Cash-Flow Maturity and Risk Premia in CDS Markets*

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I study the returns of portfolios of credit default swaps (CDS) of different maturities, leveraged to have the same risky durations. I find that average returns decrease with maturity. This variation in expected returns is captured by betas with respect to one factor: a portfolio that sells short-maturity CDSs and buys long-maturity CDSs. 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. Consistent with the beta dynamics, a conditional CDS market model explains the cross-sectional variation in returns by maturity. I develop a parsimonious model of credit risk that matches the fact that short-term CDSs are riskier, as well as the maturity-related beta dynamics.

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1 Introduction

The relation between cash-flow maturity and risk premia is a key issue in asset pricing. The price of any asset is the present value of each of its cash flows discounted at an appropriate rate. Implicit in any valuation, is, therefore, an assumption of how discount rates vary with maturity.

In economic terms, the relation between risk premia and maturity informs us about the persistence of the shocks that command a risk premium. Intuitively, a high risk premium for short-term assets suggests that investors demand risk premiums from shocks that die out quickly. This insight is featured in a growing literature that relates risk premium and maturity in equity markets (Lettau and Wachter [2007], van Binsbergen et al. [2012], Binsbergen et al. [2011], Hansen et al. [2008]). In this literature, the key question is about the persistence of (dividend- or consumption-) growth shocks that investors are concerned with and demand a risk premium to bear.

Economic growth has been in the center of macroeconomics for decades, but more recently, another class of macroeconomic shocks has been in the spotlight, these are the so-called uncertainty shocks. Shifts in some measure of aggregate uncertainty have been put in the center of business cycles (Bloom [2009]); have been linked to business cycles, aggregate stocks market returns, risk premia and the quantity of risk in the economy (Baker et al. [2013], Pastor and Veronesi [2012, 2013]); have been evoked to explain the cross-section of equity returns (Ang et al. [2006]) and why value stocks overperform growth ones (Bansal et al. [2012]Campbell et al. [2011]).

In this paper, I keep the focus on maturity, but instead of investigating growth-sensitive assets, I study uncertainty-sensitive ones, and, in this way I will shed light on the horizon of uncertainty that investors fear. Namely, I study how risk premia varies with maturity in the large, liquid, and term-structure-data-rich Credit Default Swap (CDS) market.

Credit default swaps are derivatives that work as insurance against the default of a corporation. A buyer of running-spread CDSs makes periodic payments – the CDS spread – in exchange for being compensated by the loss in bond value (compared to par) when there is a default. In other words, a buyer of CDS pays for somebody else to bear credit risk for them.

In Merton [1974] seminal work, the credit risk of firm is a function of its leverage and asset return volatility. Intuitively buying a defaultable bond is like writing a put on the total value of the assets of a firm and buying a treasury. Hence, the credit spread of a portfolio of bonds should be and empirically is (Campbell and Taksler [2003], Zhu [2009]) closely linked to the uncertainty about the values of those firms in the portfolio. Hence learning about the relation between maturity and risk premia in those markets sheds light on the horizons of uncertainty investors fear.

To study the term structure of risk premia, I construct holding-period returns of constant-duration CDS (CD CDS) portfolios of different maturities. The returns of CD-CDS portfolios are equal to the returns of CDS portfolios, scaled by a measure of their CDS spread sensitivity – like duration is for risk-free bonds.[1] In this way, for short holding periods, CD-CDS returns of various maturities

[1] I consider two measures of this sensitivity. The first measure is the lagged risky-duration, which is the risky-bond analogous of risk-free-bond duration and can be calculated from CDS spreads. The second measure is just the CDS return volatility, which I show is empirically equivalent to an average risky-duration scaling.

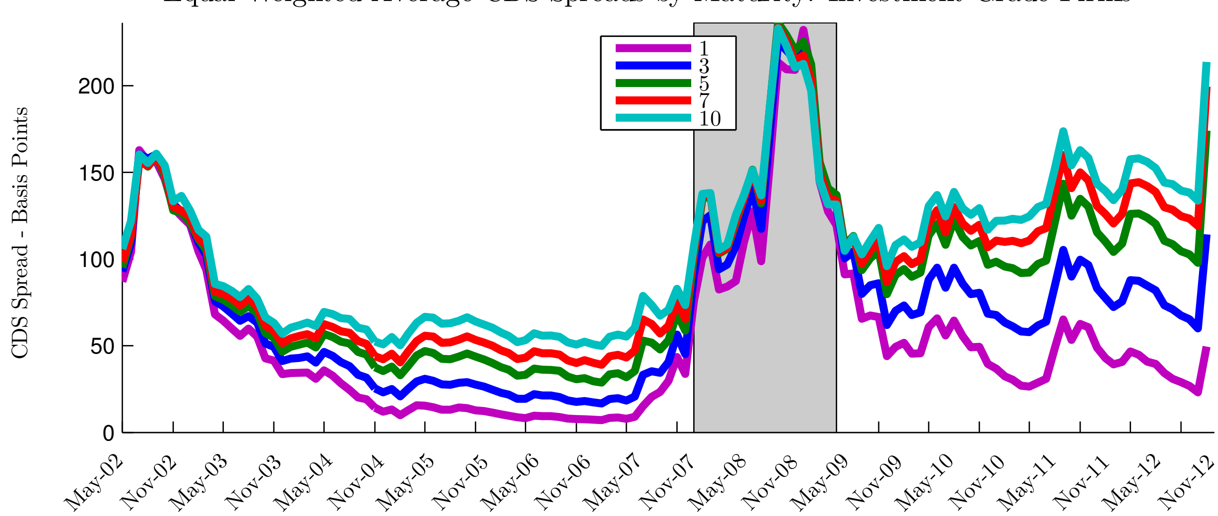
just differ in the maturity of the realized CDS *spreads* to which they are sensitive, but *do not differ* in the *size* of this sensitivity. Hence, the cross-section of risk premia of CD-CDS portfolios is directly related to the prices of *shocks to average CDS spreads of various maturities.* The pricing of those shocks informs us about the risk premia earned by CDS portfolios cash flow across maturities.

I first examine the relationship between average returns and maturity among several groups of CDSs: single-name CDSs of BBB-rated firms, single-name CDSs of lower- and higher-yielding firms, the index of U.S. investment grade CDS (CDX-NAIG index), and among the index of mostly European corporates (the ITRAXX-Europe). Within each of those groups of CDS, the average one-month returns of selling CD CDSs are decreasing in maturity. For example, within the universe of CDSs written on BBB-rated firms in the United States from April of 2002 to February of 2013, a strategy that sells short-maturity CD CDSs and buys long-maturity CD CDSs had an annualized Sharpe ratio of 0.95. I call this portfolio "LSM": *long and short maturity.*

Second, I study the shocks to which short- and long-maturity CDS portfolio returns are differentially exposed. CD-CDSs of different maturities have similar unconditional betas on a market portfolio of CD CDS, and thus, an unconditional CDS market model fails. However, the LSM portfolio prices the cross-section of CD CDS portfolios sorted on maturity. The betas on the LSM portfolio explain the variation in expected returns by maturity not only among portfolios of 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. This first exercise reduces the problem of understanding the exposures of an entire cross-section of CDS portfolios of different maturities to understanding the exposures of the LSM.

To understand what drives LSM, I plot the time series of the term structure of average CDS spreads of BBB-rated firms. In calm times, short-maturity spreads are lower and less volatile than are long-maturity spreads. In turbulent periods, which include 2002 and the financial crisis beginning in 2007, short-maturity spreads are higher and more volatile than long-maturity spreads.

Equal-Weighted Average CDS Spreads by Maturity: Investment-Grade Firms



From this behavior of CDS spreads over time, we can learn a lot about CDS curve steepeners. Those steepeners, of which the LSM is an example, are bets that the CDS curve will get steeper.

By definition, the LSM takes short-term spread risk by selling short-maturity CDS portfolios and hedges long-term spread risk by buying long-maturity CDS portfolios.

In *calm times*, the fact that short-term spreads do not move as much as long-term spreads implies the *LSM is a hedge* to overall increases in credit spreads, because long-term CDS spreads drive those increases. In *turbulent times*, the fact that short-term spreads become more volatile than long-term spreads means the *LSM* is *no longer a hedge* to across-the-board increases in CDS spreads: it is now vulnerable to across-the-board increases in spreads or, equivalently, it loads on CDS-market risk. This change in sensitivities follows from the fact that, during those turbulent times, the short-maturity spreads are moving even more than long-maturity spreads.

If the price of CDS-market risk is higher during turbulent periods than it is during calm periods, the dynamics of LSM CDS-market betas naturally suggest that a conditional CDS market model may price the cross-section of CD-CDS across maturities. Using the five-year average CDS spread of BBB-rated firms to capture time variation in the CDS-market risk premium, I show that a conditional CDS market model indeed prices the cross-section of CD CDS portfolio returns sorted on maturity as accurately as the LSM model.

To understand what those empirical results imply about the characteristics of asset prices in the economy, and in particular to the horizon of uncertainty investors are concerned with, I build a parsimonious structural credit risk model and calibrate it to match my empirical results.

The model is a CAPM and it has *three* key ingredients that vary over time: risk premia, the volatility of the return on assets of a typical BBB-rated firm, and its default boundary. One state variable drives them all. When the state is high, the economy is bad – risk premia, volatilities, and the default boundaries are all high – and vice-versa when the state is low. This one-factor model means that average CDS spreads of BBB-rated firms of any maturity also depend on just this single state variable. In this aspect, this model is analogous to that of Chen et al. [2009].

This model reduces to Merton [1974]'s model if the single state variable is constant over time. In such a world, the average CDS spread of BBB-rated firms is constant. To produce interesting dynamics, I assume that the state variable has persistent dynamics. Now, BBB CDS spreads of all maturities vary over time. In particular, they all increase when the economy deteriorates. The size of the increase across maturity, however, depends on the persistence of the state variable. *If the economy is weakly persistent, long-maturity CDS spreads rise faster than short-maturity CDS spreads in good times, but short-maturity spreads rise faster than long-maturity spreads in bad times.*

On the one hand, this dynamic of CDS spreads implies that when the economy deteriorates from a healthy starting point, both the level and the slope of the term structure of CDS spreads rise together. In terms of the returns that I study, when the economy is healthy, the LSM is a hedge to CDS-market returns. The intution for this *negative* correlation is that in good times, the fact that the economy mean reverts implies long-maturity assets are risky even if the short-term outlook is good, whereas short-term assets are relatively safe given such an outlook. On the other hand, in a bad economy, the level and the slope of the term structure of CDS spreads move in opposite directions. When the economy is bad, the LSM loads up on CDS-market risk. The intution for this *positive* correlation is that in bad times, the fact that the economy mean reverts implies that long-maturity assets are less risky than what the gloomy short-term outlook suggests, whereas short-term assets are as risky as the short-term outlook suggests.

The LSM is risky in the model because the shocks to the state variable are priced high when the state is high (and low otherwise) and these high prices coincide with LSM's high exposures. All the model's ingredients as well as the low-persistence state dynamics play an important role in obtaining those results. If default boundaries are constant and volatility dynamics realistic, the short-maturity CD CDS will always be safer than the long-maturity ones. If risky premia are constant, LSM's risk premium will be smaller or even negative. If the economy is too persistent, the LSM will be a hedge to deteriorations in economic conditions for most of the state space.

The paper is organized in six sections. 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 LSM's time-varying CDS market betas and I propose an empirical asset-pricing model based on those findings. Section 5 presents the credit-risk model that rationalizes my findings. In section 6, I offer concluding remarks.

2 Data

In this section, I first describe the data sources that I use and give an overview of the data. In the last part, I describe how I compute the returns of writing a CDS. I leave to the on-line appendix a discussion of the insitutional details of the CDS market.

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, CRSP, Compustat and Creditex. The first three default databases are standard in studies of corporate default (Duffie et al. [2007]). The last database, Creditex, is not. This database contains the outcome of CDS settlement auctions. These auctions take place shortly after a credit event and their outcome is a price for the defaulted bonds. This price serves as a reference for the payoffs of CDSs. Thus, this database is the most precise regarding CDS return computations. Finally, from Datastream, I obtain data on several Barclays government and corporate bond portfolios, and from Optionmetrics I obtain data on the risk-free term structure.

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. Documentation clauses specify what happens with the CDS in case of a debt restructuring. XR CDSs are not triggered in a debt restructuring. This type of documentation clause is the standard type for United States corporates after 2009. Before, the MR documentation clause was the standard. MR CDSs are triggered in restructurings, but only bonds with remaining time to maturity below thirty months can be traded for par in those circumstances.

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

Panel A of Figure 1 displays investment-grade single-name data. The left plot displays the average CDS spreads of investment grade public corporations at various maturities, and the right plot shows several measures of the steepness the term structure of CDS spreads. CDS spreads of all maturities spike 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. At the first two times average CDS spreads increase considerably, the slopes of term structure of CDS spreads flatten. These patterns about the steepness of the term structure are clearest in the second plot, which has the slope of the term structure at various points as well as forward CDS rates computed the same way as risk-free forwards.[2] 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. Likewise, the slopes of the term structure of CDS spreads are generally positive, but during crisis, they fall to zero or even negative. Later, I will show there is a rich time-varying relation between the steepness of the term structure of credit spreads and its level.

Panel B displays the average spreads of two CDS index: a U.S. corporate credit index – CDX-NAIG – and a mainly European one – ITRAXX-Europe. The European and U.S credit index, in their smaller sample, paint a similar picture as the single-name average. CDS spreads spike 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. The steepness of both index felt during the financial crisis, becoming inverted at times. More recently, the ITRAXX-Europe experienced another simultaneous increase and flattening of the spread curve.

2.3 CDS Holding-Period Returns

For most of my analysis, I treat all CDS as running spread CDS. 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 key calculations under the assumption that the CDS are of the upfront type, and show the results are the same. In the calculations that I display, I will assume that the coupon payments are continuous.[3] The fact that payments are quarterly make computations a little messier and will have negligible effects in close-to-zero short-term interest environments.

If there is no default, the holding-period excess return (or, simply, return; I will use the terms interchangeably) of selling a running-spread CDS with fixed payment (or spread) y per period is given by

$$rsCDS = y + \text{Capital Gain}, \tag{1}$$

[2] This approximation can be justified by a linearization around zero risk-free interest rates and risk-neutral default probabilities.

[3] In the true calculations I will take into account that payments are quarterly.

where the Capital Gain is the value of the seasoned CDS.[4] If there is a default, the return of selling a CDS is negative and equal to minus loss-given-default (LGD), that is the difference between the par value of the underlying bond and its value immediately afer default. Defining $p\left(y,\ N,t\right)$ as the time-t value of a CDS with payments y and maturity N, I can express equation 1, now with maturity supercrips and time subscripts, as

$$
\begin{aligned}
rsCDS_{t+1} &= y_t^N - p\left(y_t^N,\ N-1,t+1\right) + p\left(y_t^N,\ N,t\right), \\
&= y_t^N - p\left(y_t^N,\ N-1,t+1\right),
\end{aligned}
$$

where from the first to the second line I used the fact that $p\left(y_t^N,\ N,t\right)=0$ because in a running-spread CDS, y^N is chosen to make its initial value equal to zero. This equation means that even with data on credit spreads at all maturities (quotes or extrapolations), $rsCDS_{t+1}$ is not observable because data on $p\left(y_t^N,\ N-1,t+1\right)$, the capital gain term, would still be missing. This term, however, can be inferred from credit spreads and risk-neutral default probabilities. To see that, note that a seasoned CDS can be expressed as a current CDS of same maturity plus another asset which pays the differences between the periodic payments of the old and new CDS, $y_t^N - y_{t+1}^{N-1}$, as long as the firm has not defaulted and the CDS has not matured. The value of a current CDS is zero by definition. The value of the payments $y_t^N - y_{t+1}^{N-1}$ depends on the term-structure of risk-neutral default probabilities and risk-free discount rates. Defining the follow notation:

Parameter	Definition
τ	time of default
Θ_{t+1}	Information set at time $t+1$
$P^{RN}\left(A,\Theta_{t+1}\right)$	Time $t+1$, risk-neutral probability of event A.
$D\left(s,\Theta_t\right)$	Time t tisk-free discount function for cash flows s periods in the future.

I can express the capital gain term as

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

where

$$
RD\left(N-1,\Theta_{t+1}\right) = \int_{i=0}^{N-1} P^{RN}\left(\tau > t+1+i,\Theta_{t+1}\right) D\left(i,\Theta_{t+1}\right) di
$$

is the time-t+1, N-1-period risk duration, the sum of the risk-neutral survival probabilities and risk-free discount functions from the current date to $N-1$ periods into the future.[5] To understand what RD means, consider the example in which both the risk-neutral default probability and risk-free rates are zero. In this case, $RD\left(N-1,\Theta_{t+1}\right)=N-1$, which is just the number of installments to which the CDS buyer is entitled. Clearly $RD\left(N-1,\Theta_{t+1}\right)$ is a measure of the duration of those payments, hence the term "risky duration" for $RD\left(N-1,\Theta_{t+1}\right)$.

[4] I am doing the calculations assuming the continuous fixed payments are kept as cash until next period.

[5] This risk-duration formula is for the case coupons are continuously paid. in the empirical exercise I treat them as they really are: paid every quarter.

When there is no default during the holding period, I have reduced the task of computing CDS holding-period returns to obtaining a term structure of credit spreads, risk-neutral default probabilities and risk-free discount rates. For the term structure of CDS spreads I either use observed quotes or lineraly-extrapolated ones when needed. I infer the term structure of risk-neutral default probabilties from the CDS spread of the quotes of the closest-maturity-quoted CDS, assuming a loss-give-default of 40% and a constant hazard rate.[6] I use the term structure of risk-free rates available in the optionmetrics dataset.

When there is a default, I use the default databases to determine the loss given default and use the negative of this number as the return for that single-name CDS. For credit indexes, when there is a default I sell the position on the legacy version of the index and start trading the newer version next month.

3 Expected Returns and Betas by Maturity

In this section I study the risk premia of assets exposed to shocks to different parts of the term structure of credit spreads. That is, I study the risk premia of portfolios of CDS of different maturities.

I construct two sets of portfolio returns from selling single-name CDS. In the first type, I look only at BBB-rated firms. In the second type, I look at the whole cross section by sorting firms according to their 5-year CDS spreads at the beginning of the month. For both sets of portfolios I create equal-weight returns of selling 3,5,7, and 10-year CDS.

Short-maturity portfolios of CDSs (long risk) lose value when short-maturity credit spreads rise, whereas long-maturity portfolios of CDSs lose value when long-maturity credit spreads rise. However, for a same rise in credit spread, short-maturity CDSs increase less in value than long-maturity CDSs. In other words, CDS of different maturities have different risky durations.

It follows that to measure the risk premia commanded by shocks to credit spreads of different maturities, I cannot simply compare the risk premium of long- and short- maturity CDS. The relevant comparison is between a leveraged position on short-maturity CDS and another less-leveraged position on long-maturity CDS, with the additional leverage on the short-maturity position chosen to compensate for short-maturity CDSs lower sensitivity to underlying spreads.

The sensitivity of a CDS value with respect to a small change in credit spreads is its risk duration, which can be measured from the term structure of CDS spreads as explained in section 2.3. In Figure 2, I plot average risk durations of CDS portfolios of different maturities. The average risk durations increase fast with maturity, with the duration of a 10-year CDS being roughly three times larger than that of a 3-year CDS. Figure 2 also shows that portfolio risk-durations and return volatilities are closely tied. In fact, within a credit-quality group, the correlation between average risky duration and return volatility is always larger than 99%.

[6] I also do all caculations using the cds standard model. This model is widely used to mark CDSs to market. It assumes a loss given default of 40% and non-stochastic hazard rates that are a piecewise linear function of time.

The link between return volatility and risk duration imply that leveraging portfolios of CDS by the inverse of their return volatilizes also creates assets whose values have similar sensitivity to shocks to underlying credit spreads. Interestingly, the average returns of so-adjusted portfolios are proportional to the Sharpe ratios of the unlevered portfolios. I will focus my analysis on portfolios leveraged this way. More precisely, I leverage the BBB-rated-single-name portfolios and the indexes to have a 5% return volatility. For the spread-sorted-portfolio returns, I choose leverage such that these returns all have the same volatility as that of the 5-year CDS return within that credit-spread bin.

Table 1 reports average returns by maturity within each of the groups of CDS I analyze. The average returns earned from selling short-maturity CDS are always larger than those earned from selling long-maturity CDS. Among BBB-rated firms from April 2002 to February 2013, the average one-month return of (selling) a 3-year CDS is 124 basis points whereas that of 10-year CDS is 65 basis points, both leveraged to a 5% one-month volatility. As a consequence, a portfolio that sells 3-year CDS and buys 10-year CDS earn a monthly return of 58 basis points. Importantly, because the 3- and 10- year CDS are also strongly correlated, the long-and-short portfolio also has low volatility. As a consequence the average of 58 basis points is statistically significant, its 12-lag-Newey-West standard deviation is just 19 basis points and a 24-month block bootstrap strongly rejects the null that it is equal to zero.

To allay concerns that the significance of the risk premia is being driven by the 131-month sample, I estimate the risk premium of the long-and-short CDS factor using information on BBB Barclay's corporate bonds portfolios of intermediate and long maturity. Intuitively, if the 2000's were an exceptional year for the long-and-short portfolio, a similar long-and-short portfolio built with bonds would have had much stronger returns from 2002 to 2012 than from 1973 to 2001. Formally, I use Lynch and Wachter [2008]'s technique to combine moments of unequal sample length. The point estimates are very similar and the statistical significance slightly stronger. See the on-line appendix for details.

Sharpe ratios behave very similarly to returns. They start at high 0.63 (per year) for the 3-year portfolio and decline towards 0.41 at the 10-year maturity. The long-and-short portfolio has a 0.92 Sharpe ratio.[7]

These results are not a unique to constant-volatility portfolios. The results are very similar if I look at the returns of one-risk-duration portfolios. The annualized one-month return of selling one-risk-duration, 3-year and 10-year CDS are 58 and 10 basis points, respectively. The long-and-short portfolio has a statistically significant 48 basis points average return.

Neither are the results unique to BBB-rated CDS, nor to portfolios of single-name CDS. The same patterns arise among each of the five sets of firms sorted according to their 5-year-CDS spread and among the CDX-NAIG and ITRAXX-Europe indexes. The results among low- and high-5-year-CDS firms are as statistically strong as those with BBB-rated firms only. It is statistically weaker among the credit indexes, but the sample for the indexes is much smaller: April 2006 to May 2012.

[7] Sharpe ratios are annualized taking into account autocorrelations as in Lo [2002].

The conclusion that average returns decrease with maturity is pervasive. I next investigate whether these pattern in average returns have a counterpart in comovement: do the portfolio betas with respect to a long-and-short portfolio decrease in the same way as average returns do?

To answer this question I have to settle on a risk factor. I choose the second principal component of the returns of BBB-rated portfolios, but the results are very similar for other choices. The weights on of the second principal component are 0.74, 0.12, -0.25 and -0.61 on the 2-,5-,7- and 10-year portfolios, respectively. The average return of the second principal component, henceforth LSM for *L*ong and *S*hort *M*aturity, equals 45 basis points per month and are statistically significant.

Panel A of Table 2 reports the betas of the CDS portfolios with respect to LSM. Within each group of CDS with a similar credit quality, portfolio's LSM betas decrease monotonically with maturity. This result suggests that an empirical asset pricing model featuring the LSM can explain the difference in risk premia by maturity across all these different groups of CDS. To test this hypothesis, I evaluate the pricing performance of such a model. Besides the LSM, I include two additional factors, a CDS-market factor and a high-spread-minus-low-spread factor.

I define the CDS-market factor as an equal-weight portfolio of all 20 portfolios sorted on 5-year spreads and maturity. By definition all portfolios will have equal loadings on it, hence it will help the model match an asset-class-level risk premia, much like the market portfolio of stocks helps an empirical model match the fact that stock portfolios, on average, earn a risk premium. In a Merton-type model, the CDS-market factor is closely tied to changes in the volatility of the value of the assets of firms in the economy. This portfolio has low returns when there are across-the-board increases in CDS spreads. One reason for across-the-board increases is an increase in firms' asset value volatilities, hence the link between such returns and changes in uncertainty. If investors charge a risk premia for shifts in uncertainty about firm values and the CDS-market portfolio has low returns when uncertainty increases, the CDS-market portfolio should carry a positive risk premium.

Portfolio's average returns tend to increase with credit spreads, especially among short-maturity CDS. This positive relation between CDS spreads and average returns in the cross-section is consistent with work that finds that higher-yielding bonds command higher risk premia (Fama and French [1993], Gebhardt et al. [2005]). In this literature, the excess returns of high-yielding bonds can be tied to betas to a long-and-short portfolio that buys high-yield bonds and sells low-yield ones. I follow this tradition and use a high-spread-minus-low-spread factor to capture the variation in expected returns that is related to the level of CDS spreads.[8]

In sum, I propose the following asset pricing model:

$$ER^{i,k}_{t+1} = \beta^i_1 E\left[R^{MKT,ALL}_{t+1}\right] + \beta^i_2 E\left[HSMS_{t+1}\right] + \beta^i_3 E\left[LSM_{t+1}\right],$$

where $R^{MKT,ALL}_{t+1} = \frac{1}{20}\sum_{i\in\{3,5,7,10\}}\sum_{k=1}^{5} R^{i,k}_{t+1}$ is the return of the previously defined market portfolio of CDS, $HSMS_{t+1} = \sum_{i\in\{3,5,7,10\}} R^{i,5}_{t+1} - R^{i,1}_{t+1}$ is the return of the high-spread minus a low-spread portfolio, LSM_{t+1} is the return of the second principal component of BBB-rated portfolio returns,

[8]This factor does not explain the term structure of risk premia.

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 $\sigma\left(R_{t+1}^{5,k}\right)$.

To test the model, I rely on the fact that all factors are excess returns and use time-series tests of asset pricing models. I estimate multivariate alphas and betas by running full-sample time-series regressions of returns on factors. Figure 3 displays true and model-predicted average returns for the twenty portfolios sorted on spreads and maturity. The two line up closely. The largest differences show up in the price of risks needed to match low- and high-spread portfolios, it would have to be higher to match the low-risk ones and lower to match the high-risk ones.

Nevertheless, the three-factor model explains 99% of the cross-sectional variation in expected returns and the mean-absolute value of the model's alphas are only 12% 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 2. The rejection is partly due to the high average time-series R-squares of 96% and partly due to slight differences in LSM price of risk across the credit quality spectrum. The portfolio that rejects the model is a double long-and-short across maturities and credit quality. Because of the slight differences in LSM price of risk across credit quality, this double-long-and-short portfolio has a small positive return, and because of the high R-squares, an even smaller volatility. The fact that this strategy relies on levering small average returns means that its economic importance depends on close-to-zero trading costs, which are unlikely, hence I do not take this rejection as a serious challenge to the model.

This section's characterization of the term structure of credit risk begets a new question. What macroeconomic sources of risk LSM is a proxy for? or in other words, to what macroeconomic sources of risk are short- and long-maturity CDSs differentially exposed? In the next sections I will elaborate on this question.

4 Time Variation in Portfolios' CDS-Market Betas and in the CDS-Market Risk Premium Explain The Cross-Section of Expected Returns

In this section, I argue that the risks of short- and long-maturity CDS portfolios are time varying in a way that explains their different unconditional average returns. First, I will show evidence that when the risk premium investors demand to hold the CDS-market is high, the CDS-market betas of short-term portfolios rise relative to those of long term portfolios. This joint dynamics of risk premia and betas imply that the average risk premium of short-term assets is higher than what is implied by their unconditional CDS-market betas. In the second part of this section, I go one step ahead and ask whether the joint dynamics of betas and CDS-market risk premium can, alone, quantitatively explain the cross-sectional differences in expected returns. That is, I evaluate an empirical asset pricing model in which the price of CDS-market risk is allowed to vary, but in which I exclude the LSM factor.

4.1 Time-Varying Betas and Risk Premia

Figure 4, I plot an estimate of the conditional correlation between the LSM and the market returns – the 12-month forward-looking rolling correlation between them. The correlations vary substantially over times. They are positive at two periods: 2002 and in during the financial crisis in 2008. All other times it is negative and many times strongly, it is close to minus one most of the time from the end of 2002 to 2006 and from 2010 to 2012.

Besides suggesting that correlations vary over time, Figure 4 suggests a marked business cycle pattern. To make this clear, I use the average CDS spreads of BBB-rated firms as an indicator of macroeconomic conditions. Empirically, High credit spreads mark bad macroeconomic conditions (Gilchrist and Zakrajšek [2011]). Economically, there are many possible reasons for credit spreads to be countercyclical. Bad macroeconomic times are associated with asset prices that express higher risk aversion and higher uncertainty about firms' cash flows, both lead to higher credit spreads. I plot average CDS spreads of BBB-rated firms along with the correlations in Figure 4. The two move closely together, with both being high in 2002 and the financial crisis.[9]

The plots are suggestive, but they do not provide statistical evidence for the time-variation in LSM CDS-market betas. To do so, I estimate conditional betas and test whether they vary over time. I estimate conditional betas by running regressions of LSM on the CDS-market and on interactions of the CDS market with functions of the average 5-year CDS spread:

$$LSM_{t+1} = \alpha + f\left(Y^5_{BBB,t}, \beta\right) \times R^{MKT,ALL}_{t+1} + \varepsilon_{t+1}.$$

To facilitate the interpretation of the conditional beta, I scale the market return to have the same standard deviation of LSM and I use the z-score of Y^5_{BBB}. Table 3 report the estimates for several functions $f\left(Y^5_{BBB,t}, \beta\right)$. In the first column, I display the usual beta-estimation regression. LSM unconditional CDS-market betas are statistically indistinguishable from zero. In the second column I estimate beta as an affine function of Y^5_{BBB}. Although the point estimate implies that beta rises with Y^5_{BBB}, the result is not statistically significant. In the third column I allow the beta to differ depending on whether credit spreads are above or bellow median and found that they are statistically larger when spreads are above median (12-lag-Newey-West t-statistic of 2.57). In the forth and fifth columns I explore the non-linearity in more detail and found that the reduction in betas in good times is mostly driven by very low betas when spreads are themselves very low. In column six, I show that a quadratic functional form also leads to the conclusion that, at least initially, betas and spreads rise together in a statistical significant way. Overall, the results support the argument that there is a statistically significant positive relation between betas and the level of credit spreads, even if it is not linear.

[9] In spite of 2002 not being a NBER-designated recession, it was a turbulent year. Credit markets were hit by large corporate defaults and accounting frauds that later motivated SOX, credit spreads reflected this reality with average CDS spreads of BBB-rated firms being almost as high as during the financial crisis. Stock markets suffered heavy losses, the S&P500 had a total return of -24.6%.

The next step in the argument that time-varying betas explain the cross-section of CDS returns is to show that this time variation is related to time variation in the CDS-market risk premium. In a world in which the CDS market is the only priced factor, even if betas are time-varying, unconditional betas could still price the cross-section of assets. This result would obtain, for example, if betas were independent of the price of risk.[10] Accordingly, I now study time variation in risk premia and its relation with betas. If time-variation in betas is indeed fully captured by time-variation in average CDS spreads alone, understanding the relation between betas and the CDS-market risk premium is equivalent to understanding the relation between the CDS-market risk premium and average CDS spreads. This assumption is reasonable given the limited sample size and my desire for parsimony. Furthermore, I later conduct another test of the hypothesis that the joint dynamics of betas and returns explains the cross-section of CDS returns which does not rely on this assumption.

The relation between the CDS-market risk premium and average CDS spreads should be similar to the relation between the risk premia of defaultable bonds and their yield spreads over maturity matched Treasuries. A bond can be synthesized from a treasury and a CDS and while CDS-bond basis exist and are time-varying, they are generally small compared with the level of spreads themselves. All this means that I do not need to solely rely on the findings in my limited sample in order to understand the relation between CDS spreads and returns. I can learn from the literature that examines the bond-yield-and-bond-return relation over long samples. The conclusion there is that aggregate credit spreads vary mostly because of changes in bonds' expected returns. For example, Giesecke et al. [2011] shows average credit spreads fail to predictive 4-year defaults in a 150-year sample, time variation in credit spreads was dominated time variation in expected returns.

Reassuringly, I reach a similar conclusion in my sample. I run regressions of CDS-market returns on the average CDS spread of BBB-rated firms at the beginning of the period. I run these regressions over several horizons – one month, three months, six months and twelve months – and several specifications that allow for a non-linear relation between average CDS spreads and expected returns.

The level of CDS spreads is a strong predictor of returns and its predictive power rise with the horizon. For example, in the linear specification, R-squared values rise from 7% at one-month horizons to 55% at the one-year horizon. The non-linear specification with dummies for the 20th and 80th percentiles has roughly the same R-squared values as the linear specification, indicating that CDS spreads are particularly good return predictors when those spreads are extreme. In particular, CDS spreads above the 80th percentile are strongly associated with high future returns, for example, over the next six months CDS-market returns are on average 43.3% higher than when CDS spreads are between the 20th and 80th percentiles. This magnitude is more than three times the unconditional average of 6-month CDS-market returns, 11.9%. The results are statistically significant for most specifications, as implied both by the Newey-West t-statistics with the same number of lags as the overlapping horizon and 18-month block-bootstrap p-values.

The results in this section support the claim that both LSM CDS-market betas and the CDS-market risk premia are positively correlated. In a world where the true model was a CDS-market model with

[10] See Lewellen and Nagel [2006].

time-varying risk premia, this correlation would imply that an unconditional model would predict a too-low LSM return. I the next section I go from this qualitative statement to a quantitative test of whether the the joint dynamics of betas and returns explains the cross-section of CDS returns.

4.2 Conditional Asset Pricing Model

If the joint dynamics of betas and returns are the only source of the CDS-market-model mispricing is all that drives the alphas of LSM, a conditional one-factor model should be able to account for the cross-sectional variation in unconditional expected returns by maturity.[11] To test this proposition, I evaluate the following stochastic discount factor:

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

where b_t tracks the market risk premium $\mathbb{E}_t\left[R_{t+1}^{MKT,ALL}\right]$. Because I price zero-cost portfolios, the mean of the factor is unidentified and I choose it such that unconditional expected returns are a linear function of covariances. I model b_t as an affine function of $X_t = Y_{BBB,t}^5$. 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[12]:

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

To estimate this model I need to estimate the three covariances above. I will use a non-synchronous-trading-robust estimator for $\operatorname{cov}\left(R_{t+1}^i, y_t^5 R_{t+1}^{MKT,ALL} \right)$ because some single-name, non-five-year CDS spread quotes may be sufficiently illiquid that they reflect information with a delay. This issue 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.[13] In on-line appendix I provide evidence that liquidity-related quote delays are indeed a concern for the LSM.[14]

[11] Here I only investigate what the model implies for unconditional average returns across maturities. The model has implications about conditional average returns of these portfolios also. In the on-line appendix I provide qualitative evidence on that, I show LSM returns can also be (positively) predicted by average CDS spreads.

[12]

$$\begin{aligned} M_{t+1} &= 1 - b_t \left(f_{t+1} - E f_t \right), \\ \mathbb{E}_t R_{t+1}^e &= \mathbb{E}_t \left[\left(a + b X_t \right) \left(f_{t+1} - E f_{t+1} \right) R_{t+1}^e \right] \\ \mathbb{E} R_{t+1}^e &= \mathbb{E} \left[\left(a + b X_t \right) \left(f_{t+1} - E f_{t+1} \right) R_{t+1}^e \right] \\ \mathbb{E} R_{t+1}^e &= a \operatorname{cov}\left[R_{t+1}^e, f_{t+1} \right] + b \operatorname{cov}\left[X_t R_{t+1}^e, f_{t+1} \right], \end{aligned}$$

[13] Lack of synchronicity may also cause biases in the estimates of unconditional market betas. In unreported results, I show the corrections that I use for non-synchronous betas have little effect on the pricing errors of the unconditional CDS market model. 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.

[14] 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.

I estimate $\text{cov}\left(R^i_{t+1}, y^5_t R^{MKT,ALL}_{t+1}\right)$ as:

$$\text{estimator} = \text{cov}\left(R^i_{t+1}, \widehat{y^5_t R^{MKT,ALL}_{t+1}}\right) + \text{cov}\left(R^i_{t+1}, \widehat{y^5_{t-1} R^{MKT,ALL}_{t}}\right).$$

This estimator is similar to Scholes and Williams [1977] beta. I show the precise assumptions under which the sum-of-covariance estimator is consistent in appendix A. Panel A of Table 4 reports the covariance estimates for the 5-year-cds-spread and maturity sorted portfolios. The covariances decrease with maturity within each of the five groups of firms, hence covariances qualitatively line up with the pattern in average returns. In panel B of Table 4 I display the summary statistics of the estimated cross-sectional model. Consistently with the pattern in betas, covariances with $y^5_{t-1} R^{MKT,ALL}_t$ are positively priced, $\lambda = 0.57$ when $y^5_{t-1} R^{MKT,ALL}_t$ is standardized to have one volatility. The model fits the cross-section of expected returns as precisely and the LSM-based empirical model, like that model, it producesαs that are a fraction of average returns and it is reject by the GRS test for similar reasons. In panel D I show that LSM is redundant for pricing purposes in a conditional model, its price of risk is statistically insignificant then.

The results in this section add a lot more of detail to the behavior of the term structure of credit risk. It ties the higher unconditional riskiness of short-term assets to their high CDS-market betas in times when the CDS-market risk premium is high. In the next section, I study a parsimonious credit risk to understand the characteristics of an economy that can match those results. In doing so, I will also make explicit the implications of my results for the horizons of uncertainty investors are concerned and charge a risk premium to be exposed to.

5 Model

In this section, I describe a parsimonious credit risk model that matches the following interdependent set of facts. LSM has a high unconditional risk premium, because it is a hedge to CDS-market risk when the price of CDS-market risk is low, but LSM loads up on CDS-market risk when the price of CDS-market risk is high.

Credit risk models are usually judged by their ability to match certain moments of the average credit spreads across a number of groups of firms at different maturities (Chen et al. [2009], Chen [2010], Huang and Huang [2003], Bhamra et al. [2010].). The results that I presented before were in terms of the risk premia and betas of certain credit strategies. Traditional models and my empirical results are expressed in different units. In order to be able to understand what the empirical results imply for traditional credit-risk models I will express my results in terms of implications for the behavior of credit spreads. Instead of thinking about the LSM and the CDS-market portfolio, it

[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.

is useful to think about the elements of the term structure of credit spreads that that those two returns reflect.

LSM is a steepener in the average credit spread curve of BBB-rated firms. LSM sells short-maturity CDS (long risk) and buys just enough long-maturity CDS (short risk) to hedge them agaisnt simultaneous shifts in short- and long-maturity shifts in credit spreads, or shifts in the level of the term structure of credit spreads in the jargon of the term structure literature. It is therefore intuitive that LSM will have high returns when short-term spreads fall and/or long-term spreads rise, that is, when the credit spread curve steepens. In the on-line appendix, I show this formally using a convenient linearization as well as an empirical comparisson between the LSM and changes in a measure of the steepness of the credit curve.

While the LSM is a steepener, the CDS-market is a bet on an across-the-board drop in credit spreads. The CDS-market sells CDSs of all maturities and credit qualities, hence it has high returns when CDS spreads fall. With this characterizations, I am now ready to describe the model.

First, the model is about the term structure of CDS returns of BBB-rated firms only. In particular, I do not not attempt to explain cross-sectional differences in risk premia that are due to differences in yields across firms. The model is a structural credit risk model in the sense that a firm defaults if by the time its debt matures, its asset value falls below a certain threshold, the default boundary.

The value of BBB-rated firms follows a one-factor structure with stochastic volatility:

$$\frac{dV^i}{V^i} = \left(\delta\left(\sigma_t\right) + \mu_t\right)dt + \sigma_t dZ_t^{[1]} + \sigma_t^{id}\left(\sigma_t\right)dZ_t^i,$$

with state contingent drift $\left(\delta\left(\sigma_t\right) + \mu_t\right)$ and volatility $\sqrt{\sigma_t^2 + \left(\sigma_t^{id}\right)^2}$. The drift depends on payouts $\delta\left(\sigma_t\right)$ and on the expected return on assets of the firm $\mu\left(\sigma_t\right)$. The volatility depends on the volatility of the two shocks that hit firm value. The first shock $dZ_t^{[1]}$ is the same for all firms and has volatility σ_t – it is a shock to the value of the aggregate firm. The second shock dZ_t^i is a idiosyncratic shock and has volatility $\sigma_t^{id}\left(\sigma_t\right)$. This shock dZ_t^i is the only term in the evolution of firm value that differs across firms. Both the aggregate and idiosyncratic shocks have time-varying volatilities. These volatilities as well as the drift in firm value growth $\left(\delta\left(\sigma_t\right) + \mu_t\right)$ are all driven by a single state variable σ_t. The single state variable σ_t captures economic conditions. When σ_t is high, economic conditions are bad.

To understand what bad economic conditions imply for firm values, I further specify $\delta\left(\sigma_t\right)$ and $\sigma_t^{id}\left(\sigma_t\right)$. I set $\delta'\left(\sigma_t\right) < 0$ to reflect the fact that non-earnings driven growth in firm value is smaller during bad times because firms issue less equity and debt. Second, I make $\left(\sigma_t^{id}\right)^2 = \left(\sigma^{id,1}\right)^2 + \sigma_t^2$, such that both idiosyncratic and systematic volatility increase in bad times. $\mu_t\left(\sigma_t\right)$ is endogenous once I specify the stochastic discount factor (SDF). It then follows that, during bad economic conditions, firm value volatility is high and payouts are low.

To compute prices, I specify the exogenous SDF

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

where r is the instantaneous risk-free rate, and $\xi\sigma_t$ is the of risk of shocks to $dZ_t^{[1]}$ (which are the only source of risk). The price of risk $\xi\sigma_t$ also varies over time and is also controlled by the single state variable σ_t. This means that a bad economy is also characterized by high risk premia.

I specify the dynamics of the single state variable σ_t^2 flexibly. It follows a CIR process:

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

with constant persistence ϕ.

In total, the model has three shocks, $dW, dZ^{[1]}, dZ^{[2]}$, with a covariance matrix Σ. Defaults occur if the value of the firm falls below an exogenous value B – the default boundary – by the time its debt matures. I model the firm debt as having the same maturity as the CDSs that I price. CDSs 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 the CDS spread. On the other hand, if the firm defaults, the CDS seller has a negative payoff equal to the loss given default: $-L$. So if τ is the time of default, the CDS payoff is:

$$\begin{aligned} CDS\left(T, y\right) &= 1_{\tau>T} T \times y + \left(1 - 1_{\tau>T}\right)\left(-L\right) \\ \tau &= \begin{cases} T & \text{if } V_T < B \\ > T & \text{o.w.} \end{cases}, \end{aligned}$$

The spread of a CDS is such that

$$E[\Lambda CDS\left(T, y\right)] = 0,$$

and I compute it using Monte Carlo methods. I focus on the one- and five-year maturities. These maturities are shorter than those studied 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 CDS spreads, I have to choose a set of maturities to investigate. My choice of one- and five-year maturities 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 are more sensitive to maturity.

5.1 Calibration

I have to calibrate $\left(\xi, \bar{\sigma}, r, \sigma^{vol}, \zeta, \Sigma, L, B, \phi\right)$. I pick ξ such that the maximum Sharpe ratio in the economy is on average $\xi\mathbb{E}\left[\sigma_t\right] = 0.5$ per year. I choose $\bar{\sigma}$ such that the unconditional mean of σ_t, $\mathbb{E}\left[\sigma_t\right]$, equals 0.12. This number is consistent with an average aggregate equity volatility of 15%, if the aggregate firm has leverage 20% and its debt is risk free.[15] 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 in my sample – 1.72% per year.

[15] 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.

I pick $\sigma^{id,1} = 0.0808$ such that the average idiosyncratic volatility of a typical firm is 0.208, and thus, it has a Sharpe ratio is half that of the market (Chen et al. [2009]). For the volatility of volatility, I pick σ^{vol} such that the value of the volatility of volatility is 0.06, half the value of the average volatility. This choice translates into a volatility of the economy's maximum Sharpe ratio that is half that of its mean. For an aggregate firm with leverage 20%, this choice of volatility of asset volatility translates into a volatility of equity volatility of 7.5%. 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. I design a payoff function that reflects these facts:

$$\delta\left(\sigma_t\right) = -0.02 - 0.03\left(\frac{\sigma_t - \mathbb{E}\left[\sigma_t\right]}{\operatorname{std}\left(\sigma_t\right)}\right),$$

such that when volatility is two standard deviations below its mean, the firm issues securities worth 0.04 of its total value, and when volatility is two standard deviations above the mean, it retires securities worth 0.08 of the value of its assets. This behavior of payoffs makes default more likely in bad times, because payout-driven firm value growth is smaller at those times. Chen et al. [2009] emphasizes that having a channel that makes firms default in bad times is important, otherwise, the high risk premia in those times would mean that a negative relation exists between credit spreads and default losses. [16]

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 closer to the estimates of persistence using realized stock variance.[17] 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 high-persistence version of the model stands in for stochastic discount factors arising from models that try to match the predictability evidence from dividend-price-ratio predictive regressions.

I choose the default boundary $B = a_{boundary} + b_{boundary}\sigma_0 + c_{boundary}\sigma_t$ as a function of the initial and current level of volatility to allow for rating through the cycle as well as countercyclical default boundaries.[18] I set $a_{boundary}$, $b_{boundary}$, and $c_{boundary}$ to match the following moments: the unconditional default probabilities and average CDS spreads at the 1- and 5-year horizons; the slope

[16] I also allow for time-varying default boundaries and will calibrate those boundaries, so shutting down the dependence of payoffs to the aggregate state moves more of the burden of matching the data to the parameter that controls sensitivity of default boundaries to the aggregate state, but should not do much for the other results. Furthermore, I check other parameterizations with smaller sensitivity of payoffs to aggregate state and they behave similarly.

[17] Using 1-year realized variances of the value-weighted stock market return estimated from daily returns since July, the 1st of 1963, I estimate a slope coefficient of 0.29 in a rolling regression of variance on its 1-year lag.

[18] This exercise is similar to that in Chen et al. [2009]. Chen et al. [2009] choose $b_{boundary}$ to match the sensitivity of BBB-rated firms leverage to the consumption surplus ratio. I choose it together with $c_{boundary}$ to match another set of moments.

coefficient of a regression of 4-year default rates on 4-year spreads (Chen et al. [2009]); and the unconditional correlation between the five-minus-one CDS spread slope and the one-year CDS spread. 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 between model quantities and the data.[19]

I model the correlation structure of $\left(dW, dZ^{[1]}, dZ^{[2]}\right)$ in the following way. $\rho\left(dZ^{[1]}, dZ^{[2]}\right) = 0$ is zero, which means the idiosyncratic shocks are indeed idiosyncratic. I model the volatility shock to have time-varying correlations with the SDF. This will amplify the time-variation in expected returns of assets exposed to volatility shocks. I choose

$$\rho\left(dZ^{[1]}, dW\right) = \left\{1_{\left[\sigma>\bar{\sigma}+1.5\sigma^{vol}\right]}(-0.9) + \left(1 - 1_{\left[\sigma>\bar{\sigma}+1.5\sigma^{vol}\right]}\right)0\right\}.$$

Negative values reflect the evidence that 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.

5.2 Results

I report the results in Table 5. For the low-persistence specification, $\phi = 0.7$, the model generates reasonable default probabilities of 196 bps and 29 bps at the five- and one-year horizons, respectively. The one-year average CDS spread of 86 bps is close to the 77 bps that I measured in the data, but the five-year spread of 196 bps is is too high compared with the 114 bps that I measured in the data. The 0.67 coefficient of four-year horizon defaults on credit spreads is lower than the value that Chen et al. [2009] used. The unconditional correlation between the slope of the term structure and the short-maturity spread is -0.57 compared with -0.55 that I measured 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 CDS spreads as displayed in Figure 5.

The hump-shaped relation between the one- or five-year CDS spreads – level – and the 5-minus-1 spread – slope – implies that their correlation is time-varying. When the level of CDS spreads is low, level and slope changes are positively correlated. When CDS spreads are high or the slope is flat, level and slope changes are negatively correlated. In terms of LSM and CDS-market returns, these correlations between the level and the slope imply that LSM has time-varying CDS-market betas that are high when the CDS-market risk premium is high.[20]

The behavior of betas coupled with the pricing of volatility shocks embedded in the model imply that CDS curve steepeners, of which the LSM is an example, are risky. The returns of credit steepeners are high because credit steepeners stand to lose from increases in volatility when volatility is high.

[19] I multiply the beta-coefficients moments by 100 to make them comparable to default probabilities and spreads, which are quoted in basis points.

[20] The approximations that I developed in the last section tie LSM and market returns to changes in the CDS spreads of the firms and maturities from which they are built. In the model, I solve for the CDS spreads for BBB-rated firms. The spread changes which LSM and market are a function of are not exactly the changes in the average spreads currently BBB-rated firms, because some firm ratings are upgraded or downgraded. Practically, the two series, the change in spreads of currently BBB-rated firms and the change in the average CDS spreads of currently BBB-rated firms, are strongly correlated and I will ignore their differences in my discussion.

Because shocks to volatility are priced and its risk premium is high when volatility is high, the dynamic of the exposures of credit steepeners implies that they have high unconditional average returns.

The non-monotonic relation between the level and the slope of the term structure of CDS 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-maturity CDS is relatively safe, and thus, its spread is insensitive to small increases in volatility. The longer-maturity CDS is still risky despite the low volatility, because the quick mean reversion of the economy implies that volatility can rise substantially before the CDS matures. As a consequence, the long-maturity CDS spread is sensitive to increases in volatility. Taken together, these two facts imply that the CDS curve becomes steeper at the same time that the level of CDS spreads rise.

Consider now the negative correlation between the level and the slope of the term structure of credit spreads. When volatility is high, the short-maturity CDS is no longer safe, and thus, its spread is sensitive to changes in volatility. The long-maturity CDS now is the relatively safe one, because the quick mean reversion of volatility implies that the risks that lie in the future are likely smaller. Therefore, the long-maturity CDS spread becomes less sensitive to volatility than the short-term spread. Taken together, these two facts imply that the CDS curve becomes flatter at the same time that the level of CDS spreads rise.

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 CDS spread is 139 bps, higher than the 114 bps that I measure in the data, whereas the one-year average CDS spread is 24 bps, much lower than the 77 bps that I measure in the data. The key difference between the calibrations, however, shows up in the unconditional correlation between the level and slope of the term structure of CDS spreads: it is positive and equal to 0.75, instead of the -0.57 featured in the low persistence calibration. The flip side of this result is the lack of a hump shape in the function that maps volatilities into the slope of the term structure, for relevant values of volatility. This pattern is displayed in Figure 5. As a consequence, this calibration also fails to match the time-varying correlations between level and slope that I found in the data as well as the fact that credit steepeners are risky.

6 Conclusion

I study how risk premia vary with maturity in corporate CDS markets, by studying the cross-section of constant-duration CDSs of various maturities from April 2002 through May 2013. CD CDSs are a convenient standardization with which to study the pricing of cash flows by maturity. The cross-section of risk premia of CD-CDS portfolios of various maturities relates closely to the cross-section of prices of shocks to average CDS spreads of various maturities.

I find that the risk premia of portfolios of CD CDSs are decreasing in maturity and that this cross-sectional variation in expected returns by maturity is explained by a risk factor, LSM. This risk factor is a portfolio that sells short-maturity CD CDSs and buys long-maturity ones. This first finding reduces the task of understanding the relation of risk premia and maturity to understanding the LSM.

I then show LSM has time-varying CDS-market betas that are high and positive when proxies for the CDS-market risk premia is high, and low and negative when proxies for the CDS-market risk premia are low. This type of market-beta dynamic is exactly the kind that induces mispricing in an unconditional CDS market model when the true model is conditional. Consistent with this insight, I show that a conditional CDS market model can also price the cross-section of constant-duration CDS portfolio returns by maturity.

Finally, I develop a parsimonious credit risk model that makes sense of this study's key empirical findings. Namely, the unconditional risk premia of CD CDS portfolios is decreasing in maturities, and the CDS-market betas of short-maturity CD CDS portfolios are smaller than those of long-maturity CD CDS portfolios in good times, but larger in bad times.

In the model, the quick mean reversion of economic conditions implies that the risks of short-term and long-term CD CDSs vary differentially over time. When economic conditions are good, short-term assets are safe, but long-term assets are risky, because the good short-term outlook is expected to die out quickly. When economic conditions are bad, long-term assets become less risky than short-term assets, because the dire short-term outlook is expected to die out quickly. Since risk premia are high when economic conditions are bad, the described risk dynamics by maturity imply that short-term CD CDSs are unconditionally riskier.

In a nutshell, I reach several conclusions. First, risk premia of short-term cash flows are unconditionally higher than those of long-term cash flows. Second, this cross-sectional pattern in risk premia by maturity can be traced back to exposures to a risk factor, a portfolio that sells short-maturity CD CDSs and buys long-maturity ones. Third, the cross-sectional pattern in risk premia by maturity can be further traced to a conditional CDS market model. Finally, a parsimonious model of credit risk can rationalize the cross-sectional pattern in risk-premia by maturity as well as the differential behavior of the time series of CDS-market betas of CD CDS portfolios of different maturities.

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Appendix

A Covariances with Possible Delays in Slopes.

Let

$$
\begin{aligned}
r^{\star}_{t+1} &= \beta_1 r^{lvl}_{t+1} + \beta_2 \left(\lambda r^{slp}_{t+1} + (1-\lambda)\, r^{slp}_{t}\right) + \varepsilon_{t+1} \\
r_{t+1} &= \beta_1 r^{lvl}_{t+1} + \beta_2 r^{slp}_{t+1} + \varepsilon_{t+1},
\end{aligned}
$$

where r_{t+1} is the true return, $r^{\star}_{t+1}$ is the observed return, $1-\lambda$ is a measured of how much delay there is in the updating of the slope information and ε_{t+1} is orthogonal to current and lagged values of r^{lvl} and r^{slp}. That is, true returns follow a two-factor structure with factors being r^{lvl}_{t+1} and r^{slp}_{t+1}. 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:

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

but if I use the true slope r^{slp}_{t+1} and $r^{\star}_{t+1}$, I recover:

$$
cov\left(r^{\star}_{t+1},\ r^{slp}_{t+1}\right) = \beta_1 cov\left(r^{lvl}_{t+1}, r^{slp}_{t+1}\right) + \beta_2 \lambda \sigma^2\left(r^{slp}_{t+1}\right).
$$

The covariance of $r^{\star}_{t+1}$ with the lag of the slope, $cov\left(r^{\star}_{t+1},\ r^{slp}_{t}\right)$ is given by:

$$
cov\left(r^{\star}_{t+1},\ r^{slp}_{t}\right) = \beta_1 cov\left(r^{lvl}_{t+1}, r^{slp}_{t}\right) + \beta_2 \lambda cov\left(r^{slp}_{t+1}, r^{slp}_{t}\right) + \beta_2 (1-\lambda)\, cov\left(r^{slp}_{t}, r^{slp}_{t}\right).
$$

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

$$
cov\left(r^{\star}_{t+1},\ r^{slp}_{t}\right) = \beta_2 (1-\lambda)\, \sigma^2\left(r^{slp}_{t}\right),
$$

and adding both contemporaneous and lagged covariance yields:

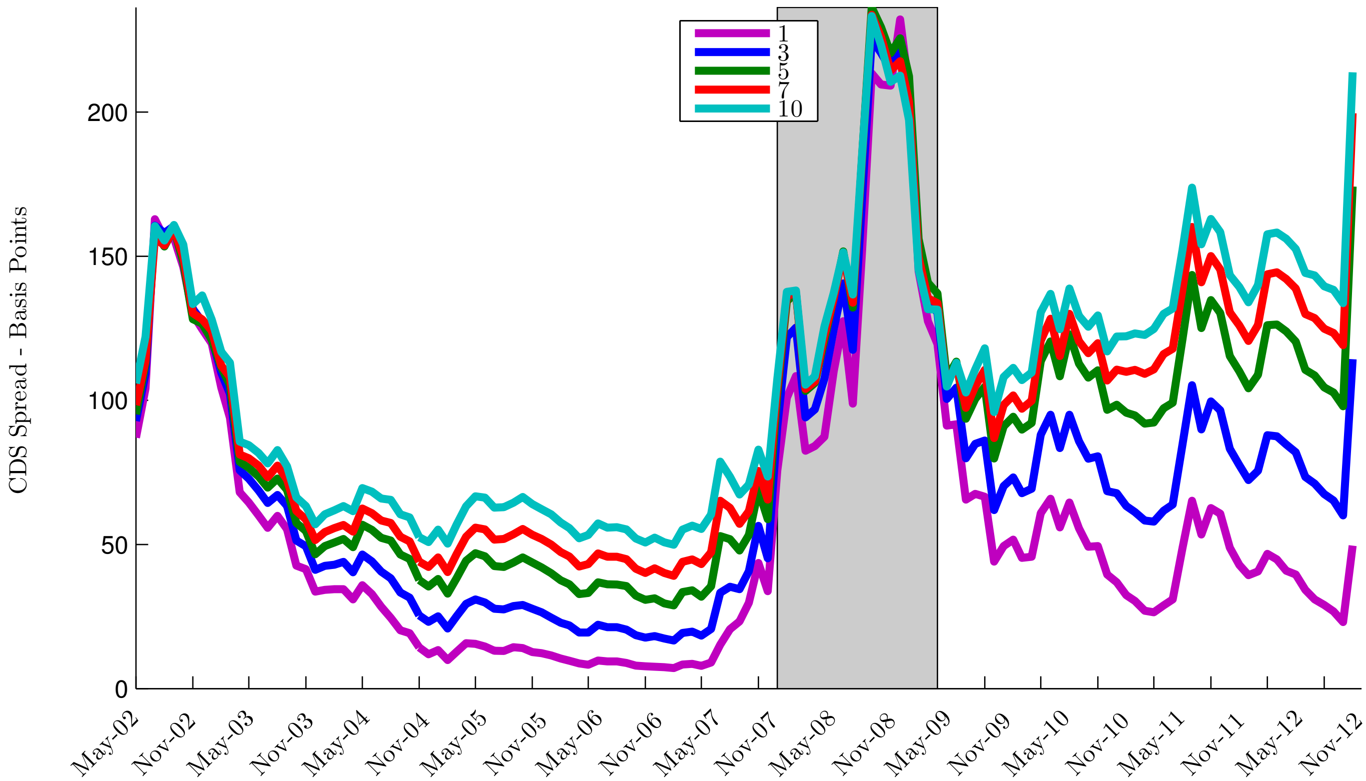
$$
\begin{aligned}
cov\left(r^{\star}_{t+1},\ r^{slp}_{t}\right) + cov\left(r^{\star}_{t+1},\ r^{slp}_{t+1}\right) &= \beta_1 cov\left(r^{lvl}_{t+1}, r^{slp}_{t+1}\right) + \beta_2 \lambda \sigma^2\left(r^{slp}_{t+1}\right) + \beta_2 (1-\lambda)\, \sigma^2\left(r^{slp}_{t}\right) \\
&= \beta_1 cov\left(r^{lvl}_{t+1}, r^{slp}_{t+1}\right) + \beta_2 \sigma^2\left(r^{slp}_{t+1}\right),
\end{aligned}
$$

which is the true covariance.

Figures

Figure 1: **The Term Structure of CDS Spreads**
The sample period is April, 2002 to February, 2013 for the single-name plot and April, 2006 to May, 2012 for the indexes plots.

Panel A: Time Series of Spreads for Investment-Grade U.S. Single Names.



Panel B: Time Series of Spreads for CDS Indexes.

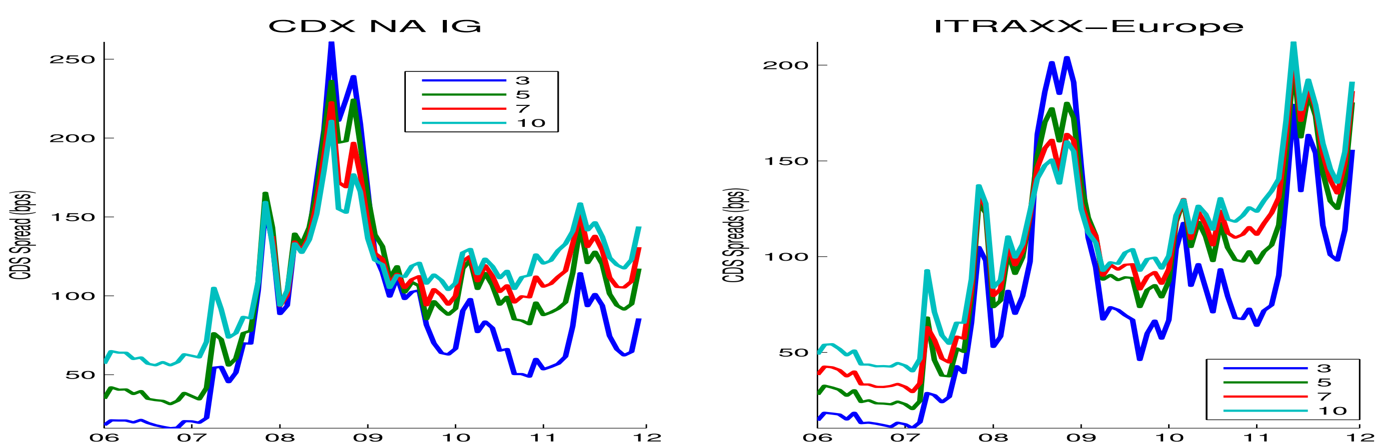
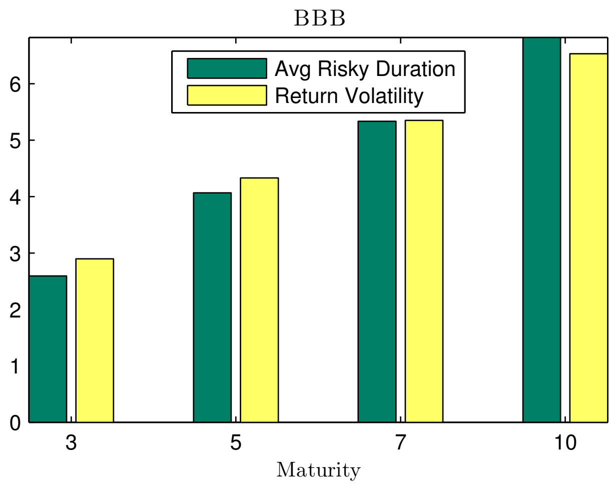


Figure 2: **The Relation between Volatility and Average Risky Duration**
Risky durations are computed from the cross-section of CDS spreads and risk-free term structures using the standard CDS model. Please see the text for details on the construction of CDS portfolios of BBB-rated firms as well as those sorted on 5-year CDS spreads.



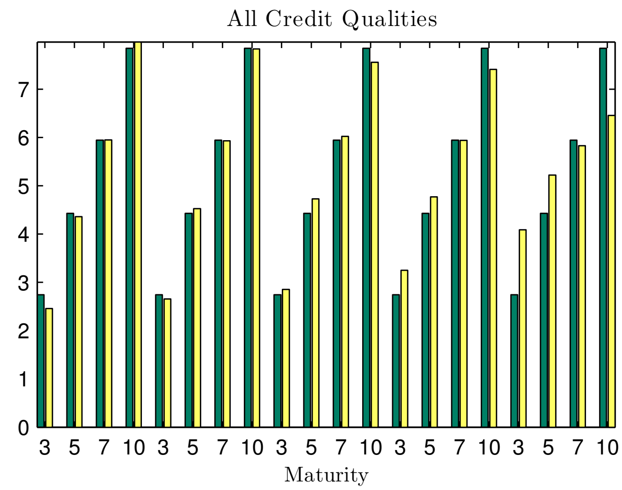


Figure 3: **Average Returns and LSM-Model Expected Returns for Portfolios Formed on 5-Year CDS Spreads and Maturity: April 2002 to February 2013.**
The green bars are time-series average monthly returns multiplied by 12. The yellow lines are model-implied expected returns. The asset-pricing model is:

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

where LSM_{t+1} is the second principal component of the CDS returns of BBB-rated firms, $R_{t+1}^{MKT,ALL} = \frac{1}{4\times N}\sum_{i\in\{3,5,7,10\}}\sum_{k=1}^{5} R_{t+1}^{i,k}$, and $HSMS_{t+1} = \sum_{i\in\{3,5,7,10\}} R_{t+1}^{i,5} - R_{t+1}^{i,1}$.

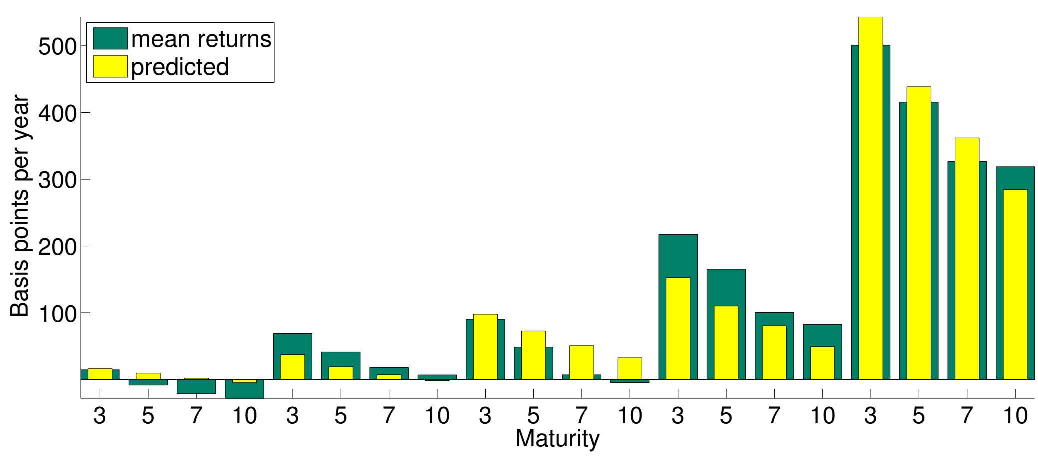


Figure 4: **Time-Varying Correlations between the Returns on the LSM and the Market**
Correlations are 12-month forward-looking between LSM and the $R^{MKT,ALL}$. Y^5_{BBB} is the average CDS spread of BBB-rated firms.

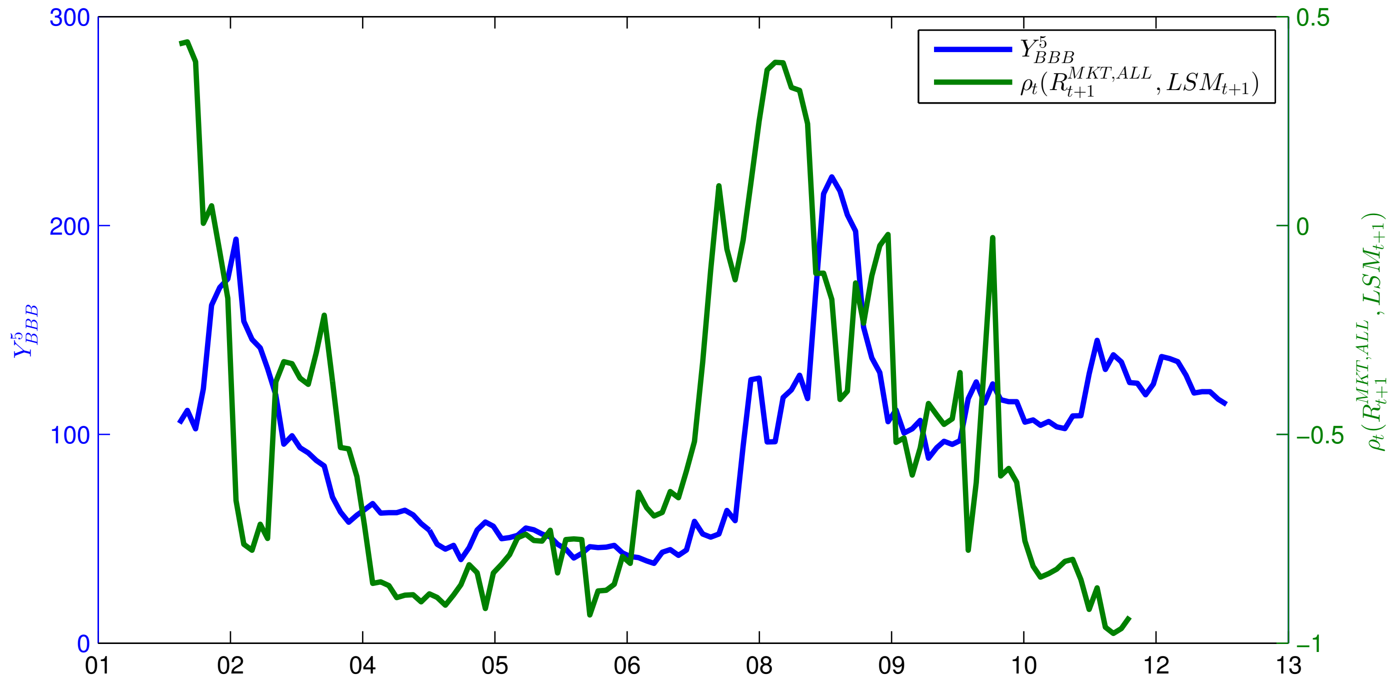
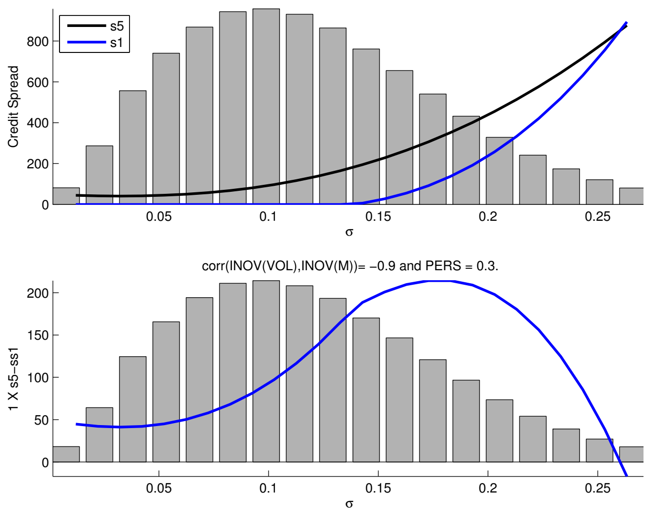


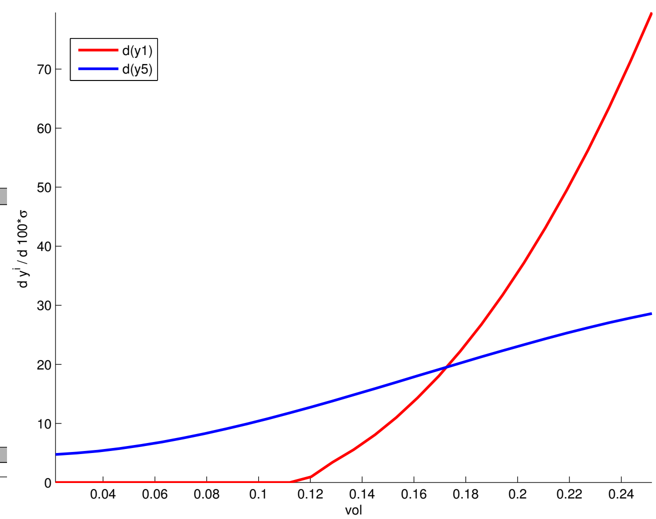
Figure 5: **The Model-Implied Relation between Slope and Level.**

Panel A: Low Persistence of Volatility.

(a) Spreads and Slope as Function of Volatility.

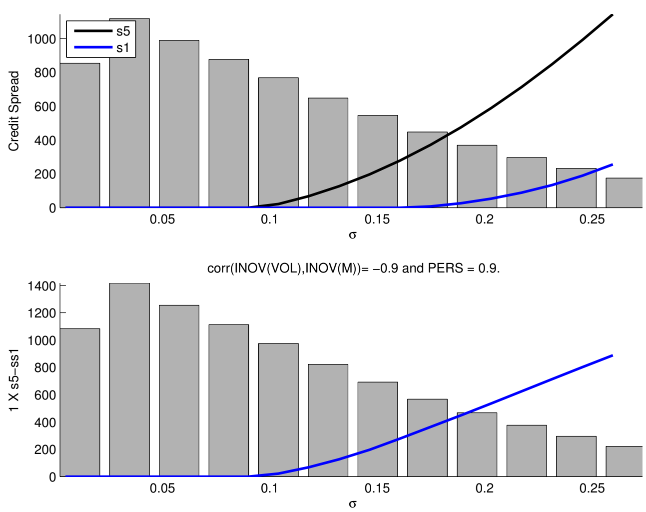


(b) $\frac{\partial Spread^N}{\partial \sigma}$

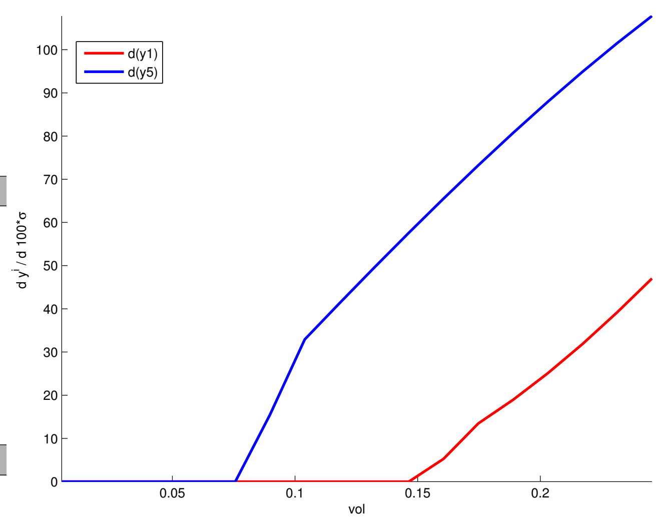


Panel B: High Persistence of Volatility.

(a) Spreads and Slope as Function of Volatility.



(b) $\frac{\partial Spread^N}{\partial \sigma}$



Tables

Table 1: **The One-Month Excess Returns of CDS Portfolios of at Various Maturities, in Basis Points.**
Standard errors are 12-lag, Newey-West and p-values are from a circular block bootstrap Politis and Romano [1994] with block size equal to 24 months. The sample period is April/2002 to February/2013 for single-name portfolios and April 2006 to May 2012 for indexes. L-S is the 3-10 portfolio, 2nd P.C. is the second principal component from {3,5,7,10}, and L-S rank has portfolio weights (1,1/2,-1/2,-1) respectively.

		3	5	7	10	L-S	2nd P.C.	L-S(Rank)
	value	123.68	100.63	73.84	65.32	58.36	45.53	71.75
BBB (cv)	s.e.	59.61	53.99	50.65	47.86	19.22	14.49	22.68
	p-value bootstrap					0.00	0.00	0.00
	Sharpe Ratio	0.63	0.56	0.44	0.41	0.92	0.95	0.96
	value	71.81	59.31	34.97	30.01	41.80	22.63	53.97
BBB (rd)	s.e.	35.32	32.79	24.58	21.92	15.44	7.20	19.78
	p-value bootstrap					0.01	0.00	0.01
	value	19.59	-0.66	-10.27	-16.71	36.29	26.50	41.10
Low Spread	s.e.	27.61	26.40	24.79	23.87	12.25	9.34	14.78
	p-value bootstrap					0.00	0.00	0.00
	value	75.91	55.35	31.29	24.13	51.78	40.70	63.81
20-40	s.e.	37.61	34.84	33.16	31.36	17.37	13.12	20.73
	p-value bootstrap					0.00	0.00	0.00
	value	112.91	73.87	37.10	24.95	87.96	67.12	106.34
40-60	s.e.	68.57	63.58	59.56	54.63	25.75	19.27	30.27
	p-value bootstrap					0.00	0.00	0.00
	value	214.36	193.71	138.42	124.92	89.44	71.73	117.09
60-80	s.e.	126.36	115.38	106.78	99.93	42.46	31.73	50.04
	p-value bootstrap					0.03	0.02	0.01
	value	597.28	545.85	459.22	467.33	129.95	107.92	173.27
High Spread	s.e.	263.41	242.75	227.87	214.27	77.19	57.56	90.36
	p-value bootstrap					0.03	0.02	0.02
	value	31.43	19.03	1.23	-3.91	35.34	27.30	44.24
CDX(cv)	s.e.	58.70	51.73	43.88	38.02	27.01	20.51	31.86
	p-value bootstrap					0.08	0.08	0.07
	Sharpe ratio	0.21	0.15	0.01	-0.04	0.52	0.53	0.55
	value	13.85	7.24	-1.19	-3.19	17.04	12.27	21.26
CDX(rd)	s.e.	31.20	25.25	19.99	15.75	17.44	9.65	20.39
	p-value bootstrap					0.17	0.09	0.15
	Sharpe ratio	0.18	0.11	-0.02	-0.08	0.39	0.51	0.42
	value	33.89	14.74	-2.65	-14.42	48.31	35.64	57.01
ITRAXX(cv)	s.e.	49.72	43.88	40.64	37.82	24.11	18.35	27.85
	p-value bootstrap					0.01	0.01	0.01
	Sharpe ratio	0.27	0.13	-0.03	-0.15	0.78	0.76	0.80
	value	16.08	5.41	-2.17	-6.56	22.64	15.96	26.43
ITRAXX(rd)	s.e.	24.48	19.09	16.19	13.89	13.73	7.75	15.74
	p-value bootstrap					0.03	0.01	0.03
	Sharpe ratio	0.26	0.11	-0.05	-0.19	0.64	0.80	0.66

Table 2: **Pricing Portfolios of CDS of Different Maturities**

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

Panel A: Portfolio Betas with Respect to LSM

	3	5	7	10
BBB	0.73	0.13	-0.23	-0.63
Low spread	-0.12	-0.32	-0.46	-0.60
20-40	-0.08	-0.46	-0.68	-0.85
40-60	0.29	-0.26	-0.71	-1.07
60-80	0.57	-0.50	-1.12	-1.80
High spread	3.08	0.91	-0.38	-1.73

Panel B: $E\left[R^{i,k}_{t+1}\right] = \beta^i_1 E\left[R^{MKT,ALL}_{t+1}\right] + \beta^i_2 E\left[HSMS_{t+1}\right] + \beta^i_3 E\left[LSM_{t+1}\right].$

	Avg $\lvert\alpha\rvert$	$\frac{Avg\ \lvert\alpha\rvert}{Avg\ \lvert ER\rvert}$	XS R^2	P-value GRS	Avg TS R^2
Values	19.14	0.12	0.99	0.00	0.96

Table 3: **Time-Varying Correlations and Risk Premia**

In Panel A, parameter estimates are in the first line and 12-lag-Newey-West t-statistics in the second. $R^{MKT,ALL}$ is standardized to have the same standard deviation as LSM and Y^5_{BBB} is the z-score of the average CDS spread of BBB-rated firms. $1\,[A]$ is an indicator for the event A. $px\,(y)$ is the the x percentile for variable y. In Panel B, t-statistics are computed from Newey-West standard errors with as many lags as twice the forecasting horizon and p-values are from a circular block bootstrap(Politis and Romano [1994]) with block size equal to 24.

Panel A: Time-varying correlations.

	1	2	3	4	5	6
const	46.09	44.83	45.24	43.93	43.93	45.48
	3.05	2.81	2.87	2.79	2.79	2.96
$R^{MKT,ALL}$	-0.03	-0.17	-0.56		-0.04	-0.12
	-0.19	-0.90	-2.68		-0.29	-0.75
$R^{MKT,ALL} \times Y^5$		0.17				0.46
		1.40				2.68
$R^{MKT,ALL} \times 1\,[Y^5 \geq p50(Y^5)]$			0.65			
			2.57			
$R^{MKT,ALL} \times 1\,[Y^5 \leq p20(Y^5)]$				-1.04	-1.00	
				-7.96	-4.56	
$R^{MKT,ALL} \times 1\,[p20(Y^5) < Y^5 < p80(Y^5)]$				-0.04		
				-0.29		
$R^{MKT,ALL} \times 1\,[p80(Y^5) \geq Y^5]$				0.10	0.14	
				0.51	0.71	
$R^{MKT,ALL} \times 1\,[(Y^5)^2]$						-0.17
						-1.78

Panel B: Time-varying risk premia.

		Dependent Variable = $R^{MKT,ALL}_{t+1}$ in %															
		1 month				3 months				6 months				12 months			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	parameter	2.88				8.96				17.51				31.55			
Y^5_{BBB}	t-statistic	2.60				3.29				4.10				6.10			
	p-value	0.00				0.00				0.01				0.01			
	parameter		3.19				7.92				21.21				46.06		
$Y^5_{BBB} > p50$	t-statistic		1.54				1.36				2.48				2.95		
	p-value		0.02				0.04				0.03				0.06		
	parameter			-3.40	-1.67			-8.92	-2.81			-16.09	-4.72			-40.22	-24.3
$Y^5_{BBB} < p20$	t-statistic			-2.06	-1.08			-2.12	-0.73			-2.12	-0.70			-3.22	-2.52
	p-value			0.03	0.12			0.04	0.24			0.08	0.33			0.11	0.22
	parameter				6.95				23.97				43.32				64.35
$Y^5_{BBB} > p80$	t-statistic				2.26				3.99				4.12				4.62
	p-value				0.01				0.01				0.01				0.01
	R^2	0.07	0.02	0.02	0.09	0.17	0.03	0.03	0.26	0.29	0.10	0.04	0.39	0.55	0.28	0.15	0.56

Table 4: **Conditional Asset Pricing Model.**

Panel A: Predicted and realized returns.

		$\hat{\mathbb{E}}R$	$\text{cov}\left(R^i_{t+1}, Y^5_{BBB} \times R^{MKT}_{t+1}\right)/100$	$\mathbb{E}_{model}R$
Low spread	3.00	19.59	3.01	15.57
	5.00	-0.66	2.86	6.73
	7.00	-10.27	2.76	2.16
	10.00	-16.71	2.73	2.42
20-40	3.00	75.91	4.78	39.36
	5.00	55.35	4.57	26.59
	7.00	31.29	4.41	18.34
	10.00	24.13	4.33	14.38
40-60	3.00	112.91	8.39	100.28
	5.00	73.87	8.13	80.80
	7.00	37.10	7.94	66.23
	10.00	24.95	7.65	55.14
60-80	3.00	214.36	14.47	196.72
	5.00	193.71	13.96	167.60
	7.00	138.42	13.68	154.57
	10.00	124.92	13.42	142.96
High spread	3.00	597.28	28.59	609.77
	5.00	545.85	27.32	529.80
	7.00	459.22	26.56	492.71
	10.00	467.33	25.28	437.50

Panel B: $E\left[R^i_{t+1}\right] = \lambda_1 \times \mathbf{cov}\left(R^i_{t+1}, R^{MKT,ALL}_{t+1}\right) + \lambda_2 \times \mathbf{cov}\left(R^i_{t+1}, y^5_t \times R^{MKT,ALL}_{t+1}\right) + \lambda_3 \times \mathbf{cov}\left(R^i_{t+1}, HSMLS_{t+1}\right)$.

	XS R^2	$E[\lvert\alpha\rvert]$	$\frac{E[\lvert\alpha\rvert]}{E[\lvert E_T[R]\rvert]}$	$E[\alpha^2]$	P-value GMM	λ_1	λ_2	λ_3	$T\lambda_1$	$T\lambda_2$	$T\lambda_3$
Values	0.99	18.98	0.12	21.20	0.00	-1.59	0.57	1.10	-2.85	2.34	2.67

Panel C: $E\left[R^i_{t+1}\right] = \lambda_1 \times \mathbf{cov}\left(R^i_{t+1}, R^{MKT,ALL}_{t+1}\right) + \lambda_2 \times \mathbf{cov}\left(R^i_{t+1}, LSM_{t+1}\right) + \lambda_3 \times \mathbf{cov}\left(R^i_{t+1}, HSMLS_{t+1}\right)$.

	XS R^2	$E[\lvert\alpha\rvert]$	$\frac{E[\lvert\alpha\rvert]}{E[\lvert E_T[R]\rvert]}$	$E[\alpha^2]$	P-value GMM	λ_1	λ_2	λ_3	$T\lambda_1$	$T\lambda_2$	$T\lambda_3$
Values	0.99	14.13	0.09	16.34	0.00	-0.19	0.30	0.37	-0.54	2.88	1.03

Panel D: $E\left[R^i_{t+1}\right] = \lambda_1 \mathbf{c}\left(R^i_{t+1}, R^{MKT,ALL}_{t+1}\right) + \lambda_2 \mathbf{c}\left(R^i_{t+1}, HSMLS_{t+1}\right) + \lambda_3 \mathbf{c}\left(R^i_{t+1}, LSM_{t+1}\right) + \lambda_4 \mathbf{c}\left(R^i_{t+1}, y^5_t \times R^{MKT,ALL}_{t+1}\right)$.

	λ_1	λ_2	λ_3	λ_4
Parameter	0.28	0.13	0.41	-0.21
t-statistic	0.20	0.17	1.20	-0.37

Table 5: **Model Implications for CDS 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 CDS spreads of BBB-rated firms who satisfy the data requirement in the 200204-201205 sample. $\beta_{s,def}$ 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].

Panel A: Low Persistence.

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

Panel B: High Persistence.

	Model	Data
$a_{boundary}$	0.25	?
$b_{boundary}$	0.20	?
$c_{boundary}$	0.20	?
$P(\tau \leq 5)$	103.11	193-314
$\beta_{s,def}$	0.18	0.89
$E[y^5]$	270.39	114
$P(\tau \leq 1)$	14.26	19-28
$E[y^1]$	68.54	77
$\rho_{slp,s1}$	0.70	-0.55