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Do corporate credit spreads predict the real economy?

Ujjal Kanti Chatterjee, Flavio Bazzana [*]

Department of Economics and Management, University of Trento, Trento, Italy

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ABSTRACT

We evaluate whether corporate credit-spreads measures contain predictive information about the real U.S. economy in a comprehensive specification that includes financial sectors' profitability, stock and bond market. We find that corporate credit spreads contain no predictive information about U.S. real GDP or consumption and that corporate credit spreads have minimal information about forthcoming recessions. In comparison, the financial sector's profitability, the Treasury bond and stock market variables contain leading information about recessions, consumption and real GDP.

1. Introduction

The relationship between credit availability and economic growth is complex. While a well-functioning financial system and easy access to credit are traditionally seen as essential for economic growth, recent studies (e.g. Cecchetti & Kharroubi, 2019; Cecchetti, Mohanty, & Zampolli, 2011; Reinhart & Rogoff, 2010, among others) suggest that high levels of debt can hinder growth. One possible explanation, as indicated in the literature (Guérineau & Leon, 2019), is that the traditional link between increased credit availability and economic growth weakens as economies develop. In contrast, another strand of research focusing on advanced economies, suggests that credit spreads, which reflect the ease of obtaining credit, are important indicators of economic development, thereby suggesting a positive relationship between credit and economic growth. In this paper, we examine this aspect of the literature to investigate the opposing views on the relationship.

Corporate bond credit spreads, the difference in yields of corporate bond indices, are shown to be an essential predictor for economic growth (e.g. Gertler & Lown, 1999; Mody & Taylor, 2004).[1] The literature finds mixed evidence that the traditional measure of corporate bond credit spreads, typically measured as the difference in yields of Moody's Aaa and Baa rated bond indices, predict real economic activities (e.g. Gilchrist & Zakrajšek, 2012; Næs, Skjeltorp, & Ødegaard, 2011; Stock & Watson, 2003, GZ hereafter). However, Moody's bond indices' traditional measure of corporate credit spreads suffers from many measurement issues.[2]

* Corresponding author.
E-mail addresses: ujjal.chatterjee@unitn.it (U.K. Chatterjee), flavio.bazzana@unitn.it (F. Bazzana).

[1] A large body of literature investigates the predictive information of financial variables about real economic activities. A partial list of financial variables used in the literature include stock prices (Fama, 1981); spreads between long- and short-term risk-free interest rates (Estrella & Hardouvelis, 1991; Estrella & Mishkin, 1995, 1998); spreads between rates on short-term commercial paper and rates on Treasury bills (Friedman & Kuttner, 1992, 1998); and yield spreads on longer-term corporate debt (Faust, Gilchrist, Wright, & Zakrajšsek, 2013; Gertler & Lown, 1999; Gilchrist, Yankov, & Zakrajšek, 2009); and for the euro area by Gilchrist and Mojon (2018) and Bleaney, Mizen, and Veleanu (2016). Clark and Kassimatis (2015) investigate macroeconomic effects on emerging-markets credit spreads.

[2] For instance, the traditional credit-spread measures use Moody's bond indices, which contain bonds with (i) a mix of seniorities; (ii) a mix of maturities; (iii) a mix of coupon rates; (iv) include callable bonds; (v) stale ratings, etc.

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To address the measurement issues with the traditional corporate bond credit spreads and the diverging views about its predictive power for economic activities, the literature (e.g. Gilchrist et al., 2009, GZ) propose market-based expected default-risk measures of corporate credit spreads. GZ and Faust et al. (2013) show that the GZ measures of credit spreads, namely, GZS and EBP, contain predictive information about real economic activities in the U.S. – an expansion in GZS and EBP results in economic contractions.[3] Adopting the GZ approach, Bleaney et al. (2016) show that the U.S. results hold in eight European economies. It is puzzling that the conclusions drawn on the role of corporate bond credit spreads and the supply of credits to explain economic growth in developed economies differ in two strands of the literature.

The strand of the literature investigating GZ measures of credit spreads does not investigate stock market variables such as bid–ask spreads as leading indicators of the real economy. GZ further argue that corporate bond market activities spill over to the stock market through the financial intermediary's profitability, affecting the real economy. GZ do not investigate the possibility of reverse causality from stock to corporate bond markets and the real economy.

The literature (e.g. Stock & Watson, 2003) argues that financial indicators, including traditional corporate bond credit spreads, are unstable predictors of economic growth. Næs et al. (2011) further show that stock market variables rather than the conventional corporate bond credit-spreads measure is a robust leading indicator of economic growth. This strand of the literature needs to investigate GZ corporate credit-spread measures or the financial sector's profitability. This paper endeavours to fill the literature gap by investigating whether GZ credit spreads and stock market variables such as bid–ask spreads are essential indicators of economic growth.

Why both bond and stock trading activities may lead economic indicators could be better explained by the financial intermediation process.[4] Fluctuations in the credit market sentiment could affect the real economy through the changes in the credit supply that financial intermediaries provide. Financial intermediaries act as marginal investors (e.g. Adrian, Etula, & Muir, 2014; He & Krishnamurthy, 2013), and they participate in a wide range of financial markets. The 2007–2009 economic meltdown has shown that intermediaries in financial distress are unwilling or unable to provide new credits, thereby hindering future economic growth. This line of arguments on the role of credit market conditions on economic growth is consistent with the financial accelerator mechanism (Bernanke & Gertler, 1989; Bernanke, Gertler, & Gilchrist, 1999; Kiyotaki & Moore, 1997). However, intermediaries trade both in the bond and stock markets and hence, stock market sentiments may affect the bond market and the real economy.

GZ argue that the lower profitability of financial intermediaries, such as securities brokers and dealers, leads to a "credit crunch" as evidenced in an expansion of EBP and a fall in stock market returns. While the GZ argument is consistent with the financial accelerator mechanism, they do not investigate whether stock market variables such as bid–ask spreads affect financial intermediaries' profitability. For instance, stock market bid–ask spreads represent financial intermediaries such as securities brokers and dealers' inventory costs of holding stocks (e.g. Bollen, Smith, & Whaley, 2004), which may drive financial intermediaries' profitability. To understand the financial accelerator mechanism better, one may investigate how the bond and stock markets affect financial intermediaries' profitability. Thus, another objective of this paper is to examine whether the stock market affects financial intermediaries' profitability.

After accounting for the stock market and the Treasury bond market variables, we find that corporate credit-spread measures have limited information about the real economy. These results are consistent with the findings in Stock and Watson (2003) that financial variables are unstable predictors of economic activities. We show the GZ measures of corporate credit spreads are also one of those measures that cannot predict real GDP or recessions.

We further find that GZ spreads lead to investments rather than consumption. This partially explains why GZ measures contain no information about real GDP.[5] This is what we expect to see in advanced economies such as the U.S. because U.S. consumption as a percentage of GDP in the sample rose from about 64% to 72%. In contrast, the Treasury bond market, as captured in the Treasury term spread and, to a lesser extent, stock market variables, contains leading information about consumption, real GDP, and recessions.

Our results also show that the U.S. financial sectors' return on assets and securities brokers and dealers stock returns are best predicted by a contraction in stock market bid–ask spreads. We find that stock market bid–ask spreads explain broker and dealers' CDS spreads of different maturities. The informativeness of stock market bid–ask spreads about financial sectors' profitability could be described as follows. Since stock bid–ask spreads are known to capture traders' inventory costs, an expansion in stock market bid–ask spreads leads to lower profitability of securities brokers and dealers and profitability of financial sectors. In addition, EBP has a lower impact on financial sectors' return on assets than that of stock market bid–ask spreads. We further find stock market variables that lead to corporate credit-spread measures and explain over 90% of some of the credit-spread measures.

The economic interpretation of our results is that U.S. stock and the Treasury bond market are the two most liquid financial markets globally. Hence, the trading patterns in these two markets are more informative about the future state of the U.S. economy

[3] The GZ corporate bond spread is a synthetic spread defined as the difference between corporate senior unsecured bond yields and yields of a synthetic bond constructed as the present value of the corresponding corporate bond coupons and principal discounted at the risk-free rates.

[4] Related literature (e.g. Bencivenga, Smith, & Starr, 1995; Levine, 1991; Levine & Zervos, 1998) contends banks along with a liquid stock market allow investors to participate in productive long-term projects, thereby stimulating economic growth. The literature (e.g. Næs et al., 2011) further argues that stock prices reflect the present value of future earnings, and hence the forward-looking stock prices must reflect future earnings growth potential. As a direct consequence, stock market returns, volatility, and liquidity contain leading information about the real economy (e.g. Beber, Brandt, & Kavajecz, 2011; Næs et al., 2011, among others).

[5] We do not conduct out-of-sample analysis since if corporate credit spreads are unrelated to real GDP in-sample, there is no need for an out-of-sample analysis.

than the corporate bond market. For instance, a sharp decline in stock market returns may affect the real economy through reduced discretionary consumption.

Our contributions to the literature are as follows. First, we demonstrate that corporate credit spreads, whether traditional or proposed in GZ, may not predict real GDP, consumption, or recessions robustly. Although an expansion (contraction) in credit spreads does reduce (increase) business investments, this change in investments is not reflected in real GDP, as consumption is the most significant contributor to GDP.

Second, we introduce several important variables into our analysis, including intermediary profitability, bond, and stock market indicators, which previous studies like GZ did not include. While GZ took an essential step in accurately computing corporate credit spreads, the results in this paper demonstrate that simple and direct measures of stock market variables, such as returns and bid–ask spreads, may offer more information about the real economy. Importantly, we show that synthetic GZ corporate credit-spread measures can be explained by readily available and computationally simpler stock market variables.

The remainder of the paper is organised as follows. Section 2 briefly notes how the GZ credit spreads are computed. Section 3 describes data. Section 4 conducts empirical analysis. Section 5 concludes.

2. GZ corporate credit-spreads measures

GZ propose an innovative measure of corporate credit spreads. The traditional measure of corporate credit spreads, the difference in yield on Moody's Aaa and Baa-rated corporate bonds, suffers from measurement issues. For instance, Moody's measure of yields on corporate bonds includes bonds of all maturities, coupon rates and seniorities. By contrast, GZ restrict their sample to non-financial senior unsecured bonds. GZ use each bond's Treasury yield curve to construct a synthetic default-free bond with the same promised cash flows. They define credit spread $S_{it}[k]$ of bond k (issued by firm i) as the spread between the yield to maturity of bond k (YTM_k) and the yield of the corresponding synthetic default-free bond.

The GZ spread (GZS in this paper) is the cross-sectional average of $S_{it}[k]$ of risky unsecured bonds issued by firms in the sample. Specifically, the GZ spread is defined as follows:

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

where N_t denotes the number of bonds in month t and $S_{it}[k]$ is the synthetic credit spread of bond k of firm i in month t.

Since GZ use senior unsecured bonds from the universe of bonds, the bond portfolio created per Eq. (1) may not constitute the market portfolio. Thus, fluctuations of yields of a sample of bond prices may not be a systematic risk. By contrast, systematic stock market variables may explain the GZ bond portfolio created above as per the asset pricing literature.

Next, GZ decompose the GZS into two components: a component that accounts for the systematic movements in default risk of individual firms and a residual component: the excess bond premium (EBP), which is the cross-sectional average of the error term in the following regression

$$\ln\left(S_{it}[k]\right) = \beta\ \mathrm{DFT}_{it} + \gamma Z_{it}^k + \epsilon_{it}^k \tag{2}$$

where DFT is a firm-specific measure of expected default, and Z is a vector of bond-specific characteristics. GZ show that GZS and EBP have important macroeconomic interpretations, and those credit spreads predict real economic activities: an expansion in GZS and EBP may signal economic contractions. As per Eq. (1), duration mismatch remains an issue with the GZ measure since all unsecured bonds of different durations are in the GZ bond portfolio. Hence, EBP, as per Eq. (2), inherits the same duration mismatch property of GZS.

3. Data

We endeavour to restrict our sample to GZ and conduct most of our analyses based on the data available on the American Economic Review website for the 1973:Q1-2010:Q3 sample. We make use of both the quarterly and monthly GZ data. The variables that are part of the original dataset are CREDIT, measured as the difference in yields of Moody's Aaa and Baa rated bonds; real FFR, the real Federal funds rate; TERM, the Treasury term-spread; real GDP, consumption, investments; excess stock returns of securities brokers and dealers (XRET_BD); returns on assets of the U.S. financial corporate sector (ROA_FS); S&P500VIX, which is VIX (the Chicago Board Options Exchange volatility index); CDS5YR_BD_Avg, CDS1YR_BD_Avg are securities brokers and dealers 5-year and 1-year CDS spreads, respectively. A detailed description of the above variables can be found in the GZ paper. The variable's definitions are described in Table 1.

We altered some of the descriptions of the variables in the dataset, such as TERM and CREDIT, for better exposition. We further had to change the TERM sign in the original dataset; TERM is supposed to be generally positive since it is defined as the difference in yields between 10-year and 3-month Treasury bonds. However, before recessions, TERM turns negative as per the literature (e.g. Estrella & Hardouvelis, 1991). In the GZ dataset, TERM is generally negative and turns positive before recessions.

We augment the dataset with stock and bond market variables. Those variables are quarterly and monthly equally-weighted stock market excess returns (referred to as XMRET) and stock market volatility (referred to as VOL_XMRET) using the stock market data obtained from CRSP (the Center for Research in Security Prices) of virtually all stocks. In most of our analysis, we do not use the stock market excess returns data found in the GZ dataset since it has some issues. For instance, the GZ dataset excess market returns for 1971:Q1 is 38.4%, which is untrue. However, we use stock market returns data from the GZ dataset to ensure robustness.

Table 1
Variables definitions.

Variable	Definition
CREDIT	The difference between Moody's AAA and BAA rated bond yields
VOL_CREDIT	Volatility of CREDIT
EBP	Excess Bond Premium, U.S. Corporate Bond Credit Spreads (Gilchrist & Zakrajšek, 2012)
GZS	Alternative Measure of U.S. Corporate Bond Credit Spreads (Gilchrist & Zakrajšek, 2012)
XMRET	Stock Market Excess Returns
VOL_XMRET	Volatility of XMRET
dVOL_XMRET	First difference in Volatility of XMRET
PSPR	SP500 Stock market bid–ask Spreads, which measures the Illiquidity of the stock market
dGZS	The first difference of GZS
Real FFR	Real Federal Funds Rate
TERM	Term Spread, the difference in 10-year and 3-months U.S. Treasuries yields
dINVEST	Log difference of business investment (INVEST)
dCONS	Log difference of personal consumption expenditures (CONS)
dGDP	Log difference of U.S. real GDP (GDP)
Recession	NBER recession binary indicator variable
ROA_FS	Returns on assets of the U.S. financial corporate sector
S&P500VIX	CBOE (Chicago Board Options Exchange) Volatility Index
XRET_BD	Brokers and Dealers Average Excess Stock Returns
CDS5YR_BD_AVG	Average Brokers and Dealers 5 Year Credit Default Swap spread
CDS1YR_BD_AVG	Average Brokers and Dealers 1 Year Credit Default Swap spread

This table describes the variables used in the analysis. The data source is described in the data section (Section 3).

Table 2
Pairwise correlations.

	GZS	EBP	XMRET	VOL_CREDIT
EBP	0.66***			
XMRET	−0.23***	−0.29***		
VOL_CREDIT	0.38***	0.56***	−0.25***	
PSPR	0.69***	0.64***	0.27***	0.46***

This table presents correlations between the variables of interest. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Quarterly sample 1973:Q1-2010:Q3.

We further compute stock market normalised bid–ask spreads (PSPR) using the CRSP data. Following the literature (e.g. Chordia, Roll, & Subrahmanyam, 2001; Chordia, Sarkar, & Subrahmanyam, 2005; Næs et al., 2011) PSPR is computed as follows:

It is the ratio of the bid–ask spreads to the midpoint price of a security and is represented as relative or proportional spreads (PSPR). For a stock i, on date t, PSPR, which measures stock illiquidity, is computed as:

$$\mathrm{PSPR}_{i,t} = \frac{\left(\mathrm{price}^{\mathrm{ask}} - \mathrm{price}^{\mathrm{bid}}\right)_{i,t}}{0.5 \times \left(\mathrm{price}^{\mathrm{ask}_{\mathrm{highest}}} + \mathrm{price}^{\mathrm{bid}_{\mathrm{lowest}}}\right)_{i,t}} \tag{3}$$

Consistent with the literature (e.g. Chordia et al., 2001, 2005, among others), we consider stocks that have a share price of more than \$5 and less than \$1000; additionally, stocks must be traded for 20 days in a month to be included in our sample. We first calculate the PSPR of each stock each trading day. Next, we estimate an equally weighted cross-sectional average PSPR of all stocks to measure monthly and quarterly aggregate stock market PSPR.

Note that PSPR measures aggregate stock market illiquidity. While there are other measures of stock market liquidity, such as stock market depth, we concentrate on PSPR since bid–ask spreads are known to capture traders' inventory costs (e.g. Bollen et al., 2004). One of our goals in this paper is to investigate the relationship between securities brokers and dealers' profitability and the inventory costs of holding securities.

We include the National Bureau of Economic Research (NBER) recession indicator from the Federal Reserve Bank of St. Louis. Finally, we use the volatility of CREDIT denoted as VOL_CREDIT to investigate whether volatility rather than the level of CREDIT is an indicator of future business cycles. We use weekly CREDIT data to find the quarterly volatility of CREDIT.

We conduct ADF (Dickey & Fuller, 1981) unit-root tests in conjunction with KPPS (Kwiatkowski et al., 1992) stationarity tests to ascertain that the variables are stationary. We find that GZS may not be stationary; hence, the first GZS (dGZS) difference is used in some of our analyses. We further investigate the first EBP (dEBP) difference to be consistent with the GZS transformation. We take the first difference of non-stationary variables for other micro variables to attain stationarity wherever required. Transformation of macro variables is done as per the practice in the literature. For example, dGDP is the log difference of real GDP. To differentiate between the transformed and untransformed data, we use the prefix "d" to identify the transformed variable.

Table 2 presents pairwise correlations between variables, and it shows that GZS and EBP are correlated with stock market variables, and those correlations are statistically significant, at least at the 1% level. Since PSPR positively correlates with the GZ measures, the results suggest that if PSPR increases (aggregate stock market bid–ask spreads rise), the GZ corporate credit spreads rise. This is what we expect to see since PSPR measures stock market illiquidity, and the GZ spreads capture negative states of the economy. Since stock volatility and liquidity move together (the correlation between VOL_XMRET and PSPR supports the relationship), stock market volatility positively relates to the GZ measures. The correlation results further suggest that XMRET is inversely related to EBP and GZS, consistent with GZ's argument. With rising volatility and liquidity, stock market returns should fall; a negative correlation between XMRET and the other two stock market variables confirms the relationship.

4. Empirical results

In this section, we present the empirical results. First, we show how credit spreads can predict the real economy in the presence of a set of control variables discussed above. Section 4.2 presents how Financial Intermediaries' Profitability is predicted using stock and bond market indicators. Section 4.3 presents the results for forecasting recessions using the indicators, and Section 4.4 investigates the relationship between GZ-spread and stock market variables.

4.1. Credit-spread, stock market, and the real economy

GZ and Faust et al. (2013) show that the GZ credit spreads predict real economic activities, such as real GDP. GZ and Faust et al. (2013) do not consider stock market variables in their analysis. This section investigates whether the GZ measures can predict real economic activities after controlling for stock market variables.

Except for the stock market variables, the independent variables are almost identical to the GZ specifications, where the term spread (TERM) and the real Federal funds rate (Real FFR) are the primary predictor variables. We further investigate the volatility of the traditional measure of corporate credit spread (VOL_CREDIT) as another indicator. Table 3 reports the results for the speciation where the log difference of real GDP (dGDP) is the dependent variable for one quarter prediction horizon using the following predictive regression:

$$X_t = \alpha + \beta X_{t-1} + \gamma C_{t-1} + e_t \tag{4}$$

where X is dGDP (or dCONS or dINV), the log difference of real GDP (consumption or investment), and C is a vector of predictor variables that include TERM, Real FFR, stock market variables and the GZ measures. The baseline model is that the dependent variable predicts itself. We investigate various models, and the most important results are shown for parsimony.

Looking from the left in Table 3, Model 1 shows that GZS is not a good predictor for real GDP growth if we only consider stock market variables and VOL_CREDIT. Since GZS has a unit root, we next investigate the first difference between GZS (dGZS) and other predictors that GZ use. Model 2 shows that dGZS weakly predicts dGDP, while TERM and XMRET predict dGDP. Models 3 and 4 show the same pattern, where EBP does not have any leading information about future dGDP. Treasury bonds and stock market variables have information about real GDP. In all models, however, volatility of corporate credit (VOL_CREDIT) has some information about dGDP.

In Table 3, we investigate whether GZS and EBP predict consumption and investment growth. Since consumption is a significant part of GDP (about 70% since 2000), a variable that predicts consumption would most likely predict GDP.

Looking at Models 5 and 6 consumption, we observe that none of the GZ corporate credit spread measures contains information about future consumption except for TERM and stock market variables. Looking at Models 8 through 10, we observe that dGZS, EBP and PSPR predict investments, and the results support the findings in GZ. As a further robustness check, we consider CREDIT, the traditional corporate credit-spread measure, instead of the GZ measures and the other predictor variables. The results show that CREDIT has no predictive power for real economic indicators, and PSPR contain some information about investments, consistent with the results reported in GZ and Næs et al. (2011). However, Næs et al. (2011) does not consider the GZ measures, and GZ do not consider aggregate stock market variables such as stock market bid–ask spreads in their analyses.

Recession states, credit spread, and the real economy

Next, we investigate whether the expansion of credit spreads is just a one-time recessionary event and can be explained away by the recession "state" of the economy. This is an essential issue since predictive information of micro-variables, such as corporate credit spreads, may be episodic (see, e.g. Stock & Watson, 2009, among others). We hypothesise that if we control for recession binary variable, credit spreads have no information about the future states of the economy because the information in credit spreads is captured by the "state" of the economy. The recession "state" captures many unobserved and observed variables besides corporate credit spreads.

We use a predictive regression, where the dependent variable is dGDP (or dCONS or dINV), and the independent variables are TERM, Real FFR, EBP, ROA_FS and XMRET. We use an additional predictor variable, "Recession" the NBER recession binary indicator. Formally,

$$X_t = \alpha + \beta X_{t-1} + \gamma C_{t-1} + \mu \,\mathrm{Recession}_{t-1} + e_t \tag{5}$$

We endeavour to make minimal changes to the GZ dataset; hence, the choice of the variables is parsimonious relative to the models we used in Eq. (4). We further use the GZ original XMRET in the dataset to ensure our computation of XMRET does not drive the results. We use EBP since GZ argues that EBP is a more precise measure of corporate credit spreads. The results are presented in Table 4.

Table 3
Economic activities and credit-spreads.

	Model 1a	Model 1b	Model 1c	Model 1d	Model 1	Model 2	Model 3	Model 4
GZS (×1000)	−0.14**				−0.33			
dGZS (×1000)						−1.33*		
EBP (×100)		−0.43***					0.15	
CREDIT (×100)								0.16
XMRET			0.03***		0.02**	0.01**	0.01**	0.01**
PSPR					−0.13	−0.12	−0.10	−0.19***
VOL_XMRET					−0.20	−0.05	−0.12	−0.10
VOL_CREDIT					−0.02**	−0.02***	−0.02**	−0.03***
TERM (×100)				0.14***		0.10***	0.11***	0.09**
Real FFR (×100)						0.01	0.01	0.02
Adj. R-Squared	0.16	0.18	0.21	0.19	0.24	0.27	0.27	0.29

(a) Real GDP growth and Financial Indicators (Quarterly Data)

	dCONS			dINVEST		
	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
dGZS (×1000)	0.03			−0.01***		
EBP (×1000)		−0.05			−1.76***	
CREDIT(×100)			0.23			−0.49
XMRET	0.03***	0.03***	0.02***	0.02	0.00	0.02
PSPR	−0.52***	−0.47***	−0.51***	−0.69	−0.53	−0.92***
dVOL_XMRET	−0.69***	−0.69***	−0.62***	0.28	−0.07	0.02
VOL_CREDIT	−0.01	−0.01	−0.01*	−0.01	0.01	0.00
TERM(×100)	0.11***	0.11***	0.09***	0.09	0.15	0.09
Real FFR	0.01	0.01	0.01	0.01	0.01	0.01
Adj. R-Squared	0.27	0.31	0.32	0.41	0.44	0.41

(b) Consumption and Investment and Financial Indicators (Quarterly Data)

This table shows the relationship between financial and economic indicators using the predictive regression $X_t = \alpha + \beta X_{t-1} + \gamma C_{t-1} + e_t$, where X is dGDP (or dCONS, dINVEST), C is a single predictor/a vector of predictors. Panel (a) presents the result for the dependent variable dGDP; for parsimony, results for all single predictors are not shown. Panel (b) presents the results for one of the following dependent variables: dCONS or dINVEST; variables are described in Table 1. Errors are corrected for heteroscedasticy adjustments. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. For parsimony, only the coefficients of γ are reported. We further control for seasonality. Quarterly data 1973:Q1-2010:Q3.

Table 4
Economic growth, credit-spreads, and recessions.

	dGDP				dCONS	dINVEST
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
TERM (×100)	0.11***	0.09*	0.10**	0.10**	0.18**	0.07
Real FFR (×100)	−0.01	−0.01	−0.01	−0.01	0.01	0.01
XMRET(×1000)	0.04***	0.03***	0.04**	0.03*	0.05***	0.02
EBP (×1000)	−3.68***		−1.41	−0.39	−0.44	−16.35***
ROA_FS (×100)				0.27**	0.28**	0.81
Recession (×100)		−0.84***	−0.87***	−0.84***	−0.40***	−0.35***
Adj. R-Squared	0.25	0.34	0.34	0.35	0.28	0.51

This table shows the relationship between financial and economic indicators using the predictive regression $X_t = \alpha + \beta X_{t-1} + \gamma C_{t-1} + \mu$ Recession$_{t-1} + e_t$, where X is dGDP (or dCONS, dINVEST); "Recession" represents the NBER recession indicator variable; variables are described in Table 1. Errors are corrected for heteroscedasticy adjustments. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. For parsimony, only the coefficients of γ and μ are reported. We further control for seasonality. Quarterly data 1973:Q1-2010:Q3.

Looking from the left, the results in Table 4, Model 1 show that TERM, XMRET, and EBP contain predictive information about dGDP. Next, in Model 2, we use a specification that omits EBP but includes "Recession" as an explanatory variable. The coefficient of "Recession" is negative and statistically significant at the 1% significance level. We expect that the recession binary must be negatively related to dGDP. While in this specification, we have omitted EBP, the adjusted R-sq. is higher than the previous model with EBP. EBP has less information about dGDP than a "Recession" binary indicator. Looking at the results in the next column in Model 3, where we have all four explanatory variables, we find that EBP contains no information about real GDP. Still, XMRET and TERM continue to be significant predictors. Importantly, comparing the adjusted R-Sq. values of Models 2 and 3, which are 34%, we find no additional information in the extended model containing EBP. We find evidence that the "Recession" indicator encompasses information contained in EBP.

Since GZ argue that financial sectors' profitability is related to economic growth, in Model 4, we include ROA_FS, returns on assets of the U.S. financial corporate sector, as an additional predictor—the results in Model 4 show that, indeed, ROA_FS is positively related to dGDP. While XMRET and TERM remain indicators of future GDP, EBP contains no information.

Table 5
Vector-autoregression results for Broker and Dealers' stock returns and CDS spreads.

	PSPR	S&P500VIX	XMRET	XRET_BD	CDS5YR_BD_AVG	CDS1YR_BD_AVG	EBP
PSPR(−1)	0.34**	2.74***	−4.49***	−10.98***	0.07	0.07	0.14*
PSPR(−2)	0.36**	0.10	0.06	0.89	−0.01	0.02	0.05
PSPR(−3)	0.20	2.16**	−2.74***	−4.38**	0.04	0.07	0.05
Adj. R-Squared	0.88	0.89	0.43	0.40	0.94	0.92	0.91

This table shows the coefficient estimates of selected variables for the VAR(3) model, which is represented as $y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 y_{t-3} + e_t$, where y is a vector of endogenous VAR variables: PSPR, S&P500VIX, XMRET, XRET_BD, CDS5YR_BD_Avg, CDS1YR_BD_Avg, and EBP; variables are described in Table 1. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Monthly sample 2003:M1-2010:M9.

Looking next in Model 5, where dCONS is the dependent variable, we find EBP contain no information about consumption. However, the results in the next column in Model 6 show that EBP includes investment information, consistent with the GZ results and our earlier findings. In summary, while ROA_FS, TERM and XMRET contain real GDP and consumption information, EBP includes no information.

Thus, we find another piece of evidence that corporate credit spreads do not contain leading information about real GDP or consumption if we control for recessions. The results thus suggest that information about future economic growth in EBP can be explained away by the recession state of the economy, thereby indicating expansions in EBP may be a one-time recessionary event.

4.2. Financial intermediaries' profitability and stock market activities

GZ argue that lower profitability of brokers and dealers (B&D) leads to an immediate increase in their near- and longer-term CDS spreads, and the effect on B&D CDS spreads is persistent. GZ state that this persistence in investors' sentiment leads to a sustained increase in EBP and the 1-year B&D CDS spread, possibly the most accurate market-based indicator of the near-term default risk of the financial sector. GZ further argue that the lower profitability of securities brokers and dealers leads to a fall in stock market returns.

Thus, we revisit the GZ analysis with the GZ monthly dataset, as in GZ, from 2003:M1 to 2010:M9 and with the quarterly dataset from 1973:Q1 to 2010:Q3. We augment the GZ dataset with the stock market variables. As in GZ, we include B&D stock returns (XRET_BD) and the U.S. financial sector's return on asset (ROA_FS) as financial intermediaries' profitability measures and investigate to what extent financial intermediaries' profitability is impacted by stock market bid–ask spreads.

Following GZ, we investigate a VAR model with the following endogenous variables: PSPR, S&P500VIX, XMRET, XRET_BD, CDS5YR_BD_Avg, CDS1YR_BD_Avg, and EBP, where S&P500VIX is VIX (CBOE volatility index); XRET_BD is B&D excess stock returns; CDS5YR_BD_Avg, CDS1YR_BD_Avg are B&D 5-years and 1-year CDS spreads, respectively. Except for PSPR, the ordering of the variables is as per GZ. Alternative orderings of PSPR, such as placing PSPR as the last variable, do not change our conclusions. Hence, we present the results with the order mentioned above.

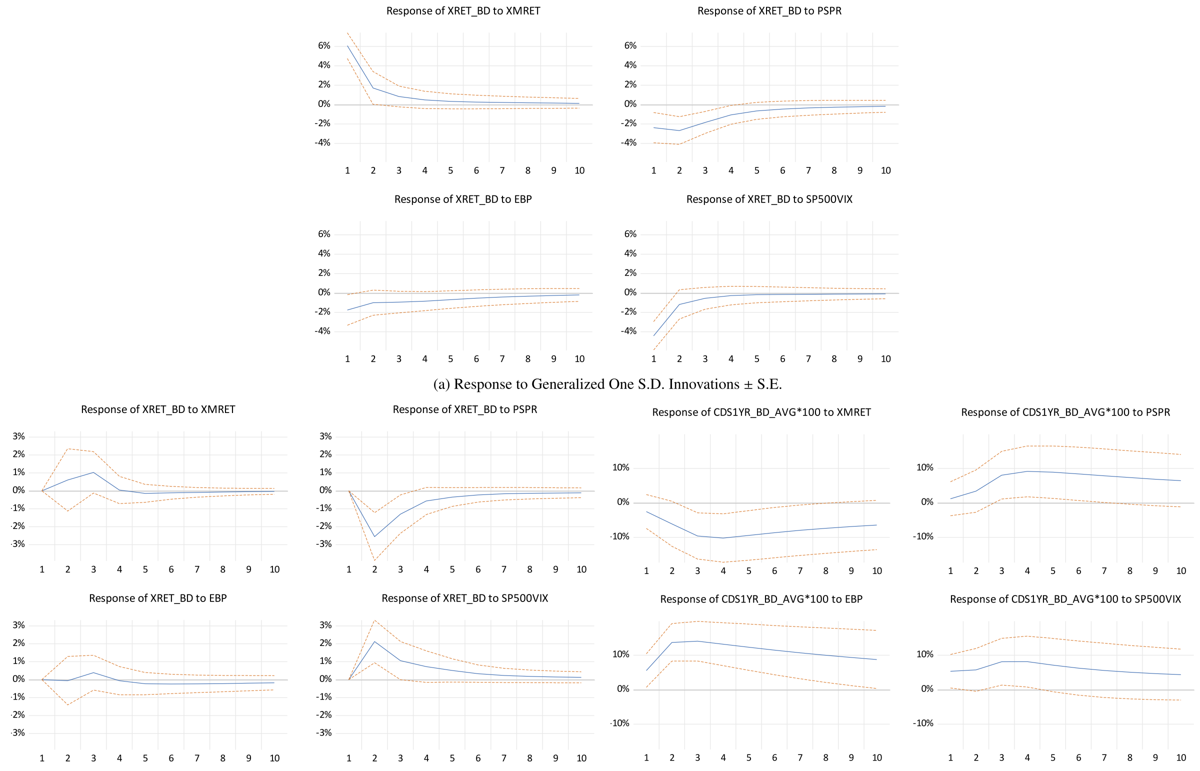
Following GZ, we use three months lags of each endogenous variable in a VAR (3) specification, which is represented as the following model:

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 y_{t-3} + e_t \tag{6}$$

where y is a vector of endogenous VAR variables: PSPR, S&P500VIX, XMRET, XRET_BD, CDS5YR_BD_Avg, CDS1YR_BD_Avg, and EBP. The corresponding results in Table 5 show that PSPR is related to XRET_BD for up to three months lags at the 1% level of statistical significance. The results show that PSPR is one of the primary drivers of XRET_BD; an increase in PSPR reduces B&D stock returns. The result is consistent with the observation made in Bollen et al. (2004) that as the market maker's inventory costs as measured by stock market bid–ask spreads rise, B&D profitability falls. Similarly, we observe that PSPR drives XMRET and S&P500VIX. The coefficient estimates of other variables are not reported for parsimony.

Having shown that stock market bid–ask spreads drive B&D stock returns, we next investigate the impulse responses of XMRET and XRET_BD to PSPR (and other) shocks. The ordering of the VAR variables is a concern under Cholesky shocks. Thus, we investigate generalised impulse responses (Pesaran & Shin, 1998), which do not depend on the ordering of variables, as per the literature (e.g. Chordia et al., 2005). We show the impulse responses for both Generalised and Cholesky orthogonalised shocks to ascertain that the results are robust to the ordering of the VAR variables.

The generalised response functions of XRET_BD to different shocks are shown in Fig. 1(a). For one standard deviation, a positive shock of XMRET in the present month increases XRET_BD by about 6% points next month. In contrast, EBP and PSPR shocks of similar magnitude reduce XMRET_BD by about 2%, which is consistent with the fact that both EBP and PSPR represent negative states of the bond and stock markets, respectively. However, S&P500VIX, while capturing the adverse conditions of the stock market, has a higher impact on XMRET_BD. That is, stock market variables negatively affect brokers and dealers' stock performance more significantly. Fig. 1(b) shows the Cholesky responses of XRET_BD to PSPR and XMRET shocks, and the results are qualitatively similar to that of the generalised PSPR shocks. By contrast, the impulse responses show that S&P500VIX shocks impact XRET_BD positively, and the impulse response is counterintuitive. This is why ordering the VAR remains an issue under Cholesky shocks, and we prefer generalised impulse responses.



(a) Response to Generalized One S.D. Innovations ± S.E.

(b) Response to Cholesky One S.D. Innovations ± S.E.

(c) Response to Generalized One S.D. Innovations ± S.E.

Fig. 1. Impulse Responses of Brokers and Dealers Stock Returns and CDS Spreads.
This figure shows the impulse responses of XMRET and XRET_BD to PSPR shocks, where the endogenous VAR variables are: PSPR, S&P500VIX, XMRET, XRET_BD, CDS5yr_BD_Avg CDS1yr_BD_Avg and EBP. Variables are described in previous tables. Fig. 1(a) shows the Generalised impulse (Pesaran & Shin, 1998), which does not depend on the ordering of the variables and responses. Fig. 1(b) shows the Cholesky impulse responses for robustness. For parsimony, responses of XMRET and XRET_BD to PSPR shocks are shown. Fig. 1(c) shows the generalised impulse response of brokers and dealers CDS spreads to different shocks; for parsimony, CDS1yr_BD_Avg is shown since CDS5yr_BD_Avg responses are qualitatively similar. Responses are shown in % point. Monthly sample 2003:M1-2010:M9.

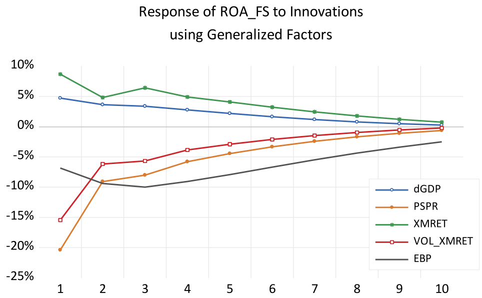
Looking next at Fig. 1(c), we find that one standard deviation positive generalised XMRET and EBP shocks in the present month impacts CDS1YR_BD_Avg by about 10% points next month. Other stock market variables have a qualitatively similar effect. Thus, the analysis above shows that corporate bonds and stock markets affect brokers and dealers' returns, consistent with our argument that corporate bonds and stock markets are essential for intermediaries.

Since XMRET_BD is a stock market-based measure of intermediary profitability, we investigate whether the accounting measure of profitability computed by the U.S. financial sector's return on asset (ROA_FS) relates to stock market variables. Since the corresponding 1973–2009 dataset is quarterly, we can include dGDP in our analysis. Including dGDP better specifies the VAR model since dGDP could account for unobservable factors and the states of the economy that may affect intermediary profitability.

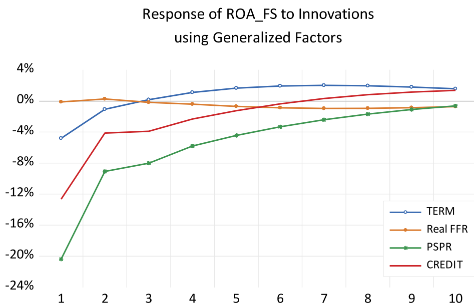
Thus, we use the following endogenous VAR(1) variables: dGDP, ROA_FS, Real FFR, TERM, VOL_XMRET, PSPR, XMRET and EBP. Since the ordering of the variables may be a concern, we report the responses of ROA_FS to different shocks in Fig. 2(a). To save space, we show the dynamic responses in one plot. We further do not show the standard errors of the responses for better comparability of the response functions. The impulse responses show that one standard deviation positive PSPR shocks in the present quarter contracts ROA_FS by approximately 20% point next quarter. This impact is higher than the impact of other shocks on ROA_FS. For instance, EBP reduced ROA_FS by about 10% points.

We replace EBP with CREDIT in the VAR(1) specification to ensure robustness. The corresponding responses of ROA_FS to CREDIT and other shocks are shown in Fig. 2(b). The response functions show that our conclusions about PSPR do not change whether CREDIT or EBP is used to measure corporate credit spreads. Comparing the responses in Figs. 2(a) and 2(b), we find that the approximately 12% point impact of CREDIT on ROA_FS is higher than that of EBP. Thus, using the quarterly and monthly results using two different measures of intermediary profitability (ROA_FS and XRET_BD), we find that stock market bid–ask spreads may be one of the primary drivers of financial intermediaries' profitability. Thus, the overall results indicate that PSPR is an essential indicator for intermediary profitability.

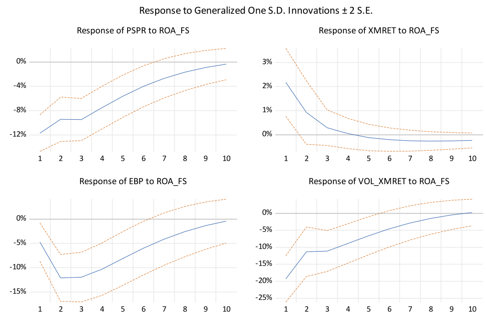
In Fig. 2(c), we show responses of stock and bond market variables to one standard deviation positive ROA_FS generalised shocks. We find that XMRET (EBP) are positively (negatively) impacted by ROA_FS shocks, and the results are consistent with the GZ results. The profitability of financial sectors affects both the bond and stock market. We also observe that positive ROA_FS shocks reduce



(a) Corporate Credit-Spreads Measure is EBP.



(b) Corporate Credit-Spreads Measure is CREDIT.



(c) Response of Financial Variables to Financial Sector's Profitability Shocks.

Fig. 2. Impulse Responses of Return on Assets of Corporate Financial Sectors.
This figure shows the impulse responses of ROA_FS, return on asset of the corporate financial sector, to different shocks, where the endogenous VAR variables are: dGDP, Real FFR, ROA_FS, TERM, VOL_XMRET, PSPR, XMRET and EBP (or CREDIT). Variables are described in previous tables. Fig. 2(a) shows responses of ROA_FS to EBP and other shocks. Fig. 2(b) shows responses of ROA_FS to CREDIT and other shocks. Fig. 2(c) shows responses of financial variables to ROA_FS shocks. Impulse responses are shown in % point. The standard error (S.E.) bands are not shown for easy comparability of the responses for Figs. 2(a) and 2(b). Quarterly sample 1973:Q1-2010:Q3.

PSPR and VOL_XMRET, consistent with our earlier results that increased profitability of financial sectors decreases stock market bid–ask spreads and corporate bond volatility. ROA_FS has about 20% points impact and is more significant than the impact on EBP (approximately 12% points).

4.3. NBER recessions and corporate credit-spreads

In this section, we investigate the relationship between recessions and credit spreads. First, we investigate whether corporate credit spreads can forecast recessions. Next, we investigate whether the sharp rise in corporate credit spreads occurs around recessions, and thus, if recessions are controlled for, credit spreads should not have any information about real GDP.

Forecasting NBER recessions

Stock and Watson (1989), Estrella and Hardouvelis (1991), Evans and Lyons (2008), among others, show that the Treasury term spread has considerable forecasting power for NBER recessions. Estrella and Hardouvelis (1991), Estrella and Mishkin (1995, 1998) further show that stock market returns are an essential short-term leading indicator of recessions. Favara, Gilchrist, Zakrajsek, and Lewis (2016) show that GZS and EBP forecast NBER recessions twelve months into the future. However, Favara et al. (2016) do not include stock market variables in their analysis.

Thus, we test the joint dynamics of GZS, EBP and stock market variables in forecasting recessions. Following Estrella and Hardouvelis (1991), we include real FFR and real GDP growth as additional predictors in some of our specifications.

We use both the static and dynamic probit models for forecasting NBER recessions. The static version of the model is as per the literature (e.g. Estrella & Hardouvelis, 1991, among others):

$$P\left(X_t = 1\right) = \Phi\left(\alpha + \beta \,\mathrm{TERM}_{t-l} + \gamma V_{t-l}\right) \tag{7}$$

where $X_t = 1$ when the economy is in an NBER recession quarter and "0" otherwise, TERM is the Treasury term-spread, V is a vector of augmenting variables that include the GZ measures, stock market returns, etc., and l is the number of lags used for estimation. We evaluate the model performance using the Pseudo R-squared values.[6]

[6] Pseudo $R^2 = 1 - \left[\frac{\log(L_u)}{\log(l_c)}\right]^{-\left(\frac{2}{n}\right)\log(L_u)}$ where L_u is the likelihood of the full model and L_c is the likelihood of the intercept only model.

Table 6
Recessions and corporate credit spreads.

Forecast horizons	One quarter		Two quarters		Three quarters		Four quarters	
EBP	0.89		1.08*		1.06***		0.60	
GZS		0.44		0.47		0.67***		0.71***
TERM	−0.51***	−0.60***	−0.78***	−0.83***	−0.75***	−0.86***	−0.85***	−1.00***
Real FFR	−0.28	−0.41**	−0.22	−0.29*	−0.03	−0.09	−0.30*	−0.36*
XMRET	−9.10***	−9.69***	−7.05***	−7.73***	−2.19	−2.58	−0.51	0.46
PSPR	−0.14	−34.21	−15.67	−30.17	−13.68	−48.52	8.64	−39.45
dVOL_XMRET	2.92	10.61	9.97	8.50	0.01	6.95	−20.62	1.12
VOL_CREDIT	8.28***	10.34***	0.74	2.06	−0.04	1.52	−0.32	1.43
dGDP	−129.81***	−126.81***	−29.58	−30.93	−13.00	−16.56	20.90	24.71
Pseudo R-Sq.	0.55	0.55	0.39	0.37	0.29	0.30	0.25	0.28

(a) Forecasting NBER Recessions; Static Probit Regressions (Quarterly Data)

Forecast horizons	One quarter		Two quarters		Three quarters		Four quarters		
TERM	−0.80***	−0.61***	−0.72***	−0.80***	−0.60***	−0.78***	−0.42***	−0.53***	−0.49***
EBP		0.50		0.40		0.86		0.26	
GZS	0.18		0.22		0.25				0.23
XMRET	−9.12***	−11.64***	−4.52*	−6.33**		0.43		4.93***	5.04***
PSPR		−3.69		−9.84		−30.19		−2.46	−8.07
dGDP		−112.28***		18.74		19.86		7.65	10.32
Real FFR		0.08		0.03		−0.06		−0.02	0.02
Pseudo R-Sq.	0.64	0.78	0.59	0.67	0.59	0.61	0.53	0.59	0.59

(b) Forecasting NBER Recessions; Dynamic Probit Regressions (Monthly Data)

Forecast horizons	1 months		3 months		6 months		9 months		12 months		
TERM	−0.36***	−0.30***	−0.46***	−0.44***	−0.32***	−0.44***	−0.39***	−0.46***	−0.32***	−0.33***	−0.36***
EBP		0.63*		0.19		0.47*		0.16		−0.19	
GZS											0.06
XMRET		−0.04**		0.00		−0.03		0.02		−0.02	−0.02
PSPR		36.29*		23.60		−4.06		−8.59		8.29	−4.85
Real FFR		0.09*		0.07		−0.04		−0.06		−0.02	−0.02
Pseudo R-Sq.	0.77	0.81	0.79	0.80	0.77	0.78	0.78	0.78	0.78	0.78	0.78

(c) Forecasting NBER Recessions; Dynamic Probit Regressions (Quarterly Data)

This table shows the results of the probit models where TERM is the term spread, V is a vector of forecasting variables. Panel (a) presents results for $P\left(X_t=1\right)=\Phi\left(\alpha+\beta\ \mathrm{TERM}_{t-l}+\gamma V_{t-l}\right)$, the static probit model. Panels (b) and (c) present results for $P\left(X_t=1\right)=\Phi\left(\alpha+\lambda\ X_{t-1}+\beta\ \mathrm{TERM}_{t-l}+\gamma V_{t-l}\right)$, the dynamic probit model as described in the text; variables are described in Table 1. Errors are corrected for heteroscedasticy adjustments. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. For parsimony, only β and γ are reported. Quarterly and monthly data for the 1973 to 2010 sample.

One of the issues with the static probit models such as Eq. (7) is that it is misspecified since they do not consider the autocorrelation structure of the binary time-series recession variable (e.g. Dueker, 1997; Nyberg, 2010). The estimation model misspecification may result in misidentifying a true recession forecasting indicator. As a result, we use the following specification to test the recession forecasting power of the variables following the literature (e.g. Nyberg, 2010) as a robustness test:

$$P\left(X_t=1\right)=\Phi\left(\alpha+\lambda\ X_{t-1}+\beta\ \mathrm{TERM}_{t-l}+\gamma V_{t-l}\right) \tag{8}$$

The results in Table 6 show that TERM forecasts recession in all forecast horizons and conforms to the existing literature (e.g. Estrella & Hardouvelis, 1991). While GZS and EBP have some recession forecasting ability at some forecast horizons, none of these indicators is consistent throughout the four-quarter forecast horizons. XMRET has some recession forecasting ability at a shorter forecast horizon; this result also conforms to the existing literature. Stock market volatility has no recession forecasting ability, while real GDP growth and federal funds rate forecast recessions at a shorter forecast horizon of one quarter. CREDIT volatility also has a shorter recession forecasting horizon. Short recession forecast horizons may not have any policy or economic implications (see, e.g. Rudebusch & Williams, 2009). This is why the literature (e.g. Estrella & Mishkin, 1995) tests the forecasting ability of TERM (and other variables) for forecast horizons of at least four quarters. Notably, the stability of forecasting variables to forecast recessions is essential. Thus, we next investigate the better specified dynamic probit models to identify the true recession indicator. The dynamic probit model results are presented in Table 6. We do not show some recession forecasting variables because none of those has any forecasting power for recessions in this specification.

The results in Table 6 show that TERM maintains its superior forecasting power for recessions at each forecast horizon. We further find that GZS and EBP have no recession forecasting power at any forecast horizon. Thus, Favara et al. (2016) results using the static probit model do not hold if the dynamic probit model is used with quarterly data.

For four a quarter forecast horizon, except for TERM, XMRET is the only variable significantly related to recessions. XMRET is positively associated with recessions at four-quarter forecast horizons, indicating that stock market returns remain positive. At the

Table 7
Relationship between GZ spreads and stock market variables.

Null Hypothesis	F-Statistic
EBP $\not\Rightarrow$ GZS	0.00
GZS $\not\Rightarrow$ EBP	0.13
XMRET $\not\Rightarrow$ GZS	6.87***
GZS $\not\Rightarrow$ XMRET	0.09
XMRET $\not\Rightarrow$ EBP	8.58***
EBP $\not\Rightarrow$ XMRET	0.90

(a) Pairwise Granger Causality Tests of GZ Spreads and Excess Stock Market Returns (Quarterly Data)

Dependent	No Lags of the Dependent			With one Quarter Lag of the Dependent				
	EBP	EBP	GZS	EBP	EBP	GZS	dEBP	dGZS
XMRET	−0.87*	−0.92**						
XMRET$_{t-1}$		−1.27***	−1.48**	−0.71***	−0.79***	−0.69***	−0.76***	−0.71***
VOL_XMRET	3.11*	1.67	−2.84		−1.47	−2.35	−3.22	−5.77
PSPR	29.20***	24.50***	71.73***		6.75***	5.77***	15.21**	58.19***
PSPR$_{t-1}$		16.31***	36.96***	6.39***			18.24***	−58.19***
Adj. R-Squared	0.48	0.56	0.65	0.73	0.77	0.91	0.17	0.61

(b) GZ Spread and Excess Stock Market Returns, Volatility and Bid–Ask Spreads (Quarterly Data)

This table shows the relationship between GZ credit-spreads measures and stock market variables, where dEBP and dGZS are the first difference of EBP and GZS; variables are described in Table 1. Panel (a) presents the Granger causality results, where optimal lag of one quarter is used as per the Schwarz (SIC) and Akike (AIC) information criteria; $\not\Rightarrow$ implies the null that one variable does not Granger cause the other. Panel (b) presents the results of the regression $X_t = \alpha + \beta X_{t-1} + \gamma C_{t-1} + e_t$, where X_t is the GZ spread measures; in some specifications, we omit X_{t-1}; C is one/more of the stock market variables; i takes the value of 1 and/or 0. Errors are corrected for heteroscedasticy adjustments. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. For parsimony, only γ is reported. Quarterly sample 1973:Q1-2010:Q3.

same time, the slope of the Treasury Yield curve turns flat or slopes downward. Somewhere between three and two quarters before recessions, XMRET turns negative and continues to be negative going into recessions. We further observe that PSPR and real FFR have no forecasting power for recessions. Note that the literature (e.g. Chatterjee, 2016; Estrella & Mishkin, 1995) that investigate stock market variables as recession forecasting indicators does not consider the dynamic probit models.

As for real GDP growth, it has some forecasting power for recessions for a quarter forecast horizon. Thus, the dynamic probit specification results conform to the findings of Estrella and Hardouvelis (1991), Estrella and Mishkin (1995) that stock market returns and real GDP growth are significant recession forecasting variables at shorter forecast horizons. However, whether we use a static or a dynamic probit model, the Treasury term spread is the best and most robust predictor of recessions at higher forecast horizons.

Forecasting NBER recessions using monthly data

Since Favara et al. (2016) conduct monthly analyses, we further estimate Eq. (7) using monthly data. Since we use monthly data, we omit real GDP growth as a predictor.

Table 6 shows results that TERM is the only variable that consistently forecasts recessions for monthly forecasts. If we compare the Pseudo R-squared values, we find that the benchmark Treasury term-spread model often performs similarly to the extended models. We find that PSPR, XMRET, and EBP are significantly related to recessions for a one-month forecast horizon. While the Pseudo R-squared value is higher for the extended model (81%) over the benchmark term-spread model (77%), one month-ahead forecast may not have any economic significance since recessions are measured quarterly. Importantly, one-quarter ahead of recession forecasting may not have any policy implications, as we discussed earlier.

The monthly results are not qualitatively different from the quarterly NBER recession forecasting results. While TERM is the only robust recession indicator, the other variables, including GZS and EBP, have limited recession forecasting power.

4.4. The GZ credit-spreads and stock market

In a VAR framework, GZ show that the GZ measures of corporate credit spreads predict stock market returns—if EBP increases, stock market returns fall. They do not consider whether stock market returns predict the GZ measures. This section conducts additional robustness tests to ensure our earlier results hold. First, we run a pairwise Granger causality test of EBP, GZS and XMRET to investigate whether the GZ measures contain leading information about stock market returns.

Table 7 presents the Granger causality test results for a one-quarter lag, which is chosen as per the Schwarz (SIC) and Akaike (AIC) information criteria. It shows that XMRET Granger causes both EBP and GZS. No evidence indicates that the GZ corporate credit spreads Granger cause stock market returns. That is, stock market returns have information about the GZ corporate credit spreads, while the reverse is invalid.

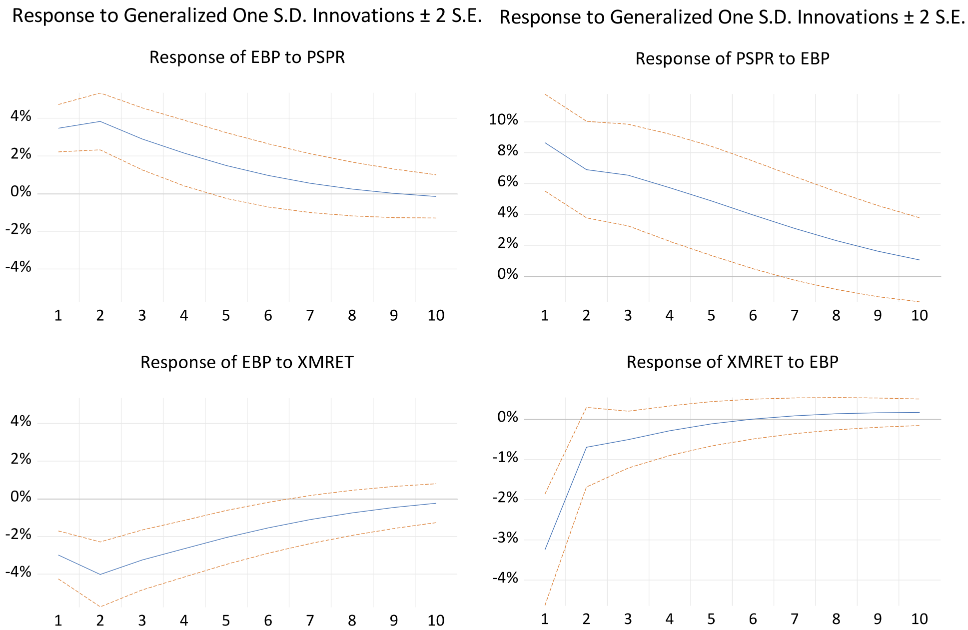


Fig. 3. Impulse Responses of EBP and Stock Market Returns and Bid–ask Spreads.
This figure shows responses of XMRET, PSPR and EBP shocks to each other, where the endogenous VAR variables are: dGDP, Real FFR, TERM, VOL_XMRET, PSPR, XMRET and EBP. Variables are described in previous tables. We show the generalised impulse (Pesaran & Shin, 1998), which does not depend on the ordering of the variables. For parsimony, selected response functions are shown. Impulse responses are shown in % of the mean of the response variables for ease of comparison. Quarterly sample 1973:Q1-2010:Q3.

With the Granger causality results in perspective, we investigate to what extent stock market activities determine the GZ credit spreads in a multivariate setup. We investigate how stock market variables explain GZ corporate bond credit spreads. The time-series regression specification is as follows:

$$X_t = \alpha + \beta X_{t-1} + \gamma C_{t-i} + e_t \tag{9}$$

where X is one of the four variables: GZS, EBP dGZS and dEBP; C is a vector of explanatory variables such as XMRET, VOL_XMRET and PSPR; i takes the value of 1 and 0. In some of our specifications, we omit the X_{t-1} term in Eq. (9). The coefficient estimates of Eq. (9) are presented in Table 7. We report the results for the models with higher adjusted R-squared values for parsimony.

Looking in the first two columns of Table 7, where we do not include lags of the dependent variable, we observe that XMRET, VOL_XMRET and PSPR capture over 50% (as measured by adjusted R-squared values) of EBP and GZS. We further keep that stock market variables and one-quarter lag of the dependent variable explain over 70%, as measured by adjusted R-squared values of GZS and EBP. While the coefficients of XMRET and PSPR are statistically significant at the 1% significance level, VOL_XMRET is not significantly related to the GZ measures. The last two columns of Table 7 show that stock market variables explain dGZS and dEBP quite well. To ensure the robustness of our results, we next use the monthly data, and the unreported data, which is available upon request, does not qualitatively change the above results. Overall, the results presented here support the VAR results we reported earlier. There is a more robust causality from the stock market to the corporate bond market as measured by the GZ spreads.

Vector-autoregression (VAR) estimates

In a VAR framework, GZ find that EBP shocks contract stock market returns; we next investigate impulse responses of EBP and stock market variables to different shocks. We have the following endogenous VAR variables: dGDP, Real FFR, TERM, VOL_XMRET, PSPR, XMRET and EBP. For parsimony, in Fig. 3, we show the generalised responses of EBP to XMRET and PSPR shocks and vice versa. We do not report the VAR coefficient estimates to save space.

In Fig. 3, we show the generalised impulse functions of selected variables. The impulse responses show that XMRET and PSPR significantly affect EBP. For one standard deviation, positive shocks in PSPR (XMRET) in the present quarter increase (reduce) EBP by approximately 2% points (4% points) of EBP next quarter. By contrast, one standard deviation EBP shock in the present quarter increases PSPR by 9% PSPR next quarter. For a similar shock in EBP, XMRET decreases by about 3% points of XMRET. Thus, we find some support for the GZ results that EBP predicts future stock market returns. However, we show that reverse causality exists. The results are consistent with our observation that if intermediaries participate in corporate bonds and the stock market, both should affect each other. Significantly, corporate credit spreads have limited information about the real economy when both corporate bond and stock variables are considered.

Table 8
Robustness.

Dependent	EBP	EBP	GZS	CREDIT
$XMRET_{t-1}$	−0.02***	−0.03***	−0.03***	−0.03***
$PSPR_{t-1}$	1.96***	1.07	2.62	−1.04
VOL_XMRET_{t-1}	0.05***	0.01	0.01	0.01
RECESSION		0.34***	0.58***	0.12***
Adj. R-Squared	0.55	0.67	0.79	0.77

(a) The relationship between Corporate Credit Spreads and Stock Market Variables (with lags of the dependent variable in the regression)

Dependent	dGDP	dGDP	dGDP	dGDP	dGDP	dGDP
$XMRET_{t-1}$				0.26*	0.28*	0.29**
$PSPR_{t-1}$				−30.46	−30.03	−35.32
VOL_XMRET_{t-1}				−0.14	−0.17***	−0.17***
EBP_{t-1}	−2.37***			−0.98		
GZS_{t-1}		−1.04***			−1.47	
$CREDIT_{t-1}$			0.33			1.11
$TERM_{t-1}$				−0.30	−0.08	−0.31
Real FFR_{t-1}				−0.38*	−0.53*	−0.36
Adj. R-Squared	0.14	0.11	0.05	0.31	0.39	0.31

(b) Predicting GDP Growth (with lags of the dependent variable in the regression)

This table conducts robustness tests; variables are described in Table 1. Panel (a) presents the prediction of corporate credit spread measures by stock market variables, where recession implies "Covid-19 induced 2020 recession" binary variables for further robustness of the results. We use a predictive regression model as in Eq. (9) described in the text: $X_t = \alpha+\beta X_{t-1}+\gamma C_{t-1}+e_t$. Panel (b) presents the results for real GDP growth predictions. Errors are corrected for heteroscedasticy adjustments. T-statistics are in parenthesis. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. For parsimony, only γ is reported. Quarterly data from 2010:Q1 to 2022:Q3.

4.5. Robustness tests

In this section, we conduct a robustness test to ensure the results remain valid for the most recent data. This is crucial because, since the publication of the GZ paper, the financial markets and the economy have undergone significant changes, including the impact of the COVID-19 pandemic. Therefore, this data selection excludes the time frame of the 2007–2009 financial crisis while encompassing recessions triggered by exogenous shocks to the economy. This data choice enables us to test for robustness.

We utilise data from the 1st quarter of 2010 through the 1st quarter of 2023 for these tests. This period encompasses the COVID-19-induced recession in 2020, during which the stock market and real GDP experienced a sharp decline followed by a rapid recovery. Using a predictive model similar to Eq. (9), Table 8 Panel (a) examines whether the stock market can explain corporate bond credit spreads. At the same time, Panel (b) investigates whether corporate bond credit spreads contain leading information about real GDP growth.

Examining Table 8, Panel A from the left, where EBP is the dependent variable, we find that when stock market returns decrease, the stock market bid–ask spread widens. Stock market volatility increases, and EBP expands in the subsequent quarter. This finding aligns with the outcomes we previously presented. Moving on to the model where we account for the COVID-19-induced recession in 2020, we observe that while stock market returns continue to lead EBP, other stock market variables are statistically unrelated to EBP. As anticipated, we also keep an increase in EBP during the 2020 recession quarters. Shifting our attention to the last two models, with GZS and CREDIT as the dependent variables, we observe that the results demonstrate qualitative similarity. Overall, we ascertain that the relationship between stock market returns and corporate credit spreads remains robust without the GZ sample period in the data.

When examining Table 8, Panel (b) from the left, we observe that EBP and GZS exhibit predictive power for dGDP, whereas CREDIT contains no informative content. In the subsequent three models incorporating stock market variables, none of the corporate credit-spreads measures contains leading information about dGDP. In contrast, stock market returns continue to provide leading information about dGDP. Overall, these results are qualitatively similar to the results we obtained earlier.

5. Conclusion

Credit growth and productivity growth are inversely related in advanced economies. In contrast, the contraction of corporate credit spreads signals an economic expansion in the U.S. and European countries. We endeavour to resolve those two opposing views in the literature by investigating the relationship between corporate credit spreads and economic indicators in a comprehensive manner. We find the traditional measure of corporate credit spreads computed as the difference in yields of Moody's Aaa and Baa-rated corporate bonds contain no information about U.S. economic growth.

We further find that the recently proposed market-based expected default-risk measures of corporate credit spreads (e.g. Gilchrist et al., 2009, GZ) do not have leading information about the business cycle. In contrast, stock and the Treasury bond market variables such as the Treasury term spread, stock market returns and the financial sector's profitability lead to consumption and real GDP.

Our results also show that the financial sector's profitability can be better explained by stock than bond market variables. We further find that the proposed alternative corporate credit spreads measures can be explained by the stock market variables such as stock market bid–ask spreads.

While GZ alternative measures of corporate credit spreads are essential, they still suffer from the duration mismatch issues that traditional corporate credit spreads have. Future research may build on the innovative concept that GZ propose. For instance, one could construct the term structure of corporate unsecured bonds of different maturities. Like the Treasury yield curve slope, the slope of the corporate unsecured bonds yield curve may have superior information about the real economy. Since our research is restricted to the U.S. sample, future research may examine the relationship between the GZ measures and economic growth in other countries with a similar specifications.

CRediT authorship contribution statement

Ujjal Kanti Chatterjee: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Flavio Bazzana:** Conceptualization, Supervision, Writing – review & editing.

Data availability

Data will be made available on request.

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