THE DETERMINANTS OF MARKET FRICTIONS IN THE CORPORATE MARKET

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Preliminary

Abstract. We construct an empirical measure of market frictions in the corporate market based on the difference between the credit default swap spread and the corporate bond spread (referred to as the basis) for a large number of firms in a new, large dataset that we construct. Under fairly standard assumptions, the two spreads should be equal; if they diverge, we argue that significant market frictions are present that prevent investors' from arbitraging away what in effect are opportunities to earn a risk-free profit. We find that the causes of market frictions can be both systematic and firm- or bond-specific, with the idiosyncratic causes accounting for the dominant part of the variation in the basis.

1. Introduction

The smooth functioning of financial markets is crucial for the health of the whole financial system and for the well-being of the economy in general. This paper is an empirical study of how various types of macroeconomic and firm-specific conditions and events may be related to frictions that interfere with the smooth functioning of the U.S. market for corporate debt. Because market frictions are inherently difficult to observe—especially in over-the-counter markets, where order flow data is not readily available—we argue that a reasonable proxy for those frictions can be constructed in terms of investors' ability to take advantage of apparent arbitrage opportunities between two related securities. In our case, the two securities are a corporate bond and a credit default swap (CDS) referenced to the bond's issuer.

Arbitrage opportunities between bonds and CDSs cannot exist if there are no impediments to the efficient functioning of the corporate cash and derivatives markets, as market participants' trades would tend to make them disappear quickly. Conversely, a market where seeming arbitrage opportunities persist is, almost by definition, not functioning smoothly; in our view, the extent of market frictions will be more pronounced the larger and the

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longer-lasting those opportunities are. Of course, if arbitrage opportunities persist, they are not real opportunities; we call market frictions anything that prevents investors from taking advantage of those opportunities.

An intuitive measure of the presence of arbitrage opportunities across corporate markets is given by the "basis," the difference between CDS and bond spreads. As has been pointed out by Duffie (1999) and reiterated by several authors, the basis should be zero under ideal conditions.[1] If the CDS spread was higher than the bond spread for a certain reference entity, investors seeking credit protection could recreate a cheaper CDS by shorting a par, floating-rate corporate bond issued by the reference entity and buying a par, floating-rate risk-free bond of the same maturity with the proceeds. Analogously, if the bond spread was higher than the CDS spread, investors wishing to take on credit risk could buy a par corporate floater and short a par risk-free floater, thereby earning a higher spread than by selling protection in the CDS market.[2]

Ideal conditions, however, do not always prevail in the markets, either because of market imperfections or because of the particular real-world characteristics of both corporate bonds and CDS contracts. While there are technical factors that may affect the basis, such as different tax treatment of cash and derivative instruments, fixed- vs. floating-rate coupons for corporate bonds, etc., those technical factors are generally not believed to account for large and persistence deviations of the basis from its natural value of zero. For example, Duffie and Liu (1999) show that the fact that most corporate bonds pay a fixed rather than a floating coupon can account for, at most, a few basis points difference in their yield, depending on the shape of the yield curve. We find that the basis moves over time and across firms by substantially larger amounts.

Various aspects of the behavior of the basis have recently attracted attention of a number of authors.[3] Blanco *et al.* (2005) test the theoretical equivalence of CDS and bond spreads for a sample of 33 U.S. and European firms from January 2001 to June 2002. Although they find that the basis is, on average, close to zero, they also report that the basis for a few firms exhibits persistent deviations from zero. They attribute these deviations to imperfections in CDS contract specifications and to measurement error. In addition, they find that frequent short-run deviations of the basis from

[1]The theoretical properties of the basis are discussed in detail by, among others, Beinstein (2005), Bomfim (2005), Duffie and Singleton (2004), and O'Kane and McAdie (2001).

[2]As has been pointed out by Beinstein (2005), investors in the CDS market typically can earn swap rates as their "risk-free" rates. Swaps have thus become the risk-free instrument of choice, even though they are not completely risk-free. Our own analysis of the basis in section 3, as well as the studies of Blanco *et al.* (2005), Houweling and Vorst (2005), and Zhu (2004) confirm this fact.

[3]For a comprehensive review of the literature, at both a theoretical and empirical level, see Meng and Gwilym (2005).

zero are consistent with CDS leading cash instruments in the price discovery process. Houweling and Vorst (2005) assemble a dataset with a larger number of firms, though spanning an earlier time period (from May 1999 to January 2001). They find a small positive basis for investment-grade firms, but a much larger one for speculative-grade firms. Moreover, CDS spreads in their sample conform more closely to the spreads predicted by a reduced-form model than to the actual bond spreads, a likely reflection of the nascent CDS market. Zhu (2004) reports a small positive average basis for a sample of 24 reference entities from January 1999 to December 2002. He also finds that the basis can deviate significantly from zero and, like Blanco *et al.* (2005), he concludes that this is because price adjustments in the CDS market often occur before adjustments in the bond market. Similar results concerning the differences in the timing of price adjustment were obtained by Hull *et al.* (2003), Longstaff *et al.* (2004), and Norden and Weber (2004).

We contribute to this growing literature by constructing a new dataset containing daily bond and CDS spreads, as well as other firm- and bond-specific variables, for a large number of firms over a long period of time. The scope of this data allows us to take a deeper look into the nature and some possible determinants of the basis and thus of frictions in the corporate market.

Our findings can be summarized in four stylized facts. First, the average basis, over time and across different bonds, is essentially zero. Thus, in the aggregate, corporate debt markets appear to be relatively frictionless. Second, there are systematic and persistent deviations over time in the aggregate basis. This suggest a significant degree of comovement among the bases of different bonds, a likely reflection of common factors or shocks that induce different responses in the CDS and bond market. Third, the dispersion of individual-specific average bases across bonds is considerable. And fourth, the persistence of deviations of the basis *from its mean* is relatively small (about two weeks). These last two facts indicate that bases that are significantly different from zero are common and that their deviations from *zero* are highly persistent. Therefore, there must be other bond- or firm-specific factors that induce frictions in the corporate market, in addition to the aggregate factors that affect all bases. Indeed, we find that bond-specific effects account for a substantially larger portion—about seven times as large—of the variation in the bases than do aggregate effects.

We are able to identify a number of factors that account for substantial fractions of the movements in both the aggregate and bond-specific basis. At the aggregate level, macroeconomic and financial variables such as uncertainty about the future path of interest rates, the slope of the yield curve, liquidity conditions in the derivative and cash market, and proxies for liquidity preferences all have a significant impact on the basis. Indeed, these factors account for as much as 75 percent of the variation in the investment-grade aggregate basis and about 55 percent of the variation in the speculative-grade aggregate basis. At the level of individual securities, we find that factors such as bond maturity, coupon size, price volatility, credit rating migrations, along with issuer implied volatility, recovery rates, and CDS liquidity proxies, account for about 35 percent of the idiosyncratic variation in the basis and for about 65 percent of its cross sectional standard deviation. Those same factors, however, appear to be largely unrelated to the variation of the persistence of individual bases away from their mean.

The remainder of the paper is organized as follows: section 2 describes the data; section 3 presents some statistics about the basis, both over time and across firms; section 4 relates the time-series behavior of the mean basis to several macroeconomic and financial variables; in section 5 we study the cross-sectional behavior of the basis; and section 6 concludes.

2. Data Description

Our analysis utilizes a large bond-level panel at the daily frequency, constructed by merging information from following four data sources: (1) Merrill Lynch corporate bond dataset; (2) Moody's DRS dataset; (3) Markit CDS dataset; and (4) Bloomberg implied volatility dataset. We now describe each source of data in turn.

2.1. **The Merrill Lynch Corporate Bond Dataset.**

The Merrill Lynch (ML henceforth) dataset contains daily information on a large number of corporate long-term debt obligations. Typically, details such as CUSIP, maturity, effective yield, and par and market values are listed for bonds issued by a given corporation.[4] The ML dataset includes only rated bonds that have at least one year remaining to maturity, a fixed coupon schedule, and exceed a certain threshold[5] We performed an additional level of filtering and eliminated all bonds not denominated in U.S. dollars and all bonds issued by non-U.S. firms. Finally, we dropped securities with non-standard features, such as embedded options, sinking-fund provisions, etc.

For each of the remaining bonds, we computed the daily spread to swaps by subtracting from the bond yield an estimated swap yield with the maturity equal to the remaining maturity of the bond.[6] Our final dataset spans the time period from January 2, 2001, to September 1, 2005, and contains 10,974 different bonds, issued by 2,737 different entities.[7]

[4]At the firm level, the database lists the credit rating of the issuer, the currency in which the bond is issued, the market where it is issued, the nationality of the issuer, etc.

[5]Investment-grade bonds must have at least $150 million outstanding, while speculative-grade bonds must have at least $100 million outstanding.

[6]Most CDS investors can earn swap rates as their "risk-free" rate (see Beinstein, 2005). Blanco *et al.* (2005) and Houweling and Vorst (2005), among others, confirm empirically that the theoretical relationship between bond and CDS spreads holds much more closely if swap rates are used as risk-free rates instead of Treasury rates. We estimated the daily swap curve using the modification of the Nelson-Siegel method due to Svensson (1997).

[7]The total number of issuers includes subsidiaries. For example, General Motors and GMAC count as two different issuers.

2.2. **The Moody's DRS Dataset.** From the information contained in the ML dataset it is generally not possible to separate senior unsecured bonds from other types of corporate obligations. Because the ISDA rules that govern most CDS contracts specify that only senior unsecured debt can be delivered to the protection-buyer in case of default of a reference entity, it is crucial to use only senior unsecured securities when calculating the basis. To identify the relevant securities, we used the Moody's DRS database, which contains detailed information on the characteristics of a large number of corporate bonds, including their seniority, coupon frequency, as well as whether or not they are backed by collateral. We used this information to select only senior unsecured bonds that pay semi-annual coupons. Out of 10,974 bonds in the original ML dataset, 7,005 of them met these requirements.

2.3. **The Markit Credit Default Swaps Dataset.** The Markit dataset contains spreads on credit default swaps of maturities between 6 months and 30 years referenced to individual institutions, as well as information on the reference entities, such as their credit rating, industry sector, region of operation, etc. On any given day, Markit collects quotes from 13 CDS dealers and from a number of customers that provide their own quotes.[8] The quotes are daily and represent an average of the midpoint between the bid and the ask quote provided by the different contributors.

Markit applies several filters to the data to eliminate outliers and stale quotes. Furthermore, if a reference entity does not have quotes from at least three different sources on a certain day for a certain maturity, no data are reported. Because our focus in on the U.S. market, we eliminated from the Markit dataset all non-U.S. reference entities, as well as quotes for CDS contracts written on U.S. entities but denominated in currencies other than U.S. dollars. We also restrict our attention on the MR, or "modified restructuring," clause, which reportedly is the most widely used in the U.S.[9]

Our CDS data starts in January 2, 2001, when Markit provided data on 78 North American companies for at least one CDS maturity under the MR restructuring clause. Over time, that number contracts has increased dramatically, with 1,110 contracts available as of the end of our sample,

[8]The 13 dealers are ABN Amro, Bank of America, Citigroup, CSFB, Deutsche Bank, Dresdner KW, Goldman Sachs, JP Morgan Chase, Lehman Brothers, Merrill Lynch, Morgan Stanley, TD Securities, and UBS.

[9]The current ISDA documentation specifies that CDS contracts can be written according to four different restructuring clauses: "cum restructuring," or CR, whereby any restructuring event is treated as a default, and the protection buyer is allowed to deliver bonds of any maturity to the protection seller upon default or restructuring; "ex restructuring," or XR, under which no restructuring event is considered a default; "modified restructuring," which considers certain types of restructuring as a default event, but limits the maturity of the debt that can be delivered in the case of restructuring; and "modified modified restructuring," or MM, which imposes different limits on the bonds that can be delivered upon restructuring.

Table 1. Number of CDS data at stated maturities in the Markit dataset

Maturity (years)	Observations	Percentage
0.5	1,469,219	34.2
1	3,281,698	76.4
2	3,028,986	70.6
3	3,531,031	82.2
5	3,880,358	90.4
7	3,239,238	75.4
10	3,120,663	72.7
15	1,908,048	44.4
20	1,973,203	46.0
30	1,234,397	28.7
Memo: 4,295,962 observations in the Markit CDS dataset		

September 1, 2005.[10] Not every firm has CDS quotes on every day after it was first included in the dataset. As reported in table 1, there is a noticeable drop-off in quote availability for maturities of six months and greater than ten years. Accordingly, we retain only quotes for maturities between one and ten years. The dataset confirms the often-reported fact that the five-year maturity is the most popular, as 90 percent of all observations in the dataset have a quote at that maturity.

2.4. **The Bloomberg Implied Volatility Dataset.** From Bloomberg, we collected daily time series of equity implied volatility data on 842 publicly traded U.S. firms that have equity options traded on their stock. The implied volatility is computed from at-the-money options as the average between the call and the put implied volatilities. As was the case for the CDS data, the number of firms in the panel increases significantly over time.

2.5. **Our Dataset.** We merged the individual datasets described above by firm and day to obtain a single dataset which consists of data on senior-unsecured bonds that pay semi-annual coupons, CDS contracts with maturities between one and ten years, and implied volatilities. We require that each firm has at least 30 (possibly nonconsecutive) observations. That is, firm i is included in the panel on day t only if bond, implied volatility, and at least some CDS data are all non missing. The resulting dataset, albeit considerably smaller than the individual component datasets, is still fairly large: It includes 1,290 bonds issued by 306 different firms for a maximum of 1,163 days. The median bond is in the panel for 471 days, while the median firm tenure is 541 days. The minimum number of days that both a bond

[10]As was the case for the ML dataset, the number of reference entities includes parent companies as well as subsidiaries.

and a firm are in the panel is 30 (our self-imposed lower limit), while the longest tenure is 1,159 days for bonds and 1,163 days for firms.

3. Computation and Description of the Basis

We can use our merged dataset to compute a measure of the difference between the CDS spread and the corporate spread, which we refer to as the *basis*, and to analyze its determinants, both in the cross-sectional and time series dimensions. In this section we first describe how we compute the basis—which, given the richness of our dataset, we are able to do for each bond, rather than for each firm—and we present some of its basic properties.

The first problem that we face when trying to compute the basis is that CDS and bonds are, in general, not available at matching maturities on any given day and for any given firm. Most papers in the literature focus exclusively on the five-year maturity, which is widely reported as being the most actively traded in the U.S. CDS market. Authors typically select only bonds that have a maturity near five years, and subtract the spread of those bonds from the CDS spread to compute the five-year basis. If we did that, however, we would significantly reduce the number of bonds that is available for our analysis. As noted in table 1 above, with the development of the CDS market, investors have become increasingly willing to trade contracts of various other maturities, and dealers have become likewise willing to provide quotes outside the five-year range. [11] We do not thus limit ourselves to just one maturity, but we rather exploit the full contents of our dataset.

Even if we are willing to use all maturities in our dataset—at least those between one and ten years, given Table 1—we still face the problem that bonds and CDS do not have the exact same maturity, except by coincidence. We could tackle this problem in two ways: one would be to use the bond yields to estimate a yield curve for each firm on each day and then interpolate bond yields at the exact CDS maturities. While feasible, this approach requires us to estimate yield curves with a number of bonds that is often very small. Since CDS data are more regularly available at most maturities between one and ten years, we prefer instead to use the CDS spreads to estimate daily credit curves for each firm in the dataset, and read off of them a CDS spread of the exact maturity of any bond the firms may have outstanding.

[11] It may be the case that not all CDS quotes reported by Markit are actual market quotes. Some may be derived from other information available on a certain firm at a certain date; for example, if a quote for, say, the three-year maturity is missing for the MR restructuring clause but is available for the CR clause, Markit may adjust the CR quote down appropriately and report it as an MR quote. Markit reports that there doesn't seem to be a significant difference in the number of imputed quotes across maturities: quotes at the five-year maturity quotes are just as likely to be imputed as any other maturity. Therefore, concentrating on the five-year maturity would not eliminate this potential problem. Note finally that many bond yields are typically matrix-priced as well, and thus suffer from the same problem. Merrill Lynch, like most other data providers, does not include a field that indicates whether the quotes are actually observed or matrix-priced.

In the following we will use the subscript i to denote a firm, the subscript t to denote time, and the subscript k to denote a bond. To fit a CDS curve for firm i on day t we use a Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) algorithm. That algorithm, which is similar to a spline and is readily available in Matlab, can be set up to fit a curve through various points subject to the condition that the curve passes exactly through the given points. Our curves, thus, never depart from the observed CDS spreads. The algorithm is convenient because it preserves monotonicity in the data and because, at points where the data have a local extremum, so does the interpolated curve. This implies that PCHIP does not introduce artificial oscillations between one point and the next, as a spline algorithm may do. Figure 1 illustrates this point: The thirty-year CDS spread for GM on September 1, 2005 was higher than the twenty-year spread; accordingly, the PCHIP curve slopes up throughout the twenty- to thirty year interval, unlike the spline curve, which is U-shaped over that time interval. Both algorithms produce interpolating curves with a continuous first derivative; the PCHIP algorithm, unlike the spline algorithm, produces curves for which the second derivative need not be continuous at the observed points. Except in cases like the one in the figure, however, PCHIP produces results very similar to a cubic spline.

In order to be able to interpolate a CDS curve, we need to impose some restrictions on our data. First, as already mentioned, we restrict the CDS maturities from which we interpolate a curve to the one- to ten-year range; second, we interpolate a curve only if the CDS spreads at the one- and ten-year maturities are not missing; and third, we require that no more than two spreads at intermediate maturities be missing. We proceed to estimate a credit curve for every firm and every day for which those conditions are satisfied.

Once we have estimated the credit curves, we can easily compute the basis for all bonds in our sample:

$$b_{itk}(m) = s_{it}(m) - c_{itk}(m), \tag{1}$$

where $s_{it}(m)$ is the CDS spread of maturity m for firm i at date t, and $c_{itk}(m)$ is the corresponding spread for bond k issued by firm i. Note that on days when one firm has more than one bond in the ML dataset, our merged dataset contains more than one basis for that firm.

Given that CDS maturities do not exactly match bond maturities, the arbitrage between the two instruments is not perfect in general. However, given the availability of CDS at many different maturities, investors that wished to take advantage of price discrepancies between the two instruments would, in most cases, have access to CDS with maturities that are no more than one year away from the maturity of a bond issued by a certain reference entity. In perfectly frictionless markets, thus, we would expect most (even though not quite all) of the price discrepancies to quickly disappear. Note

Figure 1. General Motors CDS curve on September 1, 2005

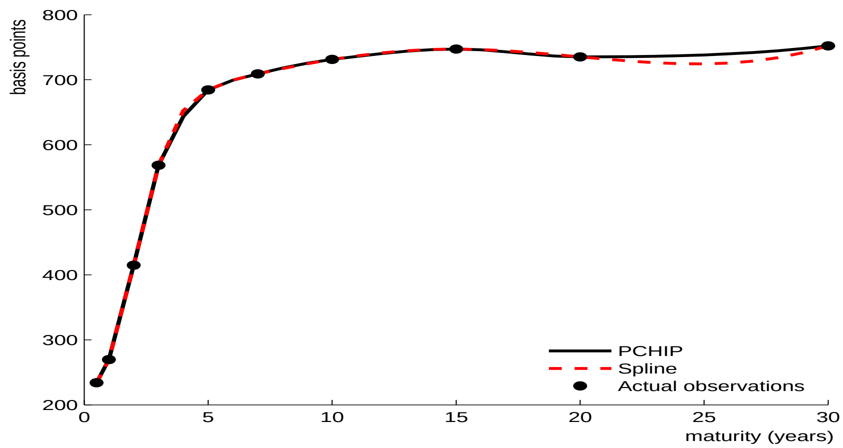


Table 2. Basis statistics

	N. Obs.	Mean	Median	St. Dev.	IQR	Skew
All firms	**606,286**	**-2.32**	**-0.35**	**32.17**	**31.33**	**0.14**
Investment-grade	**485,016**	**-3.99**	**-0.53**	**28.18**	**29.05**	**-0.37**
>$1bn outstanding	355,448	-0.39	2.28	25.13	24.52	-0.86
30 largest	206,866	4.00	4.79	23.76	27.11	-0.46
AAA	4,204	3.85	4.97	10.47	30.23	-0.88
AA	22,939	-1.20	3.87	21.91	19.58	-1.64
A	167,345	-0.87	3.59	23.57	23.08	-1.27
BBB	290,528	-6.11	-3.72	29.63	31.43	-0.13
Speculative-grade	**121,270**	**6.02**	**1.11**	**46.41**	**55.27**	**0.35**
30 largest	97,787	9.43	3.01	42.40	49.16	0.34
BB	89,536	-3.57	-4.63	38.87	42.64	0.36
B	29,677	26.01	28.44	53.23	74.01	0.20
CCC	4,057	24.88	28.35	63.90	105.01	0.13

that this arbitrage argument would remain the same if we had confined our analysis to the five-year maturity, as most authors that have done so have used bond maturities of between four and six years—i.e., one year on either side of the CDS maturity—in their analysis.

Table 2 summarizes the basis across different groups of firms. Overall, and as found by other authors, the basis is very small: just -2 basis points on average, with the median virtually at zero. For investment-grade firms, the basis is very close to zero, both in mean and in median, independently of the credit rating; this confirms the results obtained by other authors with much smaller datasets (see Blanco *et al.* , 2005, Houweling and Vorst, 2005, and Zhu, 2004). While most of the existing literature finds a small but positive basis, the mean for all investment-grade firms in our sample is about −4 basis points; this indicates that, on average, the CDS spread for those firms has been below their bond spread. That result, however, appears to be driven entirely by small firms: If we eliminate from the sample firms that have bonds outstanding (as reported by Merrill Lynch) for less than $1 billion, the average basis turns out to be almost exactly zero. The difference between large and small firms is further evidenced if we look at just the thirty firms in the sample with the largest amount of bonds outstanding—a sample which is more comparable to those used by the above-mentioned authors. For those firms, the mean and median basis are both positive, at about 4 basis points. Note finally that, independently of size and credit rating, the distributions of the investment-grade basis, even for just the largest firms, are all significantly skewed to the left, as is also evident from figures 2 and 3.

To visually assess the effect of not limiting our analysis to the five-year maturity, figure 2 plots the distribution of the basis computed from five-year CDS and bonds—the top panel—and from one- to ten-year CDS and bonds—the bottom panel. Both methods produce very similar distributions; in both cases, as was to be expected, the investment-grade basis distribution is much more concentrated than the speculative-grade distribution, and appears to have a negative skew. Even if we break down the one- to ten-year basis distribution into subsets that span two years of maturities each, the distributions remain very similar. Figure 3 plots the investment-grade—the top panel—and the speculative grade basis distributions—the bottom panel—at different maturity ranges. As is clear from the figure, the investment-grade distributions are all almost identical to each other; the two- to four-year speculative grade basis distribution is slightly more dispersed than the remaining three distributions, and is shifted a touch to the left. Overall, based on the casual observation of the figures, there does not appear to be a systematic relationship between maturity and basis in our dataset, a further confirmation that we do not introduce any spurious bias by working with all maturities. We will conduct a more rigorous analysis on this point later.

The picture is somewhat different for speculative-grade firms. For those, the basis is, on average, still fairly small, at 6 basis points; the median is even lower, at 1 basis point. The amount of outstanding bonds does not appear to make a major difference, as the thirty largest firms have mean and median bases that are only a bit larger than those of the whole sample. The difference across credit ratings, however, are remarkable. While the mean and the median for BB-rated firms are actually negative and comparable to

FIGURE 2. Distribution of the basis across time and reference entities

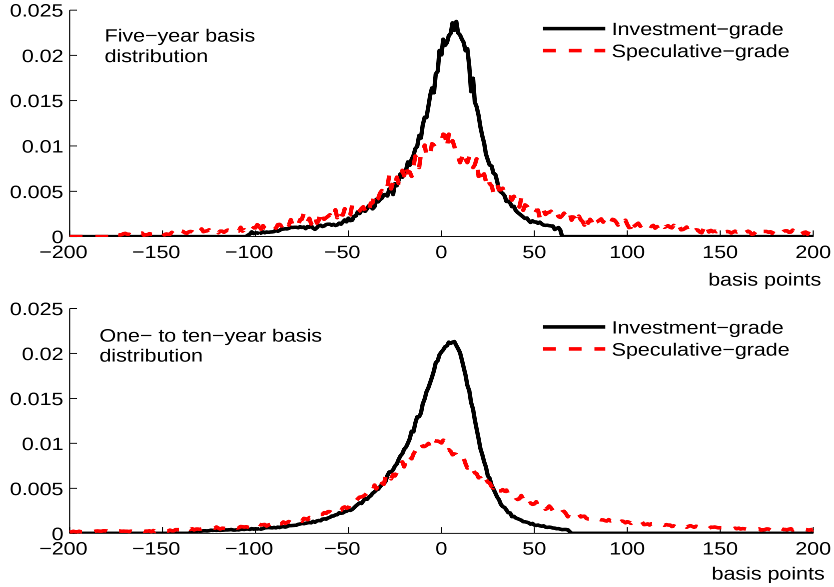


FIGURE 3. Distribution of the basis for different maturities across time and reference entities

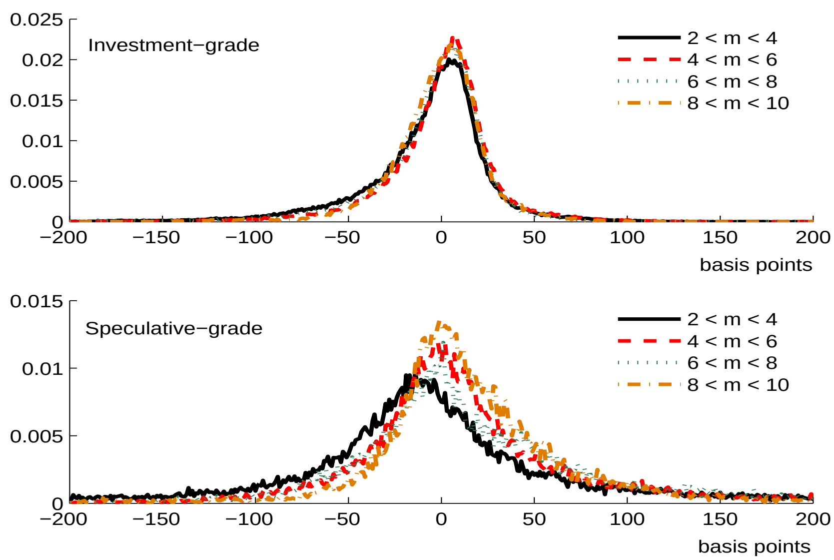


Table 3. Analysis of variance for the basis

	Pct. of Variance	F Value	Prob > F
α_k	40.39	341.05	0
β_t	4.04	37.78	0
Model	44.43	197.20	0
α_k	40.39	341.05	0
β_t·rating	6.22	30.60	0
Model	46.61	146.90	0
α_k·rating	42.02	347.73	0
β_t·rating	6.08	30.72	0
Model	48.10	151.00	0

those of investment-grade firms, the same statistics for firms rated B and CCC are much higher.[12] While the number of observations for firms at the lower end of the credit spectrum is comparatively small, a large basis appears to be a stable property for those firms. We also note that the speculative-grade distribution is skewed in the opposite direction as the investment-grade distribution, again as is evident from figures 2 and 3. The positive skewness holds for all sub-investment-grade ratings.

To impose some structure to our analysis, we specify the following simple model to describe the basis:

$$b_{kt} = \alpha_k + \beta_t + \varepsilon_{kt}, \tag{2}$$

where α_k indicates an effect specific to bond k (issued by firm i), and β_t indicates a time-specific, or aggregate, effect. The residual ε_{kt} captures anything else that has an effect on the basis b_{kt}.[13]

The first three rows of Table 3 contain an analysis of the variance of the basis that is explained by equation (2). Overall, bond-specific and aggregate effects explain about 44 percent of the variance of the basis. The majority of that explanatory power is accounted for by bond-specific effects, while aggregate effects represent only about 4 percent of the total variation. The presence of both effects is highly significant.

It is conceivable that there may be some differences in either the bond-specific or aggregate effects (or both) depending on whether a bond is rated investment-grade or as speculative-grade. We explore this possibility in the remaining rows of the table. First, in the middle rows, we interact the

[12]There are no firms rated lower than CCC in the Markit dataset that have CDS traded in their name.

[13]Since we use all available maturities between one and ten years to compute the basis, we drop the m in equation 1.

aggregate term β_t with a dummy variable that takes on the value one for bonds that are rated speculative-grade and zero otherwise. Distinguishing between classes of firms rises the percentage of the variance explained by the aggregate component by about one-third, although that fraction is still small at 6 percent. When we interact the firm-specific effect with out rating indicator as well, the fraction of the variance explained by α_k rises modestly. Overall, we conclude that our simple model in equation 2 can explain about half of the variation in the data, and that, while aggregate effects are clearly visible and significant, bond-specific effects are predominant.

The results in tables 2 and 3 indicate that, even if the basis is, on average, close to zero for investment-grade and the best of the speculative-grade firms, it is not, in general, near zero for all firms all the time. In fact, the basis distributions are quite dispersed, with interquartile ranges of 29 and 55 basis points for investment-grade and speculative-grade firms, respectively. Moreover, the bond-specific means (the α_k) are also far from concentrated. Indeed, for a number of firms, the basis appears to be substantially different from zero for long consecutive periods of time. As an example, figure 4 shows a time series of the basis for two large firms: For General Motors, the basis was mostly positive over our sample period and rose to extreme levels (in excess of 400 basis points) in the spring of 2005, following the notorious difficulties at the firm that resulted in it's debt being downgraded to junk status. Conversely, the basis for Federal Express has been negative for most of the sample period and became close to zero only starting in 2004.[14]

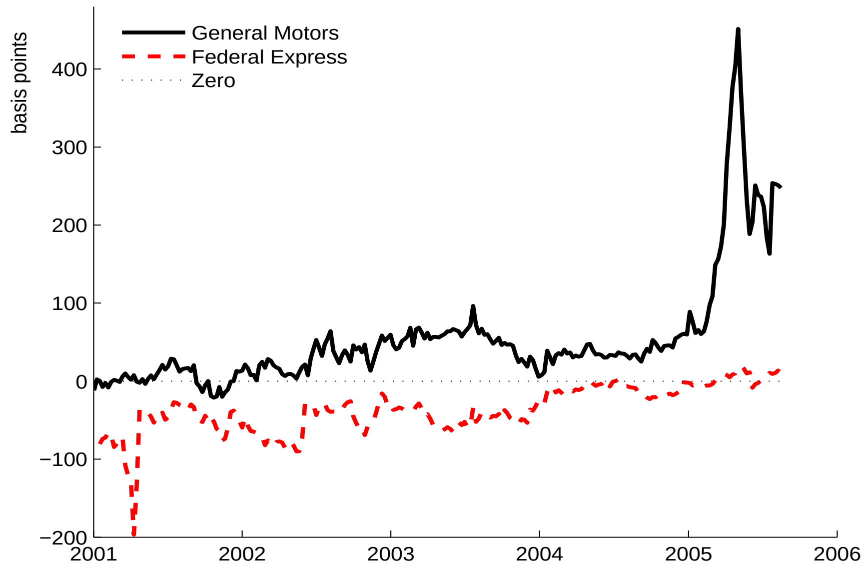
It is also instructive to look at a plot of the aggregate basis over time across our whole sample of firms. As shown in figure 5, β_t for both investment-grade and speculative-grade firms fluctuate noticeably over time and are relatively highly correlated—the correlation coefficient is 0.61 at a weekly frequency.[15] Indeed, several turning points can be easily identified, such as the summer of 2002, when investors were skittish about defaults and corporate malfeasance; mid-2003, when interest rates backed up fast after investors realized that the Federal Open Market Committee would not ease monetary policy any further; the spring of 2004, when investor realized that monetary policy tightening was about to begin; and the spring of 2005, when credit quality problems at the large U.S. automobile manufacturers roiled the credit markets.

This anecdotal evidence that the aggregate basis moves at times that are linked to specific events may be a sign that indeed there may be variables or events that affect investors' ability to take advantage of arbitrage opportunities, and thus the functioning of the corporate market. Similarly, the fact that different bonds may have such widely different basis at any given point in time may reflect individual bond characteristics as well as firm-specific

[14]We chose these two firms for purely illustrative purposes, as their bases are so significantly different from zero for such long periods of time.

[15]We plot weekly time series to highlight the cyclical properties of the bases and to eliminate some of the high-frequency noise that is present in the data.

FIGURE 4. Weekly time series of the basis for two individual firms



circumstances that may make it easier or more problematic to exploit the seeming arbitrage opportunities. In the next sections we will separately analyze the two components of the basis and we will investigate what variables correlate with them significantly.

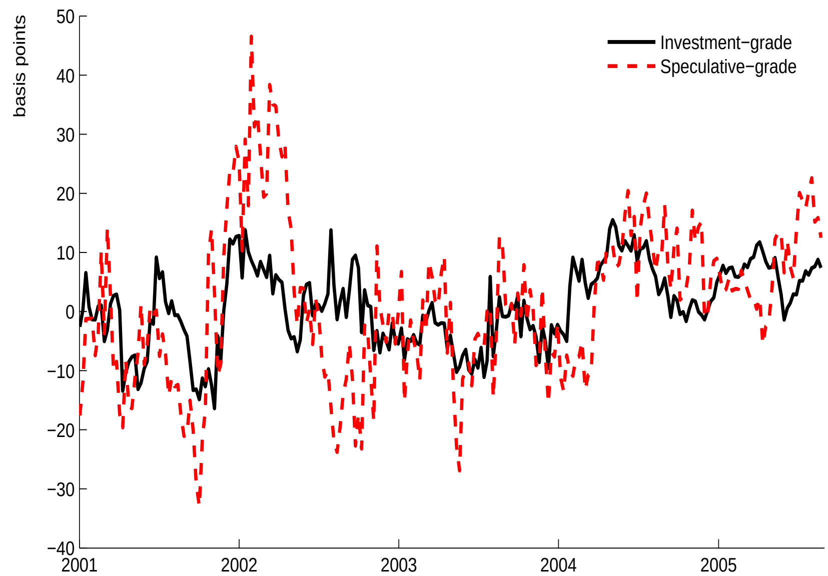
4. The aggregate component of the Basis

The heuristic description of the two previous figures suggest that there may be aggregate factors that drive a wedge between the CDS and the corporate bond market. For example, it may be the case that liquidity preferences, policy expectations, interest rate movements, and possibly other macroeconomic conditions affect the two markets differently, and therefore induce the bases of all firms to move together. In this section we study what aggregate variables correlate well over time with our measure of the mean basis across all bonds in the sample. Our strategy is simply to regress the mean basis on a set of explanatory variables, as in:

$$\beta_t = aX_t + u_t, \tag{3}$$

where X_t is a matrix containing a number of potential explanatory financial variables. To determine what exactly those variables may be, we follow the existing literature and our intuition.

FIGURE 5. Time series of the basis (weekly medians across reference entities)



There are a number of well-understood reasons why the basis may not be zero at all times. Some of those are technical in nature, others have more economic and financial meaning. Below, we briefly discuss some of them and our proposed way of accounting for their effect.

4.1. **Fixed-rate vs. floating-rate bonds.** One first obvious departure from the standard arbitrage argument that lead to the theoretical equivalence of bond and CDS spreads is that there are very few, if any, floating-rate corporate or risk-free bonds. Duffie and Liu (1999) estimate that the difference in spread between a fixed-rate and a floating-rate bond of the same characteristics is very small, of the order of a few basis points at most, and depends on the slope of the yield curve. They show that, if the yield curve is upward sloping, floating spreads should be slightly higher than fixed spreads. This suggests that the basis should be positively related to the slope of the yield curve, although the effect should be very small. It seems unlikely, thus, that the paucity of floaters could account for the relatively sizable swings in the aggregate basis over time (see figure 5).

4.2. **The slope of the yield curve.** There may be a more important reason why the slope of the term structure could lead to variations in the basis. The total cost of shorting a bond is inversely related to the steepness of the yield curve: An investor who is short a bond needs to first obtain the bond in the repo market by lending cash to the owner of the bond, and, under normal circumstances, is compensated for that loan at a short-term rate (often an overnight rate) called the repo rate. [16] The investor also has to pay the bond coupons, or accrued interest if the shorting period does not span a coupon date. The flatter (or the more inverted) the yield curve, the cheaper it will thus be to short a bond, because the negative cash flow induced by the accrued interest is offset by the repo rate received from the bond owner. This argument, like the one above, leads us to expect a positive relationship between the slope of the yield curve and the basis, as the total cost of shorting a corporate bond would be higher the steeper the curve is.[17]

4.3. **Liquidity conditions.** Market liquidity should also play an important role in determining the basis. A commonly-used measure of liquidity in either market would be the bid-ask spread; however, we do not have access to that data. Instead, Markit provides us with the number of five-year CDS quote providers for each firm on any given day; we assume that the CDS market is more liquid when that number is high, both across firms and over time. We use the average number of quotes across firms on any given day. Zhu, in a panel setting, finds that high liquidity in the CDS market tends to lead to a higher basis. While he finds the result somewhat puzzling, we tend to view is as consistent with market participants preferring the CDS market to the cash market, especially when credit quality deteriorates. Accordingly, we expect that this variable enters with a positive sign in our regressions.

A similar argument can be made for liquidity in the bond market. Again, we do not have bid-ask spread data, so we use gross bond issuance as a proxy for liquidity. On the one hand, few corporations will attempt issuing debt at times when the market is illiquid; on the other hand, a high amount of issuance usually leads to high trading activities, as dealers place the bonds and investors perhaps need to make room for them in their portfolios. We would expect that high issuance would lead to a tightening of the basis.

Besides liquidity conditions in specific markets, there may be situations that induce investors to prefer to allocate their funds to generally very liquid markets, such as the U.S. Treasury market. While we do not attempt here to characterize what the causes of such liquidity preferences might be, we proxy that behavior with the liquidity premium that investors are willing to pay to hold on-the-run Treasury securities over off-the-run securities of (roughly) the same maturity. In particular, we use the spread between the first off-the-run and the on-the-run ten-year Treasury security. Ideally, at

[16]At times the bond may be in such a high demand in the repo market that investors are willing to lend funds to the owners of the bond at a below-market rate; that rate is called a repo-special rate. Duffie (1999) shows that, if a bond is "on special" in the repo market, the basis will be theoretically positive by the difference between the repo rate and the special rate.

[17]Note that, since swaps are the risk-free instrument of choice for investors in the CDS market, there is no need for those investors to short a risk-free bond: They may just enter into a pay-fix swap instead.

time of strong preferences for safe, liquid assets, investors should shy away equally from the CDS and the corporate bond market; if it is true that it is easier to move in and out of the CDS market than the bond market, however, we should find that a high liquidity premium leads to a positive basis.

A different measure of broad market liquidity conditions is given by the swap spread over Treasury securities. Grinblatt (2002) argues that swap spreads are accounted for by differences in liquidity conditions between Treasury securities and short-term eurodollar deposits. Apedjinou (2003) finds empirically that liquidity conditions are a more important determinant of swap spreads than credit conditions, especially in more recent years. We include the five-year swap spread among our explanatory variables, and expect its coefficient to be positive, just like the coefficient for the on-the-run premium.

4.4. **Counterparty credit risk.** If investors in the CDS market, especially protection buyers, are concerned that their counterpart in the trade might default at the same time that the reference entity defaults, they may demand to pay a lower spread for credit protection. Since the cash market is not affected by counterparty credit risk, this would tend to lower the basis, everything else equal (see, for example, O'Kane and McAdie, 2001). As attested by various surveys (see Bank for International Settlements, 2005, among several others), most counterparts to CDS trades are large dealers. We thus proxy counterparty credit risk with the CDS spread of the major dealers in the market, and we would expect a negative sign for the coefficient of that variable in our regressions.

4.5. **Macroeconomic uncertainty.** The term "macroeconomic uncertainty" is typically used broadly to denote the possibility that economic conditions may take on any of a variety of different states in the more or less immediate future. A finer parsing of different uncertainties is also possible. For example, if market participants are concerned about the economy entering a recession, equity implied volatility is likely to increase, but uncertainty about the direction of short-term interest rates may very well decline, as investors anticipate an easing of monetary policy on the part of the central bank. Similarly, at times of overall good economic conditions, equity implied volatility may be generally low, but short- and long-term interest rate implied volatility may be elevated due to a potentially broad range of monetary policy choices available to the central bank. Accordingly, we use three different measures of uncertainty in our regressions: equity implied volatility, to measure sentiment about broad macroeconomic conditions; three-month eurodollar implied volatility, to measure uncertainty about monetary policy choices; and ten-year Treasury yield implied volatility, to measure concerns about the evolution of long-term interest rates induced, for example, by inflation or other types of risks.

Uncertainty, especially as measured by equity implied volatility (Blanco *et al.* , 2005) or realized volatility (Zhang *et al.* , 2005) has been found to be related to both the CDS and the bond spread. We do not have an a priori opinion as to the direction in which our three proxies may affect the basis, or even if at all. It may indeed be possible that implied volatilities affect the two markets equally, and thus that the aggregate basis is insensitive to market uncertainty. To the extent that we find significant coefficients on any of those variables, we would be led to conclude that one of the two markets seems to react more to the specific type of risk represented by the particular implied volatility.

4.6. **Other.** The presence of cheapest-to-deliver (CTD) options in the CDS market is induced by the restructuring clause used in a specific contract. The problem arises because, while at default all bonds issued by the reference entity should have the same price (the recovery value), upon restructuring that equivalence may not hold, and near-term bonds may be valued significantly more than longer-term bonds.[18] According to the revised ISDA rules governing CDS trading, only bonds within a relatively narrow window can be delivered to the protection-seller in case of debt restructuring on the part of a reference entity. For example, according to the MR restructuring clause to which our data refer, a protection buyer can deliver to the protection seller a bond with a maturity of no more than thirty months longer than the maturity of the CDS contract upon the occurrence of a restructuring event. The CTD option should introduce an extra element of risk for the protection-seller, and thus should lead to a positive basis, everything else equal; the revised ISDA rules should have significantly reduced the value of the option, however. We do not have any proxy for this option at this stage, and we suspect the overall effect should be fairly small. In future research, we plan to test that conjecture by comparing the basis computed under the MR clause to the basis that results from no-restructuring (XR) CDS.

Synthetic CDO issuance appears to be an important source of imbalances in the CDS and cash markets. Cash collateralized debt obligations, or CDO, are securities backed by pools of corporate bonds or loans. Synthetic CDO, on the other hand, reference a portfolio of credit default swaps, rather than a portfolio of cash assets. Both types of CDO divide the risk of loss of the underlying portfolio into tranches based on seniority: equity, mezzanine, senior, and super-senior. Losses in the reference portfolio will be absorbed first by the equity tranche, and then by the other tranches in order. As pointed out by Gibson (2004), buyers of a certain synthetic CDO tranche gain exposure to credit risk, effectively selling credit protection to the issuer. The issuer, in turn, typically hedges its position by selling protection on the portfolio in the form of single-name CDS to other investors. Assuming that the CDO buyers do not hedge their positions but rather seek exposure to

[18]Bomfim (2005) describes the famous case of the Conseco restructuring which led to the revised ISDA rules.

a portfolio of credit risk, as appears to be the case, CDO issuance creates an (arguably temporary) excess supply of CDS in the market, driving CDS spreads below corporate spreads, everything else being equal. According to Calamaro and Tierney (2004), synthetic CDO issuance has very recently grown in importance as a reason of negative observed CDS-bond basis. We plan to investigate this channel of divergence between CDS and cash spreads in future research.

4.7. **Results.** We include in our analysis as many of the variables discussed above as we can. Specifically, our matrix X_t in equation (3) contains: the slope of the yield curve; a transformation of the average number of dealers providing CDS quotes on any given week (a proxy for CDS market liquidity); [19] gross weekly bond issuance (a proxy for bond market liquidity); the Treasury liquidity premium and the swap spread over Treasuries (as proxies for investors' preference for liquid assets); the average CDS spread of major CDS dealers (as a proxy for counterparty credit risk); implied volatilities for ten-year the Treasury yield; three-month eurodollar rate, and the S&P 500 index (as proxies for market uncertainty); and the weekly returns on the S&P 500 (intended to proxy general perceptions about economic conditions).

The results of our regressions are reported in table 4 for investment-grade and speculative-grade credits separately. Several facts are worth mentioning. First, the behavior of interest rates appears to be an important determinant of the basis. As predicted, and consistent with what other authors have found, the slope of the yield curve is positively related to the basis. The effect is stronger for speculative-grade credits; since shorting high-yield bonds is arguably more problematic than shorting investment-grade bonds, we view this a reflecting more the difficulty of obtaining corporate bonds, especially speculative-grade ones, in the repo market than the lack of floating-rate corporate bonds in the market.

All liquidity variables have the expected sign and are highly significant for investment-grade credits, except for the Treasury liquidity premium. We interpret these findings as a sign that, at times of strong preference for liquidity, investors may find it easier to exit the CDS market than to exit the corporate bond market, thereby pushing CDS spreads higher. Conversely, at times when liquidity preferences are not a factor, investors may be more inclined to acquire cash corporate assets. In agreement with Zhu (2004), we find that a high number of CDS quote providers also tends to correlate with a higher basis. Since the number of quote providers has grown over time, this finding may be a sign that, as liquidity in the CDS market has improved, CDS have become the instrument of choice to trade credit risk. Also as

[19] Since the average number of reporting dealers has grown steadily over our sample period, including the variable in levels would have the implication of assuming that the basis may grow without limits in absolute value. We construct our measure as $l_{CDS} = 1 - exp(-\gamma N_{dealers})$, where $N_{dealers}$ is the average number of CDS dealers. We estimate the parameter γ jointly with the other parameters using nonlinear least squares.

TABLE 4. Time series regressions: investment-grade.

Variable	Investment-grade	Speculative-grade
Constant	-0.717***	-0.423**
	(0.063)	(0.018)
Yield Curve Slope	0.035***	0.049**
	(0.008)	(0.002)
No. of CDS contribs.	62.351***	33.818**
	(4.467)	(14.514)
Bond Issuance	-0.196**	-0.692
	(0.081)	(0.492)
Liquidity Premium	0.078	1.422***
	(0.170)	(0.322)
Swap Spread 5yrs	0.521***	-0.027
	(0.051)	(0.140)
CDS Dealers Spread	0.067	-0.247
	(0.054)	(0.173)
10yr Rate Implied Vol.	-0.876**	-0.300
	(0.396)	(0.887)
3mo ED Implied Vol.	-0.908	12.781***
	(1.316)	(3.990)
SP500 Implied Vol.	-0.259*	-1.069***
	(0.160)	(0.404)
R^2	0.733	0.839

T statistics in parenthesis. *** denotes significance at the 1 percent level or better; ** and * denote significance at the 5 and 10 percent levels, respectively.

expected (and different from what Zhou, 2004, finds), high bond issuance tends to lower the basis. The results are broadly similar for speculative grades, except that bond issuance and swap spread are not significant, while the Treasury liquidity premium is.

A third fact worth mentioning is that the conjecture that counterparty credit risk would tend to decrease the basis is not supported by our data. The coefficient on the CDS spread of large dealers is statistically insignificant for both investment-grade and speculative-grade credits, and has the wrong sign (positive) for the former. It could be that, precisely because the vast majority of CDS trades have a large dealer as a counterpart, counterparty credit risk is not of great concern to investors. In other words, the credit quality of those dealers has remained excellent throughout our sample period, and its variation may not have been enough to produce noticeable effect on the basis.

Table 5. The persistence of the aggregate bases.

	Unconditional		Conditional	
	$\bar{\rho}$	$\bar{h}$	$\bar{\rho}\|X$	$\bar{h}\|X$
Investment-grade	0.909	7.250	0.577	1.259
Speculative-grade	0.845	4.108	0.691	1.872

Uncertainty about macroeconomic conditions as proxied by the S&P 500 implied volatility have a negative effect on the basis. The volatility of the ten-year Treasury yield has a similar effect, but is significant only in the investment-grade case. These negative signs indicate that, at times of heightened macroeconomic uncertainty, the bond market tends to sell off at a faster pace than the CDS market. Interestingly, uncertainty about the monetary policy path, as proxied by the implied volatility on the three-month eurodollar rate, has a positive and highly significant effect on the speculative-grade basis.

Finally, we note that the R^2 are fairly high for both sets of firms, and especially so for investment-grade firms, indicating that our set of explanatory variables captured most of the aggregate variation in the basis.

The persistence of deviations of the aggregate bases away from their means is also interesting, since it gives a sense of how fast the aggregate bases tend to return to zero, and thus how fast market frictions induced by systematic effects tend to disappear. One way to study persistence is to simply look at the estimated autoregressive coefficient of the investment-grade and speculative-grade bases; another would be to examine the estimated autoregressive coefficient conditional on the explanatory variables contained in the matrix X. Table 5 contains those estimates. We find it useful to transform the correlation coefficients into half lives, which are measures of the time it takes to a process with a certain autocorrelation coefficient to return half way to its mean upon displacement. In particular, we define the unconditional half life h as:

$$h = \frac{\log(0.5)}{\log(\bar{\rho})} \tag{4}$$

and the conditional half life analogously. Unconditionally, the estimated autocorrelation coefficients are fairly high. As a consequence, it takes more than 7 weeks for the investment-grade basis to return to its mean; the speculative-grade basis takes instead more than four weeks. Conditionally on our explanatory variables, however, the half lives are much shorter, with both of them under two weeks.[20] We view this as a further confirmation that

[20]Note that, when adding a lagged basis term to equation 3, the signs and the significance of the coefficients reported in table 4 do not change.

we capture the most relevant aggregate factors that induce wedges between the CDS and cash market.

5. The bond-specific component of the Basis

As we discussed in section 3, credit default swap spreads tend to be systematically higher or lower than bond spreads for long periods of time for a number of bonds. In this section, we study possible factors that may concur to determine the average level of the basis across bonds and firms. Our dataset contains several variables that are either bond-specific or firm-specific that could potentially be informative as to why idiosyncratic types of frictions may prevail between the two markets. Bond-specific variables include maturity, credit rating, the size of the issuance, and price; firm-specific variables include the recovery rate as estimated by the contributors to the Markit dataset, the number of contributors that provide CDS quotes at the five-year maturity, the firm's equity implied volatility, and the sector in which the firm operates.

All of the variables mentioned above, which include measures of liquidity and distress, as well as purely technical factors, could potentially play a role in determining whether it could be possible or cost-effective to arbitrage away any differences between CDS and bond spreads. For example, the availability of corporate bonds in the repo market, and therefore the possibility of shorting them, may depend on the size of the outstanding bond issue. Poor liquidity in the CDS market may result in high transaction costs that may compromise investor's ability to take advantage of arbitrage opportunities. High firm-specific implied volatilities may be a sign that firms are experiencing difficulties that may create imbalances in the relative demand and supply for their securities. Finally, there may be bond-specific factors that, while not immediately obvious, may still play a role in determining the presence and the extent of market frictions.

Our list of firm- or bond-specific variables could be useful in explaining not just the behavior of the average basis across time, but also of several other properties of the basis. For example, we believe that understanding some of the factors that may help account for the dispersion of the basis across firms is equally important from the perspective of understanding frictions in the corporate market. And so is understanding the factors that may affect the persistence of deviations of each bonds' basis around its mean, as well as around the aggregate basis β_t. Our strategy is to run a series of cross-sectional regressions using the explanatory variables mentioned above. Our regressions are of the type:

$$\begin{aligned}
\alpha_k &= a_1 Z_k + \epsilon_k \\
\sigma_k &= a_2 Z_k + \epsilon_k \\
h_k &= a_3 Z_k + \epsilon_k
\end{aligned}$$

$$\phi_k = a_4 Z_k + \epsilon_k$$

where α_k denotes the bond-specific effects estimated in section 3, σ_k denotes their volatility over time, h_k is the estimated half-life of the basis deviations, and ϕ represents the "beta" of each individual basis.

Specifically,

$$h_k = \frac{\log(0.5)}{\log(\hat{\rho}_k)}, \tag{5}$$

where $\hat{\rho}_k$ is the estimate of the first-order autoregressive coefficient of each individual basis obtained from $b_{kt} = \mu_k + \rho_k b_{kt-1} + e_{kt}$. Similarly, ϕ_k, our measure of the basis "beta," is obtained from a series of regressions of the type:

$$b_{kt} = \mu_k + \phi_k \beta_t + e_{kt} \tag{6}$$

Our explanatory variables are grouped in the matrix Z_k as time averages of the variables listed at the beginning of the section,

The results are reported in tables 6 (for the average and standard deviation of the basis), and 7 (for the half-life and the "beta." From the R^2 it is clear that our variables are more effective at explaining the variation in α_k than its level, while they do not do a particularly good job at explaining either the half-life or the "beta."

For the typical firm, it seems that bond size has a positive effect on the basis, everything else equal; in other words, large bonds tend to have a higher basis than smaller bonds in our dataset. While this may seem counterintuitive, we speculate that it may reflect the difficulty of shorting bonds with a large amount outstanding, perhaps because those bonds are held by large investors who have no interest in making them available in the repo market. Consistent with this interpretation, the basis for large bonds is less dispersed around its mean. The fact that, on average, bonds of long maturity also seem to have a larger basis may also be consistent with our previous interpretation, as long bonds tend to be larger in size and may be held by "steady money" investors.

An alternative interpretation could be that holders of the largest bonds tend to resort more to the CDS market to buy protection, and are willing to pay for it. This interpretation may be partially supported by the fact that bond size and maturity also tend to significantly reduce the time the basis takes to return to its mean once it is displaced. It could be that, once the reasons for concern disappear, investors in those bonds are quick to shed protection in the CDS market, thereby returning the basis to its normal level.

Bonds that have been downgraded often also tend to have a higher and more dispersed basis on average, and so do bonds that belong (or have

Table 6. Cross-sectional regressions: basis mean and standard deviation.

Variable	α_k	σ_k
Average Maturity	5.872***	-0.005
	(1.225)	(0.517)
(Average Maturity)^2	-0.343***	-0.067
	(0.108)	(0.045)
Bond size (log)	7.905***	-1.583***
	(1.074)	(0.385)
Coupon	-3.083***	1.886***
	(0.443)	(0.198)
Implied Vol. (avg.)	0.285***	0.167***
	(0.092)	(0.033)
Implied Vol. (std.)	-0.173	0.186
	(0.215)	(0.128)
Recovery (avg.)	-1.291***	0.126**
	(0.181)	(0.063)
Credit Spread Vol.	-0.006	0.051***
	(0.014)	(0.014)
High Yield	9.800***	5.877***
	(2.041)	(0.923)
No. of Downgrades	3.183***	1.228*
	(1.109)	(0.634)
No. of Upgrades	0.777	-0.556
	(1.322)	(0.648)
No. of CDS contributors (avg.)	-0.596***	-0.043
	(0.184)	(0.056)
Sector Dummies	***	***
	F=5.571	F=3.63
R^2	0.344	0.646

T statistics in parenthesis. *** denotes significance at the 1 percent level or better; ** and * denote significance at the 5 and 10 percent levels, respectively.

belonged for at least one day) to the high-yield universe.[21] In agreement with common intuition, bonds that have been downgraded the most also tend to have longer half lives; high-yield bonds that have not been subject to many rating changes, however, have shorter half lives, everything else equal.

[21]Our high-yield indicator takes on the value of one if a bond has ever been rated below BBB, and zero otherwise. We do not separate bonds into investment-grade and speculative-grade categories because those categories are not the same over time.

Table 7. Cross-sectional regressions: basis half-life and "beta."

Variable	h_k	ϕ_k
Average Maturity	0.487	0.155*
	(0.407)	(0.083)
(Average Maturity)^2	-0.072**	-0.009
	(0.034)	(0.007)
Bond size (log)	-1.628***	-0.012
	(0.318)	(0.074)
Coupon	0.918***	0.098***
	(0.128)	(0.032)
Implied Vol. (avg.)	-0.089***	0.002
	(0.019)	(0.006)
Implied Vol. (std.)	0.185***	-0.034**
	(0.058)	(0.017)
Recovery (avg.)	0.118***	0.015
	(0.038)	(0.010)
Credit Spread Vol.	-0.007*	0.001
	(0.004)	(0.001)
High Yield	-1.321**	-0.196
	(0.622)	(0.128)
No. of Downgrades	1.122**	0.105
	(0.563)	(0.109)
No. of Upgrades	0.760	-0.121
	(0.999)	(0.083)
No. of CDS contributors (avg.)	0.127**	-0.005
	(0.056)	(0.010)
Sector Dummies	***	***
	F=4.833	F=3.63
R^2	0.105	0.039

T statistics in parenthesis. *** denotes significance at the 1 percent level or better; ** and * denote significance at the 5 and 10 percent levels, respectively.

Bonds whose issuer has a high average implied volatility over our sample tend to have higher and more volatile bases. This could again reflect the fact that investors find it easy to seek and obtain protection in the CDS market for firms that are riskier than other or that are perceived as being in distress for prolonged periods of time. The deviations of the basis away from the mean for those high-volatility firms, however, tend to be shorter, perhaps because the bond market does not take much longer to react.[22] In

[22]Both Blanco *et al.* (2005) and Zhu (1994) find that the CDS market leads the cash market in the price discovery process.

somewhat of a puzzle, the volatility of implied volatility does not seem to have an effect on either the level or the standard deviation of the average basis. We interpret the volatility of implied volatility as an indicator that a firm has undergone periods of stress while its bonds were in our sample, and thus we would expect its basis to be, on average, higher than normal if it is true that investors prefer the CDS market at times of stress.[23] We also note that a high volatility of volatility significantly lengthens the half life of the basis, and reduces ϕ_k (indeed, it is one of the few factors that enters significantly in the basis "beta" in equation 6).

High CDS liquidity, as proxied by the number of dealers willing to provide CDS quotes in the Markit dataset, tends to lower the basis, on average. Admittedly, this is not a perfect measure of liquidity, as at any given time there may be many dealers willing to provide quotes with extremely high bid-ask spreads, or many or those dealers may be providing very expensive quotes to protection seekers. Still, we find our result interesting, because it may point to poor liquidity conditions in the CDS market as a cause for high, positive bases. Also, the negative sign of the liquidity coefficient in the cross-sectional regressions is in contrast with the positive sign the corresponding coefficient has in the time series regressions. We are investigating this point further and we will report more results in future versions of the paper.

Finally, we note that high recovery rates tend to reduce the basis, as do bonds with large coupons. Intuitively, while the coupon effect may be technical in nature, the higher the recovery rate, the lower the credit risk that investors face, and thus the less incentives investors will have to seek pricey protection in the CDS market. The sector that a firm belongs to also appears to be significant in determining the level, dispersion, persistence, and "beta" of the average bond-specific basis. This may be because firms in certain sectors are more likely to experience common shocks.

6. Conclusions

We proposed to quantify the degree of corporate market functioning by the extent to which seeming arbitrage opportunities remain persistently unexploited. We defined those arbitrage opportunities in term of the basis, the difference between the CDS and corporate bond spread. We find that a large fraction of the variation in the basis across a large sample of bonds and firms is idiosyncratic in nature and reflects factors that are specific to a particular bond or firm.

Aggregate macroeconomic and financial variables account for a smaller, though certainly not negligible, fraction of the total variation in the basis. A large portion of the aggregate variation can be explained by variables related to liquidity conditions and liquidity preferences, as well as to the

[23]Our interpretation is consistent with the GM experience plotted in figure 4: GM's basis surges in the spring of 2005 when the firm's credit quality deteriorated fast and its implied volatility spiked.

shape of the yield curve and the uncertainty about future economic and financial conditions.

In future research we plan to expand our analysis to the study of market frictions in a panel setting, where bond- and firm-specific variables are allowed to have a different effect on the basis over time. In a related, event-study type of project we are also working to understand the effects of macroeconomic and monetary policy surprises on the basis. We believe that those shocks may be yet another source of frictions in the corporate market, and some preliminary results support that belief.

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