How Downward-Sloping are Demand Curves for Credit Risk?

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ABSTRACT

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ABSTRACT

We analyze European telecom debt issues between October 1999 and July 2001, and find evidence that the demand curve for telecom-sector debt slopes downwards. Consequently, industry-wide spreads rise in reaction to unanticipated new debt issuances. We separate the portion of the bonds' yield spreads driven by the issuer's credit risk from the portion driven by this "new-issuance risk". A €16 B issue by Deutsche Telekom increased spreads across all telecom issues by an estimated twelve basis points. For example, the decline in market value of a $2.8 billion British Telecom bond attributable to the Deutsche Telekom issue is estimated to be 1.54%, or $43.2 *million.*

This paper documents downward-sloping demand curves for credit risk in the European telecom bond market. As a result of this demand elasticity, bond investors are subject to "new issuance risk": the possibility that an unanticipated issuance of bonds in the industry will depress the market value of their bond holdings. This risk factor is distinct from the issuer's default risk. To our knowledge, we are the first to propose the existence of such a risk factor and to provide an estimate of its impact on yield spreads.

Our contribution is three-fold. First, we strengthen an existing body of literature examining equity demand curves. In contrast to this literature, we model demand curves for credit risk, rather than the raw quantity of securities outstanding. Second, we identify a new key component of corporate yield spreads, adding to those mentioned in the current literature: risk premia, default risk, tax effects, and liquidity effects. Third, our analysis suggests that firms may strategically time their fund raising in anticipation of their competitors' future debt issuances. Any future offerings will lower prices across the sector by moving the market down the demand curve; rational managers would choose to issue debt earlier, at a higher price.

Downward-sloping demand curves (or, colloquially, "investor appetite" effects), are frequently cited by bond traders and other financial practitioners. For instance, a recent Financial Times article[1] described a dispute between Morgan Stanley and UBS Warburg over a planned joint issuance of $1 billion in convertible bonds for Echostar, a US telecommunications firm. UBS Warburg was upset that Morgan Stanley had recently issued a similar bond for an Echostar competitor, Nextel. UBS Warburg contended that Nextel's bonds may have exhausted investors' appetite for Echostar's issuance and lowered its market price.

> "... Morgan Stanley ... thought UBS Warburg was insisting on too high a price for the offering and, as a result, Wall Street was taking too long to digest the issue .... UBS Warburg was said to be irritated that the pushing out of the Nextel offering could have spoiled Wall Street's appetite for the Echostar convertible."

However, financial modeling has largely disregarded demand-curve effects for securities pricing purposes. For example, most applications of the Capital Asset Pricing Model assume that the market portfolio is too large and diversified to be noticeably affected by changes in the number of any single firm's outstanding securities. Nevertheless, prior research has documented the existence of demand-curve effects in equity markets (see Section I). To the best of our knowledge, however, we are the first to incorporate them into a pricing model.

What theory motivates the "investor appetite" effects? Firms tend to issue debt to finance riskier projects. The purchase of these bonds by investors increases their portfolio concentration in the issuer's sector. As a result, investors' overall exposure to sector-specific risk factors - shocks to input prices, demand shocks, regulatory changes, and

[1] "Bankers Trade Insults Over $1B Notes Deal", *Financial Times*, May 28, 2001.

so on - increases. Risk aversion compels investors to demand greater compensation for bearing this incremental exposure. Consequently, the prices of bonds that are subject to these risk factors should fall as any one firm in the industry issues more debt, assuming that the debt issue is tied together with a real investment decision.

One might argue that, since investors could always hedge away any additional credit risk - possibly through the use of default swaps or other forms of "default insurance" - we would not observe these market-demand effects. This argument fails, however, when we consider that eventually some agents must bear this additional risk, whether as primary bond investors or as providers of credit derivatives. These agents should be risk averse as well, and would naturally demand greater compensation as they are asked to hold more sector-specific risk. Thus, no matter how agents transfer the additional risk among themselves, the cumulative risk borne by investors will increase; we should still observe a widening of yield spreads across the sector as industry debt levels rise.

Alternatively, "investor appetite" effects can also be explained by "industry debt capacity," a concept proposed by Shleifer and Vishny (1992). In their model, sector-specific risk factors can cause firms in the sector to experience a simultaneous reductions in cashflows. If a firm defaults, the best users of its assets - other firms in the sector - suffer from debt overhang due to their own reduced cashflows, and are unable to amass enough capital to buy the distressed firm's assets. Industry outsiders, who presumably are not the best users of these assets, are able to buy the assets at "fire-sale" prices. Thus, a greater amount of debt in the sector implies a greater degree of industry-wide debt overhang and a lower expected recovery rate on losses given default in the industry. According to this theory, the change in expected recoveries, not "investor appetite" *per se*, drives the widening of sector-wide yield spreads as firms issue more debt.

Regardless, We do not test the "risk-aversion" hypothesis against the Shleifer-Vishny theory of debt capacity. Such an analysis merits separate treatment. Whatever the theory, we do indeed confirm the presence of downward-sloping demand curves for credit risk, and measure their impact in the European telecom market. We focus on the European telecom bond market, primarily due to the remarkable amount of debt issued within a relatively short time (October 1999 to July 2001) to support bids for government-auctioned third-generation mobile-phone bandwidth licenses. For example, British Telecom grew its outstanding debt from $1.5 billion at the end of 1998 to $30 billion by the end of 2000. Over the same time period, Deutsche Telekom increased its debt burden from $33 billion to $60 billion.[2]

We model yield spreads as a linear function of a constant spread premium, the slope and the level of the swap yield curve, a proxy for the overall level of European market-wide equity returns, two measures of the issuer's own default risk (debt-coverage ratio and distance to default), and a measure of the aggregate expected losses due to default borne by telecom-sector investors. The correlation coefficient between the first principal component of yield spreads and this measure of industry credit risk is 96.7%. We estimate that yield spreads rise by nearly eleven basis points for each additional €100 million of expected losses due to default in the sector. The relationship between yield spreads and sector-wide credit risk is extremely significant (t-statistic of 48) and is robust to a number of alternative model specifications.

The rest of the paper is organized as follows. Section I reviews the existing literature on downward-sloping demand curves for equities. Section II describes the construction of the measure of sector-wide credit risk, and presents a regression model for the level of yield spreads. Section III describes the data, and section IV discusses the empirical findings. In section V we reject two alternative explanations often cited in existing literature: signalling effects and price-pressure effects. Section VI concludes.

[2] "A $250 Billion Gamble: The Telecom Sector Has Overreached Itself", *The Economist*, January 25, 2001.

I. Literature Review

Our paper touches on two issues: (i) the existence of downward-sloping demand curves for securities and (ii) the determinants of corporate yield spreads. This section surveys the existing literature on downward-sloping demand curves for equities. We discuss the literature exploring the determinants of corporate yield spreads in section II.B.

Scholes (1972) was the first to test the hypothesis that demand curves for common stocks are flat. Secondary equity offerings are associated with a drop in share prices; Scholes concludes that this reaction is associated with new information the market absorbs, rather than with amended supply.

Subsequent literature is concerned with discerning whether any observed price reaction to quantity changes is a result of downward-sloping demand curves or of the revelation of new information. The "information hypothesis" states that an offer to trade a large block of shares may signal news about the stock, entailing a price reaction. A third commonly considered explanation is that the phenomenon is a consequence of temporary "price pressure" effects. The "price-pressure" hypothesis states that any price reactions are the result of temporary imbalances in supply and demand due to trading frictions and segmented markets. These reactions will be fully reversed over the course of a few weeks, as investors trade and rebalance their portfolios.

Mikkelson and Partch (1985) and Leftwich, Holthausen, and Mayers (1990) find price reactions to large block trades. However, both sets of authors stop short of arguing that this is unambiguous evidence of non-horizontal demand curves, since the recorded phenomena are also consistent with the "information hypothesis".

The first to claim success in ruling out signalling and price-pressure effects was Shleifer (1986). He studies price reaction to inclusion (exclusion) in the S&P 500 index, events that trigger substantial purchases (sales) of the firm's stock by large S&P 500 index funds. He documents a significant price reaction to these events, and posits that this is a result of downward-sloping demand curves.

Shleifer regresses equity returns on two dummy variables: one for whether the firm's bonds were rated A or better by S&P, and one for whether the bonds were rated by S&P altogether. He interprets the insignificance of these variables as evidence against the signalling explanation that inclusion in the index certifies the quality of the stock and raises its price. Furthermore, he fails to find evidence of reversals following the initial price reaction, and argues that this precludes the "price-pressure" hypothesis.

However, later studies (Dhillon and Johnson (1991) and Jain (1987)) asserted that inclusion in the S&P 500 Index has a distinct certifying role. Therefore, Shleifer's results should not be interpreted as *prima facie* evidence in favor of downward-sloping demand curves. Furthermore, Shleifer's test of the signalling hypothesis puts faith in the rating agencies' assessment of the performance of issuing firms. If ratings are trailing measures of corporate credit quality (Hand, Holthausen, and Leftwich (1992)), then the power of this test could suffer significantly.

Bagwell (1991 and 1992) analyzes Dutch auction repurchases, in order to test the downward-sloping-demand-curve hypothesis. "In a Dutch auction, the company states the number of shares it will buy during a stipulated period, and it states a price range between which shareholder bids will be accepted. The repurchase price is the lowest price necessary to acquire the number of shares sought" (Bagwell (1992), p. 72). Bagwell finds a significant price reaction to Dutch auction announcements and expirations, and points out that this is consistent with an upward-sloping supply curve. However, little evidence is presented to reject the 'information hypothesis"; A firm's willingness to buy back its stock at a given price range could possibly convey some signal to investors.

Kandel, Sarig, and Wohl (1995) investigated the demand for stocks using the complete demand schedule of 27 Israeli IPOs that were conducted as uniform-price auctions. These events provide less information to investors than those in Bagwell's study, since bids are not capped by the maximum price the firm is willing to pay for the stock. Their results indicate a relatively elastic demand for stocks in IPOs.

Kaul, Mehrotra, and Morck (2000) present further evidence of the existence of downward-sloping demand curves for stocks. In November 1996, the Toronto Stock Exchange (TSE) made a technical change (presumably free from information effects) in the calculation of the weights for the TSE 300 Index. This resulted in major portfolio rebalancing by mutual funds trying to mimic the index. These authors document a significant impact on excess returns and an unusually high trading volume for the affected stocks, both positively associated with measures of supply and demand quantity.

The price-pressure hypothesis has been tested by a number of other authors. Hess and Frost (1982) tested the price effects of new issues of seasoned securities. They reject and concluded that no significant price movement is expected in the neighborhood of the issue day. On the other hand, Harris and Gurel (1986) examined prices surrounding changes in the composition of the S&P 500 index. They assumed that such events carry no informational content and discovered that prices increase by more than three percent immediately after an addition is announced. However, this increase is nearly fully reversed after two weeks, consistent with the price-pressure hypothesis.

II. The Model

A. The Measure of Quantity

Bond investors are faced with many risk factors, but two predominate: interest-rate risk and default risk. Investors bear more of each risk as new bonds are issued. We hypothesize that there will be separate demand curves for each risk factor. However, interest-rate risk is common to most bonds in the economy. It is unlikely that telecom firms could issue enough debt to have a significant impact on economy-wide interest-rate risk exposure and cause a movement along the demand curve. In contrast, default risk is, for the most part, sector-specific and of such a magnitude that new issuances of telecom bonds can significantly increase the overall amount of this risk borne by investors. We measure demand curves over aggregate industry default risk, in contrast to demand curves over the raw quantity of securities found in much of the existing literature.[3]

If investors do indeed have demand curves over individual risks, then previous studies have implicitly captured the amalgamated effect of multiple demand curves in the equity markets. By choosing bonds as the focal point of our study, we were able to tease out the one factor which, in our opinion, leads to downward-sloping demand curves, rather than proxy for a basket of such factors. This is not a small improvement: consider, for example, an economist trying to study demand-curve effects on the pricing of orange juice. In the absence of exact data on orange juice consumption, she is forced to use data on beverage consumption instead. As a result, our study is a more powerful test for the existence of downward-sloping demand curves for securities than its predecessors.

In order to measure the effect of market demand for credit risk, we must first quantify the outstanding credit risk in the sector. This is not trivial, since a univariate measure must aggregate across a plethora of different maturities, ratings, domiciles and bond types. Furthermore, our estimate of quantity should not depend upon market prices. Otherwise, we run the risk that any observed relationship between yield spreads and the quantity of credit risk is merely capturing the underlying dependence of both variables on prices. Our measure of quantity is the present value of expected losses due to the credit risk the market is asked to bear, and is independent of market prices. While investors undoubtably care about the higher moments of the loss distribution, the expected loss should be a reasonable proxy for the level of default risk borne by investors.

[3]This literature focuses on equity demand curves. Equities are subject to multiple risk factors (such as market risk, sector risk, and regulation risk). Bonds are also indirectly affected by the same risk factors that impact equity prices, through their effect on the default risk.

A.1. Measuring the Quantity of Credit Risk

Consider a corporate bond with a face value of F and periodic coupon payments c. The principal payment is due at t_J, and the j-th coupon payment is payable at time t_j, $j = 1, \ldots, J$. Let $r(t)$ denote the instantaneous riskfree rate at time t. In the absence of arbitrage, there exists[4] a "risk-neutral" measure P^* under which the time-t market value of a cashflow x payable at time T is

$$MV_{t,T}(x) = E_t^* \left[e^{-\int_t^T r(u)du} \, x \right], \tag{1}$$

where E^* denotes the risk-neutral expectation (Harrison and Kreps (1979)).

We denote the time of the issuer's default as τ. We take recovery rates to be proportional to the present value of all remaining promised payments. That is, at the time of default, investors recover $(1 - L_P)$ and $(1 - L_c)$ of the present value of the principal and the remaining coupon payments, respectively. We further assume no recovery of future coupons ($L_c = 1$ almost surely) and that the (possibly stochastic) recovery rates, the default time, and the riskfree rates $r(t)$ are all jointly independent.

Suppose that a firm defaults at time $\tau = s$, where $s \leq t_J$. The time-s market value of the principal payment of the bond is

$$MV_{s,t_J}(F) \quad = \quad E_s^* \left[e^{-\int_s^{t_J} r(u)\,du} \right] F. \tag{2}$$

The time-t present value of loss on principal, conditional on default occurring at time s, is given by

$$E_t^* \left[e^{-\int_t^s r(u)\,du} \right] \; L_P \, MV_{s,t_J}(F), \tag{3}$$

[4] This is subject to standard regularity conditions. See Delbaen and Schachermayer (1994).

or equivalently,

$$E_t^* \left[e^{-\int_t^{t_J} r(u)\, du} \right] \; L_P \; F. \tag{4}$$

Let $\phi(t, t_J)$ be the time-t probability of default before time t_J, conditional on no default prior to t ($\phi(t, t_J) = P_t\{\tau \leq t_J | \tau > t\}$). The present value of loss is independent of τ, so the expected value of the loss on principal given default is simply

$$E_t^* \left[e^{-\int_t^{t_J} r(u)\, du} \right] \; E[L_P] \; \phi(t, t_J) \; F. \tag{5}$$

The expected loss due to default of promised coupon payments follows in a similar manner, with the sole difference being our assumption that $L_c = 1$.

The total amount of expected loss due to default borne by investors for a given bond at time t, denoted Q_t, is

$$\begin{aligned} Q_t \;\; &\equiv \;\; \sum_{j\,:\, t \leq t_j \leq t_J} \left(E \left[e^{-\int_t^{t_j} r(u) du} \right] \; \phi(t, t_j) \; c \right) \\ &\quad + E^* \left[e^{-\int_t^{t_J} r(u) du} \right] E[L_P] \phi(t, t_J) \; F. \end{aligned} \tag{6}$$

We compute $Q_{n,t}$ for every bond n, $n \in \{1, \ldots N\}$, and then sum all of them to obtain the market-wide amount of expected loss due to default borne by investors,

$$\bar{Q}_t = \sum_{n=1}^{N} Q_{n,t}. \tag{7}$$

A.2. Implications of Our Measure of Credit Risk

This measure of credit risk imposes several restrictions on the structure of the hypothesized demand curve for corporate bonds. First, *ceteris paribus*, each issuer has an equivalent effect on market appetite. For example, a billion-dollar, ten-year 7% coupon note issued by British Telecom has the same impact as an identical bond issued by France Telecom, assuming they share the same default probabilities and recovery rates.

Second, there may be significant clientele effects with regard to credit quality. Various classes of investors may hold idiosyncratic preferences over different rating classes, or different durations of bonds. This could be the result of different levels of investor risk aversion, or even contractual prohibitions on holding certain classes of bonds.[5]

However, all twelve firms in our dataset operate in the same sector and are in good standing;[6] thus the assumption that their issuances have equivalent effects on demand is reasonable. In addition, we consider the clientele effect to be of secondary importance. Nevertheless, we test the validity of these assumptions in subsequent sections.

B. A Regression Model of Yield Spreads

Most studies (for example, Elton, Gruber, Agrawal, and Mann (2001)) have viewed yield spreads as an aggregation of the likelihood of default, a risk premium, a liquidity premium or a convenience yield, and a tax benefit premium. Collin-Dufresne, Goldstein, and Martin (2001) (henceforth CGM) attempt to estimate the default probability and risk premium portion of yield spreads. Even after the inclusion of numerous firm-specific risk indicators, market-wide measures of risk aversion, and macro-economic variables,

[5] For example, many US pension funds and insurance companies are forbidden from holding below-investment grade bonds.

[6] All firms maintained investment-grade status (a Moody's rating of Baa3 or better) throughout the sample period.

they find evidence of a missing factor that is driving yield spreads. CGM conjecture that this missing factor represents supply and demand shocks in bond markets.

Numerous authors have incorporated non-credit-risk-related determinants of yield spreads into their models. Janosi, Jarrow, and Yildirim (2001) find that the liquidity premium is a significant determinant of yield spreads. Elton, Gruber, Agrawal, and Mann find that the differences in the taxation of coupons on US government and corporate bonds explain a significant portion of corporate yield spreads. To our knowledge, no one has estimated the impact of supply and demand shocks on corporate spreads.

In our model, we ignore any liquidity and tax effects. The yield spreads are all relative to swap and LIBOR rates, so they are mostly devoid of distortional tax effects. Furthermore, despite not explicitly modeling the liquidity premium, we incorporate many of the same variables used in Janosi, Jarrow, and Yildirim's liquidity measures.

Let $s_{f,n,C}(t)$ denote the time-t spread on bond n, issued by firm f and denominated in currency C. We estimated the linear model:

$$\begin{aligned} s_{f,n,C}(t) &= \gamma_0 + \gamma_1^f S_t^C + \gamma_2^f r_t^C + \gamma_3^f R_t^M \\ &\quad + \gamma_4^f \log\left(\frac{A_{f,t}}{F_{f,t}}\right) + \gamma_5^f \log(\delta_{f,t}) \\ &\quad + \gamma_Q \log(\bar{Q}_t) + \varepsilon_{f,n,t}, \end{aligned} \tag{8}$$

where S_t^C is the slope of the C-currency riskfree term structure at time t; r_t^C is the level of the C-currency instantaneous riskfree rate at time t; R_t^M is the daily European Market return, $\frac{A_{f,t}}{F_{f,t}}$ is the debt-coverage ratio (the market value of assets divided by the face value of debt), $\delta_{f,t}$ is the distance-to-default (the difference between the market value of assets and the face value of debt, divided by assets volatility), and $\bar{Q}_t$ is the aggregate expected loss borne by telecom sector investors. The error terms, $\varepsilon_{f,n,t}$ are assumed to be mean-zero disturbances and to be independent across bonds, issuers, and time.

C. Choice of Regressors and Predicted Signs

- **Slope of the Term Structure:** S_t^C

  We measure the slope of the term structure as the difference between the ten- and two-year swap rates. A decrease in this slope may imply a economic downturn; during a business cycle trough loss rates are expected to increase and yield spreads should widen. We expect γ_1, the coefficient for S_t^C, to be positive.

- **Level of the Term Structure:** r_t^C

  The instantaneous riskfree rate for currency C is approximated by the three-month riskfree rate. Following an argument of Longstaff and Schwartz (1995), a higher riskfree rate should imply, all else equal, a greater risk-neutral drift on the firm's asset process. This in turn should decrease the likelihood of default (under a first passage model, e.g. Black and Cox (1976)), and we would expect yield spreads to follow suit. Thus we expect γ_2, the coefficient for r_t^C, to be positive.

- **European Equity Market Return:** R_t^M

  Higher market returns may indicate a rise in one or more of the risk factors driving equity prices; if similar risk factors are influencing bond pricing then fixed-income spreads should widen as well. Alternatively, a rise in market returns may indicate an increase in the degree of investors' risk aversion, leading to a widening in bond yield spreads. We expect γ_3, the coefficient for R_t^M, to be positive.

- **Debt-Coverage Ratio:** $\log\left(\frac{A_{f,t}}{F_{f,t}}\right)$

  We constructed time-series of the face value of assets $(A_{f,t})$ and liabilities $(F_{f,t})$ for each firm in our study. Debt-coverage and the likelihood of default are inversely related; we therefore expect a negative coefficient for $\log\left(\frac{A_{f,t}}{F_{f,t}}\right)$.

- **Distance-to-Default:** $\log(\delta_{f,t})$

  The distance-to-default concept is rooted in the Black and Cox (1976) style "first-passage" default models and is a key metric used by commercial default forecasters such as KMV^{TM}. Under a structural "first-passage" model, the market value of firm f's assets is a stochastic process $A_{f,t}$ with time-varying volatility $\sigma_{f,t}$. Default occurs when assets fall below the face value of the firm's liabilities at time t, $F_{f,t}$. The distance-to-default $\delta_{f,t}$ is defined as the difference between the assets and the face value of liabilities, divided by the asset volatility.

We assumed that $A_{f,t}$ evolves according to the following dynamics:

$$A_{f,t} = A_{f,t-1}e^{Z_{f,t}} + N_{f,t}, \tag{9}$$

$$Z_{f,t} = \gamma_0 + \gamma_1 \log\left(\frac{A_{f,t-1}}{A_{f,t-2}}\right) + u_{f,t}, \tag{10}$$

where the error terms $u_{f,t}$ are mean zero with stochastic GARCH(2,2) (Bollerslev (1986)) variances $\sigma_{f,t}$:

$$\sigma^2_{f,t} = \alpha + \gamma_1 u^2_{f,t-1} + \gamma_2 u^2_{f,t-2} + \gamma_3 \sigma^2_{f,t-1} + \gamma_4 \sigma^2_{f,t-2} \tag{11}$$

and $N_{f,t}$ is the change in the outstanding debt of firm f (due to issuance of new bonds or retirement of old ones) at time t. Treating the issue and retirement of debt as part of the regular lognormal evolution of the asset process, $A_{f,t}$, would have lead to large spikes in asset-volatility. These spikes would have reflected changes in capital structure, rather then changes in the underlying asset volatility *per se*.

We estimated the variance process $\sigma^2_{f,t}$ for each firm at every observation date. The resulting distance-to-default metric for firm f at time t is

$$\delta_{f,t} = \frac{A_{f,t} - F_{f,t}}{\sigma_{f,t}}. \tag{12}$$

Firms with a higher distance-to-default measure should be less likely to experience bankruptcy. In addition, distance-to-default moves inversely with the volatility of firm assets, $\sigma_{f,t}$; thus, if asset volatility rises, the distance-to-default will fall and simultaneously the risk premium on the bond will rise. For both of these reasons, we expect a negative coefficient for $\delta_{f,t}$.

- **Demand Curve Effects:** $\log(\bar{Q})$

  We entered $\bar{Q}$ in our regression model using logs, rather than levels. Our intuition was that the marginal impact of a billion Euro issue when market quantity was low should be greater than when quantity was high. As discussed above, a positive significant coefficient for $\log(\bar{Q})$ will support our conjecture of downward sloping demand curves for corporate credit risk.

  One might be concerned that any significant positive relationship between $\log(\bar{Q})$ and spreads could solely be an artifact of the correlation between $\log(\bar{Q})$ and each firm's new debt issuances. However, following CGM, we proxy for the leverage effect by including the debt-coverage ratio, and add the distance-to-default for additional robustness. This should mitigate the danger of capturing spurious correlations due to leverage effects.

Including a variable proxying for the overall level of European corporate yield spreads would have captured general trends in market-wide yield spreads. We considered several European bond indices, but declined to incorporate them in our model for two main reasons. First, they were all heavily laden with European telecom debt; a significant coefficient for any such indices would have been an *a priori* result of this weighting. Second, most of these indices were quoted in terms of a normalized index value rather than yields or spreads. Those that quoted yields made no distinction as to the currencies of the underlying bonds, rendering it impossible to calculate index spreads.

III. Estimation and Data Collection

We estimated our regression model (equation (8)) using a dataset of bonds issued by twelve European telecommunications firms over the period 10/1/99 to 7/15/01.[7] This

[7] We extended our sample period beyond the end of the second quarter of 2001 to capture the market reaction to two large issuances made by Deutsche Telecom and France Telecom in the first week of July 2001. All told, the sample period comprises 466 business days.

industry is particularly suited for our investigation for a number of reasons. Leverage across the industry increased significantly over a short period[8], driven by some of the largest corporate debt offerings in history. Additionally, the industry is dominated by a small number of firms so we were able to capture a large majority of the debt held and issued within the sector by studying only a dozen firms.

This section details our econometric methodology. First, we describe the collection and construction of a dataset containing characteristics (principal, coupon, coupon frequency, etc.) and prices of European telecom bonds. Second, we outline the assumptions used in the construction of daily yields and spreads for these bonds and in the estimation of the regressors mentioned in section II.C. Finally, we develop a methodology for a tractable estimation of $\bar{Q}$.

A. Data Collection

We constructed a database of every bond issued by these firms and listed in either Bloomberg, Datastream, or the Reuters Fixed Income Database. These sources described each bond in the dataset: its principal and coupon rates; coupon frequency; issue-, first-coupon- and maturity-dates; denominated currency and issuing firm; as well as whether or not it had floating coupon rates, convertible or callable embedded options, or "step-up" coupon provisions.[9]

The first two columns of Table I list the twelve firms covered in our dataset, and the associated two-letter abbreviation we use throughout the paper. The third column contains the principal amount of outstanding debt for each firm, as reported in the most recent financial statement available on July 15, 2001. The fourth column details the aggregate principal value of debt (as of that date) captured in our database, and the

[8] "Unburdening: Europe's telecom giants are wrestling with debt and poor rating, to the joy of financial traders", *The Economist*, May 10, 2001

[9] "Step-up" bonds have coupon rates that adjust to changes in the issuer's credit rating.

fifth column lists the ratio of debt captured in the database to total debt outstanding. The sixth column reports the number of new debt issues captured in our database, while the seventh column records the total principal amount of those new issuances.

Issuer		Outstanding Debt (as of 7/15/01)			New Issuance in Data	
Name	Abbr.	of Record	in Dataset	% incl.	Number	Principal
British Telecom	BT	€46.6 B	€35.9 B	77.0%	38	€34.4 B
Deutsche Telekom	DT	€68.6 B	€34.7 B	50.5%	57	€35.5 B
France Telecom	FT	€70.0 B	€44.0 B	62.9%	34	€37.9 B
Portugal Telecom	PT	€5.7 B	€2.8 B	49.3%	1	€1.0 B
Sonera	SO	€5.3 B	€2.0 B	37.7%	4	€1.7 B
TDC	TD	€6.9 B	€2.3 B	33.5%	13	€2.0 B
Telefonica	TF	€34.5 B	€12.2 B	35.3%	13	€8.5 B
TeleNor	TN	€5.3 B	€3.5 B	66.0%	6	€2.4 B
Vodafone	VF	€39.9 B	€27.4 B	68.6%	15	€19.2 B
Telecom Italia	TI	€31.3 B	€29.0 B	92.8%	7	€12.7 B
KPN	KP	€26.1 B	€22.6 B	86.8%	20	€21.9 B
Telia	TE	€4.1 B	€2.2 B	53.3%	7	€1.5 B
Total		€344.3 B	€218.6 B	63.5%	215	€178.5 B

Table I
Outstanding face value of debt on 7/15/2001 both as reported by the issuer and as captured in our dataset, along with the number and aggregate principal value of new debt issues in our database. All face values were converted into Euros.

The numbers in the fifth column indicate that our dataset fails to capture each firm's debt in its entirety. Some firms incorporated bank-issued lines of credit into their reported amounts of outstanding debt. The outstanding balance on lines of credit can fluctuate significantly on a day-to-day basis; it is quite difficult to obtain information on the terms of these credit agreements; and lines of credit are not traded securities and thus have no market prices. As a result of these problems, we opted to exclude lines of credit from our study. Alas, we were unable to obtain exact information as to the precise breakdown of published debt into corporate notes and lines of credit, and can only present the available figures along with the aforementioned caveats.

Some of the bonds were not directly issued by the firms mentioned above. We included in our dataset bonds issued by wholly-owned subsidiaries of the telecom firms, and bonds that were issued by a parent company as long as they were guaranteed by the telecom firm itself. As an example, three bonds in our database were issued by Sogerim S.A, a wholly-owned subsidiary of Telecom Italia, and fully guaranteed by Telecom Italia.

We collected daily bid prices from Reuters and Datastream for all available bonds. Unfortunately, these sources only capture prices for publicly traded debt; prices for any privately placed, or otherwise untraded issues were unavailable. Nevertheless, we were able to capture a significant portion of the outstanding debt for each issuer and a large majority of all debt issued during our sample period.

We cleaned and checked the data. Bonds with prices reported on only five or fewer dates were discarded, along with prices that led to non-sensible yields. As we compared data from different sources, we occasionally discovered inconsistencies; for instance, different prices quoted for the same bond, or different reported maturities and principals. We attempted to resolve contradictions by consulting the *Financial Times*, the *Wall Street Journal*, and the firms' own financial reports.

B. Yields and Spreads

Daily bond yield spreads are the dependent variable of interest in our econometric work. In this section we describe the empirical issues surrounding our computations of yields and spreads, and detail our estimation of the riskfree term structure.

We chose to exclude certain types of bonds from our spread calculations. Determining the yield on a floating-rate bond requires forecasting future coupon payments; rather than introduce such noisy inferences, we opted to focus only on fixed-rate bonds. We also omitted any convertible and callable bonds, since their market prices are distorted by the value of the option to convert and/or call them.

In addition, we excluded from our spread calculations eleven bonds issued by Telefonica Peru S.A. or Telefonica Argentina S.A. and guaranteed by Telefonica of Spain. We believe that daily fluctuations in the prices of these bonds are primarily driven by changes in the Latin-American, rather than European, bond markets. We also omitted one British Telecom index-linked bond from the spread calculations.

The criteria for inclusion in the calculation of right-hand-side variables (that is, the distance-to-default, the debt-coverage ratio and $\bar{Q}$) were different. We made every attempt to capture the amount of default risk that investors are asked to bear and include it in our measure of $\bar{Q}$. Latin-American-issued bonds represent (indirect) claims on the assets of Telefonica and were seamlessly aggregated into $\bar{Q}$ despite being held out of the spread calculations. Since the computation of $\bar{Q}$ required no market prices (see Section II.D), we were able to include the Q-contribution due to callable and convertible bonds by treating them as regular, non-option-embedded bonds.

Additionally, we included the Q-contribution of floating-rate bonds by forecasting the unknown future coupons[10] and calculating the bonds's Q-contribution as we would for a fixed-rate bond. This procedure introduces a fair amount of noise into the $\bar{Q}$ measure; however, our goal was to capture the debt burden and the ensuing default risk in their entirety. The error resulting from omitting these bonds altogether would have been far greater than any error due to mis-projection of future coupons. In contrast, mis-estimation of future coupon payments would have dramatically skewed any calculations of spreads on the floating rate bonds; consequently, the projection process was reserved for the creation of the right-hand-side measures only.

[10]The coupons on each floating-rate bond are specified as a number of basis points over a given reference rate, such as the 3-month LIBOR. We assumed that reference rates are martingales; thus today's expected value of any future 3-month LIBOR rate is just today's 3-month LIBOR rate.

The number and aggregate principal of the bonds in the dataset, separated by type and issuer, is presented in Table II. The second and third columns (under the heading "Spreads and $\bar{Q}$") list the number and total principal amount of bonds used both for the dependent spreads variable (left-hand-side) and for computing $\bar{Q}$ (right-hand-side). The fourth through ninth columns (under the heading "$\bar{Q}$ only") detail the number and aggregate principal of bonds that were were used to compute $\bar{Q}$ but not included in the spread calculations. These bonds are further broken out into floating-rate bonds, convertible or callable bonds, and a miscellaneous category. The last two columns list the total number of bonds and aggregate principal captured for each issuer in our dataset.

Issuer	Spreads & $\bar{Q}$		$\bar{Q}$ Only						Total[12]	
	Fixed		Floating		Ca/Co[11]		Other			
	#	Prin.	#	Prin.	#	Prin.	#	Prin.	#	Prin.
BT	28	€16.6 B	13	€6.6B	10	€17.3B	-	-	51	€40.6B
DT	46	€33.0 B	12	€4.4B	-	-	-	-	58	€37.5B
FT	39	€21.9 B	8	€8.8B	10	€17.4B	1	€0.2B	58	€48.4B
PT	2	€2.0 B	-	-	4	€0.8B	-	-	6	€2.8B
SO	4	€1.5 B	1	€0.5B	-	-	-	-	5	€2.0B
TD	12	€2.2 B	2	€0.1B	-	-	1	€0.1B	15	€2.4B
TF	25	€8.8 B	6	€1.8B	2	€0.2B	11	€2.1B	44	€12.8B
TN	13	€1.6 B	3	€2.1B	2	€0.1B	-	-	18	€3.8B
VF	21	€17.4 B	4	€8.1B	2	€2.6B	-	-	27	€28.1B
TI	7	€17.8 B	2	€1.5B	9	€9.9B	-	-	18	€29.3B
KP	17	€11.5 B	4	€6.7B	7	€1.2B	-	-	28	€19.4B
TE	15	€1.4 B	4	€0.9B	-	-	-	-	19	€2.3B
Total	229	€135.7B	59	€41.5B	46	€49.5B	13	€2.3B	347	€229.4B

Table II
Breakdown of Dataset Bonds by Type.

[12]These bonds are either callable, convertible, or both.

[13]Note that Table II presents all the debt in our dataset, while Table I presents only outstanding debt as of 7/15/01. As a result, the "Total" column in Tables I and II do not match.

B.1. Computation of Yield Spreads

We computed daily semi-annually-compounded yields to maturity for each priced bond in the dataset. Typically, one calculates yield spreads by netting the bond yield against a riskfree rate of the same maturity and coupon frequency. However, our dataset contains zero-coupon bonds as well as bonds that pay coupons quarterly, semi-annually, and annually. On account of this heterogeneity, any choice of a particular type of reference curve - zero-coupon, semi-annual, or otherwise - would have invariably resulted in inappropriately-calculated yield spreads for some bonds.

As a result, we opted to take yield spreads relative to the yield to maturity of a riskfree bond with the same maturity, coupon rate, and frequency. We created synthetic prices for these "replica" riskfree bonds by estimating the riskfree zero-coupon term structure (Section III.C) and assuming no arbitrage and no transaction costs.

We matched each bond to a reference curve appropriate for the bond's denominated currency; that is, all Dollar-denominated bond yields were netted against a US Dollar reference curve, all Euro- and Eurozone-currency-denominated bonds were netted against a Euro reference curve, and so on. This necessitated finding six reference curves: US Dollar, Euro, Pound Sterling, Japanese Yen, Swiss Franc, and Swedish Krona.

C. Estimation of the Zero-Coupon Riskfree Curves

In order to estimate the zero-coupon riskfree curves, we collected daily currency-specific swap yields for one- to thirty-year maturities[13] from Datastream. We chose swap yields, rather than government yields, since government bond prices are often "contaminated" by the presence of tax and other regulatory considerations that are irrelevant to our study. Following convention, the t-period swap rate was taken to be the yield to maturity on a semi-annual coupon bond maturing at time t and trading at par.

[13] Only one- to ten-year swap rates were available for the Swedish Krona.

Since the swap rates are coupon rates, we cannot use them to obtain the zero-coupon term structure directly. Instead, we estimate zero-coupon rates by fitting Svensson's (1994) extension of the Nelson and Siegel (1987) model to observed swap yields. This method parameterizes the zero-coupon yield curve in a tractable manner, yet is able to capture a wide variety of curvatures and slopes. In particular, under Svensson's model, the zero-coupon yield to maturity t periods in the future is given by:

$$y(t) = a_0 + (a_1 + a_2)\left(\frac{1 - e^{-\lambda_1 t}}{\lambda_1 t}\right) - a_2 e^{-\lambda_1 t} + a_3\left(\frac{1 - e^{-\lambda_2 t}}{\lambda_2 t} - e^{-\lambda_2 t}\right). \tag{13}$$

For each day in our sample period, the parameters $a_0, a_1, a_2, a_3, \lambda_1$, and λ_2 were chosen to minimize a weighted sum of the absolute pricing errors for all available swaps. We minimized absolute, rather than squared, errors so as to increase the weight of the medium term (one- to ten-year) rates and de-emphasize the fit of the longer maturity bonds; 86.3% of our observations belong to bonds with one to ten years till maturity, as opposed to the 8.7% of observations from longer maturity bonds.

However, the Svensson method results in volatile and sometimes even negative yields for maturities of less than one year. In order to estimate these short-term riskfree rates more reliably, we used daily LIBOR data[14] The quoted rates are currency-specific, zero-coupon, money-market yields for maturities ranging from one to twelve months.

We assumed that LIBOR yields are measured without error, and used linear interpolation to obtain the zero-coupon term structure for maturities of less than a year. Upon visual inspection, we noted that there was a "kink" between the LIBOR curve and the swap-implied zero-coupon curve. To obtain a smoother curve, we linearly interpolated between the one-year LIBOR and the three-year fitted yields. In addition, the one- and two-month LIBOR rates tended to be much more volatile than other LIBOR rates. This is probably due to market-microstructure and liquidity-related issues rather

[14]LIBOR rates were obtained from the British Bankers' Association website, *www.bba.org.uk*.

than changes in investor risk aversion and beliefs. Accordingly, we fixed the zero-coupon yields for all maturities less than three months at the three-month LIBOR rate.

D. Estimation of $\bar{Q}$

Recall that we established (section II.A.1) that

$$
\begin{aligned}
Q_{n,t} &= \sum_{j\,:\,t \le t_j \le t_J} \left(E^*\left[e^{-\int_t^{t_j} r(u)du} \right] c_n\, \phi_f(t,t_j) \right) \\
&\quad + E^*\left[e^{-\int_t^{t_J} r(u)du} \right] F_n\, E\left[L_P \right]\, \phi_f(t,t_J), \qquad (14)
\end{aligned}
$$

$$
\bar{Q}_t = \sum_{n=1}^{N} Q_{n,t}. \qquad (15)
$$

The risk-neutral discount factors, $E^*[e^{-\int_0^t r(u)du}]$, are taken from the fitted riskfree curves. All that remains is to estimate, under the physical measure, the firm-specific term structure of default probabilities $\phi_f(t,t_j)$, and expected rates of loss given default, $E[L_{P,f}]$.

D.1. Estimating Default Probabilities

We modeled the credit rating of a given issuer as a stationary, continuous-time Markov process over the eight possible Moody's major rating classes - Aaa, Aa, A, Baa, Ba, B, Caa, and D, where D denotes default.[15] Such a model has been examined extensively by Jarrow and Turnbull (1997); Jarrow, Lando, and Turnbull (1997); and Lando (1998). Transition from rating class i to rating class j is modeled as a Poisson process with

[15] The assumption of stationary and Markovian rating transitions has been questioned in recent literature. Lando and Skødeberg (2000) , and Carty and Fons (1994) find evidence of "momentum" effects in S&P and Moody's ratings transitions. Blume, Lim, and MacKinlay (1976) demonstrate a gradual increase in conservatism of the agencies' rating definitions. Nickell, Perraudin, and Varotto (2000) document business cycle effects in ratings transitions. Nevertheless, our study is conducted over a relatively short period of time (only seven quarters) and the true transition rates can be treated as stationary.

constant intensity λ_{ij}. Thus, the probability that this transition occurs over a short interval Δt is approximately $\lambda_{ij}\Delta t$. Default is the unique absorbing state in the system; the probability of transition from default to any non-default rating is zero.

Let $P(t)$ represent the transition matrix for the eight Moody's rating classes over a time-horizon of length t. Thus, the (i,j) component of $P(t)$, $P_{ij}(t)$, is the probability that an i-rated firm will have, t units of time hence, a rating of j. Under standard continuous-time Markov-chain theory,[16] there exists a generator matrix A such that

$$P(t) = e^{At}. \tag{16}$$

The instantaneous transition intensity from state i to state j is given by $\lambda_{ij} = -\frac{A_{ij}}{A_{ii}}$.

The probability of a j-rated firm defaulting within t units of time is simply $P_{j,D}(t)$, where the D-th column of $P(t)$ corresponds to the "default" state. We used an empirical one-year transition frequency matrix[17] as an estimate of $P(1)$; let $\hat{P}(1)$ denote this estimate. The implied generator matrix, $\hat{A}$, is the matrix logarithm of $\hat{P}(1)$.

In the continuous-time-Markov-chain framework, there is a positive probability of transition between any two states over any period of time t (with the exception of zero-probability transitions from default to any other state). However, there is a "peso-problem" in that some transitions are so unlikely (such as a transition from Aaa to default in one year) that they were not observed in the data. As a result, the empirical transition matrix $\hat{P}(1)$ contains several zero entries. These zeros induced negative off-diagonal elements in the implied generator matrix $\hat{A}$, even though the "true" generator matrix A has negative entries along the diagonal and non-negative entries elsewhere.

[16] See, for example, Resnick (1992).

[17] This was taken from the Moody8 dataset on the CreditMetrics' website, *www.creditmetrics.com*. This dataset was constructed from 26 years of data on primarily American firms, and only covers transitions from one rating class to another. Firms that fell out of the rating system were omitted.

We attempted to correct for the misspecification in $\hat{A}$ by making use of the fact that any row in a continuous-time-Markov-chain generator matrix sums to zero. We reset any negative off-diagonal entries in $\hat{A}$ to zero and then adjusted the diagonal elements accordingly. Using the adjusted $\hat{A}$ and relationship (16) we estimated the transition matrix (and the default probabilities) for any rating class over any time-horizon t.

The firms in our study experienced credit-rating upgrades and downgrades during the sample period. Adjusting the probabilities of default to reflect rating changes may result in significant jumps in default probabilities - and therefore overall $\bar{Q}$ - on the day of a ratings change. However, changes in rating are lagged responses to actual shifts in credit quality (Hand, Holthausen, and Leftwich (1992)). We wanted to incorporate these shifts into our analysis without generating excessive "spikes" in $\bar{Q}$.

To avoid this problem, we calculated μ_f, the firm-specific distribution of "time-in-rating-class". Each μ_f is an 8×1 vector in which the i-th element is the percentage of observations in our sample when the firm was in the i-th rating class.[18] We took these empirical rating distributions as a measure of average credit quality over the sample period. The resulting estimate of the cumulative default probability for firm f within t units of time (under the physical measure) is

$$\phi_f(t, t + \Delta) = (\mu_f \cdot P(\Delta))_{(D)}. \tag{17}$$

Admittedly, the assumptions that default probabilities are time-invariant and that transition rates are stationary are very restrictive. They imply that a firm's likelihood of default in one year is the same in October 1999 as it is in July 2001, which is unlikely given the substantial increase in industry leverage over that time.

[18]For instance, over the course of our sample, British Telecom spent roughly 90% of the time with an A rating and 10% of the time with a Baa rating, so $\mu_{\mathrm{BT}} \approx (0\ 0\ 0.9\ 0.1\ 0\ 0\ 0\ 0)'$.

Nevertheless, we feel that this methodology captures three desired effects: firms that, on average, had lower ratings in our sample period also had higher estimated default probabilities; the probability of default increased monotonically with time-till-maturity; and the default probabilities did not jump significantly in reaction to rating changes.

D.2. Recovery Rates

Several simplifying assumptions underly our treatment of recovery rates. First, we take the distribution of recovery rates to be independent from the distribution of the default time. Second, we assume that recovery rates maintain a constant first moment over our sample period. In particular, we do not account for the state of the business cycle or the level of industry-wide leverage. This is inconsistent with the Shleifer and Vishny (1992) theory in which expected recovery rates decrease as industry-wide debt levels rise.

We use the expected recovery rates provided by EnronCredit (detailed in Table III).[19] There were no recovery rates available for Sonera; we therefore took Sonera's recovery rate to be the same as TeleNor's (another Scandinavian firm of comparable size) at 26%. We took the recovery rates as of October 20, 2001 to be constant over the sample period, since we do not have access to historical data from EnronCredit.

Issuer	Recovery Rate	Issuer	Recovery Rate
British Telecom	35%	Telefonica	35%
Deutsche Telekom	35%	TeleNor	26%
France Telecom	26%	Vodafone	40%
Portugal Telecom	32%	Telecom Italia	26%
Sonera	26% (Conjectured)	KPN	30%
TDC	26%	Telia	30%

Table III
EnronCredit-estimated Recovery Rates by Issuer.

[19] See *www.enroncredit.com.*

D.3. Aggregation of $Q_{n,t}$

In order to estimate $\bar{Q}_t$, we had to aggregate $Q_{n,t}$ across all bonds and issuers. However, these bonds were denominated in a variety of currencies. We had to convert each $Q_{n,t}$ to an arbitrary common currency prior to aggregation. Since a plurality of bonds were denominated in Euros or Euro-equivalent currencies (56.1% of principal and 43.9% of the number of all bonds), we assembled daily exchange rates from Datastream and converted all $Q_{n,t}$ to Euros. This currency conversion introduced exchange-rate volatility into $\bar{Q}_t$, but we do not believe that this materially affects our results.

E. Equity Market Returns and Equity Indices

We downloaded daily equity market-capitalization values from Datastream. Where possible, we used the closing price from the main exchange of each firm's home country. When a firm was not traded on its home-country exchange, we used the stock value at the Frankfurt stock exchange. We proxied for R_t^M, the daily market-wide European stock return, with the Dow Jones STOXX^{TM} European Total Market Index.[20]

F. Balance Sheet Proxies

Our proxy variables for default risk, debt-coverage ratio $\frac{A_{f,t}}{F_{f,t}}$ and distance-to-default $\delta_{f,t}$, required firm-specific daily time-series of the market value of assets, debt, and equity. Time-series for the market value of equity, $E_{f,t}$, were easy to obtain; in contrast, the time-series for the market value of the firms' debt and assets had to be estimated from our bond data. In particular, our dataset contains a mixture of bonds, both with and without observed prices. We proxied for $D_{f,t}$, the time-series of the market value of

[20]The Total Market Index is a value-weighted index of European equities that encompasses over 95% of the "free float market capitalization of investable stock universe" of European firms. See *www.stoxx.com*.

each firm's debt, by summing, for each issuer on every observation day, the outstanding market value of all the priced bonds along with the outstanding face values of the unpriced bonds. The market value of assets was estimated as $A_{f,t} = D_{f,t} + E_{f,t}$.

This measure of $D_{f,t}$ may not be ideal. Adding the unpriced debt at face value may overstate the value of the debt, particularly so as the credit quality of most firms deteriorated over our sample period. Also, as Table I documents, we were not successful in capturing all the debt held by these firms. We considered estimating the amount of missing loans by using accounting statements, but the method of reporting debt varied greatly from issuer to issuer. We ultimately decided that balance-sheet data are too heterogenous to allow for an consistent treatment of debt across firms.

IV. Results

A. Principal Components Analysis

CGM regressed yield spreads on credit risk, market risk, or liquidity variables and then examined the principal components of the residuals. They found that there was a single factor driving the majority (58%) of unexplained yield spread changes. Similarly, we extracted the first principal component of yield spreads and compared it to $\log(\bar{Q})$.

We only used spreads for those bonds extant throughout the sample period; our dataset includes 41 such bonds.[21] Figure 1 demonstrates the similarity between the two time-series. Our results are striking; the correlation coefficient between the first principal component of our selected yield spreads (accounting for 88.7% of variation in spreads)

[21] For a small number of bonds, we encountered small "holes" (up to five-days long) in the time-series of spreads due to missing price observations. We linearly interpolated across these "holes."

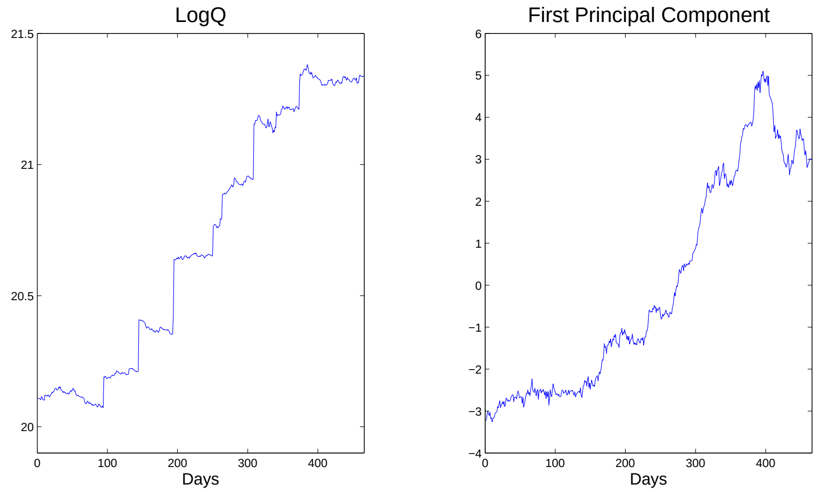

Figure 1. Time-series of $\log(\bar{Q})$ and the First Principal Component of Yield Spreads.

and $\log(\bar{Q})$ is 96.7%.[22] This suggests that the quantity measure $\bar{Q}$ may actually be the "missing factor" to which CGM refer.

B. Estimating the Model

Recall our basic regression model:

$$\begin{aligned} s_{f,n}(t,T) &= \gamma_0 + \gamma_1 S_t^C + \gamma_2 r_t^C + \gamma_3 R_t^M \\ &\quad + \gamma_4 \log\left(\frac{A_{f,t}}{F_{f,t}}\right) + \gamma_5 \log(\delta_{f,t}) \\ &\quad + \gamma_Q \log(\bar{Q}) + \varepsilon_{f,n,t}. \end{aligned} \tag{18}$$

We estimated this model (to which we refer as Model 1) via ordinary least squares; the parameter estimates (see Table IV) were supportive of our underlying hypotheses.

[22] We separate spreads by currency and obtain correlations of 95.1% for €-denominated bonds, 97.3% for £-denominated bonds, 92.3% for SFR-denominated bonds and 94.9% for $-denominated bonds.

Variable		Parameter Estimate	Standard Error	t-Stat	p-value
γ_0	Intercept	-7.5070	(0.1427)	52.6166	< 0.0001
γ_1	S^C	0.1417	(0.0073)	19.4168	< 0.0001
γ_2	r^C	0.0600	(0.0029)	20.5292	< 0.0001
γ_3	R^M	0.7629	(0.2415)	3.1594	0.0016
γ_4	$\log(\frac{A_f}{F_f})$	-0.3270	(0.0061)	53.8674	< 0.0001
γ_5	$\log(\delta_f)$	-0.0608	(0.0031)	19.5514	< 0.0001
γ_Q	$\log(\bar{Q})$	0.4130	(0.0065)	63.4380	< 0.0001

Table IV
Results of Model 1 - OLS Regression (using White's heteroskedastic-consistent covariance estimator). Number of Obs. = 29908.

The estimates for the coefficients of the slope and level of the yield curve and the market returns were all positive and highly significant. With the exception of the coefficient for the level of the yield curve, this conforms with the findings of CGM and with our expectations (see section II.C). As predicted, our estimate for γ_4 was significant and negative, confirming our intuition that as firms increase their debt-coverage they simultaneously lower their default risk. Likewise, γ_5, the coefficient for the distance-to-default, was negative and significant; raising δ_f lowers the likelihood of default.

γ_Q, the coefficient for $\log(\bar{Q})$ is positive and highly significant, as predicted by our hypothesis of downward-sloping demand curves for credit risk. New debt issuances, by a given firm as well as by its competitors, appear to widen yield spreads. It may be argued that the positive loading on $\log(\bar{Q})$ is a result of capturing leverage effects of additional debt financing; we examine and reject this argument in section IV.E.1.

C. Model Misspecification

In formulating this model, we restricted the regression coefficients to be the same across firms. This is likely to be an oversimplification, as the observations represent bonds issued by firms subject to idiosyncratic risk factors. Furthermore, the accuracy of each firm's time-series of market values of debt and assets depends upon on our varying success at capturing prices for that firm's outstanding debt.

To allow for such heterogeneity, we re-constructed our model with firm-specific coefficients for all variables except for $\log(\bar{Q})$. Although each firm may exhibit different sensitivity to the quantity of market risk, we are seeking to measure the average market-wide response to new issuances and thus force the cross-equation restriction of a common γ_Q coefficient. The resulting new model is given by:

$$\begin{aligned} s_{f,n,C}(t) &= \gamma_0^f + \gamma_1^f S_t^C + \gamma_2^f r_t^C + \gamma_3^f R_t^M \\ &\quad + \gamma_4^f \log\left(\frac{A_{f,t}}{F_{f,t}}\right) + \gamma_5^f \log(\delta_{f,t}) \\ &\quad + \gamma_Q \log(\bar{Q}) + \varepsilon_{f,n,t}. \end{aligned} \tag{19}$$

We refer to this model as the Firm Specific Regression model, or FSR.

The results, presented in Table V, reaffirm those of the more restrictive Model 1. First, γ_Q remains positive and significant. Second, the signs of γ_4^f and γ_5^f conform, for the most part, to our hypotheses. In particular, only TeleNor does not have significant negative coefficients for $\log(\delta_{f,t})$ and for $\log\left(\frac{A_{f,t}}{F_{f,t}}\right)$. We confirmed that the specification of the extended FSR Model was superior to that of the more restricted Model 1.[23]

[23] We conducted Wald tests of the hypotheses: $H_0^i : \gamma_i^f = \gamma_i, \quad \forall f \in \{1, 2, \ldots, 12\}, \quad i \in \{0, 1, \ldots, 5\}$. The p-values for each of these hypotheses are well below 0.01% (indicating that we strongly reject all null hypotheses), with the exception of the one relating to R^M. Consequently, throughout the remainder of this paper results will refer to a model with firm-dependent $\gamma_0^f, \gamma_1^f, \gamma_2^f, \gamma_4^f, \gamma_5^f$, but a common γ_3.

	S^C		r^C		$\text{Log}(\delta_f)$		$\text{Log}\left(\frac{A_f}{F_f}\right)$	
	Estimate	p-Val	Estimate	p-Val	Estimate	p-Val	Estimate	p-Val
BT	−0.1849	< 0.0001	−0.0900	< 0.0001	−0.1620	< 0.0001	−0.2212	< 0.0001
DT	−0.0665	0.0457	0.0624	< 0.0001	−0.6296	< 0.0001	−0.1001	< 0.0001
FT	0.0497	0.0014	0.0535	< 0.0001	−0.2191	< 0.0001	−0.0471	0.0048
PT	−0.1564	< 0.0001	−0.0543	0.0125	−0.0587	0.0059	−0.1555	< 0.0001
SO	−0.2484	0.0060	−0.4803	< 0.0001	−0.2708	< 0.0001	−0.2709	< 0.0001
TD	0.3010	< 0.0001	0.0921	< 0.0001	−0.4361	< 0.0001	−0.0545	0.0150
TF	0.2743	< 0.0001	0.1277	< 0.0001	−0.0520	0.2081	−0.0971	< 0.0001
TN	0.1861	< 0.0001	−0.0173	0.1309	**0.0460**	0.7338	**0.1245**	0.5842
VF	0.2412	< 0.0001	0.0989	< 0.0001	−0.1593	< 0.0001	−0.5099	< 0.0001
TI	−0.4765	< 0.0001	−0.1586	0.0020	−0.1265	0.0010	−0.2237	< 0.0001
KP	0.7457	< 0.0001	0.1328	0.1982	−0.1879	0.0013	−0.6694	< 0.0001
TE	−0.0115	0.8782	−0.0685	0.1150	−0.1413	0.1577	−0.1626	< 0.0001

Variable	Parameter Estimate	Standard Error	t-Stat	p-value
R^M	0.6445	(0.2080)	3.0983	0.0019
$\log(\bar{Q})$	0.5543	(0.0117)	47.5606	< 0.0001

Table V
Results of FSR Model - OLS Regression (using White's heteroskedastic-consistent covariance estimator). Estimates of the (negative) γ_0^f's are omitted, and estimates that do not display our theoretically-predicted signs are boldfaced. Number of Obs. = 29908.

D. Heteroskedasticity

Numerous sources of heteroskedasticity are present in our data. Individual bonds may differ in liquidity or clientele, and firms may have idiosyncratic risk factors not captured by our proxies for default risk. Market conditions may change over time, altering the sensitivity of yield spreads to $\log(\bar{Q})$. This may result in inefficient OLS estimates and artificially low standard errors. Using White's and Breusch-Pagan's tests, we rejected the null hypothesis of homoskedasticity. Both p-values were well below 0.01%.

We used White's heteroskedastic-consistent covariance matrix estimator to deal with this problem. In addition, we re-estimated the model under various specifications of the covariance matrix.[24] Our main result, a positive and significant γ_Q coefficient, was obtained across all covariance structures and estimation techniques.

E. Robustness Checks

We conducted a number of tests of model robustness. In all cases, the predictions of our hypothesis were confirmed by a positive and highly significant γ_Q.

E.1. Same-Firm versus Other-Firm $\bar{Q}$

One might argue that the positive estimate of γ_Q is merely capturing each firm's increased leverage due to its own new debt. This would imply that the portion of $\bar{Q}$ contributed by firm f, $\bar{Q}_f$, (and not portion of Q contributed by other firms in the market, $\bar{Q}_{-f}$) generates the positive γ_Q. We estimated a modified regression with $\gamma_{Q,f}\log(\bar{Q}_f) + \gamma_{Q,-f}\log(\bar{Q}_{-f})$ replacing $\gamma_Q \log(\bar{Q})$. Both $\gamma_{Q,f}$ and $\gamma_{Q,-f}$ were positive and significant (see table VI), indicating that changes in aggregate credit risk due to other firms' debt issuance do indeed have a significant and positive effect on corporate spreads.

Variable	Parameter Estimate	Standard Error	t-Stat	p-value
$\log(\bar{Q}_f)$	0.23907	(0.01005)	23.79	$< .0001$
$\log(\bar{Q}_{-f})$	0.45214	(0.01235)	36.62	$< .0001$

Table VI
OLS Regression of same-firm vs. other-firm Q. Number of Obs. = 29908.

[24] In particular, we assumed group-wise (by firm) heteroskedasticity, and autocorrelated errors (across dates). We also departed from ordinary least squares and adopted weighted least squares, with weightings proportional to the inverse of the bond's principal. Results are available upon request.

E.2. Time-Trend Inclusion

As seen previously (Figure 1), $\log(\bar{Q})$ steadily increased as firms issued new debt. It could be the case that our measures of $\bar{Q}$ are just proxying for a general widening trend in yield spreads, unrelated to any demand curve effects. Furthermore, the sample correlation of $\log(\bar{Q})$ and a linear time trend is 97.5%., making it hard to determine which of the two is driving the observed widening in yield spreads.

We therefore checked how *changes* in spreads react to *changes* in $\log(\bar{Q})$ by estimating the following regression (model ΔFSR):

$$\begin{aligned}\Delta s_{f,n,C}(t) \;&=\; \gamma_0 + \gamma_1^f \Delta S_t^C + \gamma_2^f \Delta r_t^C + \gamma_3 \Delta R_t^M \\ &\quad + \gamma_4^f \Delta \log\left(\frac{A_{f,t}}{F_{f,t}}\right) + \gamma_5^f \Delta \log(\delta_{f,t}) \\ &\quad + \gamma_Q \Delta \log(\bar{Q}) + \varepsilon_{f,n,t}. \qquad (20)\end{aligned}$$

If $\log(\bar{Q})$ merely proxies for an unrelated time-trend in the FSR model, we should obtain a significant γ_0 and an insignificant γ_Q in the ΔFSR model. Our results (see Table VII) contradict the time-trend hypothesis; γ_Q is positive and significant, even in the presence of a significant intercept γ_0. The t-statistic for γ_Q is lower than in the original FSR model, but one must be careful about comparing t-statistics across different regressions.

Variable	Parameter Estimate	Standard Error	t-Stat	p-value
γ_0	0.00175	(0.000483)	3.62	0.0003
$\Delta\log(\bar{Q})$	0.05699	(0.02369)	2.41	0.0162

Table VII
Results of ΔFSR Model - OLS Regression (using White's heteroskedastic-consistent covariance estimator). Number of Obs. = 29802.

Furthermore, the correlation between the first principal component of corporate yield spreads (PC1) and a time-trend (TT) is $\rho_{PC1,TT}$ $=90.98\%$, which albeit high on an absolute scale, is significantly lower than $\rho_{PC1,log(\bar{Q})}$ $=96.72.\%$[25] This strengthens our hypothesis that $\log(\bar{Q})$, and not an arbitrary time-trend, drives the widening in corporate yield spreads throughout the sample period.

E.3. Rating Changes

A commonly used measure of credit quality is the credit rating assigned to an issuer by agencies such as S&P or Moody's. As a robustness check, we added dummy variables to the FSR model reflecting the credit rating of the issuing firm. For simplicity, we ignore S&P's ratings, along with any placements (positive or negative) on Moody's WatchList.[26]

Moody's breaks most of its major rating classes into finer subgroups. For instance, the major rating Aa is subdivided into Aa1, Aa2, and Aa3. All twelve issuers were rated between Aa1 and Ba2 over the entire sample period. Let $1_{f,t,R}$ equal 1 if firm f is rated R at time t, where $R \in \{$Aa1, Aa2, Aa3, A1, A2, A3, Ba1, Ba2$\}$, and 0 otherwise. We omitted $1_{f,t,Ba2}$ to avoid collinearity in regressors. The resulting model is:

$$\begin{aligned} s_{f,n,C}(t) = \gamma_0^f \quad &+ \quad \gamma_1^f S_t^C + \gamma_2^f r_t^C + \gamma_3^f R_t^M + \gamma_4^f \log\left(\frac{A_{f,t}}{F_{f,t}}\right) + \gamma_5^f \log(\delta_{f,t}) \\ &+ \quad \gamma_{Aa1} 1_{f,t,Aa1} + \cdots + \gamma_{Ba1} 1_{f,t,Ba1} + \gamma_Q \log(\bar{Q}) + \varepsilon_{f,n,t}. \end{aligned} \tag{21}$$

The results are presented in Table VIII. First, γ_Q remains positive and significant, suggesting that the market-wide level of credit risk explains yield spreads even after

[25] Neither $\log(\bar{Q})$ nor PC1 can be assumed to be normal or serially uncorrelated. We therefore constructed 99% confidence intervals for $\rho_{PC1,log(\bar{Q})}$ via Monte-Carlo simulation. The resulting confidence interval is $[96.11\%, 97.31\%]$, and thus $\rho_{PC1,log(\bar{Q})} > \rho_{PC1,TT}$ with 99% significance.

[26] "...WatchList lists the names of credits whose Moody's ratings have a likelihood of changing. These names are actively under review because of developing trends or events which, in Moody's opinion, warrant a more extensive examination... In certain cases, names may be removed from this Watchlist without a change in rating," from *www.moodys.com*.

	With a $\log(\bar{Q})$ Term				Without a $\log(\bar{Q})$ Term	
Variable	Parameter Estimate	Standard Error	t - Stat	p-value	Parameter Estimate	p-value
I_{Aa1}	-0.99466	(0.03366)	-29.55	$< .0001$	-1.30770	$< .0001$
I_{Aa2}	-0.84243	(0.02788)	-30.22	$< .0001$	-1.09784	$< .0001$
I_{Aa3}	-0.82111	(0.05491)	-14.59	$< .0001$	-0.90131	$< .0001$
I_{A1}	-0.81061	(0.02421)	-33.48	$< .0001$	-0.90972	$< .0001$
I_{A2}	-0.62022	(0.02508)	-24.73	$< .0001$	-0.74487	$< .0001$
I_{A3}	-0.60631	(0.02008)	-30.19	$< .0001$	-0.71965	$< .0001$
I_{Baa1}	-0.50811	(0.03470)	-14.64	$< .0001$	-1.01638	$< .0001$
$\log(\bar{Q})$	0.43831	(0.01502)	29.18	$< .0001$		

Table VIII
Results of FSR Model with rating indicators - OLS Regression (using White's heteroskedastic-consistent covariance estimator). Only the loading on the rating indicators and $\log(\bar{Q})$ are displayed. Number of Obs. = 29908.

accounting for Moody's analysis of the issuer's credit risk. Second, without the inclusion of a $\log(\bar{Q})$ term (the right half of Table VIII), the marginal impact of a change in rating on yield spreads is counter-intuitive. For example, yield spreads are predicted to *decrease* by 30 basis points upon a downgrade from A3 to Baa1, all else equal. When a $\log(\bar{Q})$ term is included (the left half of Table VIII), the estimated marginal impacts of rating downgrades are all negative, as one would expect. We view this as further evidence of the effect of $\bar{Q}$ on the dynamics of credit spread movements.

E.4. Firm-Specific Yield Spread Sensitivity to $\bar{Q}$

If there demand curves for credit risk do slope down, the γ_Q coefficient should remain positive and significant even when we estimate the FSR model for each firm separately. To test this claim, we estimated the following seemingly-unrelated regression:

$$\begin{aligned} s_{f,n,C}(t) &= \gamma_0^f + \gamma_1^f S_t^C + \gamma_2^f r_t^C + \gamma_3 R^M + \gamma_4^f \log\left(\frac{A_{f,t}}{F_{f,t}}\right) \\ &\quad + \gamma_5^f \log(\delta_{f,t}) + \gamma_Q^f \log(\bar{Q}) + \varepsilon_{f,n,t}. \end{aligned} \tag{22}$$

We report regression estimates in Table IX. In all cases, $\gamma_{Q,f}$, the firm-f-specific coefficient on $\log(\bar{Q})$, remained positive and significant.

Firm	Number of Observations	γ_Q	Standard Error	t-Stat	p-Val
BT	4598	0.54758	(0.07907)	6.93	$< .0001$
DT	2683	0.97690	(0.04994)	19.56	$< .0001$
FT	7485	0.41897	(0.02825)	14.83	$< .0001$
PT	579	0.60206	(0.11436)	5.26	$< .0001$
SO	819	1.23541	(0.11347)	10.89	$< .0001$
TD	1031	0.83319	(0.06205)	13.43	$< .0001$
TF	1788	0.63581	(0.04697)	13.54	$< .0001$
TN	835	1.74587	(0.18340)	9.52	$< .0001$
VF	5392	0.20514	(0.02136)	9.60	$< .0001$
TI	1989	0.06433	(0.00529)	1.22	0.0224
KP	2255	2.70804	(0.05420)	49.96	$< .0001$
TE	454	0.78712	(0.18080)	4.35	$< .0001$

Table IX
Seemingly-Unrelated Regression - OLS estimates of $\gamma_{Q,f}$ (using White's heteroskedastic-consistent covariance estimator).

KPN's sensitivity to $\log(\bar{Q})$ is the highest of all firms. This may be because KPN was one of the most levered firms in our sample and had relatively low credit ratings. *The*

Economist even singled KPN out as being in "greater trouble" than its competitors.[27] This may be evidence in favor of the Schleifer-Vishny theory of industry debt capacity. KPN is more likely to default; therefore investors in KPN bonds are more likely to penalized by an industry-wide collapse in recovery values during an economic downturn.

Sonera and TeleNor also have relatively high γ_Q coefficients. Sonera in particular was singled out by *The Economist* as being overly leveraged relative to its competitors.[28] These are two of the three Scandinavian-based companies in our sample; Scandinavian bond investors may be more risk averse than their Continental counterparts.

Vodafone and Telecom Italia have the lowest (but still positive and significant) estimates of γ_Q. Both firms are parts of large manufacturing conglomerates (Vodafone owns Mannesmann AG and Telecom Italia is a subsidiary of Olivetti), and thus are more diversified and less exposed to the European telecom sector than the other firms in the study. Again, this is consistent with the industry-debt-capacity theory. Vodafone and Telecom Italia own (proportional to their size) the least amount of telecom-sector assets, and are likely to be least affected by a fall in telecom-sector liquidation values.

E.5. Clientele Effects

We tested for possible clientele effects by currency and by maturity. In particular, we split the bonds in our sample into "short-term" (less than two years to maturity) and "long-term" (two or more years until maturity) groups. Similarly, we grouped them by their denominated currency: Euro (€) and related currencies (Deutsche Mark, French Franc, Dutch Guilder, Spanish Peseta and Portugese Escobar), British Pound (£), US

[27] "Unburdening: Europe's Telecoms Giants are Wrestling with Debt and Poor Ratings, to the Joy of Financial Traders." *The Economist*, 10 May 2001. Indeed, KPN has the lowest average distance-to-default measure (0.97) of the larger firms in our dataset; compare to BT with 3.36, DT with 4.94, FT with 4.73, VF with 6.93 and TI with 3.80.

[28] Ibid.

Dollar ($), Swiss Franc (SFR) and Yen (¥). We present the estimated γ_Q coefficients for these subsamples in Table X.

	Maturity								
	All Bonds			0-2 Yrs.			2+ Yrs		
	Obs.	γ_Q	p-Value	Obs.	γ_Q	p-Value	Obs.	γ_Q	p-Value
All	29908	0.4130	$< .0001$	4044	0.16211	$< .0001$	25864	0.46443	$< .0001$
$	6756	0.73036	$< .0001$	1082	0.26308	$< .0001$	5674	0.73353	$< .0001$
£	5238	0.69814	$< .0001$	911	$\mathbf{-0.3214}$	$< .0001$	4327	0.84370	$< .0001$
€	16048	0.52989	$< .0001$	1538	0.40469	$< .0001$	14510	0.56787	$< .0001$
SFR	1427	1.09983	$< .0001$	380	0.92424	$< .0001$	1047	1.18755	$< .0001$
¥	437	0.31509	0.0026	132	0.09412	0.1767	305	1.83082	$< .0001$

Table X
Results of Model 1 - OLS Regression on Partial Samples, by Maturity and by Currency (using White's heteroskedastic-consistent Covariance estimator). Only the γ_Q coefficients are displayed, and estimates that do not conform to our hypothesis are boldfaced.

The γ_Q coefficient remains positive and significant across all denominations and maturities (except for the short-term £-denominated bonds). γ_Q coefficient is generally larger for long-term bonds than for short-term bonds. This suggests the demand curve for credit risk of long-term bonds is steeper than that for short-term bonds.

F. Fixed-Duration Portfolios

We have already demonstrated that the significance of γ_Q is robust to separating the data into subsets grouped by currency, firm, and maturity. However, even within the subset of long-term bonds, there still is substantial variation in durations. There may be clientele effects by duration that our previous analysis has failed to capture.

To address this issue, we constructed fixed-duration portfolios of bonds, in which each portfolio maintained (by balancing of the weights of its constituent bonds) a fixed duration of either 2.5 or 5 years. Each portfolio comprised two bonds, issued by the same firm and denominated in the same currency. We further restricted ourselves to bonds with recorded prices throughout the sample period. We constructed four portfolios with durations of 2.5 years and seven portfolios with durations of 5 years. A breakdown of these portfolios is presented in Table XI (left panel).

Fixed Duration Portfolios: 2.5 Years								
	Firm	Curr.	Bond 1		Bond 2		γ_Q	p-value
			Principal	Coupon	Principal	Coupon		
1	BT	\$	\$ 1.5B	$6\frac{3}{4}$%	\$ 1B	7%	0.36527	< .0001
2	FT	€	FF 2.5B	$7\frac{7}{8}$%	€915M	$5\frac{3}{4}$%	0.42933	< .0001
3	FT	\$	\$ 400M	$6\frac{7}{8}$%	\$ 500M	6%	0.29962	< .0001
4	VF	£	£2.5B	$4\frac{7}{8}$%	£3B	$4\frac{3}{4}$%	0.09139	< .0001

Fixed Duration Portfolios: 5 Years								
	Firm	Curr.	Bond 1		Bond 2		γ_Q	p-value
			Principal	Coupon	Principal	Coupon		
5	BT	£	£500M	$7\frac{1}{8}$%	£600M	$5\frac{3}{4}$%	0.21103	< .0001
6	BT	\$	\$ 1.5B	$6\frac{3}{4}$%	\$ 1B	7%	0.56360	< .0001
7	FT	€	€2.5B	$7\frac{7}{8}$%	€915M	$5\frac{3}{4}$%	0.31134	< .0001
8	FT	\$	\$ 400M	$6\frac{7}{8}$%	\$ 500M	6%	0.31623	< .0001
9	VF	€	€2.5B	$4\frac{7}{8}$%	€3B	$4\frac{3}{4}$%	0.06983	< .0001
10	TI	€	€4.5B	$5\frac{3}{4}$%	€1.75B	$6\frac{1}{8}$%	0.69490	< .0001
11	KP	€	€1.25B	4%	€1.5B	$4\frac{3}{4}$%	1.13405	< .0001

Table XI
The composition of the fixed-duration portfolios and estimation results of the associated OLS regressions. All bonds pay coupons annually.

Since the bonds in each portfolio have the same issuer and denominated currency, the FSR model simplifies to:

$$s_t = \gamma_0 + \gamma_1 S_t + \gamma_2 r_t^c + \gamma_3 R_t^M + \gamma_4 \log\left(\frac{A_t}{F_t}\right) + \gamma_5 \log(\delta_t) + \gamma_Q \log(\bar{Q}) + \varepsilon_t. \quad (23)$$

The estimated γ_Q's are presented in Table XI (right panel). For all twelve portfolios, γ_Q was both positive and highly significant, in support of our hypothesis.

V. Alternative Explanations

We have seen that the γ_Q coefficients are positive and significant for various specifications of our model. Can we now conclude that there demand curves for credit risk do indeed slope down? Or could other economic effects explain the observed phenomenon?

A. The Information Hypothesis

New issues of debt in the European telecom market may have signaled that the bidding in European bandwidth auctions would be more competitive than previously expected. The information hypothesis posits that incremental debt issuance signaled negative prospects for the entire industry. The observed increase in yield spreads is a reaction to the information content of new debt, and is unrelated to any demand curve effects.

If debt issues conveyed new information about a firm's prospects, there should be an effect on equity prices as well. Changes in $\bar{Q}$ could affect equity returns in two possible ways. First, investors could lower their expectations of future cashflows, leading to jumps in excess equity returns. Second, investors may view the firm as having greater systematic risk, and thus we should observe a rise in the CAPM β of the firm's equity. We test for both effects, and fail to find any evidence supporting the information hypothesis.

A.1. Changes in Excess Returns

We tested whether changes in $\bar{Q}$ were associated with daily excess equity returns. We assumed that the Capital Asset Pricing Model holds;

$$r_{f,t} = r_t^* + \beta^f (r_t^M - r_t^*) + \varepsilon_{f,t}, \tag{24}$$

where $r_{f,t}$ is the equity return for firm f at time t, r_t^M is the time-t market return, r_t^* is the time-t instantaneous riskfree rate in firm f's home country, and $\varepsilon_{f,t}$ are mean-zero disturbances, serially uncorrelated and uncorrelated with excess market returns.

We used the EuroStoxx Nordic Total Market Index as proxy for r_t^M for Telia, TDC, Sonera, and TeleNor, and the EuroStoxx Eurozone Total Market Index for all other firms. The riskfree rate was taken to be the three-month British-Pound LIBOR yield for British Telecom and Vodafone; the three-month Swedish-Krona LIBOR yield for Telia and Telenor; and the three-month Euro LIBOR rate for all other firms.

We wanted to explore the effects of $\bar{Q}$ on the excess returns $\varepsilon_{f,t}$. We first estimated a seemingly-unrelated regression of the Capital Asset Pricing Model for all twelve firms, and extracted the OLS residuals, $\hat{\varepsilon}_{f,t}$. We then estimated the following regression:

$$\begin{aligned} \hat{\varepsilon}_{f,t} &= \alpha_0^f + \alpha_1^f \Delta \log(\bar{Q}_{f,t}) + \alpha_2^f \Delta \log(\bar{Q}_{-f,t}) \\ &\quad + \alpha_3^f \Delta \log\left(\frac{A_{f,t}}{F_{f,t}}\right) + \alpha_4^f \Delta \log(\delta_{f,t}) + u_{f,t}, \end{aligned} \tag{25}$$

where $\Delta \log(\bar{Q}_f)$ and $\Delta \log(\bar{Q}_{-f})$ are the daily changes in the log(Q)-contributions of firm f's bonds and the bonds of its competitors, respectively; $\Delta \log\left(\frac{A_{f,t}}{F_{f,t}}\right)$ and $\Delta \log(\delta_{f,t})$ are the changes in firm f's debt-coverage ratio and distance-to-default; and $u_{f,t}$ are mean-zero errors uncorrelated with each other and with all other regressors.

Note that we split $\log(\bar{Q})$ into $\log(\bar{Q}_{f,t})$ and $\log(\bar{Q}_{-f,t})$. A significant α_1^f coefficient would not be surprising, since it would simply be capturing the relationship between the firm's risk and its increased leverage. However, the information hypothesis suggests that there should also be a significant α_2^f, the coefficient for $\bar{Q}_{-f}$; if the information revealed by competitors' debt issuance affects bond yield spreads it should also affect equities. An insignificant α_2^f would be strong evidence against the information hypothesis.

Firm	$\Delta \log(\bar{Q}_f)$	p-Val	$\Delta \log(\bar{Q}_{-f})$	p-Val
BT	0.23702	$< .0001$	0.01904	0.7115
DT	0.12690	0.0056	-0.05938	0.2289
FT	0.10396	0.0193	0.05366	0.2373
PT	0.93960	$< .0001$	0.02724	0.5369
SO	1.12568	$< .0001$	0.06827	0.1214
TD	0.08712	0.2885	0.04919	0.2645
TF	0.24943	$< .0001$	0.01751	0.7024
TN	0.26631	0.5174	0.01011	0.8991
VF	0.31044	$< .0001$	0.00546	0.9061
TI	0.44883	$< .0001$	0.01525	0.7575
KP	0.14784	0.0011	0.05148	0.2563
TE	0.07278	0.5341	0.03870	0.4576

Table XII
CAPM Residuals - OLS Regression (using White's heteroskedastic-consistent covariance estimator).

The results are presented in Table XII. The information hypothesis is not borne out in the data; the α_2^f coefficients are all insignificant. This suggests that excess equity returns are not affected by changes in the quantity of credit risk in the sector. These findings support the hypothesis of downward-sloping demand curves.

We also obtained positive and generally quite significant[29] α_1^f's, the coefficients for $\Delta \log(\bar{Q}_{f,t})$. The positive sign of these coefficients is probably capturing a manifestation of debtholder-shareholder conflict, in which increased issuances represent wealth transfers from debtholders to shareholders as the firm funds new, riskier projects.

A.2. Changes in Systematic Risk: I-CAPM

Even if changes in $\bar{Q}$ do not convey information that alters investors' expectations of future firm cashflows, they may still signal shifts in the level of telecom-sector systematic risk. If so, we may observe changes to the CAPM beta of the firms' equities, even if we do not witness any effect on excess returns. In order to test for such an effect, we allowed for a time-varying β_t^f and estimated an intertemporal-CAPM model:

$$r_{f,t} = r_t^* + \beta_t^f (r_t^M - r_t^*) + \varepsilon_{f,t} \tag{26}$$

$$\beta_t^f = \gamma_0^f + \gamma_Q^f \log(\bar{Q}). \tag{27}$$

where r_t^f, r_t^M, r_t^* and $\varepsilon_{f,t}$ are as defined previously.

If changes in $\bar{Q}$ signal shifts in telecom-sector systematic risk, then $\log(\bar{Q})$ should noticeably affect β_t^f. That is, we should estimate a significant γ_Q^f. We test the hypothesis $H_0 : \gamma_Q^f \neq 0$, and report the estimates in Table XIII. The estimated γ_Q^f's were predominantly insignificant and negative, inconsistent with the information hypothesis. The sole exception was Telia, whose γ_Q^f was both positive and significant. These results support to the hypothesis of downward-sloping demand curves.

Our results also indicate that these telecom firms were generally riskier than the overall market, as most firms had average β_t^f's greater than one. The Scandinavian

[29] Three of the Scandinavian firms - TDC, TeleNor, and Telia - have insignificant α_1^f's. This suggests that the Nordic Stoxx Total Market Index does not proxy well for the appropriate market portfolio.

Firm	E[$\beta_{f,t}$]	β_Q	t-Stat	p-Val	Firm	E[$\beta_{f,t}$]	β_Q	t-Stat	p-Val
BT	1.612	0.29522	1.19	0.2341	TF	1.569	0.03821	0.15	0.8776
DT	1.850	-0.25512	-1.03	0.3037	TN	-0.134	1.14836	1.14	0.2545
FT	2.166	-0.07838	-0.32	0.7520	VF	1.987	0.24982	1.01	0.3140
PT	1.333	-0.17762	-0.72	0.4739	TI	1.124	-0.44929	-1.81	0.0701
SO	1.203	-0.16446	-1.36	0.1740	KP	1.933	-0.45588	-1.84	0.0661
TD	0.425	-0.22684	-1.88	0.0608	TE	0.318	0.62769	2.33	0.0198

Table XIII
Intertemporal CAPM - OLS Regression (using White's heteroskedastic-consistent covariance estimator).

countries were all notable exceptions to this rule, as TDC, Telia, and TeleNor had β_t^f's that were less than one or even negative.[30]

In summary, our analysis suggests that new debt issuances do not signal new information about the firms' prospects or their level of systematic risk. Thus, the information hypothesis does not explain the observed widening of spreads in response to $\bar{Q}$. Our results still support the hypothesis of downward sloping demand curves for credit risk.

B. Price-Pressure Effects

Prior research on downward-sloping demand curves for corporate securities wrestles with price-pressure hypothesis. That is, are price reactions to new issuances the result of a temporary imbalance in supply and demand? Or is it a permanent result of movement along a downward-sloping demand-curve? Such a price-pressure mechanism may account for our results, particularly since bond markets are generally less liquid than equity markets and imbalances would naturally take longer to correct themselves.

[30] As noted previously, our proxies for Scandinavian market returns and riskfree rates are probably flawed; a better methodology would have accounted for the fact that equity holders in these particular firms probably invested in both Scandinavian and Euro-zone markets and have adjusted the reference "market portfolio" appropriately. Without precise data on the cross-section of the equity holdings of the average Scandinavian telecom shareholder, we cannot refine our analysis in this way.

In particular, the price-pressure hypothesis predicts that increases in $\bar{Q}$ cause a temporary rise in spreads followed by a complete reversal (Harris and Gurel (1986)). Demand-curve explanations, on the other hand, suggest a permanent increase in spreads, *ceteris paribus*, in reaction to a rise in $\bar{Q}$. In order to resolve these contrary predictions, we estimated the following model:

$$\begin{aligned} \Delta s_{f,n,C}(t) &= \gamma_0^f + \gamma_1^f \Delta S_t^C + \gamma_2^f \Delta r_t^C + \gamma_3^f \Delta R_t^M \\ &\quad + \gamma_4^f \Delta \log \left(\frac{A_{f,t}}{F_{f,t}} \right) + \gamma_5 \Delta \log(\delta_{f,t}) \\ &\quad + \sum_{(a,b] \in \mathcal{I}} \gamma_{(a,b]} \Delta \log(\bar{Q}_{(t-a,t-b]}) + \varepsilon_{f,n,t}, \end{aligned} \tag{28}$$

where $\Delta s_{f,t,T}$, ΔS_t^C, Δr_t^C, ΔR_t^M, $\Delta \log \left(\frac{A_{f,t}}{F_{f,t}} \right)$, and $\Delta \log(\delta_{f,t})$ are the one-day changes in spreads, slope and level of the reference curve, market return, and firm-wise logarithm of the debt coverage ratio and distance-to-default, respectively. $\Delta \log(\bar{Q}_{(t-a,t-b]})$ is the total change in $\log \bar{Q}$ over the period $(t-a, t-b]$. $\mathcal{I}$ is the set of intervals

$$\begin{aligned} \mathcal{I} &= \{(-10,-5], (-5,0], (0,5], (5,10], (10,15], \\ &\quad (15,20], (20,30], (30,45], (45,60], (60,75], (75,90]\}. \end{aligned} \tag{29}$$

Coefficients with positive a's and b's measure to what extent yield spreads react to past changes in $\log(\bar{Q})$, while coefficients with negative a's and b's measure how yield spreads move in anticipation of future $\log Q$ changes. For example, $\gamma_{(5,10]}$ measures the average effect of today's change in $\log(\bar{Q})$ on spreads five to ten days into the future.

Our results, presented in table XIV, are inconsistent with the price-pressure hypothesis. The positive and significant $\gamma_{(0,5]}$ coefficient indicates that there is an immediate rise in yield spreads over the first week following an increase in $\bar{Q}$. A price-pressure mechanism would generate a later reversal to offset this initial rise; such a reversal should manifest itself as one or more negative and significant $\gamma_{(a,b]}$ coefficients. However, all $\gamma_{(a,b]}$ coefficients subsequent to $\gamma_{(0,5]}$ are positive (but of mixed significance), save for the negative (yet insignificant) $\gamma_{(45,60]}$.

Variable	Parameter Estimate	Standard Error	t-Stat	p-value
$\gamma_{(-10,-5]}$	-0.00042	0.00963	-0.04	0.9652
$\gamma_{(-5,0]}$	0.01126	0.00966	1.17	0.2440
$\gamma_{(0,5]}$	0.02810	0.00956	2.94	0.0033
$\gamma_{(5,10]}$	0.01489	0.00938	1.59	0.1123
$\gamma_{(10,15]}$	0.01054	0.00954	1.11	0.2691
$\gamma_{(15,20]}$	0.00744	0.00971	0.77	0.4434
$\gamma_{(20,30]}$	0.01753	0.00714	2.46	0.0141
$\gamma_{(30,45]}$	0.01158	0.00608	1.91	0.0567
$\gamma_{(45,60]}$	-0.00583	0.00649	-0.90	0.3691
$\gamma_{(60,75]}$	0.00510	0.00682	0.75	0.4542
$\gamma_{(75,90]}$	0.00070	0.00636	0.11	0.9126

Table XIV
Price-Pressure Model - OLS Regression (using White's heteroskedastic-consistent covariance estimator). Only the $\gamma_{(a,b]}$ coefficients are displayed. Number of observations = 25881.

We illustrate the cumulative impact on sector-wide yield spreads due to Deutsche Telekom's June 2000 issuance of €16 billion in figure 2. To capture the time-dynamics of spread changes better, we re-estimated the above model with separate $\gamma_{[a,b)}$ coefficients for five-day intervals ranging from $(t-15, t-10]$ to $(t+115, t+120]$. We graphed the expected cumulative change in yield spreads from 15 business days before the issuance to 120 days after it. We also graph two-standard-deviation error bands, constructed used White's heteroskedastic-consistent covariance estimator.

The yield spread increase insignificant even 120 past the issuance date, contrary to the price-pressure hypothesis. Furthermore, the cumulative impact on yield spreads was larger than the previous "point-estimate" from the FSR model. In particular, this

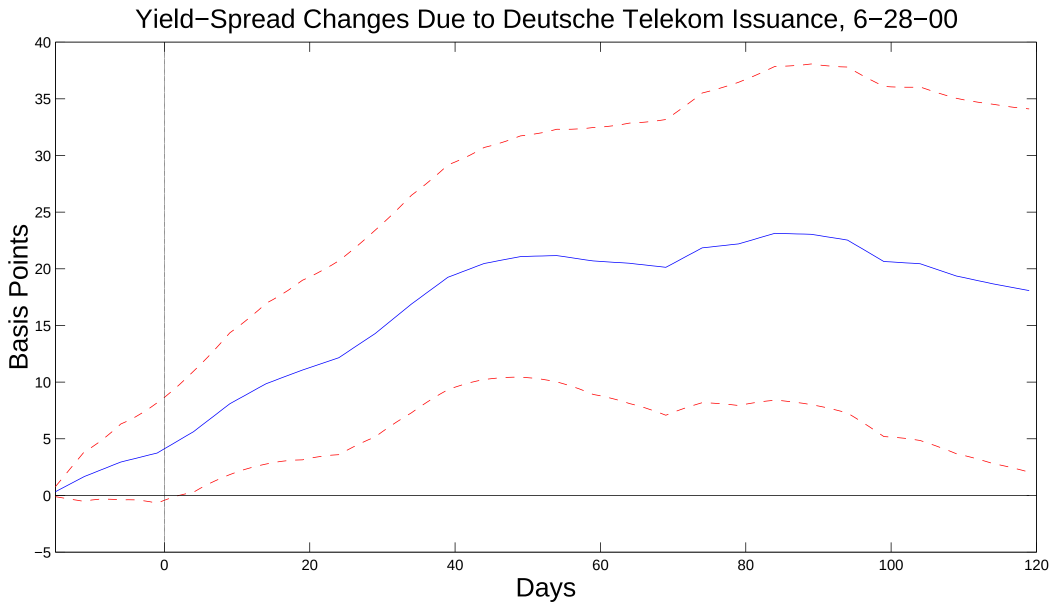

Figure 2. Dynamics of Issuance Effects Following Deutsche Telekom's €16 B Issuance.

regression suggests that Deutsche Telekom's issuance inflated yield spreads by a cumulative total of twenty basis points over roughly 40 days; our previous models (without regressors for lagged changes in $\log(\bar{Q})$ suggested only a twelve basis point increase.

The gradual rise in yield spreads is surprising. One would reason that since new issuances were announced in advance, investors would have immediately incorporated any $\bar{Q}$-effect into yield spreads. Instead, yield spreads inflated around issuance dates and continued to do so for several weeks, suggesting that the $\bar{Q}$ effect is unanticipated by investors. We would have liked to examine how yield spreads reacted to *announcements* of future issuances, but we were unable to find reliable announcement dates.

This effect could also be an artifact of market illiquidity. Investors may immediately change their valuations of telecom bonds in reaction to "surprise" debt issuances, but we only observe the resulting change in prices when a trade occurs. The significance and sign of the $\gamma_{(t+a,t+b]}$ coefficients would then be a function of the trading frequency of these bonds, and not a measure of the actual time-dynamics of demand curve effects.

Both effects - the gradual widening in yield spreads and the higher predicted cumulative impact of issuances relative to the original point-estimate - may be the result of the upward trend in $\bar{Q}$. In particular, this trend could lead to spurious correlations between lagged and current changes in $\Delta \log(\bar{Q})$. These correlations may bias our estimates of the lagged $\log(\bar{Q})$ coefficients upwards, resulting in the aforementioned effects.

VI. Interpretation and Conclusions

We documented that the quantity of credit risk, $\bar{Q}$, is a statistically significant determinant of the level of yield spreads. This effect is economically significant as well. Deutsche Telekom issued nearly €16B on June 28th, 2000, the largest issuance in our dataset. $\log(\bar{Q})$ increased by 0.2167 (from 20.4216 to 20.6383); as a result, sector-wide yield spreads increased by an estimated twelve basis points, all else equal. Deutsche Telekom's issuance reduced the market value of a $2.8 billion British Telecom bond by an estimated 1.53%, or $43.2 *million*.

To conclude, our study provides evidence that the demand curve for credit risk in the European telecom sector does indeed slope significantly downwards. The quantity of expected loss borne by bond investors, both due to a firm's own debt and due to that of its competitors, has a positive and statistically significant effect on the yield spreads of the firm's outstanding debt. This result is robust to various specifications of our regression model, and survives testing against several alternative explanations.

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