TES1 ER(-1)	TES1 ER(-2)	TES1 ER(-3)	Adj R^2
LQD ER	-0.01				**0.60**	-0.35	0.12	0.04
	(-0.59)				*(2.61)*	*(-1.07)*	*(1.02)*	
TES1 ER	0.00	**0.12**	**0.07**	0.03				0.15
	(0.33)	*(3.96)*	*(4.69)*	*(1.25)*				

For daily returns, we estimate the model using three lags. Standard errors are Newey-West with a truncation parameter of 9. Coefficients in bold are statistically significant at the 5% confidence level.
Source: Bloomberg, Barclays Research

FIGURE 20

Relative Informational Efficiency: CDX vs. LQD and TES1. Daily Returns. January 2008 – September 2014

	Intercept	CDX(-1)	CDX(-2)	CDX(-3)	LQD ER(-1)	LQD ER(-2)	LQD ER(-3)	Adj R^2
CDX	0.01				-0.01	-0.02	0.00	0.00
	(1.45)				*(-0.40)*	*(-1.25)*	*(0.11)*	
LQD ER	0.00	**0.44**	0.03	0.10				0.02
	(0.00)	*(2.23)*	*(0.22)*	*(0.61)*				

	Intercept	CDX(-1)	CDX(-2)	CDX(-3)	TES1 ER(-1)	TES1 ER(-2)	TES1 ER(-3)	Adj R^2
CDX	0.01				0.02	-0.01	-0.03	0.00
	(1.48)				*(0.47)*	*(-0.19)*	*(-0.94)*	
TES1 ER	0.00	**0.43**	**0.24**	**0.13**				0.20
	(-0.08)	*(4.40)*	*(3.25)*	*(2.98)*				

For daily returns, we estimate the model using three lags. Standard errors are Newey-West with a truncation parameter of 9. Coefficients in bold are statistically significant at the 5% confidence level. For CDX daily returns the estimation period is 1/7/2008 to 9/30/2014.
Source: Bloomberg, Barclays Research

Next, we compare LQD with CDX. Both are baskets of corporate exposures and trade as a single instrument. Both reflect an equilibrium price of "corporate exposure." However, they have a key difference: LQD trades on a centralized exchange with full price transparency, while CDX trades over-the-counter on a bi-lateral negotiated basis. The testing of their relative informational content might help reveal the relative efficiency of their market structures.

Figure 20 shows that LQD and CDX exhibit similar informational efficiency, at both monthly (not shown) and daily level. Neither helps explain the other's returns in the next period.

Figure 20 also shows that CDX demonstrates superior informational efficiency relative to TES1. All three lagged CDX daily returns provide significant information for today's TES1 return. The model R^2 is a robust 20%. In contrast, lagged TES1 returns do not help explain today's CDX return.

Conclusion

Using our proprietary measures of liquidity, we investigated informational efficiency of the USD IG corporate bond market. Our approach is to measure the degree of excess returns persistence over time, which we consider a good proxy for market efficiency. Using both monthly and daily return series, we compared return persistence among 10 liquidity strata and found that the more-liquid segments of the market are considerably more informationally efficient than the less-liquid.

We also investigated efficiency of the relatively new investment vehicles that are steadily gaining in popularity – corporate bond ETFs, and, the somewhat more established, CDX. Our finding, which we believe has important implications for investors, was that both ETFs and CDX display considerably less return persistence (and so are more informationally efficient) than even the most liquid segment of the cash corporate market.

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Appendix

FIGURE A1

Estimated Autoregression Coefficients. Various Indices. Daily Returns. Sub-Periods

Feb 07 - Dec 10

	Intercept	Lag(-1)	Lag(-2)	Lag(-3)	Adj R^2
Corp ER	0.00	**0.35**	0.17	0.06	0.23
	(-0.06)	*(6.33)*	*(1.74)*	*(1.80)*	
Tsy TR	**0.03**	-0.05	**-0.08**	0.03	0.01
	(2.41)	*(-1.57)*	*(-3.06)*	*(0.80)*	
MBS ER	0.00	0.11	0.00	-0.06	0.01
	(0.53)	*(1.43)*	*(-0.05)*	*(-1.34)*	
SPX TR	0.01	**-0.18**	-0.06	0.09	0.04
	(0.22)	*(-4.33)*	*(-1.37)*	*(1.79)*	

Jan 11 - Sep 14

	Intercept	Lag(-1)	Lag(-2)	Lag(-3)	Adj R^2
Corp ER	0.00	**0.40**	0.07	0.06	0.20
	(1.00)	*(7.68)*	*(0.93)*	*(1.44)*	
Tsy TR	0.01	0.00	0.01	-0.04	0.00
	(1.86)	*(-0.14)*	*(0.34)*	*(-1.09)*	
MBS ER	0.00	**0.14**	-0.07	-0.05	0.02
	(0.46)	*(3.13)*	*(-1.63)*	*(-1.27)*	
SPX TR	**0.07**	-0.06	0.05	-0.10	0.02
	(2.28)	*(-1.25)*	*(0.50)*	*(-1.83)*	

Based on the AIC, we estimate the model using one lag. Standard errors are Newey-West with a truncation parameter of 3. t-statistics are in parentheses. Coefficients in bold are statistically significant at the 5% confidence level.

Source: Bloomberg, Barclays Research

FIGURE A2

Estimated Autoregression Coefficients by TES Buckets. Daily Returns. Sub-Periods

Feb 07 - Dec 10

	Intercept	Lag(-1)	Lag(-2)	Lag(-3)	Adj R^2
TES1 ER	0.00	**0.35**	0.13	0.02	0.18
	(-0.26)	*(5.91)*	*(1.21)*	*(0.63)*	
TES2 ER	0.00	**0.23**	**0.25**	0.04	0.16
	(0.09)	*(2.45)*	*(2.20)*	*(0.79)*	
TES3 ER	0.00	**0.24**	**0.22**	**0.10**	0.18
	(0.29)	*(2.98)*	*(3.27)*	*(3.25)*	
TES4 ER	0.00	**0.25**	**0.21**	**0.15**	0.22
	(0.07)	*(3.85)*	*(3.01)*	*(4.21)*	
TES5 ER	0.00	**0.27**	**0.22**	**0.12**	0.22
	(0.21)	*(4.91)*	*(2.64)*	*(2.89)*	
TES6 ER	0.00	**0.35**	**0.19**	0.07	0.25
	(0.07)	*(7.58)*	*(2.00)*	*(1.66)*	
TES7 ER	0.00	**0.32**	**0.17**	**0.12**	0.24
	(-0.03)	*(7.17)*	*(2.20)*	*(3.22)*	
TES8 ER	0.00	**0.34**	0.15	0.06	0.21
	(-0.21)	*(6.07)*	*(1.93)*	*(1.76)*	
TES9 ER	0.00	**0.34**	**0.15**	**0.08**	0.21
	(-0.31)	*(6.35)*	*(2.37)*	*(2.24)*	
TES10 ER	0.00	**0.30**	**0.14**	0.07	0.16
	(0.02)	*(6.13)*	*(2.23)*	*(1.62)*	
Corp ER	0.00	**0.35**	0.17	0.06	0.23
	(-0.06)	*(6.33)*	*(1.74)*	*(1.80)*	

Jan 11 - Sep 14

	Intercept	Lag(-1)	Lag(-2)	Lag(-3)	Adj R^2
TES1 ER	0.00	**0.41**	0.04	0.04	0.19
	(0.61)	*(10.02)*	*(0.68)*	*(0.90)*	
TES2 ER	0.00	**0.44**	0.07	0.03	0.23
	(0.85)	*(9.29)*	*(1.08)*	*(0.62)*	
TES3 ER	0.00	**0.41**	0.06	**0.08**	0.22
	(0.85)	*(7.81)*	*(0.81)*	*(1.97)*	
TES4 ER	0.00	**0.37**	0.10	0.05	0.19
	(1.09)	*(5.83)*	*(1.18)*	*(1.25)*	
TES5 ER	0.00	**0.32**	0.16	0.06	0.19
	(1.13)	*(5.81)*	*(1.93)*	*(1.36)*	
TES6 ER	0.00	**0.32**	0.12	0.06	0.17
	(1.40)	*(6.29)*	*(1.47)*	*(1.58)*	
TES7 ER	0.00	**0.30**	0.09	**0.10**	0.14
	(1.61)	*(5.28)*	*(1.11)*	*(2.43)*	
TES8 ER	0.00	**0.30**	0.10	**0.09**	0.15
	(1.45)	*(4.96)*	*(1.26)*	*(2.09)*	
TES9 ER	0.00	**0.26**	0.09	**0.12**	0.13
	(1.72)	*(4.30)*	*(1.13)*	*(2.94)*	
TES10 ER	0.01	**0.26**	0.07	**0.11**	0.11
	(2.25)	*(4.93)*	*(0.87)*	*(3.01)*	
Corp ER	0.00	**0.40**	0.07	0.06	0.20
	(1.00)	*(7.68)*	*(0.93)*	*(1.44)*	

Based on the AIC, we estimate the model using one lag. Standard errors are Newey-West with a truncation parameter of 3. t-statistics are in parentheses. Coefficients in bold are statistically significant at the 5% confidence level.

Source: Barclays Research

Analyst Certification

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