Distance to Default and the GZ Spread

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Abstract

Gilchrist and Zakrajsek (2012) construct a credit spread, deemed the GZ spread, based on proprietary second market corporate bond data and demonstrate that it has greater predictive power than the Baa-Aaa and Commercial Paper Bill spreads on economic activity. Further, when the GZ spread is decomposed into a default risk component and a bond premium component, Gilchrist and Zakrajsek (2012) find that its predictive power is increased. However, to calculate the distance-to-default measure used in this decomposition, the GZ spread uses the KMV Merton model, which has been demonstrated to underperform alternative methods of calculating distance-to-default (Bharath and Shumway 2004) in terms of predicting economic activity. To further explore the role of distance-to-default in improving the predictive power of the GZ spread, we replicate the GZ spread using public bond data and decompose it into a default risk component and excess bond premium component using three distance to default models. We find that our results agree with Gilchrist and Zakrajsek in that the GZ spread contains greater predictive power than the Baa-Aaa and CP-Bill spreads for large forecast horizons, and that decomposing it into default-risk and excess bond premium components improves its predictive power for all three distance-to-default models. We also conclude that the Market Value Proxy method of calculating distance-to-default introduced by Brockman and Turtle (2003) produces the greatest improvement in predictive power over the non-decomposed GZ spread, while the KMV Merton method produces the smallest improvement.

1 Introduction

Gilchrist and Zakrajsek (2012) suggest that the power of credit spreads in predicting economic activity lies in two channels: a countercyclical channel and a cyclical channel. The countercyclical channel reflects changes in expected defaults based on the balance sheets of borrowers, while the cyclical channel measures changes in the price of bearing exposure to credit risk relative to the expected countercyclical channel.

To demonstrate the predictive power of both channels on predicting economic activity, Gilchrist and Zakrajsek (2012) use bond information from secondary markets to construct a corporate bond spread, referred to as the GZ spread. The granularity of the spread, of which individual bond information is known, allows it to be decomposed into a cyclical expected default risk component and a countercyclical excess bond premium component.

The GZ spread's predictive power on economic activity is demonstrated to be greater than comparable measures such as the Baa-Aaa and CP-Bill spreads. After decomposing the GZ spread into the expected default risk component and the excess bond premium component, the predictive power of the decomposed GZ spread is found to be larger than the GZ spread as a whole, based on the coefficient size and R^2 of an autoregression on economic indicators such as real GDP.

However, one potential pitfall of the GZ spread is its use of the KMV Merton model to calculate the distance-to-default, a key ingredient in the expected default risk component. The distance-to-default calculated using the KMV Merton model has been demonstrated to underperform alternative distance-to-default measures that do not require the iterative method demanded by the KMV Merton model (Bharath and Shumway 2004).

The goal of this paper is to assess the role of distance-to-default in the predictive power of the GZ spread. This is accomplished by replicating the GZ spread using non-proprietary corporate bond data and decomposing it into the default-risk and excess bond premium components using three models: the KMV Merton model used by Gilchrist and Zakrajsek (2012), as well as the Market Value Proxy method developed by Brockman and Turtle (2003) and the Transformed-Data MLE method developed by Duan, Gauthier and Simonato (1994).

By assessing the power of components calculated with all three methods on predicting real GDP at 1-quarter and 1-year forecast horizons, we find that the GZ spread is a better predictor of real GDP than the the the Commercial Paper Bill (CP-Bill) and Baa-Aaa spread for large forecast horizons. We also find that all three distance-to-default models produce decomposed components of the GZ spread that improve on the predictive power of the GZ spread itself. Finally, we conclude that the Market Value Proxy method is not only the simplest but also the most powerful method of decomposing the GZ spread, while the KMV method produces significantly less predictive power than either model, particularly for large forecast horizons.

2 Data

Our bond data comes from the Mergent FISD database, which includes bond offering dates ranging from 2000 through 2014. Criteria for bond selection includes bonds with maturity times no shorter than one year and no greater than one year, with par values no smaller than $1 million.

In the distance-to-default calculations, market capitalization is estimated using price and shares outstanding data from CRSP. The face value of debt is estimated using long-term and current liabilities from Compustat.

After matching a sample size of 1251 FISD observations with the CRSP and Compustat data, the sample size used in computations was reduced to 533 bond issues from 175 firms. Summary statistics of this bond data are presented in Table 1 along with the yearly average GZ spread, which is explained in the following section.

Baa-Aaa and CP-Bill spreads, industry fixed effects, credit ratings, constant maturity interest rates, and the real federal funds rate were obtained from the FRED database.

The GZ spread calculated in Gilchrist and Zabrajcek (2012) was obtained from the American Economic Review and used as a measure of comparison with our calculated GZ spread.

3 Methodology

3.1 Calculating the GZ Spread

Simply computing the spread between a bond's yield and the yield of a treasury security with the same maturity introduces bias via duration mismatch. Rather than compute the spread this way, we estimate the price of a security that pays the same coupon/par value amount and frequency as a bond k issued by firm i, discounting with Treasury yields at period t:

$$P_t^f[k] = \sum_{s=1}^{S} C(s)D(t_s), \quad D(t) = e^{-r_t t}, \quad C(s) : s = 1, 2, ..., S \tag{1}$$

Here, $C(s)$ is the payment at time s and $D(t_s)$ is the discount rate at time s where t is the fixed time difference between payments. The yield to maturity of this bond $P_t^f[k]$, is then calculated using the standard formula:

$$P_t^f[k] = \sum_{s=1}^{S} C(s)e^{-y_t^f[k]t} \tag{2}$$

The spread at time t for bond i is the difference between the bond's yield $y_{it}[k]$ and the yield to maturity of the hypothetical treasury:

$$S_{it}[k] = y_{it}[k] - y_t^f[k] \tag{3}$$

The GZ spread, S_t^{GZ}, is calculated as the average spreads over all firms i at month t:

$$S_t^{GZ} = \frac{1}{N_t}\sum_i \sum_k S_{it}[k] \tag{4}$$

The yearly means of the resulting GZ spread are presented in Table 1. In conjunction with the financial crisis of 2007-2008, the spread reaches its peak in 2008.

As a measure of comparison, we plot our GZ spread against the actual GZ spread from Gilchrist and Zakrajsek (2012) in Figure 1. We find that the two spreads have a strong positive correlation of $\rho = .413$. We also plot each spread's trend component in Figure 1 to further compare the two without considering seasonality. Comparing Figure 1 with Table 1, it appears that years in which more observations are available coincide with greater cyclicality between the two spreads, particularly during the financial crisis of 2007-2008. However, during the years 2004-2005, the number of observations is scarce and the countercyclicality between the two spreads is greatest.

We also plot our GZ spread against the Baa-Aaa spread and CP spread in Figure 2. Like the GZ spread from Gilchrist and Zakrajsek (2012), our GZ spread is higher than the Baa-Aaa and CP spreads. All three spreads have spikes in in 2007, 2009, and 2010; however, the magnitude of these spikes is far larger for the GZ spread.

3.2 Calculating the Excess Bond Premium

By predicting the GZ spread, we can decompose it into a bond premium component and a default risk component:

$$\ln S_{it}[k] = \beta DFT_{it} + \gamma' Z_{it}[k] + \epsilon_{it}[k] \tag{5}$$

$$Z_{it}[k] = [PAR_{it}[k], CPN_i[k], AGE_{it}[k] + CALL_i[k] + FIXED_{IND} + FIXED_{CREDIT}] \tag{6}$$

Here, DFT_{it} is the distance to default of firm i at time t, $Z_{it}[k]$ is a vector of bond-specific characteristics plus industry and credit rating fixed-effects, and $\epsilon_{it}[k]$ is the "pricing error." The predicted level of the spread is thus:

$$\hat{S}_{it}[k] = \exp[\hat{\beta} DFT_{it} + \hat{\gamma}' Z_{it}[k] + \frac{\hat{\sigma}^2}{2}] \tag{7}$$

Similarly to how the original GZ spread was calculated, the predicted GZ spread is averaged across all firms at month t:

$$\hat{S}_t^{GZ} = \frac{1}{N_t}\sum_i \sum_k \hat{S}_{it}[k] \tag{8}$$

The excess bond premium is then defined as:

$$EBP_t = S_t^{GZ} - \hat{S}_t^{GZ} \tag{9}$$

The resulting loading coefficients on predicting the GZ spread for three distance-to-default models are presented in Table 2. As in Gilchrist and Zakrajsek (2012), both fixed effects lack statistically significant coefficients, while the coefficients for distance-to-default are significant for all three models.

The excess bond premium, distance-to-default, and predicted GZ spread are plotted in Figure 3 for all three distance-to-default models.

3.3 Calculating Predictive Power on Real GDP

The following forecasting equation is used to determine the predictive ability of the GZ spread on an economic activity Y_t:

$$\nabla^h Y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i \nabla Y_{t-i} + \gamma_1 TS_t + \gamma_2 RFF_t + \gamma_3 CS_t + \epsilon_{t+h}, \quad \nabla^h Y_{t+h} = \frac{c}{h+1} \ln(\frac{Y_{t+h}}{Y_{t-1}}) \tag{10}$$

Here, h is the forecast horizon, c is a scaling constant, TS_t is the term spread, RFF_t is the real federal funds rate, CS_t is the credit spread, and ϵ_{t+h} is the forecast error. Lag length p is determined using the Akaike Information Criterion (AIC).

Table 3 presents the coefficients of this regression using the GZ spread itself as CS_t at both 1-quarter and 1-year forecast horizons, and Table 4 presents coefficients of the decomposed GZ spread as CS_t, also at both 1-quarter and 1-year forecast horizons.

3.4 Distance-to-Default Models

In order to calculate distance-to-default DD, assume the total value of the firm V follows a geometric Brownian motion process:

$$dV = \mu_V V dt + \sigma_V V dW \tag{11}$$

Then, according to the Black-Scholes-Merton option pricing formula, the value of the firm's equity satisfies the following equation:

$$E = V\Phi(\delta_1) - e^{-rT} D\Phi(\delta_2), \quad \delta_1 = \frac{\ln\frac{V}{D} + (r + .5\sigma_V^2)T}{\sigma_V^2\sqrt{T}}, \quad \delta_2 = \delta_1 - \sigma_V\sqrt{T} \tag{12}$$

3.4.1 KMV Method

Gilchrist and Zakrajsek (2012) use the KMV model to calculate the distance-to-default DD. In this model, define the volatility of the firm's equity:

$$\sigma_E = [\frac{V}{E}]\frac{\delta E}{\delta V}\sigma_V = [\frac{V}{E}]\Phi(\delta_1)\sigma_V \tag{13}$$

The KMV model then uses the following algorithm to calculate DD. The intuition is that (12) and (13) are two equations with two unknowns, σ_V and V, and the goal is to solve for these unknowns and in doing so obtain DD.

1. Estimate σ_E using a 250-day historical daily stock return moving window
2. Calculate $D_{i,t} = CL_{i,t} + \frac{1}{2}LT_{i,t}$ where $CL_{i,t}$ is firm i's current liabilities at t and $LT_{i,t}$ is the firm's long-term liabilities.[1]
3. Guess $\sigma_V = \sigma_E \times \frac{D}{D+E}$

[1] The convention of approximating $D_{i,t} = CL_{i,t} + \frac{1}{2}LT_{i,t}$ was proposed by KMV due to historical default observations occurring when V fell between the firm's current liabilities and long-term liabilities.

4. Plug the guess into (12) to solve for the "implied" V on each day of the 250-day moving window
5. Calculate $\ln(r_V)$, the implied daily log-returns on V.
6. Use the resulting time-series to generate new values of σ_V and μ_V.
7. Repeat steps 4, 5, and 6 with the new σ_V until $|V_{i,t} - V_{i,t-1}| < \alpha$ for a given threshold α.

The Merton DD model is then calculated over a one-year horizon:

$$DD = \frac{\ln\frac{V}{D} + (\mu_V - .5\sigma_V^2)}{\sigma_V} \tag{14}$$

3.4.2 Market Value Proxy Method

The market value of a firm is not directly observable due to intangible assets, and estimating the market value by adding market equity and market debt is similarly difficult because part of the market debt may be non-tradeable. Thus, the market value of the firm is often proxied as the sum of market capitalization MC_{it} and book liabilities BL_{it}:

$$V_{it} = MC_{it} + BL_{it} \tag{15}$$

Because the market capitalization of a firm is readily available on a daily basis, and the book liabilities are available on a quarterly basis, μ_V and σ_V are simply calculated using the following method developed by Brockman and Turtle (2003):

1. Create daily time series of V_{it} composed of daily MC_{it} and quarterly BL_{it}
2. Assess returns of the time series $\log(\frac{V_{i,t+1} - V_{i,t}}{V_{i,t}})$.
3. Calculate μ_V and σ_V of these returns and use in Merton formula:

$$DD = \frac{\ln\frac{V}{D} + (\mu_V - .5\sigma_V^2)}{\sigma_V} \tag{16}$$

The primary advantage of the Market Value Proxy method is that it is more stable for firms with extreme equity-to-debt ratios, whereas the implied V resulting from the KMV Merton model causes the distance to default to reach unrealistic levels for these firms. The Market Value Proxy also requires just one calculation per bond observation, while the KMV Merton model demands 250 calculations per iteration to solve for the implied V.

3.4.3 Transformed-Data MLE Method

The transformed-data maximum likelihood estimation (MLE) method introduced by Duan, Gauthier, and Simonato (2004) also observes that the firm market value is not directly observable, but can be estimated by applying a transform to the firm equity E. This transform is the inverse with respect to firm market value V of (12), which results in the "implied" V (this is the same "implied" V from step 4 of the KMV Merton model). The log-likelihood function for n observations of E, with $\boldsymbol{E}$ representing the past n observations of E, is then calculated to be the following equation:

$$L(\mu_V, \sigma_V, \boldsymbol{E}) = -\frac{n-1}{2} ln(2\pi) - \frac{1}{2}\sum_{t=2}^{n} ln(\sigma_V^2 h_t) - \sum_{t=2}^{n} \frac{\hat{W}_t^2}{2\sigma_V^2 h_t} - \sum_{t=2}^{n} ln(V_t) - \sum_{t=2}^{n} ln(\Phi(d_1(V_t, \sigma_V, D_t, \tau_t))) \tag{17}$$

$$\hat{W}_t = ln(V_t) - ln(V_{t-1}) - (\mu_V - \frac{\sigma_V^2}{2})h_t \tag{18}$$

$$h_t = t_i - t_{i-1} \tag{19}$$

In this equation, the only unknown values are μ_V, σ_V because V_t is left as a function of σ_V. Therefore, the maximum likelihood estimators $\hat{\mu}_V$ and $\hat{\sigma}_V$ can be obtained by maximizing the function, which is done numerically.

The Transformed-Data MLE method solves a significant problem with the KMV Merton model, which does not include $\hat{\mu}_V$ in its iterative process, eschewing the information contained in this variable. Solving a likelihood function allows us to use the information contained in both $\hat{\mu}_V$ and $\hat{\sigma}_V$ because we express V in terms of $\hat{\sigma}_V$, and are therefore still solving for two variables.

4 Results

Table 3 presents coefficients from the regression given in (10), with CS_t represented by the GZ spread. As measures of comparison, the regression is also calculated with the Baa-Aaa CP-Bill spreads as CS_t.

When CS_t is excluded from the regression, the R^2 is lowest for both forecast horizons. When the GZ spread is introduced, the R^2 of the regression does not change using the 1-quarter forecast horizon, but rises from .386 to .448 in the 1-year forecast horizon. Interestingly, the R^2 for the Baa-Aaa and CP-Bill spreads has the opposite relation; it increases in the 1-quarter time horizon but stagnates in the 1-year horizon. One potential reason for this effect is the large variation in the GZ spread compared with the two comparable spreads, as evidenced in Figure 2. At the quarterly level, this variation is more likely to hide the predictive information of the spread. However, the 1-year spread showcases the increased predictive power of the GZ spread over the comparables also found by Gilchrist and Zakrajsek (2012).

Table 4 presents the same regression results as Table 3, except with the GZ spread replaced with its components, the predicted GZ spread and excess bond premium. Each of the three distance-to-default models is used to produce these components.

For both time horizons, every model not only improves the R^2 of the regressions from Table 3, but also produces higher R^2 measures than any regression from Table 3. At the 1-quarter level, the predicted GZ spread is significant at the 1% level, while the excess bond premium is not statistically significant using the KMV model and significant at the 10% level using the Market Value Proxy and Transformed-Data MLE methods of calculating distance-to-default. At the 1-year level, the opposite effect occurs: the excess bond premium is statistically significant at the 5% level for the Market Value Proxy and Transformed-Data MLE methods and the predicted GZ spread is not statistically significant using any method.

The shift in significance from the predicted GZ spread to the excess bond premium from short to long forecast horizons agrees with the results from Table 3, in that the large seasonal effects of the GZ spread dominate at short forecast horizons, and the excess risk incurred by firms over the predicted cyclical default risk becomes more apparent and powerful for large time horizons.

Comparing the results of the three distance-to-default models, the KMV Merton model produces the smallest improvement on R^2 for both forecast horizons. The KMV Merton-produced components of the GZ spread also lose significance as the forecast horizon increases, indicating that the KMV Merton distance-to-default is the weakest explanatory variable in calculating the predicted GZ spread and thereby the excess bond premium. This indication is validated in Table 2, where the KMV Merton model distance-to-default has the lowest, least significant loading coefficient.

Figure 3 further supports the superiority of the Market Value Proxy and Transformed-Data MLE over the KMV Merton model in decomposing the GZ spread because both values produce large, positive values for distance-to-default, compared with small values varying from positive to negative values using the KMV Merton model. As a result, the excess bond premium has higher procyclicality with the predicted GZ spread using the KMV Merton model, which may explain the lack of information conveyed by the excess bond premium using this model.

Both the Market Value Proxy and Transformed-Data MLE have statistically significant components at the 1-quarter forecast horizon and improve the R^2 from Table 3 from .448 to .572. Using the 1-year forecast horizon, both models see a shift in significance from the predicted GZ spread to the excess bond premium, but the Market Value Proxy method dramatically improves the R^2 from Table 3, nearly doubling the R^2 from the regression lacking a CS_t coefficient and improving the R^2 from the regression using the GZ spread as CS_t from .448 to .716. The Transformed-Data MLE method produces less impressive results, with an R^2 of .504. The Market Value Proxy coefficients are also larger than those of the Transformed-Data MLE for both forecast horizons, with this difference becoming more apparent at the 1-year level.

Because the shift from a 1-quarter forecast horizon to a 1-year forecast horizon produces the greatest improvements in the R^2 of the regressions and also shifts significance away from the predictive GZ spread and towards the excess bond premium, the excess bond premium appears to be a more powerful predictor of economic activity given that it is not overshadowed by seasonal variance. In addition, because the Market Value Proxy coefficients reflect the largest shift of significance but also the largest improvement in R^2 from Table 3, it produces the largest improvements over using a non-decomposed credit spread to predict real GDP.

5 Conclusion

As in Gilchrist and Zakrajsek (2012), we find that the GZ spread has greater predictive power than the Baa-Aaa and CP-Bill spreads for large forecast horizons. Because the difference in the GZ spread's predictive power over the Baa-Aaa and CP-Bill spreads increases from the 1-quarter to 1-year forecast horizon, we conclude that this increase in predictive power is driven by the excess bond premium.

By decomposing the GZ spread into a cyclical default-risk component and a countercyclical excess bond premium, we observe not only that the combined components have more predictive power than the GZ spread itself, but that at larger time horizons, this predictive power shifts from the default-risk component to the excess bond premium and produces the largest improvements. This effect is in agreement with the observations of the non-decomposed GZ spread.

This effect is the largest using the Market Value Proxy method to calculate distance-to-default, which results in the largest improvements of predictive power of the decomposed GZ spread over the non-decomposed GZ spread. However, this effect is smallest using the KMV Merton model, which produces the lowest and least significant improvements in predictive power. Therefore, we conclude that the Market Value Proxy method is not only the simplest measure of distance-to-default, but the most powerful in exploiting the predictive power of the excess bond premium.

6 References

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Year Issued	# Observations	Offering Amt. ($Mil.)	TTM	Coupon	Offering Yield	S^{GZ}
2000	20	3.668	6.450	7.485	7.548	1.636
2001	44	3.908	6.500	6.042	6.068	1.632
2002	14	1.332	7.857	5.605	5.675	1.277
2003	17	1.144	8.882	5.634	5.688	1.969
2004	10	1.146	7.300	5.761	5.769	1.954
2005	7	1.100	7.000	4.724	4.754	2.793
2006	21	1.510	8.905	5.936	5.908	2.089
2007	29	1.419	9.448	6.063	6.131	2.316
2008	46	1.439	8.065	6.274	6.337	3.827
2009	60	1.456	7.950	5.921	6.035	3.752
2010	55	1.269	8.164	4.318	4.355	1.899
2011	67	1.216	7.522	3.836	3.880	1.799
2012	76	1.263	8.421	3.194	3.226	1.829
2013	43	1.425	7.628	2.600	2.634	1.242

Table 1: Summary statistics for FISD bond data and yearly GZ spread.

Explanatory Variable	KMV	MVP	MLE
DD	0.032	0.035	0.043
	(0.670*)	(1.356**)	(1.197**)
PAR	0.112	0.109	0.106
	(5.023**)	(4.944**)	(4.709**)
CPN	0.879	0.852	0.849
	(6.719***)	(7.295***)	(6.960***)
AGE	0.026	0.026	0.026
	(5.114***)	(5.068***)	(4.915***)
$FIXED_{CREDIT}$	0.390	0.250	0.239
	(1.418)	(0.878)	(0.797)
$FIXED_{IND}$	0.107	0.079	0.146
	(0.593)	(0.436)	(0.814)

Table 2: Loading coefficients from a regressing $\log(S^{GZ})$ on DD and bond-specific characteristics with a sample of 533 bonds from 175 issuers from 2000: 2014. Standard deviations are clustered at the firm (i) and time (t) levels and used to calculate the reported t-statistics. KMV, MVP, and MLE methods of calculating DD are reported.

Financial Indicator	Forecast Horizon: 1 quarter				Forecast Horizon: 4 quarters			
Term Spread	-0.657	-0.557	-1.131	-0.751	-1.320	-1.161	-5.346	-2.101
	(-0.565*)	(-0.479*)	(-0.942**)	(-0.647*)	(-0.802**)	(-0.580*)	(-2.271***)	(-1.213**)
Real FFR	-0.953	0.905	-1.498	-1.079	-1.891	-5.533	-3.052	-2.632
	(-1.039**)	(0.493*)	(-1.514**)	(-1.174**)	(-0.976**)	(-0.542*)	(-2.415***)	(-1.653**)
CP-Bill Spread		-1.864				0.689		
		(-1.166**)				(0.159)		
Baa-Aaa Spread			-1.887				-6.184	
			(-1.389**)				(-2.138***)	
GZ Spread				-0.274				-1.494
				(-1.207**)				(-1.528***)
Adjusted R^2	0.486	0.493	0.512	0.486	0.386	0.392	0.386	0.448

Table 3: Coefficients of financial indicators used to predict real GDP for the sample period 2000 : 2014. An OLS regression was used on ${}^{h}Y_{t+h} = \frac{c}{h+1}\ln(\frac{Y_{t+h}}{Y_{t-1}})$, where h is the forecast horizon ($h = 1$ for one quarter and $h = 4$ for 4 quarters), c is a scaling constant (400 for one quarter and 100 for four quarters), and Y_t is the real GDP in quarter t. A lag length of $p = 1$ for the autoregressive component $\sum_{i=1}^{p} Y_{t-i}$ was determined using the Akaike Information Criterion (AIC) for both forecast horizons. Coefficients for the constant and autoregressive components are not reported as in Gilchrist and Zakrajsek (2012).

	Forecast Horizon: 1 quarter			Forecast Horizon: 4 quarters		
Financial Indicator	KMV	MVP	MLE	KMV	MVP	MLE
Term Spread	1.098	0.884	1.151	0.003	-1.662	-0.356
	(0.584*)	(0.469*)	(0.613*)	(0.001*)	(-0.760*)	(-0.134)
Real FFR	-0.588	-0.798	-0.510	-0.787	-1.205	-0.551
	(-0.408*)	(-0.539*)	(-0.350)	(-0.298)	(-0.730*)	(-0.255)
Predicted GZ spread	-1.044	-1.079	-1.023	0.212	0.116	0.054
	(-1.776***)	(-1.814***)	(-1.742***)	(0.181)	(0.145)	(0.051)
Excess Bond Premium	0.017	0.031	-0.012	-0.005	-0.521	-0.195
	(0.313)	(0.420*)	(-0.472*)	(-0.069)	(-1.854**)	(-0.824**)
Adjusted R^2	0.571	0.572	0.572	0.392	0.716	0.504

Table 4: Coefficients of financial indicators used to predict real GDP for the sample period 2000 : 2014. Three distance-to-default models were used to calculate the predicted GZ spread and excess bond premium: KMV-Merton (KMV), Market Value Proxy (MVP), and Transformed-Data MLE (MLE).An OLS regression was used on ${}^{h}Y_{t+h} = \frac{c}{h+1}\ln(\frac{Y_{t+h}}{Y_{t-1}})$, where h is the forecast horizon ($h = 1$ for one quarter and $h = 4$ for 4 quarters), c is a scaling constant (400 for one quarter and 100 for four quarters), and Y_t is the real GDP in quarter t. A lag length of $p = 1$ for the autoregressive component $\sum_{i=1}^{p} Y_{t-i}$ was determined using the Akaike Information Criterion (AIC) for both forecast horizons. Coefficients for the constant and autoregressive components are not reported as in Gilchrist and Zakrajsek (2012).

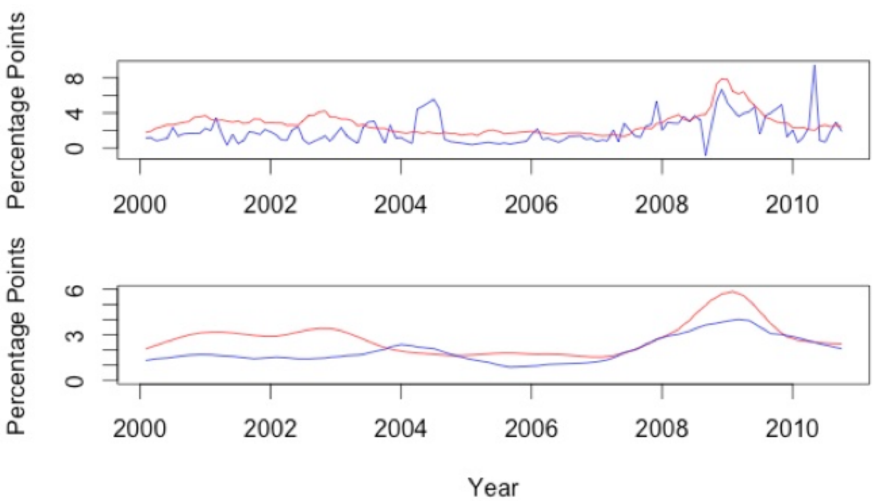

Figure 1: Calculated S_t^{GZ} (blue) versus actual S_t^{GZ} (red) from Gilchrist and Zabrajcek (2012). The top figure presents the raw data from both spreads. The bottom figure presents the isolated trend component from a seasonal trend decomposition into seasonal, trend, and residual components using a monthly frequency to define the seasonality.

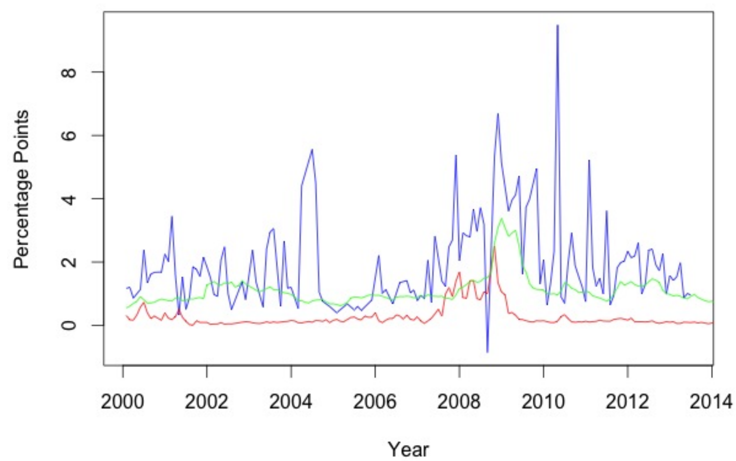

Figure 2: S_t^{GZ} (blue) versus the Baa-Aaa spread (green) and CP (Commercial Paper) spread (red).

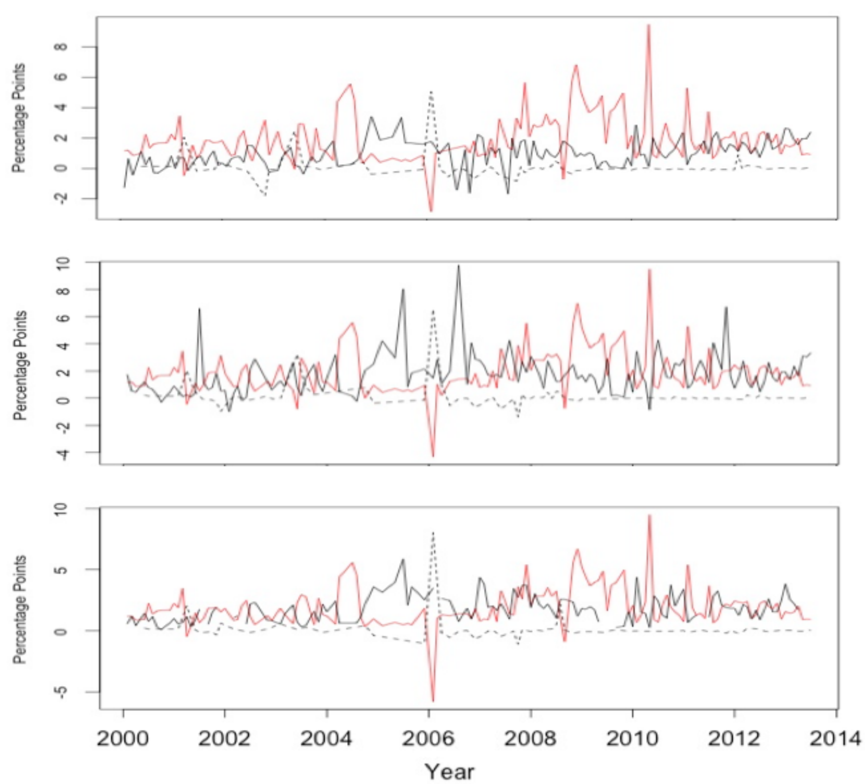

Figure 3: Distance to Default (black), the Expected Bond Premium (dotted black), and $\hat{S}_t^{GZ}$ (red). The top panel presents results from the KMV method of calculating distance-to-default, the middle panel presents results from the Market Value Proxy method, and the bottom panel presents results from the Transformed-Data MLE method.