Cash-Flow Maturity and Risk Premia in CDS Markets*

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Abstract

I study the returns of portfolios of Credit Default Swaps of different maturities but the same volatility. I find average returns decrease with maturity. This variation in expected returns is captured by betas with respect to a factor: a portfolio that sells short-maturity CDSs and buys long-maturity ones. This portfolio is a market-timing factor. Its CDS-market betas are high when the price of CDS-market risk is high, but low otherwise. Accordingly, a conditional CDS CAPM explains the cross-sectional variation in returns by maturity. I embed a conditional CAPM within a structural model of credit risk and show the maturity-related beta dynamics emerge endogenously.

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1 Introduction

A class of papers ties the maturity of the cash flows of an asset to its expected returns. Lettau and Wachter [2007] argue value stocks have lower maturity cash flows and show a stochastic discount factor with only dividend growth as a priced shock can rationalize the value premium. Similarly, Van Binsbergen et al. [2010] show short-term dividend strips on the S&P 500 have higher returns than the index as a whole. On the other hand, Hansen et al. [2008] argue the cash flows of the value portfolio have higher maturity in the sense they are more exposed to shocks to the long-run component of consumption growth.

Another strain of the asset-pricing literature estimates the credit risk premium embedded in credit spreads of single-name Credit Default Swaps. Berndt et al. [2004] estimate firm-by-firm risk-neutral and natural default probabilities from credit spreads and both macroeconomic and firm-specific data, by imposing parsimonious assumptions on the dynamics of the variables studied. Pan and Singleton [2008] estimate the natural and risk-neutral dynamics of the risk-neutral default probabilities of three sovereigns. These studies, however, focus more on the overall level of credit risk premia and less on distinguishing differences in risk premia by maturity.

I study the relation between credit risk premia and maturity. To do so, I construct holding-period returns of Credit Default Swaps (CDSs) of different maturities and scale them by the inverse of their volatility. The volatility scaling reveals differences in expected returns of cash flows subject to credit risk at different horizons that are hard to see when comparing the returns of unscaled CDSs. Unscaled CDSs of different maturities have different sensitivities to shocks to the overall level of credit spreads – a kind of duration – and it turns out duration acts as a confounding variable that hazes the relation between maturity and returns.

Initially, I focus my analysis on portfolios of BBB-rated, single-name, U.S. corporate CDSs. BBB-rated firms are a natural starting point for the analysis because this rating category is widely studied in the credit risk literature (Chen [2010], Chen et al. [2009]). I later study the behavior of risk premia by maturity within low- and high-yielding names, and within the most liquid corporate credit indexes – the U.S investment grade indexes (CDX-NAIG) and the European corporate credit indexes (ITRAXX-Europe). I study CDSs instead of bonds because they are more liquid and because they allow me to build

\footnote{The BBB-rated firms are also the riskiest firms that can be included in the main U.S. corporate CDS index – the CDX-NAIG. Index inclusion should be correlated with higher underlying liquidity, because one of the criteria for inclusion is underlying liquidity itself.}
a rich cross-section of portfolios that are homogenous in everything but maturity. The latter feature will play a central role in my analysis, and the better liquidity means the differences in expected returns that I unveil are more likely to be tradable.

I find portfolios that sell short-maturity CDSs have higher volatility-adjusted returns than portfolios that sell long-maturity CDSs. Among CDSs on BBB-rated U.S. corporations from April of 2002 to May of 2012, a strategy that exploits this difference in expected returns – selling short-maturity and buying long-maturity CDSs – had an annualized Sharpe ratio of 0.98 (P-value of 0.04%). I call this portfolio LSM – long and short maturity. The high average return of the LSM portfolio is a consequence of two salient features of the data. First, a single factor explains most variation of maturity-sorted-portfolio returns and the weight of each portfolio on this factor is roughly proportional to portfolio maturity – loadings on 10-year CDSs are about three times loadings on 3-year CDSs. As a corollary, a portfolio of short-term CDSs can be well hedged with a portfolio of much fewer long-term CDSs. Second, the holding-period returns of selling unscaled long-maturity CDSs are only slightly higher than the holding-period returns of selling short-maturity CDSs. Accordingly, a portfolio that sells short-maturity CDSs and hedge this position with long-maturity CDSs has high holding-period returns as well as low volatility.

These differences in expected returns by maturity are not captured by the loadings on a market portfolio of CDSs, that is, a CDS-CAPM fails. However, the differences in expected returns by maturity do have a counterpart in comovement: the LSM portfolio prices the cross-section of CDS portfolios formed on maturity. The betas on the LSM portfolio not only explain the variation in expected returns by maturity among CDSs of BBB-rated firms, but also among both lower- and higher-yielding firms. In other words, the risk premium on exposures to LSM carries similar prices among low- and high-yielding CDSs.

Next, I analyze the failure of the CDS-CAPM and LSM’s role in pricing the cross-section of expected returns by maturity. I find the LSM is a market-timing factor, that is, the LSM has high CDS market betas when the price of CDS market risk is high, and low otherwise. That the LSM is a market-timing factor follows from two results. First, I show LSM’s conditional CDS market betas are higher when the level of credit spreads is high or the term structure of CDS spreads is flat, and lower when the level is low and the term structure steep. I measure conditional betas with a regression of LSM returns on the CDS market returns as well as CDS market returns interacted with measures of the level and steepness of

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2For example, the fact that firms of different riskiness may endogenously select different debt maturities can drive variation in expected returns across portfolios of bonds with heterogeneous constituents as empirically unveiled by Helwege and Turner [1999] and theoretically discussed by Chen et al. [2012]. That CDS spreads lead bonds more often than the reverse has been show in Collin-Dufresne and Bai [2011], Forte and Pena [2009], and Blanco et al. [2005]. Furthermore, Longstaff et al. [2005] argue that whereas bond’s reflect both a default risk premia and a liquidity risk premia, CDSs reflect only the former.
the term structure of CDS spreads. The coefficients on the interactions are both statistically significant with T-statistics of 2.41 and 4.41 for the level and slope respectively.

The second part of the argument the LSM is a market-timing factor is that high levels and flat term structures of CDS spreads forecast high CDS market returns. Considerable evidence suggests the time-series variation in average corporate-bond yield spreads reflects variation in expected returns. For example, Giesecke et al. [2011] show credit spreads fail to predict default losses in their 150-year sample, and Gilchrist et al. [2009], Philippon [2009] show average credit spreads are high when economic conditions are weak – and those times are associated with high risk-premia. The evidence regarding the predictive power of average CDS spreads is in line with those studies: the level of CDS spreads is a strong predictor of CDS holding-period returns of all maturities. For example, at the one-year horizon, the level of CDS spreads forecast CDS market returns with a 43% R-squared, a 2.25 T-statistic, and a 0.04 P-value. I complement the evidence on the information content of levels and show the steepness of the term structure of CDS spread curve is procyclical and predicts – negatively – CDS returns of all maturities. A measure of the steepness of the term structure of CDS spreads forecasts one-year CDS market returns with a 27% R-squared (T-statistic of 2.49) and a negative coefficient. In addition, I show flat term structures are markers of troughs of business cycles. A flat slope is associated with a higher likelihood of being in an NBER-defined recession, lower growth of industrial production, lower CFNAI, and higher VIX. Accordingly, a flattening of the credit curve reflects deteriorating economic conditions as measured by the same indicators.

Together, these results about the joint dynamics of LSM’s market betas and risk premia shed light on why the unconditional CDS-CAPM – an asset-pricing model with the CDS market return as a single factor – fails to price the cross-section of CDSs by maturity. Even if shocks to the CDS market return are the only priced shocks that CDSs of various maturities are exposed to, but such shocks have time-varying prices of risk, an unconditional CDS-CAPM would overprice short-term assets. Consider two assets of different maturities, but same unconditional market betas. These assets’ risk premia are equal to an average of betas multiplied by risk prices. The joint dynamics of LSM’s betas and risk premia imply this average is larger for short-term assets, because short-term asset’s market betas are high when the price of market risk is high.

These results lead me to test the hypothesis the failure of the CDS-CAPM is solely due to a failure to account for time-varying risk premia. To do so, I evaluate a Stochastic Discount Factor (SDF) that instead of featuring the LSM return, features the CDS market factor scaled by a proxy for conditional expected
returns, the lagged average five-year CDS spread of BBB-rated firms. When I use a covariance estimator robust to updating delays in CDS quotes, the conditional model prices the cross-section of CDS returns by maturity as accurately as the LSM model. In particular, the conditional model produces expected returns that are monotonically decreasing in maturity and achieves a cross-sectional R-square of 96%. Furthermore I cannot reject the null the LSM is irrelevant once the scaled return is included in the SDF. The empirical behavior of LSM’s conditional CDS market beta is remarkable – it varies considerably, even flipping signs. What can explain it? I show the maturity-related beta dynamics emerge endogenously when I embed a conditional CAPM within a structural model of credit risk. I build a structural credit risk model with exogenous but countercyclical default boundaries. The model features stochastic volatility of the SDF, of the change in value of the aggregate firm, and of the change in value that is idiosyncratic to each firm; all controlled by a single state variable with persistent dynamics. When the persistence of volatility is calibrated to match the persistence of the volatility of the market portfolio of stocks, the model generates a hump-shaped relation between the (five-minus-one) slope and the (5-year) level of credit spreads. I show this behavior of credit spreads translated to CDS market and LSM’s holding-period returns implies time-varying LSM CDS market betas that are high when risk premia are high, the level of credit spreads is high and the slope of the term structure of credit spreads flat.

The intuition for this result is that in good times, low volatility and low default boundaries implies the short-term CDS will continue to be safe even if conditions deteriorate a little further, whereas for the longer maturity asset, this same increase has a meaningful effect. On the other hand, when volatility and default boundaries are high enough, the short-term asset is at risk and each increase in volatility increases this risk meaningfully further. The effect on the longer-term yields is limited, because the quickly decaying volatility means some of the current increase in volatility is going to have little effect on the asset’s longer-term prospects. With volatility as persistent as equity price-dividend ratios, volatility and the slope generally move together, resulting in a positive unconditional correlation between slope and spreads, in contrast with both the data and the low-persistence calibration. The intuition that shocks to volatility have a dampened effect on longer-term assets no longer holds, because the shock to volatility implies volatility will still be high far into the future.3

I organize the paper in eight sections. I follow the introduction with a literature review, and then in section 2, I describe the data and explain how I compute CDS returns. In section 3, I construct portfolios and study their average returns and exposures. In section 4, I study the predictability of CDS returns.

3The statement about persistence is in the context of my model in which volatility has constant persistence.
In section 5, I study the LSM’s time-varying market betas and I propose an empirical asset-pricing model to price returns by maturity based on those findings. In section 7, I study the relation between holding-period returns and credit spreads. In section 7, I present a structural credit-risk model that rationalizes my findings. Finally, in section 8, I conclude.

**Literature Review**

Fama and French [1993] find betas with respect to TERM – the difference between the long-term government bonds minus one-month t-bill return – and DEF – the difference between the return on a market portfolio of corporate bonds and the long-term government bond – can explain the cross-sectional variation in corporate bonds expected returns across ratings. They don’t study the returns of corporate bonds of different maturities. Gebhardt et al. [2005] study the returns of bonds of different maturities, but their focus is different. Their lowest maturity portfolio has a maturity of 5.23, followed by 9.46 years; they do not study the short end of the curve, perhaps for liquidity reasons pertinent in bond market, and neither are their portfolios comprised of bonds of the same firms. Importantly, their TERM pricing factor is the same as Fama and French’s and made solely from government bonds. Antje Berndt [2010] study European CDS returns but they focus on the credit risk dimension instead of maturity. Longstaff and Rajan [2012] study the pricing of CDO’s and decompose the spreads on the CDX indexes; they do not focus on maturity.

This paper is also related to Binsbergen et al. [2011], who explore the behavior of the term structure of equity yields – similar to bond yields, but referencing risky dividends instead of fixed cash flows. Like the term structure of credit spreads, the term structure of equity yields is also flatter during bad times – October 2002, the beginning of their sample, and 2009, the financial crisis.

The paper is also related to Lettau [2011], which propose a conditional CAPM to explain the cross-section of expected returns of equity, commodities, government bonds and currency returns. I show that a conditional model also explains the cross-section of expected returns by maturity across in CDS markets.

The methodology to study credit risk premia by maturity I use is different from the methodologies of Berndt et al. [2004] and Pan and Singleton [2008] use to study credit risk. This difference reflects several my focus on portfolios of CDSs instead of single names, the relatively narrow objective of my analysis – estimate a particular set of expected returns moments and covariances – and the desire to keep to a minimum the assumptions about the dynamics of the variables I study, which I argue, played a crucial role in my analysis.
Consider first my interest in portfolios, Berndt et al. [2004] and Pan and Singleton [2008] estimates the firm-by-firm distributions of quantities of interest. To analyze the covariances of portfolios returns with variables of interest I would have to model not only the marginal distributions analyzed in those papers but also the joint distributions among hundreds of firms: a much more complex and hard to estimate object. For example, estimating the joint distribution of default times, part of what is need to extend Berndt et al. [2004], is already a daunting task – see Duffie et al. [2007].

Second, both Berndt et al. [2004] and Pan and Singleton [2008] assume a single-factor model for the risk neutral dynamics of risk neutral intensities and constant loss given defaults (in Pan and Singleton [2008] just for part of the analysis). This means that given the parameters that govern the dynamics of risk-neutral intensities, one can infer the whole curve from the spreads on a CDS of any maturity. Pan and Singleton [2008] motivates this assumption by showing that a single factor drives most of the time series variance of credit spreads at all maturities. This seemingly harmless assumption rules out a multi-factor structure for portfolio yields – and therefore the second factor in returns, which is the focus of this paper – unless it comes from non-linearities or from the yields of different subsets of firms behaving in a systematically different fashion. Heterogeneous cross-sectional behavior of intensities does not seems to be the cause of the multi-factor structure in returns, because when I break the sample according to five-year credit spreads, the flattening of the term structure happens simultaneously for all credit-spread bins.

In this way, the methodology that I employ avoids the challenges of first estimating complex joint distributions – while also avoiding the misspecification fears that accompany such exercises – when all one is after are estimates of a selected set of first and second moments. Of course, taking a more structured approach has advantages even for this narrow task. Conditional on no misspecification, ML estimators are more precise. Fortunately, for the moments in which I am interested, the methods I used provided sufficiently tight answers. Nevertheless, future projects exploring what a sufficiently flexible model would mean for the quantities I study here would be of interest.

My empirical results are also useful to help distinguish between different credit-risk models that currently match the unconditional average of the term structure of credit spreads and default probabilities. For example, Chen et al. [2009] use the stochastic discount factor (SDF) implied by an external habit formation model – Campbell and Cochrane [1999] – to price BBB-rated bonds of maturity at 4 and 10 years. They show such SDF can generate credit spreads and default probabilities (at those maturities) similar to the ones in the data. Bhamra et al. [2010] match the same moments with an SDF from a long-run risk model.
with regime shifts. These two models have similar unconditional implications about the credit-spread term structure; nevertheless, they have different predictions about the time-series behavior of the term structure of credit spreads. In Chen et al. [2009], the term structure becomes only slightly flatter when expected returns rise – the 10 minus 4 slope falls 15 bps when risk premium moves from the top 10% to the bottom 10% of its distribution. On the other hand, in Bhamra et al. [2010], 5-year credit spreads double when the economy jumps to the bad state, whereas 10-year spreads increase by about 50% (Bhamra et al. [2010], Table V), implying a strong flattening of the term structure. Furthermore, the jump to the bad state carries a positive risk premium that is qualitatively consistent with the positive returns of the LSM strategy. Bhamra et al. [2010], however, cannot address the time-varying correlations between the level and the slope of credit spreads, because volatility can only take two values in their model.

Finally, the paper also contributes to a long literature in credit risk that explores the determinants of credit spreads (Merton [1974], Berndt et al. [2004], Collin-Dufresne et al. [2001], Longstaff et al. [2005], Campbell and Taksler [2003], Bhamra et al. [2010], Schaefer and Strebulaev [2008], Zhu [2009], Chen [2010]).

2 Data

In this section, I first describe the data sources that I use and I give an overview of the data. I then briefly talk about the institutional details of the CDS market. In the last part, I describe how I compute the returns of investing CDSs.

2.1 Description of Data Sources

I use CDS spread quotes for single names and credit indexes from MarkIt, stock return information from CRSP, balance sheet information from Compustat, and default date and recovery rate information from Moody’s and Creditex. From Datastream, I obtain data on Libor and swap rates of different maturities, and also data on several Barclays government and corporate bond portfolios.

For single names, I use mid-price quotes on dollar-denominated Credit Default Swaps of documentation clause XR. I use those quotes at tenors 1, 3, 5, 7, and 10 years. For credit indexes, I use mid-price quotes on the same tenors and across all series and versions of the index.
2.2 Summary Statistics of Yields

Panels A and B of Figure 1 display the time series of average credit spreads of a portfolio of BBB-rated firms, of the CDX-NAIG U.S. corporate credit index, and of the ITRAXX-Europe index of European/Asian corporates. The portfolio of single names spikes on three separate occasions: at the beginning of the sample in late 2002, during the financial crisis around late 2008 and early 2009, and more recently in late 2011 and early 2012. The credit indexes, in their smaller sample, paint a similar picture with spikes during the financial crisis and more recently with the European-heavy index’s latest spike being almost as extreme as that observed during the financial crisis.

Panel C of Figure 1 shows the slope of the term structure of credit spreads for BBB-rated single names at several points. The slopes evaluated at different points move together, being low in the beginning of the sample and during the financial crisis. They have recently fallen, but still remain high. The second plot shows approximated forward CDS rates. In this approximation that I will motivate later, forward rates are computed as one would compute forward rates for the risk-free term structure. Long-term forward rates are generally higher than short-term ones, but during crisis episodes, the gap between short-term and long-term forwards closes.

The plot on the left side of Panel C of Figure 1 plots the 10 minus 3 slope for a portfolio of BBB-rated single names, for the CDX-NAIG credit index and for the ITRAXX-Europe. They move together after and before the crisis, but during it, the indexes became flatter than the portfolio of single names. This joint behavior of the indexes can have several explanations. First, compositions effects are present. The indexes reflect the credit risk of 125 names chosen every March and September. The portfolio that I built includes BBB- or higher-rated public firms whose CDSs are traded by three or more dealers and for which quotes for the full term structure of CDSs are available. This portfolio is rebalanced monthly instead of every March and September. Because of the equal-weighting scheme, small differences in composition engendered by the discussed dissimilarities can be large if a few extremely inverted-term-structure firms are in the indexes but not in the portfolios. Second, even if the composition was the same, basis between the index and underlying CDSs do arise and those can be quite volatile, as described in section 2.3.3.

Panel A of Table 1 displays the summary statistics for portfolio credit spreads of different maturities.
The term structure of credit spreads is on average slightly upward sloping, whereas the term structure of volatilities is gently downward sloping. The same pattern can be seen from the amplitudes – the difference between minimum and maximum sample values – which decrease almost monotonically with maturity. The fact that the volatility decays slowly with maturity implies the return volatility of selling CDSs of different maturities rises quickly with maturity, as reported in Panel B of Table 1. The annualized volatility of an one-year CDS is 202 bps, whereas that of a 10-year CDS is 12.4 %. The skewness of CDS returns revolve around -0.40, which is not a particularly large number given the turbulent sample period. For example, in the same sample the returns of the Fama-French momentum factor have a -2.49 skewness whereas the stock market excess return has a skewness of -0.62.

Table 1

2.3 CDS Market Institutional Details

CDSs are traded predominantly in over-the-counter markets even though recently (last quarter of 2011), in anticipation of regulatory changes pushing more credit derivatives to central clearing houses and exchanges, electronic trading platforms have started appearing both for single names and credit indexes.\(^5\) The credit derivatives market saw rapid growth in the 2000s, with the total notional outstanding in CDS contracts going from $ 10 trillion in June of 2005 to about $30 trillion in December of 2011, after peaking at almost $60 trillion in 2007, as depicted in Panel A of Figure 2. Since that time, total notionals have fallen but it is not clear whether economic exposures followed the same path, because this fall in total outstanding values happened at the same time industry participants were trying to net offsetting trades among themselves. To gain some perspective of the magnitude of those contracts, note the much-studied market for equity derivatives had a total notional outstanding in Dec 2011 of less than $6 trillion, whereas CDSs had a total of $ 28.6 trillion of which $16.8 trillion were single-name instruments and $10.4 trillion were indexes products (the residual are non-index multi-name CDSs). The total outstanding in indexes products is almost double the total in equity derivatives.

Figure 2

Much of these notionals refer to five-year contracts, but the amount of longer- or higher-maturity CDSs is not trivial. In Panel B of Figure 2, I plot the time series of a breakdown of total notionals outstanding by maturity. One-year or younger CDSs represented between 5% and 15% of the volume, and five-year or older CDSs represented between 12% and 23% of the volume.

Of course, total notionals are a rather raw measures, because they do not measure the economically interesting net exposures. As of December 2010, those exposures amounted to $2.3 trillion. That is, if all firms default and their assets become worthless, then protection sellers would lose $2.3 trillion. This scenario is extreme, but it highlights the economic significance of credit derivatives.

Next I discuss the details of CDS contracts and the most important changes that these contracts have experienced in recent years. I first go over the details for single-name CDSs, followed by those of credit indexes.

2.3.1 Single Names

Credit default swaps are similar to insurance contracts on a corporation’s bonds. The buyer of protection (short risk) on a CDS pays periodic coupons, for example, quarterly, as long the underlying firm has not had a credit event. When a credit event occurs, the CDS buyer receives a payoff economically equivalent to the difference between the face value of the reference bond and the value of this instrument after the default. This payoff can take two forms: the CDS buyer may sell the CDS seller the underlying bond for a price equal to the bond’s par value, or the CDS buyer may receive a cash amount equal to the difference between the bond par value and the price of the same bond in a settlement auction occurring after the credit event. The auction mechanism is more recent and has become the standard settlement mechanism in ISDA’s benchmark CDS contract. Since 2005, more than 100 credit auctions have occurred successfully, including some high-profile ones such as those of Lehman Brothers, General Motors, Delta Airlines, American Airlines, and Eastman Kodak.

Besides the periodic payments and the payments upon default, CDSs may also involve economic transfers upfront. Before March 2009, the standard CDS contract for non-high-yield corporations had the CDS premium set such that no economic upfront payments were made. In this way, if a corporation were riskier, this added risk would show up only in higher periodic installments. This way of setting CDS periodic payments’ is not the case for the standard CDS contract on all firms after March 2009 and on

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high-yield ones even before. The standard contract now is a fixed-coupon one which means the periodic payments are fixed at a constant fraction of the notional, and the differences due to risk are off set by initial economic transfers.

In the United States, the fixed coupons come in 100 and 500 basis (per year) points, with safer names being traded at 100 basis points and riskier names at 500. For example, if the market priced Kodak as a larger default risk than Apple, but both were traded at the 100-basis fixed coupon, the purchaser of Kodak would pay more or receive less of an initial payment than the purchaser of Apple protection.

Even though the standard CDS contract is now the fixed-coupon one, single names are still quoted in running spreads. To translate those quotes to upfront payments, one has to use the so-called standard CDS model.\textsuperscript{7} This model features a set of assumptions about recovery rates and the shape of the term structure of hazard rates under which there a one-to-one mapping is present between upfront payments and running spreads.

Of course, CDS are over-the-counter instruments, and what I described are non-binding standards. A priori, nothing stops a hedge fund from asking a dealer desk for a customized contract; however, practically speaking, these custom-made contracts are likely to be less liquid and hence one should avoid them if the standard contracts are sufficiently close to the desired economic payoff.

2.3.2 The 2009 CDS Big Bang

In March of 2009, CDS contracts changed along a number of dimensions. Importantly, as discussed above, the new standard for CDS contracts is no longer the running-spread. CDSs now have fixed coupon payments of either 100 or 500 bps and offsetting upfront payments. A non-exhaustive list of other changes include the hard-wiring of the use of an ISDA committee to formally define a credit event and the use of auctions to settle CDSs in case of credit events.\textsuperscript{8}

2.3.3 Credit Indexes

The two main corporate credit indexes are the CDX-NAIG, where NA stands for North America and IG for investment grade, and the ITRAXX-Europe.\textsuperscript{9} These indexes are CDSs whose underlyings are bonds

\textsuperscript{7}http://www.cdsmodel.com/cdsmodel/
of multiple issuers (instead of a single issuer). Like the fixed-coupon individual CDSs, the indexes also feature an upfront payment and a fixed installment. In case of default, the protection buyer receives \( \frac{\text{Notional}}{\text{Number of Firms}} \times LGD \), where \( LGD \) stands for loss given default. Between the announcement of a default and the time of the settlement auction, the credit spread on the index will reflect the (risk-neutral) expected loss given default of that entity. After a default, a new version of the index is rolled out, with a smaller notional and excluding the defaulted name. This new version tends to become liquid after the settlement auction, with market participants choosing to roll into the new index by then.

Credit events are not the only way the constituents of these indexes change. Every March and September, new indexes series are created and the constituent list is revised, for example, including new names to make up for those who defaulted or excluding names that no longer match the index requirements (e.g., because of a rating downgrade). This rolling process also ensures that indexes will always exist with remaining maturities close to the nominal maturities. Remember by that time, the indexes will be six months old, which means a five-year index is truly a four and a half one year one. Finally, with each roll, the index committee sets a new fixed coupon. Market participants tend to roll into the new series of the indexes: this pattern is clear in a plot of notional traded as a function of date. The notionals traded on old vintages decrease quickly whereas those traded on new vintages increase.

The credit indexes, such as the single-name CDSs, are also traded at various maturities: 1,3,5, 7, and 10 years. The five-year tenor is the most liquid, but other maturities excluding the one-year are also liquid – at least as measured by the relatively tight bid-ask spreads. For example, from March 2012 to May 2012 the on-the-run five-year CDX-NAIG index traded on a 97-basis-points average spread and its bid-ask spreads were 1.04 bps, 0.56 bps, 1.40 bps and 1.21 bps for the 3-,5-,7- and 10-year maturities, respectively. This information was not available for the one-year contract because the number of dealers covering this market was bellow the Markit threshold of three dealers, which indicates this tenor is less liquid than the remaining tenors.

Finally, although the indexes are sometimes not exactly portfolios of CDSs (e.g., they may have different fixed spreads), their cash flows are quite similar, and we can reasonably expect arbitrageurs to keep those differences in line with trade costs. That said, from January 2011 to June 2012, the average differences between the model and index spreads, the index basis, for on-the-run indexes were:
<table>
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<tr>
<th>CDX-NAIG</th>
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<tbody>
<tr>
<td>Average</td>
<td>std</td>
</tr>
<tr>
<td>1Y</td>
<td>-11bps</td>
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<tr>
<td>3Y</td>
<td>-3.4bps</td>
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<tr>
<td>5Y</td>
<td>+1.5bps</td>
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<td>7Y</td>
<td>+6.92bps</td>
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<tr>
<td>10Y</td>
<td>+8.85bps</td>
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</tbody>
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Source: MarkIt.

These averages and volatility in basis will be important when comparing portfolios of CDSs and credit indexes results.

### 2.4 Constructing CDS Holding Period Returns

For most of my analysis, I will treat all CDSs as running spread CDSs. This assumption is true for non-high-yield single names before March 2009 and implies some approximation after that date. In unreported results, I replicate some equivalent calculations under the assumption that the CDSs have fixed coupons, and show the results are the same. In the calculations that I display, I will assume that the coupon payments are continuous, because it makes calculations clearer. The fact that payments are quarterly make computations a little messier and will have negligible effects in close-to-zero short-term interest environments.

The holding-period excess return (or, simply, return; I will use the terms interchangeably) of selling a running-spread CDS of maturity \( N \), spread per period \( y_t^N \) is given by

\[
rsCDS_{t+1} (y_t^N, N) = 1_{\tau > t+1} \left[ y_t^N - p \left( y_t^N, N - 1, t + 1 \right) + p \left( y_t^N, N, t \right) \right] + (1 - 1_{\tau > t+1}) LGD_{t+1},
\]

\[
= 1_{\tau > t+1} \left[ y_t^N - p \left( y_t^N, N - 1, t + 1 \right) \right] + (1 - 1_{\tau > t+1}) LGD_{t+1},
\]  

(1)

where \( 1_{\tau > t+1} \) is an indicator that \( \tau \), the default time, is greater than \( t + 1 \), \( p \left( y_t^N, N - 1, t + 1 \right) \) is the price at time \( t + 1 \) of a \( N - 1 \) periods CDS with fixed coupon \( y_t^N \), and \( LGD_{t+1} \) is the loss given default at time \( t + 1 \). Data are available for all the variables above except \( p \left( y_t^N, N - 1, t + 1 \right) \), which is the value.

\(^{10}\)In the true calculations I will take into account that payments are quarterly.
of a \( N - 1 \) periods CDS with a fixed coupon \( y_t^N \) at time \( t + 1 \). This valuation can be written as

\[
p(y_t^N, N - 1, t + 1) = p(y_{t+1}^{N-1}, N - 1, t + 1) + (y_t^N - y_{t+1}^{N-1}) \times RD(N - 1, \Theta_{t+1}), \tag{2}
\]

where

\[
RD(N - 1, \Theta_{t+1}) = \int_0^{N-1} P^{RN}(\tau > t + 1 + i, \Theta_{t+1}) D(t + 1, t + 1 + i, \Theta_{t+1}) di
\]

is the value today of a stream of payments of 1 that lasts until \( t + 1 + N \) or \( \tau \), whichever comes first. \( P^{RN}(\tau > t + 1 + i, \Theta_{t+1}) \) is the risk-neutral probability that the firm survives until \( t + 1 + i \), and it is controlled by state variables \( \Theta_{t+1} \), and \( D(t + 1, t + 1 + i, \Theta_{t+1}) \) is the discount function that discounts risk-free cash flows at \( t + 1 + i \) to \( t + 1 \), also controlled by state variables \( \Theta_{t+1} \).

The first term of equation 2 is the price of a running-spread CDS with maturity \( N - 1 \) at time \( t + 1 \), and is zero by definition. The second term is the present value of a stream of payments equal to the difference between the fixed payments of the contract sold at time \( t \), \( y_t^N \) and the fixed payments on a contract that offers the same default protection at time \( t + 1 \), \( y_{t+1}^{N-1} \). This formula has an intuitive interpretation. If you sell an \( N \)-period CDS at time \( t \), and at time \( t + 1 \) purchase an \( N - 1 \) period CDS with the same notional, your net payoffs will be a stream of \( y_t^N - y_{t+1}^{N-1} \) lasting for the minimum of the time the firm survives \( \tau - t + 1 \) and \( N - 1 \).

The valuation of those payoffs depends on risk-neutral survival probabilities and the risk-free discount function. Suppose both are 1 (no discount and no defaults); then \( RD(N - 1, \Theta_{t+1}) = N - 1 \) is the number of installments to which you are entitled to. Clearly \( RD(N - 1, \Theta_{t+1}) \) is a measure of the duration of those payments. In more general settings, the duration idea is similar, hence the term "risky duration" for \( RD(N - 1, \Theta_{t+1}) \).

The valuation problem of an aged CDS now depends on \( \{P^{RN}(\tau > s, \Theta_{t+1}), D(t + 1, s, \Theta_{t+1})\}_{s=t+2}^{t+N} \) and \( y_{t+1}^{N-1} \). The discount rate function \( \{D(t + 1, s)\}_{s=t+2}^{t+N} \) can be bootstrapped from Libor rates and swaps as is common in the fixed-income literature. The risk-neutral default probabilities and the \( N - 1 \) CDS spreads may have to be extrapolated from quotes on the CDSs of other maturities. To illustrate the relative importance of these two terms, note that in a linear approximation close to zero capital gains
\[ y_t^N - y_{t+1}^{N-1} = 0 \], the capital gains of the CDS strategy are given by

\[
CG_{t+1} \approx GC_0 + \frac{\partial GC}{\partial (y_t^N - y_{t+1}^{N-1})} |_{x,y=x_0,y_0} (y_t^N - y_{t+1}^{N-1}) + \frac{\partial GC}{\partial \Theta_{t+1}} |_{x,y=x_0,y_0} (\Theta_{t+1} - \Theta_0),
\]

\[
\approx RD (N - 1, \Theta_0) (y_t^N - y_{t+1}^{N-1}).
\]

The fact that \( RD (N - 1, \Theta_0) (y_t^N - y_{t+1}^{N-1}) \) does not depend on \( \Theta_{t+1} \) means only shocks to \( y_{t+1}^{N-1} \) have a first-order impact on capital gains. For this reason, I verify the robustness of my conclusions to several extrapolation methods for \( y_{t+1}^{N-1} \) in unreported calculations. Next, I talk about how I treat default and other issues.

**Default Treatment for Single Names** For the defaults covered by the Creditex database, which has the outcome of all settlement auctions since 2005, I use the default date and recovery rate provided by Markit. These data are ideal for computing CDS returns, because they measure the exact payoff to CDS traders.\(^\text{11}\) I complement this database with Moody’s Investor Service database on corporate defaults. This database will take care of the defaults before 2005 and also those between 2005 and 2009 that were not settled by auctions (non-standard until then). This database has information on the price of bonds after the default, which I use to compute recovery rates. Sometimes, I observe CDS quotes after Moody’s reports a default. I ignore those quotes and treat such CDSs as if a default had occurred and the recovery rate was the one implied by Moody’s data.\(^\text{12}\)

**Data Gaps and Non-default Missing Quotes** I find 90 cases in which the CDS quote of a firm becomes unavailable and for which I cannot detect a default. Firms can exit the database because they were acquired, because their CDSs stopped being traded, or because of an undetected default. The latter case is unlikely. I study only public firms, so a missed default would have to be missed by CRSP, Moody’s, and Creditex databases simultaneously. I find 999 returns missing due to gaps in the data. Whenever a gap is present, I input a missing return, which means the strategy unwinds the position one month before the gap. My return universe has a total of 48,475 returns (for each maturity), so the number of gaps is

\(^{11}\)I also do a manual check to ensure all public companies for which a settlement auction was held are included in my database. I need this manual check because I match CDS data in Markit with CRSP data in a two-stage procedure where I first match companies by ticker and names, using a high threshold for spelling distances and then I manually check for the quality of the matches. This conservative matching process means some companies may be left out if both identifiers differ across the databases. But no Creditex default will be left out, because I go back and match any previously unmatched firm that eventually defaults.

\(^{12}\)I also entertain the alternative that the default has not happened and I just offload those CDSs at quoted spreads and take no more positions from the on and the results are very similar.
about 2\% the number of returns. I replicate the key results in a continuously-quoted database only, and the results are unchanged.

**Default Treatment for Credit Indexes**  As explained before, when a default by any constituent of an index occur, the expected recovery rate and the default should manifest itself in the spreads of the current version of the index trade (i.e., spreads go up just enough to acknowledge the expected disbursements due to this default), so by trading out of the index shortly after a default, I already account for default losses without explicitly computing those payoffs.

### 3 Expected Returns by Maturity and Their Betas

In this section, I show the expected returns of the constant-volatility CDS portfolios are decreasing in maturity and this cross-sectional variation in expected returns can be explained by betas with respect to a portfolio that sells short-maturity CDSs and buys longer-term ones.

#### 3.1 Portfolios of Single Names

I focus on the returns of portfolios of CDSs of BBB-rated firms. Later I study portfolios sorted on 5-year credit spreads without censoring based on ratings.

I construct portfolios monthly. I form equally-weighted portfolio returns by averaging the returns of all CDS of BBB-rated firms that satisfy the following criteria. First, they must have CDS quotes on 1-, 3-, 5-, 7-, and 10-year tenors at the beginning of the month. Second, at least three dealers must quote their 5-year CDSs. Last, their five-year credit spreads at the beginning of the period must be smaller than the 95th percentile among all BBB-rated firms. This latter criterion avoids a few high-spread CDS returns dominating the equally weighted portfolio.\(^{13}\)

For each maturity 3, 5, 7, and 10, I then calculate equal-weighted monthly excess return from selling those CDSs are then calculated. I then divide each of these portfolio returns is then divided by their sample portfolio volatility and multiply by 500, such that all portfolios have volatility equal to 500 bps per month, roughly the volatility of the value-weighted market portfolio of stocks. I create constant volatility portfolios.

\(^{13}\)Again, I will also study 5-year spread sorted portfolios which will not suffer from such censorship.
because differences in returns of cash flows of different maturities are going to show up more starkly among those portfolios.

To see why, note that a CDS is a bundle of forward CDSs of different maturities. Each forward with the same premium and same notional:

$$rsCDS^N = rsCDS^1_{t+1} \left( y_t^N \right) + rsCDS^{1 \rightarrow 2} \left( y_t^N \right) + \cdots + rsCDS^{N-1 \rightarrow N} \left( y_t^N \right).$$

The returns of CDSs of different maturities, therefore, reflect both the expected return of each forward, but also the quantity of those forwards of which one is made. The latter effect is going to be particularly influential in the excess return of the entire bundle (the CDS). For example, in a world with a flat term structure of credit spreads, a constant term structure of credit-risk premia shows up as CDS returns that grow linearly with maturity, and non-flat term structures of risk premia would show up as concave or convex term structures of full CDS realized returns. Clearly, simple CDS average returns are not objects on which one wants to focus when looking for differences in cash-flow returns by maturity.

Consider instead the constant volatility portfolios on which I focus. The inverse of volatility adjustment is roughly equivalent to leveraging CDS returns by a measure of their duration. In this case, riskier short-maturity cash flows show up as higher low-maturity constant-volatility CDS returns. Moreover, this leverage adjustment makes intuitive sense, because the adjustments make portfolios more comparable much like portfolios of stocks sorted on different characteristics are.\(^{14}\)

Finally, whatever factor prices the cross-section of scaled portfolios also prices any linear combination of them, including the original unlevered CDSs.

In Figure 3, I display the monthly returns of constant-volatility CDSs and also their annualized Sharpe ratios, along with two-standard-deviation error bars. The returns decrease monotonically from 184 bps per month at the one-year maturity to 42 bps per month at the 10-year maturity. The annualized Sharpe ratios go from 0.83 to 0.27. The error bars show the 122-month sample means of those returns have high volatilities compared with their point estimates, but those individual error bars do not allow for inferences about differences in expected returns, because of the strong correlation between returns of different maturities. To test the null that returns are decreasing on maturity, I construct a portfolio that sells short-maturity CDSs and buy long-maturity CDSs. I construct this long and short portfolio as the

\(^{14}\)Portfolios of stocks sorted on, say, size or book to market do not have volatilities that vary by factors of 3 or more as in the credit portfolios I study.
second principal component, a slope factor, of those returns. This procedure uses the information in all portfolios instead of focusing on just the extreme portfolios as the popular ad hoc choice of weights $1, 0, \ldots, 0, -1$.

Figure 3 about here.

Figure 4 displays the results of the principal component analysis. I focus on the analysis of excluding the one-year CDS, because of the evidence suggesting this maturity is particularly illiquid. The first principal component (PC) accounts for 99% of the variation in returns, with the slope factor accounting for the other 1%. Although the first PC accounts for so much of the volatility, it cannot do much in terms of cross-sectional pricing, because it is a level factor, which means factor loadings are roughly constant across maturities. The second PC is a slope factor, and its loadings are monotonically decreasing in maturity, suggesting that they may indeed capture the pattern of expected returns.

Figure 4 about here.

In Table 2, I display the summary statistics of the first two principal components. The first statistical factor has an average return of 1.33% per month and a volatility of 9.94%, resulting in a monthly Sharpe ratio of 0.13 and an annualized Sharpe ratio of 0.39 (P-value $> 10\%$), where the annualized Sharpe ratio accounts for possible autocorrelation in returns as in Lo [2002]. Although this first factor accounts for a large fraction of the volatility of all series and has high mean returns, its mean return is not statistically significant. The P-values for the null the mean return is zero are always below 5%, no matter which way I compute standard errors; neither 24-lag Newey-West T-statistics nor the 12-month-window circular block bootstrap of the entire sample result in P-values greater than 5%.

Table 2 about here.

The second principal component, the LSM return henceforth, is much less volatile, with a monthly standard deviation of 1%. Its expected returns are lower than those of the first factor, but its much lower volatility translates into a higher Sharpe ratio of 0.45 at monthly horizons and 0.98 (P-value $< 0.00$) at yearly horizons.
Accordingly, this factor’s mean returns are statistically different from zero, as implied by both the 12-lag Newey-West T-statistic of 2.48 and the block bootstrap P-value.

I estimate mean returns in a sample of 122 months. To increase the precision of those mean-return estimates, I construct an alternative estimator of mean returns that relies also on a long time series of bond returns. CDSs and bonds are tied by a no-arbitrage relation; hence, their returns should be correlated. This correlation implies bond expected returns should be informative about CDS expected returns. The longer time series of bond returns implies more information about bond mean returns that can be harnessed to shed light on CDS mean returns. To incorporate the information in bond’s returns into CDS mean returns estimates, I construct corporate bond excess returns by subtracting from a Barclay’s corporate bond portfolio the Barclay’s government bond portfolio with the closest duration, where duration is measured as the slope coefficient of a regression of returns on yields. I do this procedure for the Barclay’s intermediate maturity and long maturity, obtaining two return series. I use a GMM estimator that can handle moments with unequal sample sizes to estimate the factor’s mean returns. This estimator is the long estimator in Lynch and Wachter [2008]. For more details, see section ?? in the Appendix.

Using the information in bonds has little impact on the point estimates of the factors’ expected returns reported in Panel B of Table 2. The first factor has almost the same mean return in both estimates, but its T-statistic increases to 2.64 (from 1.78), when the information in the bond returns is incorporated. The LSM return has a slightly lower estimate of mean returns – 40.7 bps per month versus 45.06 bps per month – when I take into account the information in both bonds. However, its Newey-West 24-lags T-statistic also increases from 2.48 to 2.80. This high Sharpe ratio adds to the pattern in betas to suggest this statistical factor is a strong candidate for pricing the cross-section of CDS returns. I tackle this question now. Because the two factors are returns, I use time-series tests of asset-pricing models (Cochrane [2005]). More precisely, I test the model:

\[ r_{CDS_{t+1}} = \beta_1 E [R_{1st_{t+1}}] + \beta_2 E [LSM_{t+1}] . \]

I display actual and model-implied expected returns in Panel A of Table 3. The model closely fits the returns of all maturities and, as a consequence, the GRS test cannot reject it. Even though time-series tests are powerful because they fix factors’ risk premia to be the factors’ sample average returns, the fact that there are 2 factors to price 4 portfolios gives rise to doubts about the result’s reliability. To allay those fears, I show the maturity factor constructed from BBB assets successfully explains the cross-sectional
dispersion of expected returns by maturity among CDSs of other levels of credit risk, for a total of 20 portfolios.

[Table 3 about here.]

3.1.1 Returns by Maturity among Other Levels of Riskiness

Now I broaden my analysis to include all public firms with traded CDSs. I sort firms into five groups according to their five-year credit spreads. Then for each spread group, I compute equal-weighted returns of selling CDSs of maturities 3, 5, 7, and 10. Next, as I did previously for BBB-rated firms, I create constant-volatility returns where I choose the volatility of the five-year CDS return as the reference volatility for each group. The first plot of Figure 5 reports the average return of all 20 portfolios. Strikingly, among all risk classes, returns always fall monotonically with maturity. Average returns also rise with credit spreads. This pattern in returns is consistent with the result that lower-graded corporate bonds have higher returns than higher-graded ones in Fama and French [1993] – the five-year credit spread can be thought of as an updated rating.

[Figure 5 about here.]

The sorts on credit spreads add another dimension to expected returns. To account for this extra dimension, I add a third factor to the asset-pricing model that I used in the last section. I also replace the overall CDS portfolio made solely from BBB-rated firms with one made from all firms. In sum, I propose the following three-factor model:

\[ ER_{t+1}^{i,k} = \beta_1^i R_{t+1}^{MKT, ALL} + \beta_2^i [HSMS_{t+1}] + \beta_3^i E [LSM_{t+1}] , \]

where \( R_{t+1}^{MKT, ALL} = \frac{1}{4 \times N} \sum_{i \in \{3,5,7,10\}} \sum_{k=1}^{5} R_{t+1}^{i,k} \) is the return of a market portfolio of CDSs of all ratings and maturity, \( HSMS_{t+1} = \sum_{i \in \{3,5,7,10\}} R_{t+1}^{i,5} - R_{t+1}^{i,1} \) is the return of a high-spread minus a low-spread portfolio, and \( R_{t+1}^{i,k} \) is the return of a portfolio of maturity \( i \) and credit risk \( k \), scaled to have volatility equal to \( \sigma \left( R_{t+1}^{5,k} \right) \). I add \( HSMS_{t+1} \) to account for the differences in expected returns induced by credit-spread sorts.
The first plot of Figure 6 reports the realized returns of each portfolio minus the expected return predicted by the non-maturity factors in blue and the maturity-factor-predicted returns in red. This maturity factor explains 63% of the cross-sectional variation in expected returns that the first two factors could not explain. This first plot also says the betas on the HSMLS portfolio do not line up with maturity.

The second plot of Figure 6 reports the realized returns of each portfolio in blue and the model-predicted returns in red. The three-factor model explains 94% of the cross-sectional variation in expected returns and the mean-absolute value of the model’s alphas are only 25% of the original mean-absolute value of mean returns. The model, however, is still statistically rejected (P-value <-0.01) as reported in Panel B of Table 3. The rejection occurs because the high average time-series R-square of 96% implies that even small pricing errors are significant enough to reject the model.

I also consider a second set of returns that isolates the maturity effects from the spread-risk effects on average returns. In this way, I can sidestep the pricing of credit risk that is related to credit spreads while still studying the pricing of term risk. I call those returns that isolate maturity effects hedged returns. For each sort on credit spreads, I compute their first principal component (PC) and then construct a hedged return by subtracting from the raw return the product of its weight in the level factor times the level factor. I display those returns in the second plot of Figure 5. The average returns of the hedged portfolios are also decreasing in maturity.

For these hedged returns, I consider a single factor model:

$$E \left[ R_{i,k,hedged}^{t+1} \right] = \beta_2 E \left[ LSM_{t+1} \right],$$

where $R_{i,k,hedged}^{t+1} = R_{i,k}^{t+1} - \gamma_i R_{1st,k}^{t+1}$ is the $i$th hedged return. This procedure isolates the maturity-related expected returns by first hedging each portfolio with respect its own spread group’s overall portfolio, but at the same time, it demands the risk premium for maturity exposures to be the same across different levels of credit risk. The third plot of Figure 6 displays actual and realized CDS returns for this model. Again, realized and expected returns are close as summarized by the 93% cross-sectional R-squared. Furthermore, a GRS test (Pval>0.1) cannot reject the model as reported in Panel C of Table 3. These test results are
subject to the caveat that standard errors do not account for the estimation error in the hedge ratio of the two portfolios.

### 3.1.2 The Long-Short Maturity with Credit Indexes

In this section, I show constant-volatility short-maturity CDSs also have higher returns than long-maturity among the two main corporate CDS credit indexes – the CDX-NAIG and the ITRAXX-Europe. These results help address several concerns regarding the robustness of the findings among single-name portfolios.

First, because the indexes are more liquid than the single names, liquidity alone is not likely to be driving the results that I show. Second, because of small bid-ask spreads (about 1 bps in 2011 overall maturities), the results using the indexes also imply an easy and cost-effective way exists to construct the strategies that I study here; hence it is of use to practitioners. Third, credit indexes have quotes for seasoned CDSs (e.g., 4 years and 11 months); hence no curve extrapolation is needed for this first-order component of returns, and hence the returns with the index provide some validation for the extrapolation that I employ with single names. Fourth, the ITRAXX-Europe covers European and Asian firms. This geographical dispersion helps allay fears that a phenomenon particular to U.S. firms drives the results I show.

That said, the sample of returns of credit indexes is smaller: from 200603 to 201205, which makes inference less reliable. Panel A of Table 4 has the summary statistics of the slope factor of indexes’ returns of maturities 3, 5, 7, and 10. The annual Sharpe ratios are 0.76 and 0.53 for the ITRAXX and CDX indexes, respectively. These ratios are smaller than the approximate 0.9 of the single-name portfolios. The 24-lag Newey-West T-statistics for mean returns are 1.76 and 1.5, which means two-sided P-values of 7.5% and 13.3%, respectively. An alternative inference with a bootstrap from an AR(12) yields P-values of 5% or less for both.

Next I compare the returns of the strategies from single names and the indexes. The results are in panels B and C of Table 4. At monthly horizons, the R-squares are low – 10% and 19% – for ITRAXX and CDX, respectively – but grow quickly with the window size: 65% and 52%, respectively, at six month horizons. Several factors preclude index and single-name portfolios’ returns from being perfectly correlated.
Differences in portfolio composition: the CDX indexes include closed firms and debt of higher-than-BBB-rated firms. Second, differences in the timeliness of the quotes may be present, with some single names being updated less often than the index. This explanation is consistent with the quick rise in R-squares as correlation windows expand. Third, because of transaction costs, differences in the credit spreads of portfolios with the same cash flows – basis – can and do arise between the index and a hedging portfolio of single-name CDSs. If the basis are time varying and volatile, as they seem to be, these basis will be yet another source of differences.

4 Predicting CDS Market Returns

In this section, I build the first part of the argument the LSM is a market-timing portfolio. I study CDS returns predictability. I evaluate the predictive power of measures of the level and steepness of the term structure of credit spreads. I follow a large literature in credit risk when I evaluate the return-forecasting power of the level of credit spreads. For example, Giesecke et al. [2011] shows average credit spreads fail to predictive 4-year defaults in a 150-year sample. I also study the slope of the term structure of credit spreads because the level of credit spreads alone may be an imperfect predictor of CDS market returns. Some of its volatility may also reflect time-varying expectations about future changes in credit spreads. The slope is a natural addition because, after shifts in level, it captures most of the common volatility in the term structure of CDS spreads. In the appendix B.4, I develop a set of identities and approximations that tie the steepness of the term structure of CDS spreads to expected returns.

I find both the level and the slope, individually, forecast CDS market returns. However, when both are combined, the slope only marginally improves level-based forecasts.

4.1 Predictive Regressions

The first issue I have to discuss is the choice of predictors: the measures of the level and the slope. I measure the level as the average 5-year CDS spread of the BBB-rated firms which satisfy the same data requirements that I use in the BBB-portfolio construction. On top of those requirements, I also censor CDS spreads above 30,000 bps when I construct the mean spread, because I want to avoid a outlier dominating the average. BBB-rated firms are widely studied in the credit risk literature; the most famous yield spread BBB-AAA uses the yield of BBB-rated firms to benchmark risk. BBB-rated firms are also
the riskier firms that can belong to the liquid U.S. Corporate CDX-NAIG index. Belonging to the index probably has a positive liquidity spillover. All said, all results follow with a broader version of the level that incorporates non-BBB rated firms.

I measure the slope with the steepener slope (SS), which is a linear combination of CDS spreads whose innovations are the same as the innovations to an approximation of the LSM returns. I develop the approximation in Section 6, where I also show the steepener slope is strongly correlated with other more straightforward measures of the slope, such as the difference between the 10- and 3-year average CDS spreads.15

Before reporting the results of the predictive regressions, I have to explain how I do statistical inference in an environment with overlapping data. I compute standard errors in two different ways. First, I use a Newey-West weighting scheme with as many lags as twice the forecasting horizon. Second, I compute standard errors as in Hodrick [1992]. Besides producing asymptotic standard errors, I also construct small-sample P-values based on a 30-month block bootstrap of the entire sample.

In Panel A of Table 5, I report the results of the overlapping regressions of CDS returns of various maturities on the steepener slope. At the 12-month horizon, the SS predicts the returns of the market portfolio – marked as Avg – with a 20% R-squared, a -2.45 Hodrick [1992] T-statistic, and a 0.04 P-value. The in-sample predictability rises with the holding-period horizon, reaching a 48% R-squared at the two-years horizon from a 1% R-squared at the monthly horizon. I complement this evidence from realized CDS market returns by using an alternative set of proxies for risk-premia: business-cycle indicators and realized stock market returns. Recessions are times of high expected returns (Lettau and Ludvigson [2003], Fama and French [1989]); for example, buying the S&P 500 in NBER troughs and holding it for 12 months has yielded an average return of 20% (T-statistic of 7.5) in the 141 years since 1871; of the 29 NBER-defined cycles, the S&P 500 had positive returns in the year following troughs in 27. Panel A of Table 6 contains the results of regressions of the steepener slope on several measures of business cycles and VIX. The steepener slope is pro-cyclical. A flatter slope is significantly associated with a higher probability of recession (T-Statistic = -2.92), a lower CFNAI (T-stat=2.46), and a lower industrial production growth (T-stat =2.96); it is also associated with higher levels of VIX(T-stat=−1.49), but not statistically so. Panel B of the same table analyzes the changes in the steepener slope at various horizons. A flattening of the steepener slope is associated with a higher likelihood of recessions, lower CFNAI, lower

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15I also reproduce most calculations in this paper replacing the steepener slope by the 10-minus-3 spreads and the same results obtain.
industrial production growth, and an increase in VIX. These results are statistically significant for horizons six months or larger. In Panel C of Table 6, I show the SS also predicts lower stock-market returns from horizons six months or larger. The SS forecasts the value-weighted stock market return with a 34% and 5% R-squared at the one- and two-year horizons respectively. However, unlike before, the results are weaker statistically: the only evidence of statistical significant comes from the 24-month-horizon T-statistic of -2.87.

In Panel B of Table 5, I report the results for the predictive regressions using the average 5-year CDS spread of BBB-rated firms in Panel B of Table 5. At the 12-month horizon, the 5-year CDS spread predicts the returns of the market portfolio – marked as Avg – with a 43% R-squared, a -2.25 Hodrick [1992] T-statistic, and a 0.04 P-value. The R-squared is more than double that of the slope regression. The predictive power of 5-year CDS spreads also rises with the forecasting horizon, reaching a R-squared of 69% at the 24-month horizon, from a 2% R-squared at the one-month horizon.

The negative relation between slope and future returns and the positive relation between levels and future returns can be seen in the time-series plots in Panel A of Figure 1. The sample begins with stressed credit markets. The 2001 recession was officially over in November, but credit markets were far from calm. In December of 2001, Enron Corporation went bankrupt after accounting frauds revealed a much weaker balance sheet than previous though. WorldCom followed in July of 2002. Anecdotal evidence suggests the accounting frauds in these companies were a blow to investors’ confidence in the balance sheet of other companies and is consistent with frailty in default prediction (Duffie et al. [2009]). CDS spreads were high and slopes flat. Afterwards, slopes rose (and levels felt) and then stabilized until early 2007. Just before the great recession of 2008-2009, the term-structure was steep, and as economic conditions unraveled, the term-structure saw a flattening that ended up with short-term spreads surpassing the long-term ones even for the high-grade CDSs that I study. Meanwhile, the level of credit spreads rose, reaching the sample maximum. The recovery was equally striking. In early 2009, with the recession reaching its official end in
June, the term-structure began to grow steeper again, hitting a steepness without historical precedence in my admittedly small but eventful sample. At the same time, the level of credit spreads felt, though not as low as in the mid 2000’s.

Another noticeable pattern in the regressions of panels A and B of Table 5 is that predictive coefficients of returns and CDS spreads decrease (in absolute value) with maturity; both the spreads and returns of short-maturity CDSs are more predictable than the returns of longer-maturity ones. This differential predictability of spreads of different maturities is consistent with the findings of Binsbergen et al. [2011], who show the returns of short-maturity dividend strips are more predictable than those of the S&P500 – that is, the entire bundle of strips. The differential predictability by maturity also suggests that the returns of the LSM portfolio themselves may be predictable.

I have shown both the slope and the level predict returns. In Panel C of Table 5, I evaluate them jointly. After controlling for the level of credit spreads, the slope does not have marginal market-return forecasting power. At the 12-months horizon, the T-statistic on the steepener slope is -1.1 (P-value>0.10). The level, on the other hand, is still significant – T-statistic of 2.25 and 5% P-value. This result underlies my decision to use the average 5-year spread as a conditioning variable later in the paper.

5 The Time-Varying Correlations and a Conditional Asset Pricing Model

The level of CDS spreads is counter cyclical (Gilchrist and Zakrajšek [2011]) and tracks expected returns and not defaults (Giesecke et al. [2011]). The slope of the term structure of credit spreads is pro cyclical and also tracks expected returns. In this section, I show the level and the slope also track LSM’s time-varying CDS market betas. When the level is low or the slope steep, LSM’s market betas are negative, but when the level is high or the slope flat, LSM’s market betas switch sign.

The joint dynamics of LSM’s market betas and expected returns sheds light on why the unconditional CDS-CAPM – an asset-pricing model with the CDS market return as a single factor – fails to price the cross-section of CDSs by maturity. Even if shocks to the CDS market return are the only priced shocks that CDSs of various maturities are exposed to, but such shocks have time-varying prices of risk, an unconditional CDS-CAPM would overprice short-term assets. Consider two assets of different maturities, but same unconditional market betas. These assets’ expected returns are an average of betas times risk
prices. The joint dynamics of LSM’s betas and risk premia imply this average is larger for short-term assets, because short-term asset’s market betas are high when the price of market risk is high.\textsuperscript{16}

In the second part of this section, I test the hypothesis the failure of the CDS-CAPM is solely due to time-varying risk premia.\textsuperscript{17} I evaluate a Stochastic Discount Factor (SDF) that instead of featuring the LSM return, features the CDS market factor scaled by the proxy for conditional expected returns that I studied in the previous section, the lagged average five-year CDS spread of BBB-rated firms.

### 5.1 LSM’s Conditional Market Betas

In Panel A of Figure 7, I plot an estimate of the conditional correlation between the LSM and the market returns – the 12-month forward-looking rolling correlation between them – as well as the average 5-year BBB CDS spread and the steepener slope. The correlation is highest and positive – close to 0.5 – in the two stress periods of my sample – 2002 and the financial crisis. In both episodes, CDS spreads are high and the slope is flat. The correlation turns negative – around 0.8 – in the calm period between the two stress periods when the level of CDS spreads is low and the slope is steeper than average. These results are consistent with Binsbergen et al.\[2011\]’s finding that the CAPM betas of short-maturity dividend strips increase more than the betas of long-maturity dividend strips during recessions.

![Figure 7 about here.]

Next, I show the time-variation in betas that we see in the plot is statistically significant. In Table 7, I display the outcome of a regression

\[
LSM_t = \alpha + \beta R_{t}^{MKT,ALL} + \gamma \left( x_{t-1} \times R_{t}^{MKT,ALL} \right) + \epsilon_t,
\]

where \( x_t \in \{0, y_t^5, SS_t \} \). The first column shows LSM’s market beta is close to zero and statistically insignificant. The second and third diagonals show the coefficients \( \gamma \) on \( y_{t-1}^5 \times R_t^{MKT,ALL} \) and \( SS_{t-1} \times R_t^{MKT,ALL} \), respectively. Both coefficients are statistically significant with T-statistics of 2.41 and -4.41,

\textsuperscript{16}See Lewellen and Nagel [2006] for the consequences of ignoring time-variation in expected returns and betas in a single-factor model (CAPM in their case).

\textsuperscript{17}There are many alternative hypotheses explanations for the failure of the CDS-CAPM. For example, the LSM may be correlated with other state variables relevant for the portfolio problem of the representative investor, or the returns of CDS market portfolio may be imperfectly correlated with the returns on total wealth.
respectively. The positive coefficient on $y_{t-1}^5 \times R_{t}^{MKT, ALL}$ implies LSM’s market betas rise with average 5-year spreads. The negative coefficient on $SS_{t-1} \times R_{t}^{MKT, ALL}$ imply LSM’s market betas are high when the steepener slope is flat.\footnote{In unreported regressions, the same broad pattern also holds for an alternative specification that defines the level measure as an equal-weighted average of all CDS spreads and the slope as the difference between the 10-year and 3-year spreads.}

[Table 7 about here.]

5.2 Liquidity and Betas

Before estimating a stochastic discount factor without the LSM, I have to discuss potential problems regarding the timeliness of the single-name CDS spread quotes of non-five-year maturities. This discussion is relevant (for pricing the cross-section of returns by maturity) now but not before, because the LSM – the factor that prices the cross-section of CDSs by maturity – is, by definition, synchronized with portfolio returns; both are constructed from the same quotes.\footnote{Lack of synchronicity may also cause biases on the estimates of unconditional market betas. In unreported results, I show the corrections that I use for non-synchronous betas do not reduce the unconditional CDS-CAPM importantly. Delays may also influence the joint pricing of 5-year-spread- and maturity-sorted portfolios. In unreported results, I use the SDF method to evaluate the 3-factor model and show the results are unchanged relative to those that I show in previous sections, which use time-series methods.}

The candidate to replace the LSM, however, does not need to share the same convenient automatic synchronization.

I evaluate the possibility maturity-related quote delays by showing, in Table 8, the autocorrelations of LSM returns at various lags. The first three autocorrelations are positive and statistically significant – reported in the column single names. This positive autocorrelation may reflect updating delays but may also reflect legitimate predictability.\footnote{Another instance of lack of liquidity, small quote depth and large price impacts, generates negative autocorrelations. The positive sign, then, supports the view updating delays are the relevant effects of liquidity in the markets that I study.}

To disentangle which force is driving LSM’s predictability, I compute the same autocorrelations for LSMs built from other, more liquid, assets. I compute autocorrelations for LSMs that are made from the CDX-NAIG index, the ITRAXX-Europe index, and from a subset of single-name CDSs that are quoted by nine or more dealers. For the index, the most liquid instruments, the autocorrelations are much smaller and statistically insignificant in the first three-months that were significant for single names. For the LSM that is made from more liquid single-names, the first and third lags of the autocorrelation are smaller, but still significant.
An updating delay does not necessarily imply traditionally-estimated covariances are invalid – they may just make those covariances noisier. Unfortunately, this benign scenario is unlikely here. In Panel B of Figure 7, I plot the time series of the sum of 12-month forward-looking correlations between the LSM and the market, and the LSM and the lagged market. The sum of correlations vary more than the contemporaneous correlations. In crisis, the sum of correlations gets closer to 1, instead of 0.5, and stays positive for longer. If a conditional-CAPM model is true and the true betas follow a dynamic similar to that of the sum correlations, the traditionally-estimated market covariances will still fail to capture expected returns by maturity. Given the described shortcomings of the traditionally-estimated covariances in a setting with updating-delays, I use an alternative covariance estimator, the sum-of-covariances estimator:

$$\hat{\text{cov}}(R_{t+1}^i, X_t R_{t+1}^{MKT, ALL}) = \text{cov}(R_{t+1}^{i*}, y_t^5 R_{t+1}^{MKT, ALL}) + \text{cov}(R_{t+1}^{i*}, X_t f_t),$$

where $R_{t+1}^i$ is the (unobserved) portfolio return had there been no delays and $R_{t+1}^{i*}$ is the cum-delay observed return. In appendix C, I formally show if true returns follow a two-factor structure, but the observed returns reflect both contemporaneous and delayed information about the second factor, and true cross-lagged correlations are zero, then the sum-of-covariances estimator delivers the true covariance matrix. This procedure can be seen as a specialization of the Scholes and Williams [1977]’s procedure to deal with non-synchronous returns in the case where the true factor is always more up to date than the observed returns.

Finally, other studies provide evidence of updating delays in CDS spreads. Mayordomo et al. [2010] investigate the possibility of delays in CDS quotes at the five-year tenor. In periods fewer CDS transactions occur, Mayordomo et al. [2010] show the five-year quotes on the Markit database is lead more often than it leads, in a daily basis, the quotes on the CMA database. Collin-Dufresne and Bai [2011] also found the contribution of five-year CDSs to price discovery in relation to bonds – as summarized by the Gonzalo and Granger [1995] measure – falls as the financial crisis worsens, with bonds surpassing CDSs for high-yield names during the worst of the crisis. If the same features that cause delays in 5-year CDSs have an amplified effect on the slope of the term structure of CDS spreads, these results add to the evidence that the autocorrelation of the LSM is indeed driven by updating delays.
5.3 Conditional Asset Pricing Model

Both expected returns of the market portfolio of CDSs and the market betas of the LSM portfolio vary with the level of CDS spreads and the slope. In particular, the LSM portfolio has higher (CDS) market betas when the level of CDS spreads is high. This joint dynamics of market betas and market expected returns implies a CDS-CAPM – a model whose single factor is the CDS market return – predicts too small an average return for the LSM portfolio. If this source of mispricing is all that drives the alphas of the LSM, a conditional one-factor model should be able to account for the cross-sectional variation in expected returns by maturity. To test this proposition, I evaluate the following stochastic discount factor:

\[ M_{t+1} = 1 - b_t \left( R_{t+1}^{MKT,ALL} - E \left[ R_{t+1}^{MKT,ALL} \right] \right) + c (HSMLS_{t+1} - E [HSMLS_{t+1}]) , \]

where \( b_t \) tracks the market risk premium \( E_t \left[ R_{t+1}^{MKT,ALL} \right] \). Because I price zero-cost portfolios, the mean of the factor is unidentified and I choose it such that unconditional expected returns being a linear function of covariances. I model \( b_t \) as an affine function of \( X_t = y_t^5 \), the average five-year CDS spread. As shown previously, the level of CDS spreads tracks bonds’ expected returns and the focus on a single variable is a parsimonious solution to the choice of conditioning variables. In the end, accounting for time-varying risk premia changes the one-factor model into a two-factor model

\[ E R_i^{t+1} = cov \left( R_{t+1}^{i}, R_{t+1}^{MKT,ALL} \right) + bcov \left( R_{t+1}^{i}, y_t^5 R_{t+1}^{MKT,ALL} \right) + ccov \left( R_{t+1}^{i}, HSMLS_{t+1} \right) , \]

I estimate \( cov \left( R_{t+1}^{i}, y_t^5 R_{t+1}^{MKT,ALL} \right) \) as the sum of \( cov \left( R_{t+1}^{i}, y_t^5 R_{t+1}^{MKT,ALL} \right) \) and \( cov \left( R_{t+1}^{i}, y_{t-1}^5 R_{t}^{MKT,ALL} \right) \), and report the results in Panel A of Figure 8. Although the covariances with the lagged factor are smaller than those with the contemporaneous market, the cross-sectional difference in those covariances is much larger than the differences in the contemporaneous covariances. This pattern in the dispersion of betas implies the covariances between returns and the lag of the scaled factor – \( cov \left( R_{t+1}^{i}, X_{t-1} f_t \right) \) – play an important role in pricing the cross-section of returns by maturity. The small dispersion of the contemporaneous covariance – \( cov \left( R_{t+1}^{i}, y_t^5 R_{t+1}^{MKT,ALL} \right) \) – implies that without the delay correction, the pricing
performance of the scaled model is weak.

Panel A of Table 9 confirms the importance of \( \text{cov} \left( R_{t+1}^{\text{true}}, R_{t+1}^{\text{MKT,ALL}} \right) \) for the cross-sectional pricing of returns by maturity: the risk premium on the scaled factor is positive and significant – T-statistic of 2.14. The other factors are also – at least marginally statistically significant, with the caveat that the standard errors do not reflect the estimation error of the covariances. As a flip side of the significant factors, the scaled-factor model has a good cross-sectional fit. The mean absolute value of the model’s alpha is 19% of the mean absolute value of the original expected returns, and its cross-sectional R-squared is 96%. This R-square compares favorably to the 94% of the steepener-slope model and with the return-based 3-factor model that I estimated in previous sections. In Panel A of Figure 8, I display the realized and model-predicted returns.

I benchmarked the scaled-factor model against the 3-factor model that was estimated using time-series methods. I now compare the scaled-factor model with a return-based model – \( R_{t+1}^{\text{MKT,ALL}}, HSMLS_{t+1}, \) and \( LSM_{t+1} \) – estimated the same way. The main difference between the estimation techniques is that unlike time-series methods, the SDF approach does not constrain prices of risk to be equal to the factor’s mean returns. The benchmark model has a cross-sectional R-squared of 97%, and the mean absolute value of its pricing errors is 18% of the mean absolute average returns. The null that the \( HSMLS \) is not marginally important for pricing – that is, its loadings on the SDF are zero – cannot be rejected. This result suggests both maturity- and spread- risk premia may be manifestations of a single phenomenon.

The slightly better performance of this LSM-based model, compared with the conditional one, however, is not statistically significant. In Panel C of Table 9, I show \( LSM_{t+1} \) is redundant when \( y_5 R_{t+1}^{\text{MKT,ALL}} \) is included and vice versa. Overall, this comparison adds to the evidence that \( LSM_{t+1} \) plays the role of a scaled factor.

[Figure 8 about here.]

[Table 9 about here.]
6 The Relation between the Holding-Period Returns that I Study and Credit Spreads

In this paper, I focus on holding-period returns. The credit-risk literature often focus on explaining the levels of credit spreads; credit risk models, for example, are built to fit credit-spread moments. In this section, I develop approximations that tie holding-period returns to credit spreads. In particular, I show the LSM is an instance of a steepener in the CDS curve. A steepener in the CDS curve is a strategy that profits from the steepening of the credit curve – a rise in long-term spreads relative to short-term spreads – and loses from the flattening of the curve. I show the innovations to an approximation to LSM returns are equal to the innovations in a measure of the steepness of the term structure of credit spreads, henceforth steepener slope. I further show the change in the steepener slope – a simple proxy for its innovations – is strongly correlated with the true LSM return and prices the cross-section of CDS returns by maturity as accurately as the LSM. Besides examining the LSM, I also argue the CDS market return is a level bet on the credit curve. A level bet profits from an overall fall in credit spreads.

These approximations and the tests that confirm their validity let me interpret my results in light of existing credit-risk models that are built for credit spreads. In particular, I rely on those approximations to interpret the results of the Merton-model extension that I develop later. The model will have implications for the level and the slope of the term structure of credit spreads as a function of a relevant state variable.

6.1 The LSM is a Steepener in the Credit Curve

6.1.1 The Approximation

I develop an identity and an approximation that links the LSM returns to changes in a measure of the steepness of the term structure of CDS spreads: the steepener slope. First, in Appendix B, I show the one-month returns of selling an \( N \)-period CDS are approximately

\[
R_{t+1/12} \approx RD (N - 1/12, \Theta_0) \times \left( -y_{t+1}^{N-1} + y_t^N \right) + \frac{y_t^N}{12},
\]

where \( RD \) is the risky duration of a stream of payments with maturity \( N - 1 \) approximated around state variables \( \Theta_0 \), and \( y_t^N \) is the credit spread of a CDS of maturity \( N \) at time \( t \). The first part of the return is the capital gain – or loss – \( RD (N - 1/12, \Theta_0) \times \left( -y_{t+1}^{N-1} + y_t^N \right) \) and the second part is the income from
coupons.

The LSM is a portfolio of CDS of different firms and maturities. Abusing notation by designating \( y_N^t \) the equal-weighted average of CDS spreads of maturity \( N \) at time \( t \), the one-month return on the LSM can be written as

\[
LSM_{t+1} \approx \sum_{N=\{3,5,7,10\}} \omega_N \left[ RD(N-1, \Theta_0) \times \left( -y_{t+1}^{N-1} + y_t^N \right) + \frac{y_t^N}{12} \right],
\]

where \( \omega_N \) is the weights that the LSM places on each maturity \( \omega_N = \frac{L_N}{\sigma_N} \), which is the ratio of the second factor loading on maturity \( N \) to its volatility. \( LSM_{t+1} \) can then be decomposed into two parts:

\[
LSM_{t+1} \approx SS_{t+1}(\Theta_0) + \Psi_t,
\]

where \( \Psi_t = \sum_{N=\{3,5,7,10\}} \omega_N \left[ RD(N-1, \Theta_0) \times y_t^N + \frac{y_t^N}{12} \right] \) and

\[
SS_{t+1} \equiv \sum_{N=\{3,5,7,10\}} \omega_N RD(N-1, \Theta_0) \times \left( -y_{t+1}^{N-1} \right),
\]

is what I define as the steepener slope \( SS \). \( SS \) is the linear combination of CDS spreads whose innovation is the same as the innovation to the approximated LSM return; the difference between the approximated LSM return and the steepener slope \(-\Psi_t\) does not depend on any \( t+1 \) variable.

To understand why I call the steepener slope a slope, in Appendix B.2, I go over a simplified version of the steepener slope and show it is proportional to the slope of the term structure of CDS spreads at a given point. In the next section, I corroborate those calculations with empirical evidence that the steepener slope is strongly correlated with several measures of the steepness of the term structure of CDS spreads.

### 6.1.2 Empirical Relationship between True Returns and Changes in the Steepener Slope

I begin by confirming empirically that the steepener slope tracks the slope of the term structure of CDS spreads. In Panel C of Table 10, I report the correlations between the steepener slope and the slope of the term structure of CDS spreads at several points, both for levels and changes. In levels, the minimum correlation is 0.96, whereas in changes, it is 0.69; the averages are 0.99 and 0.83, respectively.
Next I evaluate the relation between LSM returns and changes in the steepener slope. To do so, I run a regression of the LSM on the steepener slope and report the results in Panel A of Table 10. The R-squares and slope coefficients go from 55% to 89% as horizons increase from 1 month to 12 months. Similarly, the coefficients go from 0.56 to 0.98. The approximation and the true return differ the most when the steepener slope moves are extreme. This timing of the differences is no coincidence: the steepener slope fixes the weights of CDS spreads whereas the true return weights them by their current risky duration. The smoothness of returns arises because risky durations fall when CDS spreads, go up and vice-versa, such that extremes moves in spreads will result in less impact on returns than on an approximation that fixes risky durations.

The R-square of 55% at the one-month horizon alone is worrying for the approximation, but the fact that these R-squares rise with the horizon makes this moderate R-square less of a concern. More importantly, in the next test, I provide more evidence that the relevant covariances between returns and the LSM are kept intact in the steepener slope.

6.1.3 Changes in the Steepener Slope Prices the Cross-Section of Returns by Maturity

In this section, I use the changes in the steepener slope to price the cross-section of CDS returns formed on maturity. The point is to evaluate the approximation of the LSM by showing that whatever is lost in it, does not affect the cross-sectional pricing.

Because the changes in the steepener slope – $\Delta SS$ – are not returns, I will use cross-sectional methods to evaluate $\Delta SS$’s pricing power. Otherwise, I use the same set of assets and extra pricing factors that I used in the analysis of the LSM portfolio. Namely, I begin pricing the portfolios made from CDSs of BBB-rated firms and then I extend the tests to include both safer and riskier portfolios. For this broader exercise, I evaluate the changes in SS in two ways. First, I use hedged portfolios as test assets for a single-factor model:

$$E \left[ R_{t+1}^{i,k,hedged} \right] = \beta_{\Delta SS}^i \Delta SS,$$

where $\beta_{\Delta SS}^i$ is the beta of return $i$ on $\Delta SS$ and $\lambda_{\Delta SS}$ is the risk premium for exposure to $\Delta SS$, estimated from a cross-sectional regression of returns on betas. And second, I use a three-factor model,

$$ER_{t+1}^i = \alpha + \beta_{\text{MKT,ALL}}^i \lambda_{\text{MKT,ALL}} + \beta_{\text{HSMLS}}^i \lambda_{\text{HSMLS}} + \beta_{\Delta SS}^i \lambda_{\Delta SS},$$
where $\beta^i_{MKT}, \beta^i_{HSMLS}$, and $\beta^i_{\Delta SS}$ are the multi-variate betas with respect to market $R_{t+1}^{MKT, ALL}$, the high-spread-minus-low-spread $HSMLS_{t+1}$, and the change in the steepener slope $\Delta SS$:

$$ER^i_{t+1} = \alpha + \beta^i_{MKT,ALL} \lambda_{MKT,ALL} + \beta^i_{HML} \lambda_{HSMLS} + \beta_{slp} \lambda_{\Delta SS}.$$ 

I use GMM to account for autocorrelation and heterocedasticity in returns, and for the use of estimated betas as well. The standard errors, however, do not account for the uncertainty about the hedge ratio that I use when forming hedged portfolios. I report the results for the hedged portfolios in panels A and B of Table 11. The BBB steepener slope does a good job pricing the cross-section of returns by maturity. When pricing the 16 non-high-yield hedged portfolios, the model achieves a cross-sectional R-squared of 92% and the maturity risk-premium is 7.47, with a T-statistic of 4.2, which is close to the 6.4 price of risk estimated from the subset of BBB-rated firms. When I add the four highest-yielding hedged portfolios for a total of 20 portfolios, the R-squared falls but is still reasonable at 82%; the price of risk is 4.68 (T-statistic of 2.6). The worse fit relative to the pricing achieved by the LSM factor is partially due to the fact that the risk-price estimate is reduced to match the high-yield portfolios at the cost of higher pricing errors for the non-high-yield portfolios – I test the LSM return in a time-series setting, which fixes the risk premium at the time-series average. For both models, the formal test that all alphas are zero rejects the null.

The results for the unhedged portfolios are in Panel C of Table 11. The model achieves a 95% cross-sectional R-squared and importantly, the premium on the steepener slope is 4.26, again close to 4.68 of the estimate with hedged returns.\(^{22}\)

\(^{22}\)The results are very similar if instead of raw returns and the factors as they are I compute their innovations using the past change in steepener slope, the past equal weight average of all returns, and the past HSMLS – high spread minus low spread – portfolio.
7 Model

7.1 Set-Up

In this section, I describe a parsimonious model that matches both the fact that the term structure of credit spreads is flat in bad times – when risk premia and volatility are high – and the fact that the sign of the correlation between the steepness of the term structure and the level of the term structure is positive in good times – low risk premia and low volatilities – and negative in bad times.

The model features a single state variable $\sigma$ that drives the volatility of shocks to the stochastic discount factor (SDF), the volatility of the systematic and idiosyncratic shocks to the value of the assets of a typical BBB-rated firm, its default boundary, and payout policy. $\sigma$ follows a CIR process:

$$d\sigma_t^2 = \phi(\bar{\sigma}^2 - \sigma_t^2)dt + \sigma_{vol}^t \sigma_t dW_t,$$

where $\phi$ measures the degree of persistence, $\bar{\sigma}$ the long-run mean, $\sigma_{vol}$ the volatility of innovations to $\sigma_t^2$, and $dW_t$ is a Brownian motion. The total value of the firm (equity and debt) follows a geometric Brownian motion with state-contingent expected growth and volatility:

$$\frac{dV_t}{V_t} = (-payout_t + \mu_t)dt + \sigma_t dZ_t^{[1]} + \sigma_{id}^t dZ_t^{[2]},$$

where $dZ_t^{[1]}$ and $dZ_t^{[2]}$ are Brownian motions, $\mu_t$ is the expected return of the total assets of the firm, and $payout_t$ captures changes in the value of the firm resulting from net payouts. For example, if a firm sells equity without changing its debt, $payout$ is negative. To capture the counter-cyclicality of $payouts$, I use a simple functional form:

$$payout_t = \mu_{payout} + \beta_{payout} \frac{\sigma_t - \bar{\sigma}}{\sigma_{vol}}.$$

Idiosyncratic volatility is given by

$$\left(\sigma_{id}^t\right)^2 = \left(\sigma_{id,1}^t\right)^2 + \sigma_t^2,$$

which implies a single-factor structure in the idiosyncratic volatilities of all BBB-rated firms. The stochas-
The discount factor is exogenously specified as:

\[
\frac{d \Lambda}{\Lambda} = -rdt - \xi \sigma_t dZ_t^{[1]},
\]

where \( r \) is the instantaneous risk-free rate, and \( \xi \sigma_t \) is the time-varying price of risk of shocks to \( dZ_t^{[1]} \). In this setting, the instantaneous expected return on the assets of a typical firm, its Sharpe ratio, and the economy’s maximum Sharpe ratio (conditional) are given by:

\[
\begin{align*}
\mu_t &= \xi \sigma_t^2 + r, \\
\text{sr}_t &= \frac{\xi \sigma_t}{\sqrt{(\sigma^{id,1})^2 + 2\sigma_t^2}}, \\
\max \text{sr}_t &= \xi \sigma_t.
\end{align*}
\]

In total, the model has three shocks, \( dW, dZ^{[1]}, dZ^{[2]} \), with a covariance matrix \( \Sigma \). Following Chen et al. [2009], defaults occur if the value of the firm falls below an exogenous value \( B \) – the default boundary – by the time its debt matures. I will model the firm debt as having the same maturity of the CDS to be priced. Its payoffs are as follows. If the firm survives, the protection seller gets a fixed payment \( T \times y \), where \( T \) is the CDS maturity and \( y \) is its premium. On the other hand, if the firm defaults, the CDS seller has a negative payoff equal to the loss given default: \(-L\). So if \( \tau \) is the time of default, the CDS payoff is:

\[
CDS(T, y) = 1_{\tau>T} T \times y + (1 - 1_{\tau>T}) (-L)
\]

\[
\tau = \begin{cases} 
T & \text{if } V_T < B \\
> T & \text{o.w.}
\end{cases}
\]

The yield of a CDS is such that

\[
E[\Delta CDS(T, y)] = 0,
\]

and I compute it using Monte Carlo methods. I focus on the one- and five-year maturities. These maturities are shorter than those studies in Chen et al. [2009] – 4 and 10 years – and Bhamra et al. [2010] – 5- and 10-year maturities. Because the objective of this model is not to fit an exhaustive list of the moments of the entire term structure of credit spreads, I have to choose a set of maturities to investigate. My choice of one and five years allows me to examine one commonly studied maturity – five years – but with a focus on the short end of the slope of the term structure where expected returns seem to be more sensitive to
maturity.

7.2 Calibration

I have to calibrate \( (\xi, \sigma, r, \sigma^{\text{vol}}, \zeta, \Sigma, L, B, \phi) \). I pick \( \xi \) such that the median maximum Sharpe ratio in the economy is \( \xi \sigma = 0.5 \) per year. I choose \( \sigma = 0.12 \). This number is consistent with an aggregate firm with leverage 1/5 and riskless debt with an equity volatility of 0.15, which is in the low range of the annual volatility of a broad stock-market index.\(^{23}\) I set the risk-free rate to zero at all the times. The effects of interest rates on the quantities that I study are likely to be small and the short-term interest rate was small – 1.72% per year.

I pick \( \sigma^{id,1} = 0.0808 \) such that the average idiosyncratic volatility of a typical firm is 0.208 as in Chen et al. [2009], which motivates this choice in order to match the empirical evidence that the typical stock Sharpe ratio is half that of the market. The total asset volatility of a typical firm is on median 24%.

For the volatility of volatility, I pick \( \sigma^{\text{vol}} = 0.06 \), which is half the average volatility. This choice translates into a volatility of the economy-wide Sharpe ratio half of the median economy-wide Sharpe ratio. The same \( \sigma^{\text{vol}} = 0.06 \) translates into a volatility of volatility of 7.5% for an aggregate firm with leverage 1/5.

From January 1996 to May 2012, the standard deviation of rolling one-year S&P500 realized volatilities is 8.14%.

Both debt (Jermann and Quadrini [2012]) and equity issuance are countercyclical and can have sizable effects on the value of a firm. For example, the market value of equity of the average firms grows by 13% in five years due to non-returns-related reasons (Daniel and Titman [2006]). The rolling average of net payouts – the dividend yield minus net equity issuance calculated in Roberts et al. [2007] – was -0.61% in the last decade, and -0.48% from January 1990 to December 2010. These empirical patterns in payoffs motivates me to design a payoff function that reflects these facts. I choose \( \zeta = 0.03 \frac{\Omega - \sigma}{\sigma^{\text{vol}}} \) such that when volatility is two standard deviations below its mean, the firm issues securities worth 0.06 of its total value, and when volatility is two standard deviations above the mean, it retires securities worth 0.06 of the value of its assets. This behavior of payoffs makes default more likely in bad times because firms issue less at those times. Chen et al. [2009] emphasizes having a channel that makes firm defaults in bad times is important, otherwise, the high risk premia in recessions would mean a negative relation exists between

\(^{23}\) The average book leverage of public firms is 25.1% (Rauh and Sufi [2012]) and the median book-to-market ratio is 1.21. Dividing the first by the second yields 0.207.
spreads and default losses. Chen et al. [2009] use time-varying default boundaries or stochastic volatility to match the data. I also allow for time-varying default boundaries and will calibrate those boundaries, so shutting down this dependence of payoffs moves more of the burden of matching the data to the sensitivity of default boundaries to the aggregate state, but should not do much for the other results.\textsuperscript{24}

I choose $L = 1 - 0.449$ following Huang and Huang [2003]. I study the results with $\phi = 0.7$ – a one-year decay of 0.3 – and $\phi = 0.1$ – a one-year decay of 0.9. The smaller persistence is consistent with the dynamics of realized stock volatility in the sample that starts in 1996. In terms of time-varying expected returns, the lower persistence is consistent with components of expected returns estimated by Kelly and Pruitt [2011] and to a certain extent Lettau and Ludvigson [2001].

The higher persistence reflects the slowly moving expected returns captured in price-dividend ratio predictive regressions. I think of this high-persistence version of the model as standing in for stochastic discount factors arising from models that try to match the predictability evidence embedded in dividend price ratios (Campbell and Cochrane [1999], Bansal and Yaron [2004]). Alternatively, this highly persistent specification can be interpreted as models that rely on persistent stochastic volatility of the the return on total wealth to obtain high risk prices as in Bansal et al. [2012] and Campbell et al. [2011].

As in Chen et al. [2009], I choose the default boundary $B = a_{\text{boundary}} + b_{\text{boundary}} \sigma_0 + c_{\text{boundary}} \sigma_T$ as a function of the initial and terminal date level of volatility to allow for both rating through the cycle, and countercyclical default boundaries. I set $a_{\text{boundary}}$, $b_{\text{boundary}}$, and $c_{\text{boundary}}$ to match unconditional default probabilities and credit spreads at the 1- and 5-year horizons, a coefficient of 1 on a regression of 5-year default rates (Chen et al. [2009] match 4-year default rates with a coefficient of 0.89), and the unconditional correlation between the 5-minus-1 slope and the 1-year credit spread of -0.55. Because I need to match six moments with three parameters, I cannot match all the moments exactly, so I minimize the square of the difference of model moments and the data, multiplying the two beta coefficients by 100 to make then comparable to default probabilities and spreads, which are quoted in basis points.

I model the correlation structure of $(dW, dZ[1], dZ[2])$ in the following way. $\rho(dZ[1], dZ[2]) = 0$ is zero, which means the idiosyncratic shocks are indeed idiosyncratic. I model the volatility shock to have time-varying correlations with the SDF, which will amplify the time-variation in expected returns of the CDSs above and beyond what stochastic volatility of the SDF and the firm value generate. I choose $\rho(dZ[1], dW) = \begin{cases} 1_{[\sigma > \bar{\sigma} + 1.5 \sigma_{\text{vol}}]}(-0.9) + (1 - 1_{[\sigma > \bar{\sigma} + 1.5 \sigma_{\text{vol}}]}) 0 \end{cases}$. Negative values reflect the evidence that

\textsuperscript{24}I check other parametrizations with smaller sensitivity of payoffs to aggregate state and they perform similarly.
discount-rate shocks and returns are negatively correlated. It also reflects a view that both discount-rate shocks and volatility shocks are priced – they are indistinguishable in this model – as in Campbell et al. [2011] and Bansal et al. [2012]. Finally, I did not investigate more complex but promising specifications of volatility, such as those featured in Drechsler and Yaron [2011].

7.3 Results

I report the results in Table 12. For the low-persistence specification, \( \phi = 0.7 \), the model generates reasonable default probabilities of 196 bps in 5 years and 29 basis points at 1 year. The 1-year credit spread of 86 bps is close to the 77bps in the data, but the 5-year spread is too high at 196 bps versus the 114 bps in the data. The coefficient of 5-year defaults on spreads of 0.67 is on the low side of what Chen et al. [2009] calibrated for four years. The unconditional correlation between the slope and the short-term spread is -0.57 versus -0.55 in the data. Importantly, the model generates this low correlation through a non-monotonic relation between volatility and the slope of the term structure of credit spreads as displayed in Figure 9.

The non-monotonic relation between the one-year credit spread and the 5-minus-1 slope translates into time-varying correlations between the slope and the level of credit spreads. As in the data, this time variation is tracked by the level of credit spreads or the steepness of the term structure. When the level of credit spreads – or volatility (in the model they move together) – is low, changes in the level and in the slope are positively correlated. When credit spreads are high enough or the slope flat enough, changes in the level and slope become negatively correlated.

In the model, as in the data, both high average credit spreads and flat slopes of the term structure occur when risk premia is high. In the model, these two phenomena are a consequence of high values for the state variable that controls both firm value and discount-factor volatilities.
As a consequence of the non-monotonic relation of the slope of the term structure, the relation between risk premia and the slope, and the time-varying correlation between volatility shocks and shocks to the SDF make the returns of credit steepeners due to volatility exposures high. The returns of credit steepeners are high because credit steepeners stand to lose from increases in volatility when volatility is high. Because shocks to volatility are priced and risk premia are high when volatility is high, these exposures of credit steepeners imply high average returns.

The non-monotonic relation between the level and the slope of the term structure of credit spreads is key to the model’s ability to match the facts above. To understand why it arises, consider the positive correlation first. When volatility is low, the short-term CDS is safe and further small increases in volatility do not change that and yields behave accordingly. The longer-term asset, even when volatility is low, is risky enough and further increases in volatility have an effect on its yield. The curve, therefore, gets steeper when volatility increases from an initially low level. On the other hand, when volatility is high, both the short-term asset and the long-term asset are at risk, and further increases in volatility affect then both. However, because volatility is expected to mean revert quickly, the effects on the longer-term CDS yield are dampened, and hence, the credit curve flattens.

To understand the role of the persistence of volatility, I also produce a calibration with highly-persistent volatility – \( \phi = 0.1 \). This calibration generates reasonable default probabilities at the one-year and five-year horizons of 28 bps and 215 bps, respectively. The five-year average credit spread is 139 bps, higher than the 114 bps in the data, whereas the one-year average credit spread is 24 bps, much lower than the 77 bps in the sample. The key difference, however, shows up in the unconditional correlation between the level and slope of the term structure of credit spreads: it is positive and equal to 0.75, whereas this number is -0.55 in the data. The flip side of this result is the lack of a hump shape in the function that maps volatilities into slopes for relevant values of volatility as displayed in Figure 9. As a consequence, this calibration featuring highly-persistent volatility also fails to match the time-varying correlations between level and slope that I found in the data.

8 Conclusion

I study the cross-section of U.S. corporate CDS returns by maturity. I find a portfolio that sells short-term CDSs and hedges them with long-term CDSs – LSM, as I call it – has high returns and low volatility. Furthermore, the betas with respect to this portfolio are able to explain the cross-section of CDS expected
returns by maturity.

The LSM portfolio has strongly time-varying correlations with what I call the market portfolio of CDSs – a portfolio that sells CDSs of all firms and all maturities with equal weights. When credit spreads are low or the term structure of credit spreads is moderately steep, the market beta of the LSM portfolio is negative. When credit spreads are high or the term structure of credit spreads is flat, the market beta of the LSM portfolio switches sign and becomes positive.

At the same time, high levels of credit spreads and flat term structures predict high CDS market returns and vice versa. This joint dynamics of LSM’s market betas and market risk premia imply that even if shocks to CDS market returns are the only priced shocks, a CDS-CAPM that fails to account for time variation in expected returns would also fail to price the cross-section of expected returns, as it fails to do in the data. In such a case, a conditional model, however, should price the cross-section of returns by maturity and it does. A market-timing portfolio whose returns equal the market return scaled by a proxy for market expected returns – the average five-year credit spread – prices the cross-section of returns by maturity as accurately as the LSM. To reach this conclusion, it is fundamental to use illiquidity-robust covariance estimates.

The behavior of the betas of the LSM portfolio – higher when risk premia are also higher – that I unveil empirically arises endogenously when I embed a conditional CAPM in a structural credit-risk model. The model features countercyclical default boundaries and low-persistence stochastic volatility of firm value and the SDF. In the model, when credit spreads are high, the slope and the level of the term structure of credit spreads move together – LSM’s market betas are negative. In those times, short-term assets are safe, and increases in volatility do not change their safe status. The prices of longer-term assets, however, do reflect the deterioration of conditions at those times. When spreads are high, short-term assets are at risk and further increases in volatility have a large effect on their values. Increases in volatility also have an effect on longer-term asset values, but this effect is dampened by the fact that conditions are likely to improve quickly, because they mean revert quickly in the model.
References


Appendix

A Computing Holding-Period Returns

A.1 Single Names

Extrapolating the Curve I will focus on monthly returns for the 1,3,5,7 and 10 year maturities. Since single names are not quoted for non-integer year intervals, I will have to extrapolate the CDS curve to obtain the spreads 1 month off the quotes. I will do so with linear interpolation, such that:

\[ y_{t}^{N-1} = \frac{23}{24}y_{t}^{N} + \frac{1}{24}y_{t}^{N-24}. \]

This simple procedure generalizes the across quotes shape of the curve to its local behavior. The results are similar if I instead use extrapolations from a cubic spline, or those implied by the model commonly used by practitioners in valuing CDSs, which I discuss below. Furthermore, when I study credit indexes, I will not need to extrapolate spreads, and, therefore, those results can be a check on the validity of the procedure I proposed.

Computing Risky Duration I use a simple model for risk neutral default probabilities and loss given default. This model is used by Market participants to convert the CDS quotes from running spreads to upfront payments like CDS are traded nowadays. The same model was used in Veronesi and Zingales [2010]. Risk neutral default probabilities are non-stochastic and given by\(^{25}\)

\[ P(\tau \leq T, \Theta_t) = \int_{0}^{T} \exp(-\lambda(s)) \, ds, \]

\(^{25}\)A more complicated model that allows for doubly-stochastic hazard rates (Duffie [2005]) in an affine way does not generate very different predictions regarding risky duration.
with \( \lambda(s) \) is piecewise linear:

\[
\lambda(s) = \begin{cases} 
\lambda_1 & \text{if } 0 \leq s < 1 \\
\lambda_2 & \text{if } 1 \leq s < 3 \\
\lambda_3 & \text{if } 3 \leq s < 5 \\
\lambda_4 & \text{if } 5 \leq s < 7 \\
\lambda_5 & \text{if } 7 \leq s < 10 
\end{cases}
\]

and the loss given default for the senior unsecured debt is a constant equal to 60%. So in this case the subvector of \( \Theta_t \) that controls the risk neutral default probabilities is \( (\lambda_1, \ldots, \lambda_5) \).

Under these assumptions I can bootstrap \( \lambda_1 \) to \( \lambda_5 \) from CDSs of maturity 1, 3, 5, 7 and 10 by solving numerical integrals. To see how, note that the \( N \) periods CDS yield satisfies:\(^{26}\)

\[
\int_{i=0}^{N} P_{0}^{RN} (\tau > t + i) D_0(i) y_0^N \, di = \int_{i=0}^{N} P_{0}^{RN} (\tau > i) \lambda_i D_0(i) LGD_i \, di \\
y_0^N = \frac{\int_{i=0}^{N} \left( \int_{0}^{i} \exp(-\lambda(s)) \, ds \right) \lambda(i) D_0(i) \, di}{\int_{i=0}^{N} \left( \int_{0}^{i} \exp(-\lambda(s)) \, ds \right) D_0(i) \, di} \cdot 0.6
\]

I bootstrap the risk-free discount function \( \{D_0(t + 1 + i)\}_{i=1}^{N-1} \) from Libor rates (first year) and swap rates (years 2 to 10) and I solve the integrals above for \( \lambda(s) \) using quadrature. With the \( \{\lambda(s)\}_{s=1:5} \) in hand I compute the risk durations by computing another numerical integration, also at a date \( t \) by quadrature:

\[
RD(N, \Theta_t) = \int_{i=0}^{N} P_{0}^{RN} (\tau > t + i, \Theta_t) D(t, t + i, \Theta_t) \, di.
\]

I do this for every firm and for every date.

### A.2 Credit Indexes

As discussed before, credit indexes age, which means that I do not need to extrapolate one-month-off-the-quoted-curve spreads. I also adopt a slightly different approach when computing risk duration for the indexes. Following Markit’s model choice when valuing indexes, I will use a constant hazard rate model instead of a piecewise linear one when computing risky durations. The differences are negligible.\(^{27}\)

---

\(^{26}\)This is the model used to translate upfront and running spread CDS. See [http://www.cdsmodel.com/cdsmodel/](http://www.cdsmodel.com/cdsmodel/).

B Approximation for CDS Returns

B.1 The Approximation

Let $R_{t+1}$ be the 1-month holding period return of selling a $N$-periods CDS

$$R_{t+1/12} = \left(1_{\tau>t+\frac{1}{12}}\right) \left[ RD \left(N - \frac{1}{12}, \Theta_{t+\frac{1}{12}}\right) \times \left(-y_{t+1/12}^{N-1} + y_t^N\right) + \frac{y_N^N}{12} - (1 - 1_{\tau>t+\frac{1}{12}}) \LGD_{t+\frac{1}{12}},\right]$$

There are three classes of time $t + \frac{1}{12}$ variables affecting those returns: the jump to default counter $1_{\tau>t+\frac{1}{12}}$ along with the $\LGD_{t+\frac{1}{12}}$, the state variables $\Theta_{t+\frac{1}{12}}$, which drive the risky duration $RD \left(N, \Theta_{t+\frac{1}{12}}\right)$, and the credit spread $y_{t+\frac{1}{12}}^{N-\frac{1}{12}}$. The first variable, the jump to default counter, is likely to drive a small fraction of the volatility of $R_{t+1/12}$, such that ignoring it will probably have a small effect on monthly beta computations for investment grade firms. This is the case because monthly default rates for BBB-rated corporations are likely tiny.

$$R_{t+\frac{1}{12}} \big|_{\text{no def 1}} = RD \left(N - \frac{1}{12}, \Theta_{t+\frac{1}{12}}\right) \times \left(-y_{t+1/12}^{N-1} + y_t^N\right) + \frac{y_N^N}{12}$$

and approximating these returns close to $y_{t+1}^{i-1} = y_{t+1}^i$ and an arbitrary $\Theta_0$:

$$R_{t+\frac{1}{12}} \approx RD \left(N - \frac{1}{12}, \Theta_0\right) \times \left(-y_{t+1/12}^{N-1} + y_t^N\right) + \frac{y_N^N}{12} +$$

$$\left(\frac{\partial RD \left(N - \frac{1}{12}, \Theta_{t+1}\right)}{\partial \Theta_{t+1}}\right) \big|_{\Theta=\Theta_0 \text{ and } y_{t+1/12}^{i-1} = y_{t+1/12}^i} \left(\Theta_{t+\frac{1}{12}} - \Theta_0\right) \times \left(-y_{t+1/12}^{N-\frac{1}{12}} + y_t^N\right),$$

note that the derivative in the second line evaluated at the approximation point are zero, hence the following result obtains:

$$R_{t+\frac{1}{12}} \approx RD \left(N - \frac{1}{12}, \Theta_0\right) \times \left(-y_{t+1/12}^{N-\frac{1}{12}} + y_t^N\right) + \frac{y_N^N}{12}. \quad (3)$$

B.2 The Simple SS

Consider steepener slope made from CDSs of two maturities $s < l$:

$$SS_{t+1}^{simple} = \omega_s \times RD \left(s - 1, \Theta_0\right) \times \left(-y_{t+1}^{s-1}\right) + \omega_l \times RD \left(l - 1, \Theta_0\right) \left(-y_{t+1}^{l-1}\right),$$
and let $\omega_s$ and $\omega_l$ in this example to capture two properties of the LSM portfolio. First, it sells short term CDS and buy long term ones, hence $\omega_s > 0 > \omega_l$. Second, it is immune to level shocks to the term structure of credit spreads: $|\omega_s \times pv01_s^{s-1}| = |\omega_l \times pv01_l^{l-1}| \equiv 1$. To see this, note that the first factor in returns is similar to the change in the average spread across maturity and, since the 2nd factor is by definition uncorrelated with the first, hence the immunity property. In this case:

$$SS_{t+1}^{simple} \propto y_{l+1}^{l-1} - y_{l+1}^{s-1},$$

(4)
clearly $y_{l+1}^{l-1} - y_{l+1}^{s-1}$ is the slope of the term structure of credit spreads from $s - 1$ to $l - 1$ at time $t + 1$, hence a steeper term structure mean high returns for this version of the LSM portfolio.

B.3 Forward Spreads are Approximate Slopes of the Term Structure of CDS spreads

I tie the steepness of the term structure of CDS spreads to the difference between forward and current CDS rates of certain maturities. Later, I tie forward CDS rates to expectations about future CDS spreads and forward CDS returns. As a corollary, these two together tie the slope of the term structure to expectations about future CDS spreads and forward CDS returns. The identities therefore provide an ex-ante motivation for investigating the return-forecasting power of the steepness of the term structure of CDS spreads.

Let a forward CDS from $s$ to $v$ be a CDS contract for which the premia payments and the protection begin at a date $t + s$, that is, $s$ periods into the future, and stop at the earlier of the default time and $t + v$. Note the default leg of a CDS of maturity $T$ and that of a portfolio made of a CDS of maturity $S$ and a Forward from $S$ to $T$, all with the same notional, are equal. If there are no arbitrage opportunities and Forward CDS are tradable, the fixed premium legs of these two contracts must cost the same:

$$y_t^{(T)} \times RD (N, \Theta_t) = y_t^{(S)} \times RD (S, \Theta_t) + f_t^{S \rightarrow T} \times E_t [RD (N - S, \Theta_{t+S})],$$

hence:

$$f_t^{S \rightarrow T} = \frac{\alpha_t}{\alpha_t - \beta_t} y_t^{(T)} - \frac{\beta_t}{\alpha_t - \beta_t} y_t^{(S)},$$

where $\alpha_t = RD (N, \Theta_t)$ and $\beta_t = RD (S, \Theta_t)$ are the now-familiar risky durations from 0 to $N$ and 0 to $S$, respectively, and $\frac{\alpha_t}{\alpha_t - \beta_t} - \frac{\beta_t}{\alpha_t - \beta_t} = 1$. In this way, forward rates are a weighted average of the long-maturity and short-maturity CDS spreads, with weights that add to 1 and depend on the risky durations of the
long- and short-maturity components of the forward. Forward spreads, defined as the difference between the forward rate and the rate on a $S$-period CDS, are given by:

$$f_{S^T} = \frac{\alpha_t}{\alpha_t - \beta_t} \left( y_t^{(T)} - y_t^{(S)} \right),$$

which is proportional to the slope of the term structure of CDS spreads between $S$ and $T$, with a proportionality coefficient of $\frac{\alpha_t}{\alpha_t - \beta_t}$. Clearly, the forward spread is a function of both CDS spreads and risky durations. However, much like in the return approximation, close to a flat term structure, $y_t^{(T)} = y_t^{(S)}$, the forward spread is a function only of the slope of the term structure and a fixed proportionality coefficient

$$f_{S^T} = \frac{\alpha_0}{\alpha_0 - \beta_0} \left( y_t^{(T)} - y_t^{(S)} \right),$$

where $\alpha_0$ and $\beta_0$ depend on the approximation point chosen for the term structure of risk neutral default probabilities and risk-free rates. An interesting approximation point involves setting (RN) default probabilities and risk-free rates uniformly equal to zero. In such a case, the forward spread equation reduces to that of forward spreads of default-free bonds: $f_{S^T} = \frac{T}{T-S} \left( y_t^{(T)} - y_t^{(S)} \right)$.

B.4 Forward Spreads Embed Expectations about Future Returns and Future Changes in Spreads

In Appendix B.5, I show the $s$-periods return of a forward CDS from $s$ to $v$, $v > s$, is approximately

$$rs f_{v}^{s} |_{\tau > t + s} \approx RD (v - s, \Theta_0) \left( f_{l}^{v} - y_{l + s}^{v - s} \right). \quad (5)$$

The decomposition of 5 is now immediate, abusing notation by using $rs f_{l+1}^{s-1+l-1}$ in place of $\frac{rs f_{l+s-1}^{s-1+l-1}}{RD_0(l-s)}$:

$$f_{s}^{s-1+l-1} = \mathbb{E}_t \left[ rs f_{l+s-1}^{s-1+l-1} \right] + \mathbb{E}_t \left[ \Delta y_{l+s-1}^{l-s} \right], \quad (6)$$

higher forward spreads can mean high expected returns of selling forward CDSs, expectations of an increase in spreads or a combination of both. Note both the returns and the changes in spreads are over a holding period equal to the time the forward takes to become active, and the maturity of the predicted spreads equals the difference $l - s$. 

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B.5 Approximating Forward Returns

The $s$ periods return of a forward CDS from $s$ to $v$ is given by:

$$\rho_{t+s}^{s \rightarrow v} = p \left( f_{t+s}^{s \rightarrow v}, v - s, t + s \right),$$

which is the price at time $t + s$ of a fixed coupon CDS with coupon equal to the Forward rate $f_{t+1}^{s \rightarrow v}$ and maturity $v - s$. From previous results in section 2.4 this price can be rewritten as:

$$\rho_{t+s}^{s \rightarrow v} \approx RD(v - s, \Theta_{t+s}) \left( f_{t}^{s \rightarrow v} - y_{t+s}^{v-s} \right) + (1 - 1_{\tau > t+s}) \text{LGD}_{\tau},$$

which, like the returns of CDSs, depends on a realized credit spread $y_{t+s}^{v-s}$, the state variables that drive risky duration $\Theta_{t+s}$, the loss-given-default and the default counter $1_{\tau > t+s}$. Using the same approximation described in Section 6.1.1, I obtain:28

$$\rho_{t+s}^{s \rightarrow v} \mid \tau > t+s \approx RD(v - s, \Theta_0) \left( f_{t}^{s \rightarrow v} - y_{t+s}^{v-s} \right).$$

C Covariances with Possible Delays in Slopes.

Let

$$\begin{align*}
    r_{t+1}^{*} &= \beta_1 r_{t+1}^{lvl} + \beta_2 \left( \lambda r_{t+1}^{slp} + (1 - \lambda) t_{t}^{slp} \right) + \varepsilon_{t+1} \\
    r_{t+1} &= \beta_1 r_{t+1}^{lvl} + \beta_2 r_{t+1}^{slp} + \varepsilon_{t+1},
\end{align*}$$

where $r_{t+1}$ is the true return, $r_{t+1}^{*}$ is the observed return, $1 - \lambda$ is a measured of how much delay there is in the updating of the slope information and $\varepsilon_{t+1}$ is orthogonal to current and lagged values of $r_{t+1}^{lvl}$ and $r_{t+1}^{slp}$. That is, true returns follow a two-factor structure with factors being $r_{t+1}^{lvl}$ and $r_{t+1}^{slp}$. The observed returns reflect up-to-dated information on the level factor, but reflect both lagged and contemporaneous changes in the slope factor. I want to recovery the true covariances:

$$\text{cov}_{true} = \beta_1 \text{cov} \left( r_{t+1}^{lvl}, r_{t+1}^{slp} \right) + \beta_2 \sigma^2 \left( r_{t+1}^{slp} \right),$$

28Now the approximation is around $f_{t}^{v-s} = y_{t+s}^{v-s}$.
but if I use the true slope \( r_{t+1}^{slp} \) and \( r_{t+1}^* \), I recover:

\[
cov \left( r_{t+1}^*, r_{t+1}^{slp} \right) = \beta_1 \text{cov} \left( r_{t+1}^{lvl}, r_{t+1}^{slp} \right) + \beta_2 \lambda \sigma^2 \left( r_{t+1}^{slp} \right).
\]

The covariance of \( r_{t+1}^* \) with the lag of the slope, \( \text{cov} \left( r_{t+1}^*, r_t^{slp} \right) \) is given by:

\[
cov \left( r_{t+1}^*, r_t^{slp} \right) = \beta_1 \text{cov} \left( r_{t+1}^{lvl}, r_t^{slp} \right) + \beta_2 \lambda \text{cov} \left( r_{t+1}^{slp}, r_t^{slp} \right) + \beta_2 (1 - \lambda) \text{cov} \left( r_t^{slp}, r_t^{slp} \right).
\]

If the contemporaneous level return and slope returns are uncorrelated with the lagged slope returns – which I will assume in this section – then:

\[
cov \left( r_{t+1}^*, r_t^{slp} \right) = \beta_2 (1 - \lambda) \sigma^2 \left( r_t^{slp} \right),
\]

and adding both contemporaneous and lagged covariance yields:

\[
cov \left( r_{t+1}^*, r_t^{slp} \right) + \text{cov} \left( r_{t+1}^*, r_{t+1}^{slp} \right) = \beta_1 \text{cov} \left( r_{t+1}^{lvl}, r_{t+1}^{slp} \right) + \beta_2 \lambda \sigma^2 \left( r_{t+1}^{slp} \right) + \beta_2 (1 - \lambda) \sigma^2 \left( r_t^{slp} \right)
\]

\[
= \beta_1 \text{cov} \left( r_{t+1}^{lvl}, r_{t+1}^{slp} \right) + \beta_2 \sigma^2 \left( r_{t+1}^{slp} \right),
\]

which is the true covariance.
Figure 1: The Term Structure of BBB Rated Firms Credit Spreads: April 2004 to May 2012, 122 Months.


Panel C: Slopes and Forwards.

Comparing Different Slopes
Figure 2: **Summary Statistics About CDS Markets: April 2004 to May 2012, 122 Months.**

**Panel A:** Total Notional Outstanding of CDS and Equity Derivatives in $MM (source BIS).

![BIS - CDS and Equity Derivative - Total Notional Outstanding](image1)

**Panel B:** Fractions of Total Notional Outstanding of Single Name CDS Broken Down by Maturity (source BIS).

![BIS - CDS and Equity Derivative - Fraction of Total Notional Outstanding](image2)
Figure 3: Average Monthly Excess Returns of Selling Constant Volatility (500 Bps) Portfolios of CDSs of BBB Rated Firms of Maturities 1,3,5,7 and 10 Years and Their Annualized Sharpe Ratios: April 2004 to May 2012, 122 Months.

I construct individual CDS returns using information on defaults, recovery rates, credit spreads, and the term structure of risk-neutral default probabilities, which I obtain from the term structure of CDS spreads as described in the text. I form portfolios at the beginning of each month using all CDSs of BBB-rated firms meeting the data requirements. For each maturity 1,3,5,7 and 10, I compute equal-weighted monthly excess return from selling those CDSs. Each of these portfolio returns is scaled such that all portfolios have volatility equal to 500 bps per month. Panel A displays the time-series average monthly returns along with two-standard-deviations error bars. I compute standard errors using a circular block-bootstrap of the entire sample in windows of 6 months as described in Politis and Romano [1994]. Panel B displays the annualized Sharpe ratios of portfolios of different maturities. The annualization takes into account autocorrelation by using the procedure described in Lo [2002]. I obtain standard errors for Sharpe ratios from the same bootstrap that I used for sample means.

Panel A: 500-bps volatility returns, monthly.

Panel B: Annualized Sharpe Ratios.
Figure 4: Principal Component Analysis of the Returns of Constant-Volatility Portfolios of CDSs of BBB Rated Firms at Different Maturities: April 2004 to May 2012, 122 Months. Panel A contains the analysis including all maturities but one year. Panel B adds one-year CDS returns. The first graph of each panel plots the factor weights, whereas the bottom graph plots the fractions of variance explained by each factor. Panel C and D contains the monthly returns and cumulative monthly returns of the factors.

Panel A: Using 3,5,7,10 year maturities.

Panel B: Using 1,3,5,7,10 year maturities.

Panel C: Monthly Returns.

Panel D: Cumulative Returns.
Figure 5: **Average Returns of Portfolios of CDSs (sold) Formed on 5 Year Credit Spreads and Maturity: April 2004 to May 2012, 122 Months.**

I construct individual CDS returns using information on defaults, recovery rates, credit spreads, and the term structure of risk-neutral default probabilities, which I obtain from the term structure of CDS spreads as described in the text.

I form portfolios monthly. First, at the beginning of each month and using all firms that meet the data requirements, I determine the 20th, 40th, 60th, and 80th breakpoints for five-year CDS spreads and allocate firms accordingly. For each 5-year CDS spread quintile, I compute the equal-weighted monthly returns of selling 3-, 5-, 7-, and 10-year CDSs. Next, I leverage each portfolio to have the same volatility as the five-year CDS return in its CDS spread quintile.

Hedged portfolios returns are the returns of portfolios of CDSs hedged against the first principal component of returns within this portfolio 5-year CDS spread quintile.

The **top** figure displays the mean returns of unhedged portfolios. The **bottom** figure displays the mean returns of hedged portfolios.

![Realized Returns by Maturity Across Different Credit Riskness (5YR CREDIT SPREAD)](image)

![Realized Returns by Maturity Across Different Credit Riskness (5YR CREDIT SPREAD) – 1st PCP Hedged](image)
Figure 6: **Average Returns and LSM-Model Expected Returns for Portfolios Formed on 5 Year Credit Spreads and Maturity: April 2002 to May 2012.**

The blue bars are time-series average monthly returns multiplied by 12. The red lines are model-implied expected returns. In the first two plots, the asset-pricing model is:

\[
ER^{i,k}_{t+1} = \beta_1 E[R^{MKT,ALL}_{t+1}] + \beta_2 E[HSMS_{t+1}] + \beta_3 E[LSM_{t+1}].
\]

In the last plot, the asset-pricing model is:

\[
E\left[R^{i,k}_{t+1} - \gamma^i R^{1st,k}_{t+1}\right] = \beta_2 E[LSM_{t+1}], \ \forall k \in \{1, 2, \ldots, 5\},
\]

where \(\gamma^i\) is the regression coefficient of \(R^i_{t+1}\) on \(R^{1st}_{t+1}\). \(LSM_{t+1}\) is the 2nd PC of the CDS returns of BBB-rated firms, \(R^{MKT,ALL}_{t+1} = \frac{1}{4 \times N} \sum_{i \in \{3, 5, 7, 10\}} \sum_{k=1}^{5} R^{i,k}_{t+1}\), and \(HSMS_{t+1} = \sum_{i \in \{3, 5, 7, 10\}} R^{i,5}_{t+1} - R^{i,1}_{t+1}\).
Figure 7: Time-Varying Correlations between the Returns on the LSM and the Market

The level, the slope, and the 12-month forward-looking correlation between changes in level and slope. I defined level as an equal-weighted average of 5-year CDS spreads and the slope as the steepener slope, all for BBB-rated firms.

Panel A: $\rho_t(R_{t+1}^{MKT}, LSM_{t+1}), Lvl_t = y_t^5$ and $Slp_t = SS_t$.

Panel B: $\rho_t(R_{t+1}^{MKT}, LSM_{t+1}) + \rho_t(R_t^{MKT}, LSM_{t+1}), Lvl_t = y_t^5$ and $Slp_t = SS_t$. 


Figure 8: The Pricing of Portfolios with a Conditional Model.

Panel A displays the covariance between returns and either the scaled factor (top) or its lag (bottom). Panel B displays average realized returns and model-predicted returns for the scaled-factor model, which features $R_{t+1}^{MKT,ALL}, HSMLS_{t+1}$ and $\bar{y}_t R_{t+1}^{MKT,ALL}$ as pricing factors. $R_{t+1}^{i,k}$ is the return of selling a portfolio of $i$-year CDSs of firms whose five-year CDS spreads are in quintile $k$, leveraged to have the same volatility as the 5-year CDS return in that CDS spread group. $R_{t+1}^{MKT,ALL} = \frac{1}{4\times N} \sum_{i\in\{3,5,7,10\}} \sum_{k=1}^{5} R_{t+1}^{i,k}$, $HSMLS_{t+1} = \frac{1}{4} \sum_{i\in\{3,5,7,10\}} (R_{t+1}^{i,5} - R_{t+1}^{i,1})$, and $\bar{y}_t$ is the average 5-year credit spread.

Panel A: Covariances with the Scaled Factor.

Panel B: Scaled-Factor Model.

Panel C: 3-Factor Model.
**Figure 9: The Model Implied Relation between Slope and Level.**

**Panel A: Low Persistence of Volatility.**

**(a)** Spreads and Slope as Function of Volatility.

**(b)** Derivative of Spreads with Respect to Volatility.

**Panel B: High Persistence of Volatility.**

**(a)** Spreads and Slope as Function of Volatility.

**(b)** Derivative of Spreads with Respect to Volatility.
Table 1: Summary Statistics for Credit Spreads and CDS Returns of BBB rated firms: April 2004 to May 2012, 122 Months.

For the spread statistics in Panel A, I censor observations with spreads larger than 50% and less than 3 dealers quotes.

Individual CDS returns are constructed using information on defaults, recovery rates, credit spreads and the term structure of risk neutral default probabilities. The term structure of risk neutral default probabilities is estimated for every firm and every date from the cross-section of CDS spreads under the assumption that risk neutral intensities are piecewise linear and that loss given default is fixed and equal to 60%. Credit spreads one month away from quoted maturities are linearly extrapolated.

Portfolios in Panel B are formed at the beginning of each month using all CDSs of BBB rated firms meeting the data requirements. I compute equally-weighted monthly returns of selling CDSs of maturities 3,5,7 and 10 years. $E[R]$ is the mean return, $\sigma$ is the standard deviation of return, Sharpe ratio is the monthly Sharpe Ratio, Sharpe Ratio yr is the yearly Sharpe ratio computed from the monthly one, taking into account return autocorrelation (Lo [2002]), and T-stat NW is the return T-statistic computed using Newey-West standard errors with 24 lags.

### Panel A: Credit Spreads, in bps.

<table>
<thead>
<tr>
<th></th>
<th>1yr</th>
<th>2yrs</th>
<th>3yrs</th>
<th>5yrs</th>
<th>7yrs</th>
<th>10yrs</th>
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</thead>
<tbody>
<tr>
<td>$E[CDS^i]$</td>
<td>77</td>
<td>86</td>
<td>96</td>
<td>114</td>
<td>122</td>
<td>130</td>
</tr>
<tr>
<td>p50$(CDS^i)$</td>
<td>52</td>
<td>68</td>
<td>82</td>
<td>110</td>
<td>117</td>
<td>127</td>
</tr>
<tr>
<td>std$(CDS^i)$</td>
<td>76</td>
<td>71</td>
<td>69</td>
<td>63</td>
<td>59</td>
<td>55</td>
</tr>
<tr>
<td>std$(E[CDS^i])$</td>
<td>22</td>
<td>21</td>
<td>20</td>
<td>19</td>
<td>18</td>
<td>17</td>
</tr>
<tr>
<td>max$(CDS^i)$</td>
<td>343</td>
<td>306</td>
<td>321</td>
<td>292</td>
<td>286</td>
<td>282</td>
</tr>
<tr>
<td>min$(CDS^i)$</td>
<td>10</td>
<td>16</td>
<td>23</td>
<td>40</td>
<td>52</td>
<td>63</td>
</tr>
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</table>

### Panel B: CDS Returns (Annualized, in bps).

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<th>5</th>
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</thead>
<tbody>
<tr>
<td>$E[R]$</td>
<td>74.67</td>
<td>108.43</td>
<td>124.48</td>
<td>108.23</td>
<td>116.15</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>202.56</td>
<td>530.91</td>
<td>806.83</td>
<td>998.38</td>
<td>1244.74</td>
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<tr>
<td>Sharpe R</td>
<td>0.37</td>
<td>0.20</td>
<td>0.15</td>
<td>0.11</td>
<td>0.09</td>
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<tr>
<td>Sharpe R yr</td>
<td>0.79</td>
<td>0.52</td>
<td>0.43</td>
<td>0.32</td>
<td>0.29</td>
</tr>
<tr>
<td>T-stat NW</td>
<td>2.72</td>
<td>2.02</td>
<td>1.88</td>
<td>1.49</td>
<td>1.36</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.31</td>
<td>-0.43</td>
<td>-0.47</td>
<td>-0.36</td>
<td>-0.15</td>
</tr>
<tr>
<td>N obs</td>
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<td>122.00</td>
<td>122.00</td>
<td>122.00</td>
<td>122.00</td>
</tr>
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</table>
Table 2: Summary Statistics for the 1st and 2nd Principal Components of the Returns of BBB Constant-Volatility CDSs: April 2004 to May 2012, 122 Months.

In Panel A, $E[R]$ is the time-series average of monthly returns, $\sigma$ is the time-series standard deviation of monthly returns, $\text{Sharpe}_R$ is the monthly Sharpe ratio and $\text{Sharpe}_R\text{ yr}$ is the yearly Sharpe ratio computed from the monthly one, taking into account return autocorrelation (Lo [2002]), $T$-stat NW is the mean-return $T$-statistic computed using 24-lag Newey-West standard errors, P-val SR is the one sided P-value of the annual Sharpe ratio against the less than zero null. I use a 12-month block bootstrap to obtain the distribution of the Sharpe ratio. In Panel B, the first two columns contain the estimates using just the intermediate portfolio of bonds as an additional source of information. The last two columns use both the intermediate and the long portfolio of bonds. The return on the intermediate portfolio of bonds is the return on the Barclay’s intermediate corporate-bond index minus the return on the Barclay’s index of U.S. treasuries of similar duration. The return on the long portfolio of bonds is the return on the Barclay’s long-term bond portfolio minus the return on the Barclay’s index of U.S. treasuries of similar duration.

**Panel A: Using CDS Information Only.**

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<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>$E[R]$</td>
<td>133.03</td>
<td>45.06</td>
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<tr>
<td>$\sigma$</td>
<td>994.17</td>
<td>100.35</td>
</tr>
<tr>
<td>$\text{Sharpe}_R$</td>
<td>0.13</td>
<td>0.45</td>
</tr>
<tr>
<td>$\text{Sharpe}_R\text{ yr}$</td>
<td>0.39</td>
<td>0.98</td>
</tr>
<tr>
<td>P-val SR</td>
<td>0.10</td>
<td>0</td>
</tr>
<tr>
<td>T-stat NW</td>
<td>1.78</td>
<td>2.48</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.31</td>
<td>0</td>
</tr>
<tr>
<td>N obs</td>
<td>122</td>
<td>122</td>
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</tbody>
</table>

**Panel B: Using Bond Information From January 1973 to May 2012.**

<table>
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<td>132.83</td>
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<tr>
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<td>2.59</td>
<td>3.43</td>
<td></td>
<td>2.64</td>
</tr>
<tr>
<td>$\text{Sharpe}_R$</td>
<td>0.13</td>
<td>0.45</td>
<td></td>
<td>0.13</td>
</tr>
</tbody>
</table>

$R_{t+1}^i$ is the holding-period return of a constant-volatility portfolio of i-year CDSs of BBB-rated firms, $R_{t+1}^{1st}$ and $LSM_{t+1}$ are the first and second principal components of $R_{t+1}^i$, $i = \{3, 5, 7, 10\}$, respectively. $R_{t+1}^{i,k}$ is the return of a constant-volatility portfolio of i-year CDSs of firms whose five-year CDS spreads belong to the k-th quintile of five-year CDS spreads. $R_{t+1}^{MKT,ALL} = \frac{1}{20} \sum_{i \in \{3,5,7,10\}} \sum_{k=1}^{5} R_{t+1}^{i,k}$, $HSMS_{t+1} = \sum_{i \in \{3,5,7,10\}} R_{t+1}^{i,5} - R_{t+1}^{i,1}$, $R_{t+1}^{2nd,BBB} = R_{t+1}^{2nd}$, $ER_T$ is the mean return, $\beta \times \lambda$ is the model-implied expected return, $\lambda$ is the factor mean return estimated from the factor sample mean, and GRS is the GRS-statistic for the test that all the $\alpha$s are zero and P-val is its P-value.

**Panel A:** $ER_{t+1}^i = \gamma^i E[R_{t+1}^{1st}] + \beta^i E[LSM_{t+1}]$, only BBB-rated Firms.

<table>
<thead>
<tr>
<th></th>
<th>3</th>
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<th>7</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$ER_T$</td>
<td>99.90</td>
<td>74.31</td>
<td>50.40</td>
<td>41.60</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>s.e.$\beta_1$</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>0.73</td>
<td>0.13</td>
<td>-0.24</td>
<td>-0.62</td>
</tr>
<tr>
<td>s.e.$\beta_2$</td>
<td>0.02</td>
<td>0.02</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>$\beta \times \lambda$</td>
<td>99.25</td>
<td>72.63</td>
<td>55.94</td>
<td>38.35</td>
</tr>
<tr>
<td>$ER_T - \beta \times \lambda$</td>
<td>0.64</td>
<td>1.67</td>
<td>-5.54</td>
<td>3.25</td>
</tr>
<tr>
<td>T-stat NW24</td>
<td>0.26</td>
<td>0.40</td>
<td>-3.35</td>
<td>1.31</td>
</tr>
</tbody>
</table>

Summary Statistics

| $\frac{1}{N} \sum_{i=1}^{N} |\alpha_i|$ | GRS | P-val GRS |
|---|---|---|
| 2.78 | 1.02 | 0.60 |

**Panel B:** $ER_{t+1}^{i,k} = \beta_{1}^k E[R_{t+1}^{MKT,ALL}] + \beta_{2}^k E[HSMS_{t+1}] + \beta_{3}^k E[LSM_{t+1}]$.

| $\frac{1}{N} \sum_{i=1}^{N} |\alpha_i|$ | $\frac{\sum_{i=1}^{N} |\alpha_i|}{\sum_{i=1}^{N} |ER_i|}$ | XS $R^2$ | GRS | P-value GRS | $< R^2 >$ |
|---|---|---|---|---|---|
| 36.48 | 0.25 | 0.94 | 3.74 | 0.00 | 0.96 |

**Panel C:** $E[R_{t+1}^{i,k} - \gamma^i R_{t+1}^{1st,k}] = \beta_{2}^k E[LSM_{t+1}]$, $\forall k \in \{1, 2, \ldots, 5\}$.

| $\frac{1}{N} \sum_{i=1}^{N} |\alpha_i|$ | $\frac{\sum_{i=1}^{N} |\alpha_i|}{\sum_{i=1}^{N} |ER_i|}$ | XS $R^2$ | GRS | P-value GRS |
|---|---|---|---|---|
| 5.34 | 0.25 | 0.93 | 0.26 | 1.00 |
Table 4: Summary Statistics of Returns of the 2nd Principal Components of Credit Indexes of Different Maturities: March 2006 to May 2012, 74 Months.

Panel A reports the summary statistics of the second principal component of constant-volatility returns of the two main corporate Credit Indexes at different maturities. The ITRAXX-Europe features European and Asian companies whereas the CDX-NAIG features U.S Investment grade firms. $E[R]$ is the sample average return of the factor, $\sigma$ is its volatility, Sharpe ratio is the monthly Sharpe Ratio, Sharpe Ratio yr is the yearly Sharpe ratio computed from the monthly one, taking into account return autocorrelation (Lo [2002]), T-stat NW is the 24-lag Newey-West T-statistic of mean returns, P-val Ar12 is the one-sided P-value of the mean return in which the data is bootstrapped from an AR(12). The bottom panels (B and C) contain the results of a regression of the second principal component of returns extracted from single-name portfolios on those extracted from credit indexes. For details on the construction of the returns of single-name portfolios and credit indexes, see the text.

### Panel A: Summary Statistics.

<table>
<thead>
<tr>
<th></th>
<th>ITRAXX-Europe</th>
<th>CDX-NAIG</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>2nd Factor</td>
<td>2nd Factor</td>
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<tr>
<td>$E[R]$</td>
<td>35.64</td>
<td>27.30</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>172.94</td>
<td>154.42</td>
</tr>
<tr>
<td>Sharpe R</td>
<td>0.21</td>
<td>0.18</td>
</tr>
<tr>
<td>Sharpe R yr</td>
<td>0.76</td>
<td>0.53</td>
</tr>
<tr>
<td>T-stat NW</td>
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<td>1.50</td>
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<tr>
<td>P-val Ar12</td>
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<td>0.05</td>
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<tr>
<td>Skewness</td>
<td>-0.73</td>
<td>0.01</td>
</tr>
<tr>
<td># of Obs</td>
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<td>74</td>
</tr>
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</table>

### Panel B: Relation between ITRAXX Returns and Single-Name Portfolio Returns.

$\text{LSM}_{t+1}^{singles} = \alpha + \beta \text{LSM}_{t+1}^{itraxx} + \varepsilon_{t+1}$

<table>
<thead>
<tr>
<th>hp horizon</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>T-stat $\alpha$ NW12</th>
<th>T-stat $\beta$ NW12</th>
<th>$R^2$</th>
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<td>1</td>
<td>38.07</td>
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<td>3</td>
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<td>1.80</td>
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<td>6</td>
<td>25.24</td>
<td>0.59</td>
<td>1.62</td>
<td>5.52</td>
<td>0.36</td>
</tr>
<tr>
<td>12</td>
<td>7.46</td>
<td>0.99</td>
<td>0.55</td>
<td>9.55</td>
<td>0.58</td>
</tr>
</tbody>
</table>

### Panel C: Relation between CDX Returns and Single-Name Portfolio Returns.

$\text{LSM}_{t+1}^{singles} = \alpha + \beta \text{LSM}_{t+1}^{CDX} + \varepsilon_{t+1}$

<table>
<thead>
<tr>
<th>hp horizon</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>T-stat $\alpha$ NW12</th>
<th>T-stat $\beta$ NW12</th>
<th>$R^2$</th>
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<tbody>
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<td>30.54</td>
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<td>6</td>
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<td>0.80</td>
<td>1.81</td>
<td>5.55</td>
<td>0.52</td>
</tr>
<tr>
<td>12</td>
<td>15.33</td>
<td>1.19</td>
<td>1.28</td>
<td>7.02</td>
<td>0.70</td>
</tr>
</tbody>
</table>
Table 5: Predicting the CDS Returns of Various Maturities: April 2002 to May 2012, 122 Months.

$SS_t$ is the steepener slope. $R^N_{t+h}$ is the return of a equal-weighted portfolio of N-year CDSs over holding period $h$. $R^MKT,ALL_{t+1} = \frac{1}{1/N} \sum_{i \in \{3,5,7,10\}} \sum_{k=1}^5 R^k_{t+1}$. $SS_t$. All independent variables are Z-scores. Standard errors are computed either using a Newey-West weighting scheme with as many lags as twice the forecasting horizon, or as in Hodrick [1992]. Bootstrapped P-values are obtained from a 30-month circular block bootstrap.

Panel A: $R^N_{t \rightarrow t+h} = a + \beta SS_t + \varepsilon_{t \rightarrow t+h}$

<table>
<thead>
<tr>
<th>Horizon</th>
<th>Maturity</th>
<th>$\beta$</th>
<th>$R^2$</th>
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<th>T-stat H92</th>
<th>P-value Btsp</th>
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<td>-5.41</td>
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Panel B: $R^N_{t \rightarrow t+h} = a + \beta Y^5_t + \varepsilon_{t \rightarrow t+h}$

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<th>Horizon</th>
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<th>$\beta$</th>
<th>$R^2$</th>
<th>T-stat NW 2H</th>
<th>T-stat H92</th>
<th>P-value Btsp</th>
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<td>0.04</td>
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<tr>
<td>24mo</td>
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</table>

Panel C: $R^MKT,ALL_{t \rightarrow t+h} = a + \beta_{slp} SS_t + \beta_{lvl} Y^5_t + \varepsilon_{t \rightarrow t+h}$. 

<table>
<thead>
<tr>
<th>Horizon</th>
<th>$\beta_{slp}$</th>
<th>$\beta_{lvl}$</th>
<th>$R^2$</th>
<th>T-stat $slp$ H92</th>
<th>T-stat $lvl$ H92</th>
<th>P-value $slp$ BotStrp</th>
<th>P-value $lvl$ BotStrp</th>
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</thead>
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<td>-6.27</td>
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<td>1.17</td>
<td>0.19</td>
<td>0.12</td>
</tr>
<tr>
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<td>2.25</td>
<td>0.11</td>
<td>0.05</td>
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<td>0.71</td>
<td>-1.59</td>
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<td>0.23</td>
<td>0.06</td>
</tr>
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</table>
Table 6: The Relation Between the steepener Slope and Macro Variables: April 2002 to May 2012, 122 Months.

USREC is a dummy variable for NBER-defined recessions. CFNAI is Chicago’s FED index of economic activity, INDPG is the growth in industrial production, VIX is S&P500 VIX and DVIX is the change in VIX, \( r_{mkt_t+\text{horizon}} \) is the value-weighted stock market return and \( r_{f_t+\text{horizon}} \) is the 1-month risk-free rate accumulated over the indicated horizon. All variables in Panel A and B are standardized to have unit variance. The steepener slope \( SS \) is the linear combination of CDS spreads whose innovations are the same as the innovations to the approximated return of the LSM portfolio. For more details see the text. T-stat NW 2H is the Newey-West T-statistic computed using as many lags as twice the horizon considered. P-val Bootstrap is the P-value of the coefficient in question, whose distribution comes from a circular 18-month block bootstrap of the entire sample.

**Panel A: Level of Steepener Slope and Macro Variables.**

\[
Econ_t = \alpha + \beta SS_t + \varepsilon_t
\]

<table>
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<th></th>
<th>200204-200812</th>
<th></th>
<th>200204-201205</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>( \beta )</td>
<td>TNW 2H</td>
<td>R^2</td>
<td>( \beta )</td>
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<td>USREC</td>
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<td>-1.56</td>
<td>0.06</td>
<td>-0.40</td>
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<tr>
<td>CFNAI</td>
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<td>1.96</td>
<td>0.11</td>
<td>0.38</td>
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<tr>
<td>INDPG</td>
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<td>1.58</td>
<td>0.04</td>
<td>0.31</td>
</tr>
<tr>
<td>VIX</td>
<td>-1.22</td>
<td>-5.23</td>
<td>0.39</td>
<td>-0.25</td>
</tr>
<tr>
<td>VOL</td>
<td>-0.98</td>
<td>-3.48</td>
<td>0.22</td>
<td>-0.24</td>
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</table>

**Panel B: Changes in Steepener Slope and Macro Variables.**

\[
Econ_{t+\text{horizon}} = \alpha + \beta \Delta SS_{t+\text{horizon}} + \varepsilon_{t+\text{horizon}}
\]

<table>
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<th></th>
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<th></th>
<th>1yr</th>
<th></th>
<th>2yrs</th>
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<td>R^2</td>
<td>( \beta )</td>
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<td>R^2</td>
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<td>-3.55</td>
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</table>

**Panel C: Stock Return Predictability (Slope and Returns in bps).**

\[
\log (r_{mkt_{t+\text{horizon}}}) - \log (r_{f_{t+\text{horizon}}}) = \alpha + \beta \Delta SS_t + \varepsilon_{t+\text{horizon}}
\]

<table>
<thead>
<tr>
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<th>P-val Bootstrap</th>
<th>R^2</th>
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Table 7: **Conditional and Unconditional Relation between \( LSM_{t+1} \) and \( R_{t+1}^{MKT,ALL} \).**
The dependent variable is change in the LSM return. The independent variables are \( R_{t+1}^{MKT,ALL} \), \( R_{t+1}^{MKT,ALL} \times y_{t-1}^5 \) and \( R_{t+1}^{MKT,ALL} \times SS_t \). Point estimates are in the first row and 12-Lag Newey-West T-statistics in the second row.

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<td></td>
</tr>
<tr>
<td>( R_t^{MKT,ALL} \times SS_{t-1} )</td>
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<tr>
<td>( R^2 )</td>
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Table 8: **The Autocorrelations of the LSM Returns among Various Trading Instruments.**
The autocorrelations of the returns of the LSM at various lags and among various trading instruments. Those instruments are single-name CDSs, the CDX-NAIG index, the ITRAXX-Europe index, and a subset of the single-name CDSs that is quoted by nine or more dealers.

**Panel A: Autocorrelations.**

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<th>ITRAXX</th>
<th>single names, liquid</th>
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<td>0.05</td>
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<td>0.03</td>
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<tr>
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<td>0.02</td>
<td>-0.04</td>
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**Panel B: T-statistics.**

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<th>single names, liquid</th>
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<td>0.31</td>
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<td>-1.12</td>
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<td>0.08</td>
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<td>-0.79</td>
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<td>0.17</td>
<td>-0.34</td>
<td>-0.54</td>
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<td>0.70</td>
<td>0.02</td>
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</table>
Table 9: Cross-Sectional Tests of the Conditional Asset Pricing Model.

\[ R_{t+1}^{MKT, ALL} = \frac{1}{4 \times N} \sum_{i \in \{3, 5, 7, 10\}} \sum_{k=1}^{5} R_{t+1}^{i,k} \] is an equal-weighted return of selling constant-volatility CDSs of all maturities and CDS spread quintiles. \( HSMLS_{t+1} = \frac{1}{3} \sum_{i \in \{3, 5, 7, 10\}} R_{t+1}^{i,5} - R_{t+1}^{i,1} \). \( y_t^5 \) is the mean five-year CDS spread for BBB-rated firms. The covariance \( \text{cov}(R_{t+1}^i, y_t^5 \times R_{t+1}^{MKT, ALL}) \) is estimated as \( \text{cov}_T \left( R_{t+1}^i, y_t^5 \times R_{t+1}^{MKT, ALL} \right) + \text{cov}_T \left( R_{t+1}^i, y_{t-1}^5 \times R_{t}^{MKT, ALL} \right) \), where the subscript \( T \) marks sample moments. The standard errors of \( \lambda \) do not reflect the fact that in estimating the covariances, I have used estimates of the sample mean.

**Panel A:**

\[ E \left[ R_{t+1}^i \right] = a \times \text{cov}(R_{t+1}^i, R_{t+1}^{MKT, ALL}) + b \times \text{cov}(R_{t+1}^i, y_t^5 \times R_{t+1}^{MKT, ALL}) + c \times \text{cov}(R_{t+1}^i, HSMLS_{t+1}). \]

| XS | \( R^2 \) | \( |\alpha| \) | \( \frac{|\alpha|}{ER} \) | \( E[\alpha^2] \) | P-value GMM | \( \lambda_1 \) | \( \lambda_2 \) | \( \lambda_3 \) | \( T\lambda_1 \) | \( T\lambda_2 \) | \( T\lambda_3 \) |
|-----|---------|---------|----------|---------|----------|--------|--------|--------|--------|--------|--------|--------|
| Values | 0.96 | 28.86 | 0.19 | 35.71 | 0.00 | -0.00 | 0.03 | 0.00 | -2.27 | 2.14 | 1.82 |

**Panel B:**

\[ E \left[ R_{t+1}^i \right] = \lambda_1 \times \text{cov}(R_{t+1}^i, R_{t+1}^{MKT, ALL}) + \lambda_2 \times \text{cov}(R_{t+1}^i, LSM_{t+1}) + \lambda_3 \times \text{cov}(R_{t+1}^i, HSMLS_{t+1}). \]

| XS | \( R^2 \) | \( |\alpha| \) | \( \frac{|\alpha|}{ER} \) | \( E[\alpha^2] \) | P-value GMM | \( \lambda_1 \) | \( \lambda_2 \) | \( \lambda_3 \) | \( T\lambda_1 \) | \( T\lambda_2 \) | \( T\lambda_3 \) |
|-----|---------|---------|----------|---------|----------|--------|--------|--------|--------|--------|--------|--------|
| Values | 0.97 | 26.76 | 0.18 | 32.04 | 0.00 | 0.00 | 0.08 | 0.00 | 0.11 | 2.85 | 0.21 |

**Panel C:**

\[ E \left[ R_{t+1}^i \right] = \lambda_1 \text{cov}(R_{t+1}^i, R_{t+1}^{MKT, ALL}) + \lambda_2 \text{cov}(R_{t+1}^i, HSMLS_{t+1}) + \lambda_3 \text{cov}(R_{t+1}^i, LSM_{t+1}) + \lambda_4 \text{cov}(R_{t+1}^i, y_t^5 \times R_{t+1}^{MKT, ALL}). \]

<table>
<thead>
<tr>
<th>Param</th>
<th>( \lambda_1 )</th>
<th>( \lambda_2 )</th>
<th>( \lambda_3 )</th>
<th>( \lambda_4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Values</td>
<td>-0.00</td>
<td>0.00</td>
<td>0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>T-statistic</td>
<td>-0.49</td>
<td>0.61</td>
<td>0.28</td>
<td>0.53</td>
</tr>
</tbody>
</table>

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Table 10: **Regressions of LSM Returns on the BBB Steepener Slope: April 2002 to May 2012, 122 Months.**

I run overlapping regressions of the LSM returns on the steepener slope at several horizons. The LSM return is the second principal component of constant-volatility, maturity-sorted portfolios of CDSs of BBB-rated firms. The steepener slope $SS$ is a linear combination of CDS spreads whose innovations equal the innovations to the approximated LSM. For details on the approximation, see text. Horizon is the horizon over which the regression is run, $b$ is the slope coefficient of the regression, T-stat NW12 is the 12-lag Newey-West T-statistic of the slope $b$.

**Panel A:** LSM Returns and Changes in the Steepener Slope.

\[
R_{t+\text{horizon}} = a + b\Delta SS_{t+\text{horizon}} + \varepsilon_{t+1}
\]

<table>
<thead>
<tr>
<th>Horizon</th>
<th>$b$</th>
<th>T-stat NW12</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.56</td>
<td>5.78</td>
<td>0.55</td>
</tr>
<tr>
<td>3</td>
<td>0.80</td>
<td>11.69</td>
<td>0.77</td>
</tr>
<tr>
<td>6</td>
<td>0.89</td>
<td>20.28</td>
<td>0.86</td>
</tr>
<tr>
<td>12</td>
<td>0.98</td>
<td>14.37</td>
<td>0.89</td>
</tr>
</tbody>
</table>

**Panel B:** The Steepener Slope and the Level of CDS Spreads at Several Maturities.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>3</th>
<th>5</th>
<th>7</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho(\text{levels})$</td>
<td>-0.55</td>
<td>-0.40</td>
<td>-0.20</td>
<td>-0.09</td>
<td>-0.01</td>
</tr>
<tr>
<td>$\rho(\Delta (s))$</td>
<td>-0.37</td>
<td>-0.27</td>
<td>-0.15</td>
<td>-0.10</td>
<td>-0.00</td>
</tr>
</tbody>
</table>

**Panel C:** The Steepener Slope and the Slopes of the Term Structure of CDS Spreads.

<table>
<thead>
<tr>
<th></th>
<th>1-10</th>
<th>3-10</th>
<th>1-7</th>
<th>3-7</th>
<th>1-5</th>
<th>3-5</th>
<th>avg</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho(\text{levels})$</td>
<td>0.98</td>
<td>0.96</td>
<td>0.99</td>
<td>0.98</td>
<td>0.97</td>
<td>0.98</td>
<td>0.99</td>
</tr>
<tr>
<td>$\rho(\Delta (s))$</td>
<td>0.81</td>
<td>0.84</td>
<td>0.75</td>
<td>0.85</td>
<td>0.69</td>
<td>0.80</td>
<td>0.83</td>
</tr>
</tbody>
</table>
Table 11: Cross-Sectional Pricing with the BBB Steeper Slope: April 2002 to May 2012, 122 Months.

The risk premium on the factor is estimated from a cross-sectional regression of returns on betas, the standard errors are obtained through GMM as described in Cochrane [2005]. The long-run covariance matrix is estimated with a Newey-West weighting scheme with 12 lags. The P-values are for the test that all the $\alpha$s are jointly zero.

In **Panel A**, the pricing factor is the change in the steepener slope and the test assets are all hedged portfolios but those whose five-year spreads are higher than the 80th percentile breakpoint, for a total of 16 portfolios. In **Panel B**, everything is the same as in A, with the addition of the highest-yielding portfolios among test assets. **Panel C** evaluates the 3-factor model – mkt, hsml, steepener slope – using the 20 unhedged returns as test assets.

### Panel A: All Hedged Portfolios, but Highest-Yielding Ones.

<table>
<thead>
<tr>
<th>$ER_T$</th>
<th>3</th>
<th>5</th>
<th>7</th>
<th>10</th>
<th>3</th>
<th>5</th>
<th>7</th>
<th>10</th>
<th>3</th>
<th>5</th>
<th>7</th>
<th>10</th>
<th>3</th>
<th>5</th>
<th>7</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>34.70</td>
<td>3.41</td>
<td>-14.31</td>
<td>-23.80</td>
<td>47.11</td>
<td>9.79</td>
<td>-21.32</td>
<td>-35.58</td>
<td>70.28</td>
<td>17.01</td>
<td>-36.34</td>
<td>-50.95</td>
<td>97.47</td>
<td>29.78</td>
<td>-52.90</td>
<td>-74.34</td>
</tr>
<tr>
<td>$s.e. \beta$</td>
<td>2.42</td>
<td>0.98</td>
<td>-1.22</td>
<td>-2.18</td>
<td>4.39</td>
<td>1.22</td>
<td>-1.65</td>
<td>-3.96</td>
<td>7.66</td>
<td>1.83</td>
<td>-2.17</td>
<td>-7.31</td>
<td>14.18</td>
<td>2.70</td>
<td>-4.19</td>
<td>-12.69</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.20</td>
<td>0.44</td>
<td>0.17</td>
<td>0.50</td>
<td>0.96</td>
<td>0.36</td>
<td>0.49</td>
<td>0.60</td>
<td>1.69</td>
<td>0.76</td>
<td>0.73</td>
<td>1.66</td>
<td>2.53</td>
<td>1.37</td>
<td>1.24</td>
<td>2.14</td>
</tr>
<tr>
<td>$\beta \times \lambda$</td>
<td>18.14</td>
<td>7.39</td>
<td>-9.14</td>
<td>-16.39</td>
<td>32.94</td>
<td>9.15</td>
<td>-12.39</td>
<td>-29.70</td>
<td>57.52</td>
<td>13.70</td>
<td>-16.31</td>
<td>-54.91</td>
<td>106.48</td>
<td>20.27</td>
<td>-31.49</td>
<td>-95.26</td>
</tr>
<tr>
<td>$ER_T - \beta \times \lambda$</td>
<td>16.56</td>
<td>-3.98</td>
<td>-5.17</td>
<td>-7.41</td>
<td>14.17</td>
<td>0.64</td>
<td>-8.93</td>
<td>-5.87</td>
<td>12.76</td>
<td>3.31</td>
<td>-20.03</td>
<td>3.96</td>
<td>-21.41</td>
<td>9.51</td>
<td>-21.41</td>
<td>20.92</td>
</tr>
</tbody>
</table>

### Panel B: All Hedged Portfolios.

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>$T - \text{stat}$</th>
<th>$\lambda$</th>
<th>$X S$</th>
<th>$R^2$</th>
<th>$P\text{-val}$</th>
<th>$\alpha_i = 0 \forall i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.47</td>
<td>4.20</td>
<td>0.92</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Panel C: Full Returns,

$ER_{t+1}^i = \alpha + \beta_MKT,ALL \lambda_{MKT,ALL} + \beta_HSMLS \lambda_{HSMLS} + \beta_{slp} \lambda_{SS}$.

<table>
<thead>
<tr>
<th>$\lambda_0$</th>
<th>$\lambda_1$</th>
<th>$\lambda_2$</th>
<th>$\lambda_0$</th>
<th>$\lambda_1$</th>
<th>$\lambda_2$</th>
<th>$\lambda_0$</th>
<th>$\lambda_1$</th>
<th>$\lambda_2$</th>
<th>$\lambda_0$</th>
<th>$\lambda_1$</th>
<th>$\lambda_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>147.29</td>
<td>434.24</td>
<td>4.26</td>
<td>0.95</td>
<td>1.23</td>
<td>1.56</td>
<td>2.24</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 12: Model Implications For Credit Spreads And Default Probabilities.
I obtain default probabilities from Moody’s. The lower numbers refer to the 1983-2007 sample and the higher numbers to the 1920-2007 sample. The CDS spreads are the average credit spreads of BBB-rated firms who satisfy the data requirement in the 200204-201205 sample. $\beta_{s,\text{def}}$ is the coefficient of a regression of a default indicator over 4 years on credit spreads at the beginning of the sample as reported by Chen et al. [2009]. The correlation between the slope and the short-term credit spread is computed from the same credit spreads that I use to compute the averages.

**Panel A: Low Persistence.**

<table>
<thead>
<tr>
<th></th>
<th>Model</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_{\text{boundary}}$</td>
<td>0.25</td>
<td>?</td>
</tr>
<tr>
<td>$b_{\text{boundary}}$</td>
<td>0.75</td>
<td>?</td>
</tr>
<tr>
<td>$c_{\text{boundary}}$</td>
<td>0.20</td>
<td>?</td>
</tr>
<tr>
<td>$P(\tau \leq 5)$</td>
<td>195.80</td>
<td>193-314</td>
</tr>
<tr>
<td>$\beta_{s,\text{def}}$</td>
<td>0.67</td>
<td>0.89(4)</td>
</tr>
<tr>
<td>$E[y^2]$</td>
<td>197.17</td>
<td>114</td>
</tr>
<tr>
<td>$P(\tau \leq 1)$</td>
<td>28.59</td>
<td>19-28</td>
</tr>
<tr>
<td>$E[y^1]$</td>
<td>85.92</td>
<td>77</td>
</tr>
<tr>
<td>$\rho_{\text{slp},s1}$</td>
<td>-0.57</td>
<td>-0.55</td>
</tr>
</tbody>
</table>

**Panel B: High Persistence.**

<table>
<thead>
<tr>
<th></th>
<th>Model</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_{\text{boundary}}$</td>
<td>0.25</td>
<td>?</td>
</tr>
<tr>
<td>$b_{\text{boundary}}$</td>
<td>0.20</td>
<td>?</td>
</tr>
<tr>
<td>$c_{\text{boundary}}$</td>
<td>0.20</td>
<td>?</td>
</tr>
<tr>
<td>$P(\tau \leq 5)$</td>
<td>103.11</td>
<td>193-314</td>
</tr>
<tr>
<td>$\beta_{s,\text{def}}$</td>
<td>0.18</td>
<td>0.89(4)</td>
</tr>
<tr>
<td>$E[y^2]$</td>
<td>270.39</td>
<td>114</td>
</tr>
<tr>
<td>$P(\tau \leq 1)$</td>
<td>14.26</td>
<td>19-28</td>
</tr>
<tr>
<td>$E[y^1]$</td>
<td>68.54</td>
<td>77</td>
</tr>
<tr>
<td>$\rho_{\text{slp},s1}$</td>
<td>0.70</td>
<td>-0.55</td>
</tr>
</tbody>
</table>