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Constructing the term structure of the U.S. corporate credit spread components – is there a relationship with the real economy?

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Abstract: This paper decomposes the credit spread of U.S. corporate bonds into a component driven by issuer default-risk and a component common to all bonds in the market. It then uses these components to develop a procedure for constructing their term structure. The first result of the thesis is the consequent ability to observe the time developments of maturity-specific credit market indicators and examine their yield curve configurations. Further, the predictive power of the term structure latent factors on economic activity are assessed. The paper thus finds the growth rates of GDP and its constituents, as well as of monthly activity indicators, to be negatively associated with the slope factor of the component based on default-risk and with the level of the common component in credit spreads.

Keywords: Macro-finance, Term structure, Level factor, Slope factor, Business cycles

JEL: E32, E43, E44, G01, G12

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1 Introduction

Before the unexpected exogenous shock of the coronavirus outbreak, there was a debate in the financial markets about the business cycle (in the U.S. and elsewhere) approaching its peak[1]. In late spring of 2019, the debate intensified as a leading economic indicator exposed a worrying sign: the yield curve of the U.S. government bonds had inverted. In other words, interest rates on short-term U.S. government borrowings became greater than the interest rates on long-term borrowings[2]. The sizeable attention given to this specific dynamic of this financial measure raises the question: why is an indicator of a financial market – be it sovereign debt – telling of the position of the economy in the business cycle?

While the question specifically regarding U.S. government debt has been answered, the links between financial markets and the macroeconomy are far beyond this level and exploring this interconnection through a macro-finance approach is arguably instrumental for macroeconomic research regarding business cycles. Among many reasons why this is true, financial variables have the undisputable advantage of being timely. Since the typical frequency for macroeconomic data is monthly or more often quarterly, evaluation of economic health (through measures such as real GDP growth, or changes in production, employment and consumption) can be undertaken mostly after observing these aggregates at these intervals. Conversely, financial data is predominantly daily. This means that any change in a financial variable found to be indicative of aspects of the economy can immediately suggest an economic implication in real time and crucially lead to a quicker policy response.

This paper proposes to leverage this nexus and study another financial indicator and its relationship with the real economy. With the starting point of acknowledging that the relevance of the U.S. government debt market lies in its national element, the focus turns towards another market that aggregates nation-wide characteristics. Moreover, recognising the advantageous structure of debt markets and their available parallel with the government case suggests that a fit market to examine is the U.S. corporate credit market – with information captured in the credit

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[1] See, for example, FT article *Should we really be worried about an inverted yield curve?,* 16th June 2019; J.P. Morgan *Mid-year Market Outlook 2019: Central Banks Stay Easy and in Sync,* 5th July 2019; Goldman Sachs Outlook for 2020 *A break in the clouds*, 20th November 2019;

[2] As per the Fed data, the 10-year minus 3-month spread inverted on the 22nd of March 2019 and stayed negative for the period between the 24th of May and the 10th of October 2019: https://fred.stlouisfed.org/series/T10Y3M . The 10-year minus 2-year spread was inverted for a few days in August 2019: https://fred.stlouisfed.org/series/T10Y2Y

spreads of corporate bonds. The insightful difference between indicators of government debt versus corporate debt is that the latter depicts the domestic conditions of doing business.

The novelty of this work lies in going beyond investigating the credit spreads, by constructing and analysing their term structures. The term structure (or synonymously yield curve) refers to the life span of a debt instrument – its term to maturity. It is a snapshot of a point in time which depicts the relationship between the value of the indicator (such as yield to maturity, credit spread or another interest rate) and its term to maturity. By observing this snapshot at multiple points in time and concluding the relationship is conditionally persistent, it is revealed that the value of rates is to a certain degree a function of the term to maturity – in other words there is a structure to how the term to maturity affects rates: the term structure. This concept is vital in the context of linking credit markets with economic conditions – this is clearly shown in the case of the relationship between government bonds and business cycles. In this relationship, it is not the absolute level of yields that contains economic meaning – it is instead the term structure which is expected to have a certain (upward sloping) shape during expansionary periods and the reverse (or inverted) shape towards the end of business cycles. In order to visualise the concept of the term structure and illustrate its importance, Figure 1.1 presents the yield curve of Treasury securities (the means through which the U.S. government borrows) at two distinct points in time: in February 2007 and in December 2009. The panel on the right shows a typical shape of the yield curve where securities of longer maturities have higher rates; the panel on the left shows an uncommon yield curve, predominantly downward sloping – the event that separates these two points in time is the global financial crisis between December 2007 and June 2009.

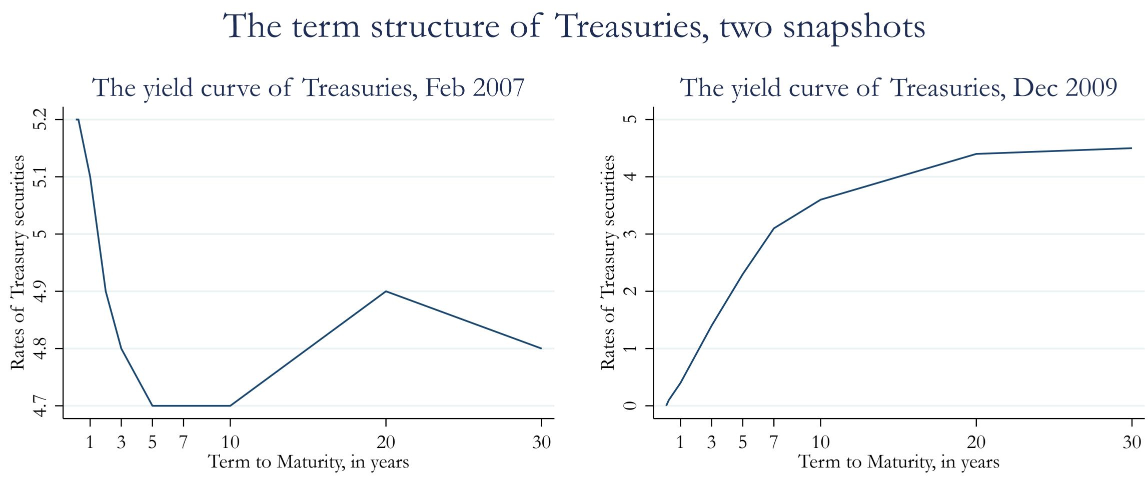

Figure 1.1: The term structure of Treasury securities. Author's rendering of data from the Federal Reserve, 2020

Thus, the main purpose of this paper is to construct the term structure of the adequate indicators of the corporate credit market, which to the knowledge of the author is novel in the literature. The construction is motivated by the possibility that these term structures could explain changes in economic activity. Thus, once the indicators are formed, incipient exploration of the relationship with economic activity is performed, by assessing the effect of term structures on different indicators of the real economy. The analysis finds a negative association between the corporate credit market measures and the real economy, which hinder economic growth through the investment channel. More specifically, the negative effect comes from the term structure slope of the default-risk based element of the credit spread and from the level of the common element of the credit spread.

The remainder of this paper is structured as follows: Section 2 covers the theoretical framework, uncovering the finding that credit spreads of individual bonds contain a common factor, apart from the idiosyncratic factor rooted in firm-level credit risk. Section 3 describes the steps employed in deriving the aggregate market indicators. It first presents the separation of the two underlying components of the credit spread, then the methodology of their aggregation. Section 4 presents the procedure of constructing term structures in the corporate credit market and displays its implementation in the case of the credit spread and its components. Section 5 summarizes the maturity specific information in the yield curves and examines the structure of the underlying term factors. This comprised information is utilised in Section 6 to assess the effect of the credit market term structures on the macroeconomy. Finally, Section 7 concludes. In order to ease the comprehension of the text necessarily reliant on financial terms, Table 1.1 below lists the definitions and explanations of the important elements used throughout the text relating to bond characteristics, market aspects and pricing theory.

Table 1.1: Definitions and explanations of financial terms used in this paper

Definitions and explanations of financial terms	
Bond characteristics	
Bond:	Type of debt security issued by firms (corporate bonds) or governments (sovereign bonds/ government debt) in order to finance operations. It is similar to a bank loan, but it is created to be traded on a market - thus, the lenders are investors in the bond market. In this context, interchangeable with the terms 'fixed-income security', 'debt', 'credit' or 'loan'.
Maturity date:	The maturity date of a bond is the date at which the last payment associated with the bond is due - the date at which the bond matures.
Term to maturity:	The term to maturity - or simply, maturity - of a bond is the period of time (with usual units of months or years) until the maturity date.
Coupon rate/ Interest rate:	Semi-annual interest payments forming part of the income stream from the bond, expressed as a fraction of face value.
Face value/ Par value:	The nominal price of the bond promised by the issuer to the buyer, to be paid at the maturity date.
Pay-offs from bonds:	The issuer of the bond (the borrower) promises to the buyer a stream of income that is either fixed or determined according to a specified formula. In the case of Zero-coupon bonds, the lender (the buyer) pays today's market price to purchase the bond, for a promised higher face value; the pay-off is the difference between these amounts. In the case of a coupon-baring bond, the lender is also promised regular interest payments on top of the face value.
Yield to maturity:	Measure of the annualised rate of return to an investor who buys the bond and holds it until maturity. It accounts for both coupon income as well as the difference between the purchase price of the bond and its par value.
Yield curve/ term structure:	The (graphical) relationship between the yield to maturity and the term to maturity of a bond.
Options:	A type of derivative securities (securities that provide pay-offs dependent on the value of the assets they derive) applied to bonds. There are two types of options: call or put options.
Call option/ callability:	Contract offering the right to buy a bond at a given exercise price on or before the option's expiration date (this is profitable if the actual value of the bond is above the exercise price). This option affects the yield to maturity of the bond and thus, its credit spread.
Default	Failure of the issuer firm to pay the bondholder the promised payments. In this case the bond is restructured and the amount salvaged by the bondholder as a fraction of initial face value is called the 'recovery rate'. The possibility of default represents the highest risk for bond investors; for this reason, this risk is also called 'credit risk'. Default occurs when the value of equity (market value of the firm) drops below the value of the firm's debt (Merton, 1974).

(Merton) Distance to Default	Measure of a firm's default risk pioneered by Merton (1974) which calculates the distance in standard deviation units between the firm's expected value and its default point.
Risk premium	An expected return in excess of that on risk-free securities. The term can refer to specific types of risk as well; for example, default risk premium refers to added returns due to baring the risk of default.
	Market aspects
Treasury marketable securities/ 'Treasuries': T-bills; T-notes; T-bonds.	A form of U.S. government debt, that can be sold in the secondary market. According to the official website of the U.S. Treasury , there are three types of nominal securities (in short called "Treasuries"): 1) bills (zero-coupon obligations maturing in less than one year) – called T-bills. 2) notes (obligations paying semi-annual coupon, maturing in one to ten years) – called T-notes. 3) bonds (obligations maturing in over ten years) – called T-bonds. The treasury currently issues notes of 2, 3, 5, 7, and 10-year maturities and bonds of 30-years maturities – called T-bonds.
Credit spread	The level of the yield to maturity of a corporate bond in excess of the yield to maturity of a Treasury security with the same maturity.
Policy rate/ Instantaneous interest rate	The main policy rate in the U.S. is the rate of Federal Funds (RFF) – where Federal (or Fed) funds are the funds in the reserve account of each member bank of the Federal Reserve System, which is required to maintain a minimum balance here. In the Fed Funds market, banks with excess funds lend to those with a shortage. These loans, which are usually overnight transactions, are arranged at a rate of interest called the Federal funds rate. (Today the market has evolved to the point that many large banks use Fed funds as one component of their total sources of funding.) The RFF and rate on the shortest-term T-bills are often interchangeably called the instantaneous risk-free interest rate, as they are viewed as not having default risk.
Credit rating – Investment/ Speculative grade bonds	Bond default risk is measured by credit-rating agencies, of which the major ones are Moody's, Standard & Poor's (S&P) and Fitch. Each rating firm assigns letter grades to reflect its assessment of bond safety. The top rating is AAA or Aaa. Investment grade bonds are rated BBB and above by S&P or Baa and above by Moody's. Speculative grade bonds (or junk bonds) are rated BB or lower by S&P, or Ba or lower by Moody's, or an unrated bond.
	Bond pricing theories
Expectations hypothesis:	The theory stating that yields to maturity are determined solely by expectations of future short-term interest rates.
Liquidity preference theory:	The theory stating that investors demand a risk premium on long-term bonds. Its basis is that shorter-term bonds are more liquid than longer-term bonds, through offering more price certainty and by trading in more active markets with lower bid–ask spreads.

Note: Unless otherwise specified, definitions are based on the textbook Essentials of Investments, 9th edition – Bodie, Kane, Marcus (2013). Definition of Treasuries from: https://www.treasurydirect.gov/instit/marketables/marketables.htm

2 Financial indicators and the real economy

2.1 The Treasury term structure and economic activity

The term structure of Treasury securities has long been recognised as an important indicator, far beyond describing the government debt market. Significant attention has been given to the capacity of the yield curve to be a leading indicator of the economy – meaning that it has forward-looking properties – particularly in predicting recessions. In 1998, Estrella and Mishkin famously found the slope of the yield curve to have predictive power over recessions[3] beyond two quarters ahead. The financial rationalisation of this relationship lies in the expectations hypothesis, which explains long term rates as the market's expectations of future short-term rates – i.e. the rate on the 10-year bond is the expected instantaneous rate in ten years' time. Since this discovery, market participants and economists started following developments of the Treasury yield curve closely, especially in periods when the curve flattens, with the potential of inversion (Estrella and Trubin, 2006). This caution is rooted in the finding that every recession experienced by the U.S. in the last four decades was preceded by a downward sloping curve – specifically through a negative spread between the yield of long-term and short-term Treasuries.

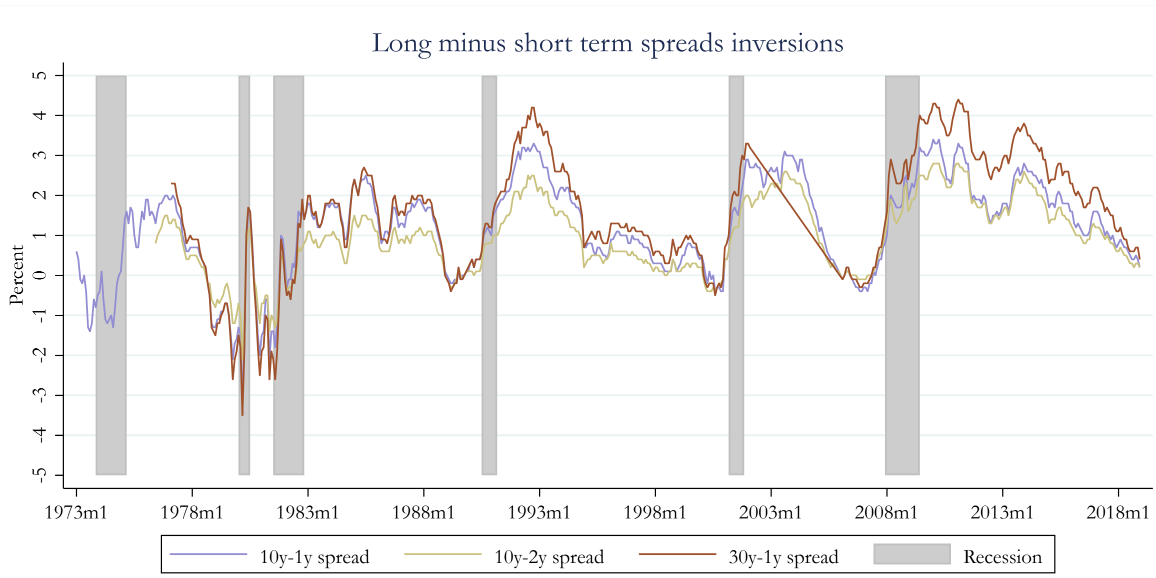

Figure 2.1: Spreads between long- and short-term Treasuries become negative before recessions.
Author's rendering of data from the Federal Reserve, 2020.

[3]Throughout the text, recessions are referred to as the periods between the peak and the through of the business cycle, as defined by the National Bureau of Economic Research (NBER) – while expansions are the reverse.

This fact is shown in Figure 2.1, which depicts the movement through time of the differences between three distinct combinations of long-term and short-term Treasuries (10-year minus 1-year, 10-year minus 2-year, and 30-year minus 1-year spreads). The subtext here is that in the periods preceding recessions investors expected a decrease in interest rates, sign of a higher relative risk in the short run and weakening market conditions.

As such, a vast literature has emerged modelling the term structure of Treasury securities and connecting it to the real economy. This literature is relevant here as, on the one hand, it gives insights into the connection between the economy and this leading financial indicator beyond the expectations rationale and reveals how economic effects of Treasuries should be accounted for in the models presented below. On the other hand, it serves as a guide to modelling the term structures of the indicators built here – specifically summarising the maturity specific information content.

The foundational aspect in creating term structure models is summarising the information contained across the maturity spectrum at each point in time. Currently, the two prevalent procedures in this field of research are the Nelson-Siegel approach and affine no-arbitrage term structure models (Piazzesi, Diebold and Rudebusch, 2005). The first approach was pioneered by Nelson and Siegel (1987) and offers a pre-specified functional form of the yield curve, where the intercept is interpreted as the long-term level of interest rates and the coefficients of the two function terms depending on maturity translate into the short-term component and the medium-term component. This specification allows the fitted curves to have a constant (upward or downward) slope, or to have a hump or an S-shape, which are the typical shapes observed in the data. Thus, the parameters effectively model the unobservable level, slope and curvature factors of the yield curve at one point in time. The second approach is largely modelled starting from the basis of factor analysis (FA)[4]. The objective of FA is to identify the underlying factors or latent constructs that can explain the intercorrelation among the variables (here, instruments of different maturities), where each variable (indicator) is a function of the factors (Sharma, 1996). These functions are assumed to be linear, or affine. The manner in which this algorithm works is that it forms one common factor that can explain as much as possible of the variation in the values of different maturities; then it repeats this step with the remaining variation and so on. Since the curve of maturities exists at each point in time, these factors present different scores at each point

[4] The similar alternative is Principal Component Analysis (PCA), that reduces the number of variables to a few components such that each component forms a new variable and the number of retained components explains the maximum amount of variance in the data. Principal components are usually used to form an index, while latent factors in FA explain the intercorrelations between indicators (Sharma, 1996).

in time. This paper uses FA in order to give the obtained yield curves a defined structure, and thus the FA approach is detailed and estimated below (in Section 5).

Building on the factor decomposition of the Treasury yield curves regardless of the approach employed, a vast strand of the literature incorporates this together with selected macroeconomic indicators into a vector-autoregressive model (VAR) to explain dynamics between real economic activity and the term structure of interest rates. Whereas one type of such models constrains the impact to be unidirectional from economic activity to the yield curve, the other type of VAR models allows for bidirectional impacts. The latter type of models is more common, however, the seminal work which propelled the focus on term structure models more broadly is Piazzesi and Ang (2003), who use a unilaterally restricted no-arbitrage VAR. Their model includes three latent factors of the yield (interpreted as level, slope and curvature) and two macroeconomic factors, which are indexes representing inflation (comprising consumer, producer and market commodity prices) and real activity (comprising unemployment and its growth rate, growth rate of industrial production and an index of 'help wanted' ads). They find that macroeconomic factors explain up to 85% of changes in the short and middle portions of the yield curve and approximately 40% of the longer end, where the latent factors stand out. It is important to mention, however, that this article covers yields of up to 5 years maturity, which in this paper and other research is considered on the shorter end of the maturity spectrum, that in general spans 10 to 30 years. Nevertheless, it points towards the real economic variables that affect Treasury yields.

Allowing reciprocity, a later model by the same authors (Piazzesi, Ang and Wei, 2006) finds the level of the observable short rate to have predictive power over GDP, complemented weakly by the long-minus-short term spread. Additionally, a significant bidirectional impact is discovered between the term structure and real activity (through manufacturing capacity utilization), inflation, and monetary policy instruments by Diebold, Rudebusch and Aruba (2006) in their model which brings together the macroeconomic factors with latent factors of the yield curve determined through a dynamic version of the Nelson-Siegel approach. The applicable implication of these findings is that elements of the yield curve of Treasuries are required controls in predicting GDP and other real economic variables.

2.2 The credit spread and its components

In a similar fashion to the government bond market, the corporate bond market is suggestive of the U.S. economy as it encompasses an extensive spectrum of the private business sector in the country. In an insightful and different fashion from the government bond market, it is comprised of a highly heterogenous base of companies, rather than a singular overarching institution. For these reasons, the aggregate indicators of this market could be expressive from the standpoint of the average firm in the U.S. This is why this paper examines the corporate bond market.

In order to capture information in this market, the appropriate measure to examine is the yield to maturity of corporate bonds stripped of the yield to maturity of Treasuries of the respective maturity – in other words, the credit spread. This is the case since bond yields include interest rate risk captured in the term structure of interest rates (Collin-Dufresne, Goldstein and Martin, 2001). Thus, the credit spread is the widely used representative of credit markets in the literature and also in this paper. However, since this object has a high information content, it needs to be dissected in order to understand its underlying drivers and their distinct economic meaning.

The traditional view on what drives credit spreads of corporate bonds is that their main determinant is default risk of the issuer firm. The associated literature of structural models has its origin in the insights of Black and Scholes (1973) who value equity and debt using contingent-claims analysis, with the first model constructed by Merton (1974). Although typical measures for the riskiness of a bond are predominantly firm valuation indicators accompanied by certain bond characteristics, two notable factors influencing the risk of default of a bond are the risk-free (instantaneous) interest rate and the slope of the term structure of interest rates, vastly proxied by a long term Treasury rate (e.g. ten years) less the instantaneous rate (e.g. one or three months T-bill rate). The financial justification of this inclusion is that a higher interest rate implies an increase in the value of the firm's assets while analogously, by the expectations hypothesis, the long-minus-short difference is a predictor of future changes in short-term rates in efficient markets (Longstaff and Schwartz, 1995). Additionally, there is the indirect effect on the credit spreads through the market channel, given that a weaker economy potentially leads to lower amounts that lenders can salvage from defaulted loans (lower recovery rates). This line of work reinforces the wide impact of Treasury rates but, more notably, reveals one category of drivers of the credit spread – namely indicators of default risk in firms.

A prominent branch of work based on the traditional view points towards an unexpected finding that there exists a common factor in the credit spreads of corporate bonds. A crucial implication of this discovery is that if there is an omitted factor driving spreads, this is not idiosyncratic. This is suggested by Collin-Dufresne, Goldstein and Martin (2001), who look at the U.S. market between 1988 and 1997 and regress issue-level changes in spreads on several proxies for changes in the risk of default, recovery rates and liquidity premium of issuers, finding that these can explain only about 25% of observed credit spread changes. Further, they find the residuals to be highly cross-correlated and through principal component analysis find them to be driven largely by one common factor. In the same time, probationary inclusion of aggregate financial and liquidity factors predominantly related to the Treasury and equity markets did not explain the bulk of this common factor. Similar findings appear in other papers, such as Huang and Huang (2012), that also attribute only a small fraction of the change in credit spreads to credit risk, especially for bonds with shorter terms to maturity – around 20% explained for investment grade bonds and 30% for speculative grade bonds.

The topical article that connects corporate credit spreads with the macroeconomy is Gilchrist and Zakrajsek (2012) – work that guides a sizeable portion of the current paper, predominantly in separating the common component from the spread and extracting economic information from financial indicators. Using data on the U.S. corporate bond market between 1973 and 2010, the authors first explain credit spreads using a structural type of approach. A unique feature of their paper is that they do not use the common credit spread measurement which detracts the Treasury rate of closest maturity from the corporate yield, but instead create a similar measure proprietarily (and call it the "GZ spread")[5]. Once they regress the GZ spread on measures of credit-risk, they single out the disturbance term. While the authors do not conduct analysis on this error term in the lines of Collin-Dufresne, Goldstein and Martin (2001), they do use previous research to argue its definition to be the "cyclical changes in the relationship between measured default risk and credit spreads—the so-called excess bond premium" (p1693). This is an important channel linking the bond market to the macroeconomy, since a higher excess bond premium (EBP) is interpreted to signal a decrease of the capacity of the financial sector to bear risk, in turn associated with a contraction in the supply of credit – which has negative consequences on the real economy. The effect of both the idiosyncratic default-risk factor and the EBP in credit spreads on economic activity is tested and found to be significantly negative. Additionally, the afore mentioned channel through which the EBP affects the real economy is analysed by examining the impact of shocks to the EBP, endorsing the relevance of the channel.

The evidence of a common factor determining credit spreads beyond the firm-level credit-risk drivers motivates this paper to develop the description of the credit spread as having two underlying components. Thus, the portion of the credit spread driven by firm-specific measures of default risk is coined the 'idiosyncratic component' (IC). The remainder, containing collective determinants, is coined the 'common component' (CC). This separation is important as it allows

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[5] They construct a "synthetic risk-free security that mimics exactly the cash flows of the corresponding corporate debt instrument" (p1694). The price of this security discounts the cash flows at the continuously compounded zero-coupon Treasury rates. The risk-free yield obtained from here is subtracted from the yield to maturity of the original bond, to obtain the GZ spread.

for a deeper and more focused exploration of credit spreads, especially given the purpose of this paper to understand the dynamics between the real economy and the overall corporate credit market (rather than distinguishing among firms). This separation is achieved starting from the firm-level, where measures of default-risk are used to obtain the individual IC and subsequent CC. This approach largely resembles that employed by Gilchrist and Zakrajsek (2012) and d'Avernas (2017). Further, this paper departs from this literature as it does not aggregate the overall extracted components but instead focuses on maturity specific effects, by constructing their term structures.

2.3 The term structure of the credit spread

What motivates the exploration of the term structure of the credit spread and of its underlying components is the possibility of additional information contents found through the displayed structure of the yield curves compared to the holistic objects. To this extent, it is relevant to point to the so-called reduced-form approach explaining corporate credit spreads. This is an alternative – or complementary – approach to structural models based on contingent-claims analysis, which diverges from accounting for the firm value process in explaining spreads and takes prices of corporate bonds as inputs. This framework is designed to model the term structure of the credit spread instead of explaining the determinants of specific spreads and thus it is useful for the current research to offer a framework of interpreting the observed yield curves in the data. A distinguished paper in this field is written by Duffie and Singleton in 1999, who develop an intricate model, distinct for specific types of fixed-income derivatives.

A more concentrated model is implemented in a critical 1997 paper written by Jarrow, Lando and Turnbull. They develop a Markov model – allowing the slope of the yield curves to vary – whereby they find consistently positive slopes in yield curves of the safest ratings. Further, as ratings lower, the slope towards the long end of the maturity spectrum flattens (beyond the 15 years to maturity mark, approximately) while it becomes steeper for shorter maturities. This process intensifies and shifts the slope at shorter and shorter maturity marks as credit risk increases (i.e. for lower ratings) until almost the entire curve becomes flat and then downward sloping for speculative grade bonds. In other words, there appears to be a medium-term effect in the shape of a hump that moves to the north-west of the yield curve graph as the default risk increases in the form of lower rating categories. The model was implemented on market data as of the 31st of December 1993, with positive results. Even simplified versions of these models, which constrain the yield curve to be linear, find results in the same line. For example, Fons (1994) models the term structure of credit risk allowing only for constant slope. He shows that the yield curve of investment grade bonds is upward sloping, becoming flatter with less-safe rating categories and turning negative for speculative grade bonds. Yield curves observed from market data computed as of the 30^{th} of September 1993 encourage the model results.

One instructive point to add is that the empirical literature focusing on the term structure of credit spreads is scarce and is largely limited in scope to the firm level rather than the aggregate market level. For example, Han, Subrahmanyam and Zhou (2017) use the concept of the term structure of the credit spread – however, they proxy this spread by the daily spread of credit default swaps and only look at the firm level spreads with the scope of describing firm fundamentals and riskiness. Moreover, "constructing the term structure" of this object only goes insofar as using the difference between one spread of longer maturity (i.e. five years) and one spread of shorter maturity (i.e. one year) and labelling it the slope – common computation in this type of literature. Another example is from Leland and Toft (1996), who examine different maturities of corporate debt in the context of studying optimal capital structure of issuers, concluding that "credit spreads increase with maturity up to 20 years at the optimal leverage ratio" (with optimal leverage ratio itself depending on the term to maturity). Their model also distinguishes between different levels of risk in issuers influencing the shape of the term structure of their credit spreads (parameters are chosen to match the U.S. credit market).

Landschoot (2004) represents an example that looks at the aggregate market level, rather than issue level spreads. He studies the corporate credit spreads of investment grade Euro bonds between 1998 and 2002, examining changes in spreads across time for different ratings and maturities. The aggregation of spreads and their maturity specific information is achieved through using an extended Nelson-Siegel approach to construct the spot rate at each maturity using the yield to maturity of the underlying bonds in the market (constructed separately for different rating categories). Thus, the extent of the creation of the term structure is the division of spot rates in yearly maturities from 2 to 10 years (without explaining the exact approach or choice of division). These maturities are then considered separately, for each rating category, to regress the one period change in the credit spread on firm fundamentals and the level and slope of the term structure of interest rates. This paper is relevant for the current research insomuch as it aggregates corporate bonds in the market and accounts for different terms to maturity as influencers of credit spreads. Nonetheless, its scope is to examine the causality of credit risk characteristics (such as measures of liquidity and volatility) on changes of the credit spread, whereas the sensitivity to macroeconomic variables is presented solely through the negative effect of the level and the slope of the default-free term structure.

3 Deriving the aggregate credit market indicators: the credit spread and its components

Given that, on the one hand, credit spreads contain market information and that, on the other hand, the term structure is a telling forward-looking indicator, this paper proposes the construction of the term structure of corporate credit indicators – more precisely, of the option adjusted credit spread, its idiosyncratic component and its common component. Accordingly, the separation of the idiosyncratic and common components of the credit spread and the aggregation of bond-level data into market indicators are prerequisites for the term structure construction.

3.1 Data description

The dataset used is comprised of monthly bond-specific data from a large cross-section of U.S. companies, spanning the period from January 1973 to December 2018 and containing market and accounting characteristics at the firm-level as well as bond characteristics. The data sources for security-level information are Lehman/Warga (periods between 1973 and 2004 – when the database was terminated) and ICE BofAML[6] (periods between January 1997 and December 2018 – the most recent available date), with the information from ICE BofAML being kept for the observations which appear in both databases, as it is more recent. As bond data is not as readily available as stock returns or macroeconomic data, the combination of these two databases forms the most comprehensive dataset attainable in terms of time span. The subsequent dataset can be considered representative of the U.S. corporate bond market since the underlying companies are part of one or more of the main U.S. indices[7]. In order to use firm-level characteristics to determine credit spreads, the bonds in the dataset are matched with their issuers for firms included in the Centre for Research in Security Prices (CRSP) and S&P's Compustat databases, which contain equity market and accounting data.

Merging two separate data sources, while doubling the timespan of the dataset, raises a few challenges – in particular in the form of missing data. Overcoming this without distorting information or losing a significant portion of data implies a lengthy and meticulous data cleaning process beyond the choice of observations to use from a theoretical standpoint. The mismatch between the two underlying datasets appears in bond characteristics – most impactfully, the ICE

[6] Bank of America Meryl Lynch

[7] NYSE, NYSE MKT, NASDAQ and Arca, in the case of CRSP and, additionally to these, S&P 500, S&P 400, S&P 600, S&P/TSX Composite, or Russell 3000 indices in the case of Compustat: https://wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/crsp/stocks-and-indices/overview-crsp-us-stock-database/

database (which starts in the late 1990s) does not contain data on callability. To resolve this, the bonds which are not also covered by the Lehman/Warga database (i.e. with no information on callability), are assumed to be non-callable. While this assumption does not depict reality accurately, it can be considered a decent approximation of the market starting in the early 2000s, when the amount of callable bonds started to decrease. Further, age and face value do not appear in both databases and are left missing in the overall dataset. In the case of firm characteristics missing in specific time periods, mean imputation is utilised using the respective firm's mean over time.

In a similar fashion to Gilchrist and Zakrajsek (2012) and d'Avernas (2017), the dataset is curated to contain non-financial firms that are not part of public administration, with a market capitalization of over $10 million. Only senior unsecured debt is retained (due to differences between the two datasets), for bonds with maturity between half a year and thirty and a half years and observations with a credit spread below 5bps or above 3000bps are excluded from the sample, in order to eliminate extreme values. The resultant dataset contains 19,963 bonds across 1,974 companies. The number of bonds in the dataset being one order of magnitude larger than the number of firms implies there are several issues of bonds per company on average. As depicted in the table of summary statistics (Table 3.1), indeed the average firm has around 17 bonds issued at one point in time; additionally, the median firm has 11 issues which points to a significant positive skewness.

Table 3.1: Summary Statistics

Summary Statistics

Variable	Mean	St. Dev.	Min.	P50	Max
Bond characteristics					
Number of bonds per firm and month	16.66	17.55	1.00	11.00	109.00
Months to maturity	146.45	104.08	6.00	109.00	365.00
Credit Rating			D	BBB1	AAA
Option adjusted spread (bps)	180.38	215.42	5.00	118.00	3000.00
Firm characteristics					
Total debt to Market value of assets	53.7%	17.5%	-0.5%	56.4%	241.6%
Net income to Book value of assets	0.3%	0.7%	-62.3%	0.4%	34.9%
Equity volatility	0.27	0.19	0.00	0.22	12.00
Distance to default (St. dev. units)	6.76	3.65	-31.10	6.34	119.40

Note: Sample period: Jan 1973 to Dec 2018; Observations: 1,246,693;
Number of bonds: 19,963; Number of firms: 1,974.

Table 3.1 also shows that average term to maturity in the sample is just under 12 years while the median bond matures in just over 9 years. This reveals a positive skewness caused by longest-term issues. The span of credit rating covers both investment grade and speculative grade bonds, with the median bond of rating BBB1 within investment grade. The credit rating utilized within this analysis is an average of ratings by Moody's and S&P where information on both is displayed, or alternatively the rating assigned by the existing agency[8].

The distribution of the data in terms of number of bonds per firm, of credit rating and of term to maturity is important in understanding the significance of aggregate indicators and thus is discussed at large in the respective sections.

The bond characteristic topical to the present paper is the credit spread, or option adjusted spread (OAS). In the present paper the spread used is the option adjusted spread, sourced together with the other bond characteristics from Lehman/Warga and ICE BofAML. It is defined as the difference between the yield to maturity of the respective bond and a Treasury security of similar maturity[9]. As depicted in Table 3.1, the OAS averages around 180bps while its median lands at 118bps. Its distribution is sizeably positively skewed due to few extremely large observations – which are expectedly positively correlated with default risk and recession periods. Despite this, 95% of the data lies between 30bps and 520bps.

Lastly, firm characteristics displayed in the table are indicative of the firm default risk. They show that the average firm in the sample has debt (in all forms, including bonds and bank loans) surpassing half of its market value, it makes positive profits amounting to 0.3% of its assets at book value and has a relatively low volatility in share price compared to the observed maximum. The mean distance to default of 6.76 implies that the market value of the average firm is about 7 standard deviation units above its value of debt. It is also notable that the sample contains firms which are obliged to default on their debt (with negative distance to default up to -31.1 standard deviations).

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[8] More precisely, the index of ratings is created in the following way: Firstly, each categorical rating is assigned a numerical value; secondly, a rounded average is calculated between the numerical values correspondent to the different ratings (or the only non-missing rating is used); lastly, the numerical values are converted into new categories by letters.

[9] In the Lehman/Warga database this was called 'credit spread'. The closest available version of the OAS measure is in aggregated index form from the ICE database, and is accessible on the FRED website with the following reference: Ice Data Indices, LLC, ICE BofA US High Yield Index Option-Adjusted Spread [BAMLH0A0HYM2], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/BAMLH0A0HYM2, March 16, 2020.

3.2 Idiosyncratic vs common components in the credit spread

As discussed above in section 2.2, the market credit spread consists of two components – the idiosyncratic component (IC) and the common component (CC). This section describes how these constituents are extracted and estimated from the OAS measure, using a technique largely based on Gilchrist and Zakrajsek (2012) and d'Avernas (2017). The baseline idea behind obtaining the constituents is that the IC is linearly derived from firm characteristics that reflect its level of default risk. Consequently, the portion of the spread that cannot be explained by this idiosyncratic driver is interpreted as the CC. While both guide papers use the Merton distance to default as the main measure of default risk, d'Avernas suggests augmenting the measure with an indicator of leverage, an indicator of profitability and volatility of the firm's stock returns.

Empirically, to obtain the two components a panel OLS regression is run on the individual OAS using relevant firm characteristics. The panel OLS regression centrally includes two layers of fixed effects (FE): time FE as well as bond-level FE. On the one hand, the cross-section FE capture drivers of OAS individual to each bond which are time-invariant and are thus part of the idiosyncratic element. On the other hand, time FE account for homogenous changes across time – in other words time specific factors that affect all bonds in the market in that period. Thus, time FE are part of the common element in spreads. Notably, through the time FE specification, the impact of changes in monetary policy (i.e. changes in the instantaneous rate) is captured, as well as other changes at the market level such as the on the term spread of Treasuries.

In estimating the relationship between credit spreads and default-risk, double clusters are formed for standard errors – at the firm and period level – to ensure robustness to both serial correlation and cross-section dependence[10]. Additionally, for almost all variables the natural logarithm is used in order to account for heteroskedasticity, given the strong skewness of the data[11]. Thus, the logarithm of the OAS of bond i at time t is assumed to linearly depend on a vector of firm-level and bond-level characteristics, time specific market factors and bond specific factors:

Equation 3.1

$$\ln(OAS_{it}) = \beta \boldsymbol{X}_{it} + c_i + \gamma_t + \epsilon_{it}$$

[10] Double layers of FE and clusters are possible with the STATA user command - reghdfe -

[11] The exception is DD, which is measured in standard deviation units.

In Equation 3.1, $\boldsymbol{X}_{it}$ is the vector of measures of default risk, c_i and γ_t are the cross-section and time FE and ϵ_{it} is the disturbance term, assumed to be normally distributed. The main independent variables of the regression are measures of the credit default risk of each firm: the Merton distance to default (DD), the logarithm of the ratio of total debt over the market value of assets (lev); the logarithm of the ratio of net income to the book value of assets (inc); and the logarithm of the monthly volatility of equity returns (vol).

As controls, both guide papers use some bond characteristics – specifically (in logarithms) duration, face value, coupon, age, maturity and a dummy variable for callability; they also interact these controls with the dummy variable, to capture the distinct behaviour of callable bonds in relation to each control. In the present case, the only control used in the regression is the logarithm of the coupon rate[12]. The reasons why the other controls are not included are twofold – on the one hand, data limitations on age and face value render them unreliable; moreover, a sub-sample where both types of information are present cannot be extracted as the two variables are missing from the different databases, so the intersection is virtually empty; there is also no theoretical base for using a subsample that has either one of them but not the other. On the other hand, maturity and duration are not included as they relate to the term structure of the OAS and its components, effect which needs to be preserved for subsequent yield curve construction. In the case of callability, this is not a mandatory control in the present case given that the spread is adjusted for options. However, since an assumption is made about what its missing values represent (i.e. non-callable bonds), the categorical variable is controlled for in one specification, used in interaction with the coupon variable. Additionally, credit rating effects are controlled for as well, through dummy variables for rating[13]. Thus, the three specifications of the logarithm of the OAS are as follows:

[12] The coupon rate is expressed in decimals, as a proportion of face value, to which the constant 1 is added, to account for the zero-coupon bonds when taking logarithms.

[13] Industry effects were first included too but were collinear with the FE.

Equation 3.2:

$$\ln(OAS_{it}) = \beta_1 DD_{it} + \beta_2 \ln(vol_{it}) + \beta_3 \ln(lev_{it}) + \beta_4 \ln(inc_{it}) + c_i + \gamma_t + \epsilon_{it}$$

Equation 3.3:

$$\ln(OAS_{it}) = \beta_1 DD_{it} + \beta_2 \ln(vol_{it}) + \beta_3 \ln(lev_{it}) + \beta_4 \ln(inc_{it}) + \beta_5 \ln(coup_{it}) + c_i + \gamma_t + \epsilon_{it}$$

Equation 3.4:

$$\ln(OAS_{it}) = \beta_1 DD_{it} + \beta_2 \ln(vol_{it}) + \beta_3 \ln(lev_{it}) + \beta_4 \ln(inc_{it}) + \beta_5 \text{call} * \ln(coup_{it}) + c_i + \gamma_t + \epsilon_{it}$$

The first specification contains only the credit default risk measures, without bond-level controls. The second and third include the logarithm of the coupon rate, with the difference between them being that in the third specification this is in conjunction with callability. The results of the regression specifications employed can be seen in Table 3.2. All measures of risk have the expected effect on the credit spread, with a higher spread being associated with a higher level of risk, expressed through a lower distance to default, a higher leverage ratio, a smaller income ratio and higher equity volatility. It appears that a higher coupon ratio pushes up the OAS, and the effect is accentuated for callable bonds. As shown in the table, all regressors are highly significant in all three specifications. Moreover, credit rating effects are impactful throughout, with all rating categories being significant at the 1% or 5% level – this result is as expected, since the credit rating is an assessment of the default risk of the asset.

It is important to note the sizeable difference between the 'Adjusted R-squared' statistic and the 'Adjusted R-squared within' statistic between each other and the miniscule difference across specifications. While the former statistic is an indicator of the overall variation in the data that can be explained by the regressors, the latter statistic accounts for the explained variation within each bond. This difference is due to the FE, indicating the magnitude of their importance.

In order to obtain the estimate for the idiosyncratic component, the exponent of the predicted values of the regression is computed. It includes the estimated effect of the default-risk measures as well as the cross-section FE:

Equation 3.5:

$$\widehat{IC_{it}} = \exp\left(\hat{\beta}\boldsymbol{X}_{it} + c_i + \frac{\widehat{\sigma^2}}{2}\right)$$

The equation includes the estimated variance of the disturbance term, σ^2, given the assumption that errors are normally distributed. Consequently, the common component of the OAS is calculated as the difference between the OAS and the IC, which notably includes time FE:

Equation 3.6

$$\widehat{CC_{\iota t}} = OAS_{it} - \widehat{IC_{\iota t}}$$

Table 3.2. Panel FE Regressions

Panel FE regressions

	Logarithm of Option Adjusted Spread		
	Specification (1)	Specification (2)	Specification (3)
Distance to default	-0.00281**	-0.00288**	-0.00296**
	(0.00130)	(0.00130)	(0.00129)
Log of Equity volatility	0.119***	0.118***	0.118***
	(0.00897)	(0.00899)	(0.00894)
Log of Leverage ratio	0.409***	0.407***	0.405***
	(0.0238)	(0.0238)	(0.0237)
Log of Income ratio	-2.677***	-2.681***	-2.685***
	(0.322)	(0.322)	(0.322)
Log of coupon		1.255*	-1.270
		(0.665)	(0.977)
Log of coupon * Callability			2.204***
			(0.747)
Constant	4.705***	4.617***	4.668***
	(0.0810)	(0.0959)	(0.0953)
Observations	1,243,425	1,243,425	1,243,425
Adjusted R-squared	0.8035632	0.8035958	0.8036413
Adjusted R-squared within	0.1790930	0.1792295	0.1794382
Credit Rating effects	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes
Clusters at month and firm level	Yes	Yes	Yes

Two-way clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.3 Aggregation of bond-level indicators

In order to aggregate the individual spreads into market spreads, the main method used is a simple average, similar to the case of Gilchrist and Zakrajsek's (2012) GZ spread index. The aggregation using the median is also studied as a robustness check. In order to understand the forces affecting the underlying data through this aggregation, an in depth look into the structure of the bond data is mandatory.

Firstly, the firms in the dataset have a varying number of bonds issued on the market, ranging from one to over one hundred. With the scope of accurately representing the corporate bond market in the U.S., all issues of all firms are utilized (as opposed to singling out one bond or averaging), even if a higher number of bonds issued acts as a greater weight for the particular issuer in the subsequent aggregates. Still, in order to understand the effect of this aspect, additional information is required regarding how data changes together with the change in the number of bonds per firm. This information is captured in Table 3.3, which categorises firms in terms of the amount of bonds issued and splits them into deciles.

Table 3.3: Breakdown by deciles of the number of bonds issued by each firm

Average values for each percentile of Number of bonds per firm and month

Deciles of bonds per firm	Option adjusted spread	Months to Maturity	Market capitalization ($M)	Total debt to market value of assets	Net income to book value of assets	Monthly equity volatility
1st	275.44	161.79	144.77	63.44%	0.20%	0.33
2nd	232.48	165.83	492.36	60.99%	0.23%	0.29
3rd	200.77	160.59	965.68	60.18%	0.26%	0.27
4th	196.65	150.97	1,701.53	59.22%	0.26%	0.27
5th	193.03	142.01	2,860.73	56.55%	0.27%	0.26
6th	174.95	140.35	4,917.70	54.69%	0.31%	0.26
7th	156.89	140.21	8,560.41	50.14%	0.37%	0.26
8th	148.59	139.34	16,138.51	49.19%	0.36%	0.26
9th	122.27	132.47	32,131.27	46.25%	0.43%	0.25
10th	102.73	130.90	125,437.90	35.90%	0.64%	0.23

Thus, the first decile shows the characteristics of firms that issue an amount of bonds contained in the 1st decile of the bonds-per-firm distribution. Surprisingly, there is an almost perfectly monotonous relationship between the number of bonds a firm issues and all measures displayed below: on average a firm that issues more bonds has a greater market capitalization, is less indebted, more profitable and its equity is less volatile compared to the average firm with fewer issues; its bonds have lower yields above the risk-free rate (i.e. lower OAS) and shorter maturity. It is important to indicate that face value of these securities cannot reliably be compared, given that this information is missing for roughly half of the dataset, specifically starting from the early 2000s. However, looking at the average face values for each decile does not show any pattern, despite the parallel increase of the firm size. Thus, the assumption made is that there is no significant difference in face values of bonds issued by companies with a different amount on bonds on the market – this assumption is plausible together with the argument that larger firms, which are more capital intensive, issue additional bonds rather than bonds with larger face value. Thus, the higher number of bonds of assumingly similar values issued by larger firms effectively put a greater weight on larger firms in the aggregation of the credit spread and other measures. This is not seen as a negative, since it is reasonable to think that larger firms have a greater influence on market forces. Additionally – and not surprisingly – larger firms, with more bonds issued, appear to be a safer investment, aspect which is translated in their lower credit spread.

Secondly, the rating structure of the bonds spans the entire range of ratings, including speculative grade as well as investment grade. While the median bond is part of the investment grade range, with rating of BBB1, the distribution of ratings is presented in Figure 3.1. Here it can be observed that almost 90% of bonds across the overall period are investment grade (having credit BBB3 or above), with the mean around rating A3. As rating is a meaningful image of the level of risk of a bond and thus its credit spread, it is favourable to see that the vast majority of bonds do not have extreme ratings, including the safest AAA, and also that the most populated category is below 20% of the sample.

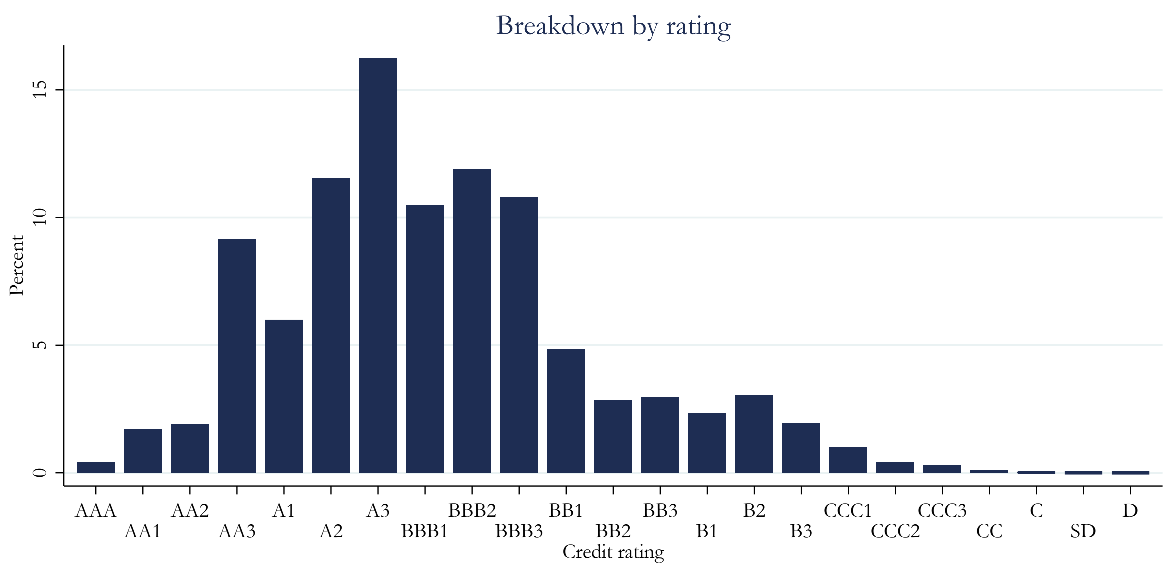

Figure 3.1: Bonds breakdown by credit rating

In order to put the current market credit spread into context, Figure 3.2 below replicates Figure 1 in Gilchrist and Zakrajsek (2012) – noting that the most prominent difference between the GZ spread and generally used credit spreads such as the OAS is that in the latter case the risk-free yield does not follow the specific cash flows of each bond. The figure shows the GZ spread next to other spreads commonly examined over time, more specifically the Commercial-Paper bill spread (the difference between 30-Day AA Nonfinancial Commercial Paper Interest Rate and the Market yield on U.S. Treasury securities at 1-month constant maturity, quoted on investment basis) and the Baa-Aaa spread (the difference between the yields of the indexes of industrial bonds rated Baa and rated Aaa), all available on the Federal Reserve's website[14]. The market credit spread constructed in this paper is added next to these widely used default-risk indicators and the GZ spread – both the simple average and median versions.

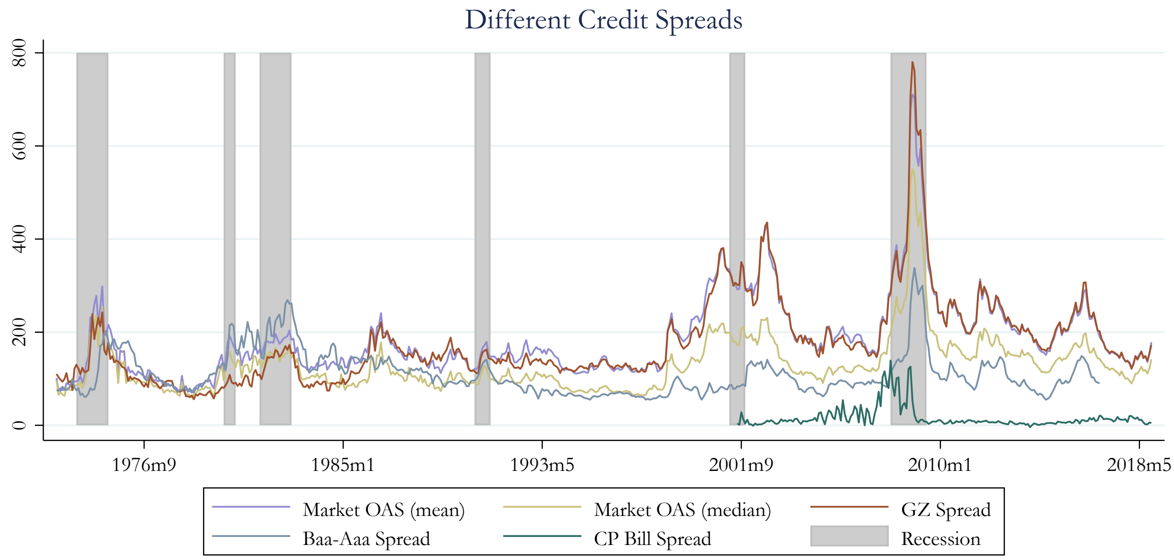

Figure 3.2: Different credit spreads. Author's rendering of data from the Federal Reserve, 2020.

The first aspect to be noted in the graph is that all credit spreads are countercyclical, rising during all recessionary periods throughout the timespan, with the most reactionary by far being the whole market credit spreads. The present market credit spread calculated using means is almost overlapping with the GZ spread but still diverges, especially around recessionary periods, given the difference in risk-free rates used and slight differences in the datasets. The market credit spread aggregated through medians is lower than the version obtained through means across the board, which shows that the positive skewness in the data is persistent across time. Concomitantly, despite the difference in levels the two curves seem to move together, which suggests robustness in market

[14] Standard spreads:
https://www.federalreserve.gov/datadownload/Download.aspx?rel=H15&series=f46dfe5b41bce023e3fe386f09d6b06f&filetype=spreadsheetml&label=include&layout=seriescolumn&from=12/01/1996&to=10/31/2019
Data from Gilchrist and Zakrajsek (2012): https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/recession-risk-and-the-excess-bond-premium-20160408.html#figure1

level fluctuations. The cyclicality of the market credit spreads is the indication that they contain information about the real economy.

Using the same aggregation methods, the two components of the OAS can be visualized. More specifically, the simple average of the individual $\widehat{IC_{it}}$ is computed over each period to obtain the market idiosyncratic component, $\widehat{IC_t}$. The series is shown together with the actual market OAS, in Figure 3.3. As shown in the legend, the figure includes all three specifications from section 3.2, nevertheless they fully overlap[15]. Additionally, the median OAS and IC are added and, as in the case of the overall credit spread, the median IC follows the same fluctuations as the average IC, but at persistently lower levels. This image uncovers that the majority of the variation in credit spreads is due to market factors, whereas idiosyncrasies appear to dictate the baseline level of the overall spreads.

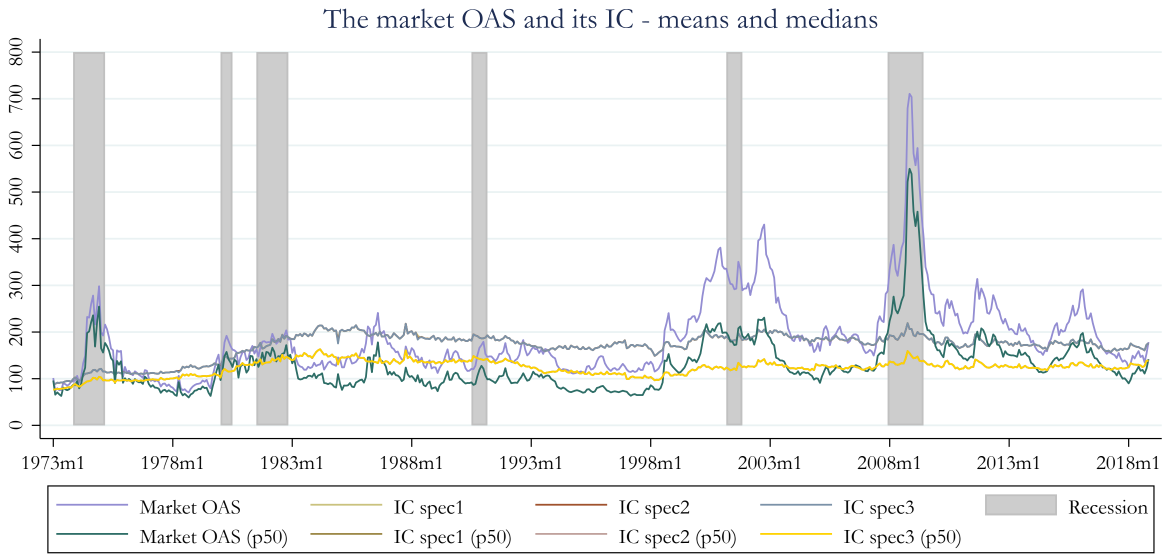

Figure 3.3. The aggregate option-adjusted credit spread (OAS) and its idiosyncratic component (IC) – obtained through means and medians. The IC represents the predicted values from regressing the OAS on firm-level default risk measures, including cross-section fixed effects and excluding time fixed effects

The market CC is plotted in Figure 3.4. The figure includes the average CC and the median CC, as well as the EBP created by Gilchrist and Zakrajsek (2012), which is examined as a benchmark for the suitability of the component extraction approach. The fluctuation of the CC is largely that observed in the OAS, which enforces the findings in the literature regarding a common factor driving credit spreads, discussed in Section 2.2. The CC demonstrates a countercyclical behaviour through surges concomitant with recessions. Beyond this, prior to the new millennium the CC

[15] Given the confirmed overlap between specifications, the third specification is used going forward.

levels tend to be negative during expansionary period, while they permanently increase thereafter and remain positive after the global financial crisis. Addressing the differences between the mean and median CC, the largest divergence between them is of 100 basis points, at the peak of the financial crisis, while for the rest of the period the mean CC is subtly larger than the median and presenting the same fluctuations. If the CC is compared to the EBP obtained by Gilchrist and Zakrajsek (2012), the two indicators are very similar in absolute terms and in their cyclical behaviour. However, the they diverge during the 1980s, when the EBP is positive the CC is negative, and after the 2001 recession, when the EBP becomes smaller than the CC and negative in between recessions. On the one hand, this disparity in the behaviours of the indicators is likely due to some dissimilarities in the datasets and due to the technique of Gilchrist and Zakrajsek of regressing the GZ spread to obtain their equivalent of the IC: the lack of inclusion of time FE and the inclusion of the first three principal components of the nominal Treasury yield curve that proxy its level, slope and curvature, interacted with the callable bonds. On the other hand, it is due to the difference between the GZ spread and the OAS.

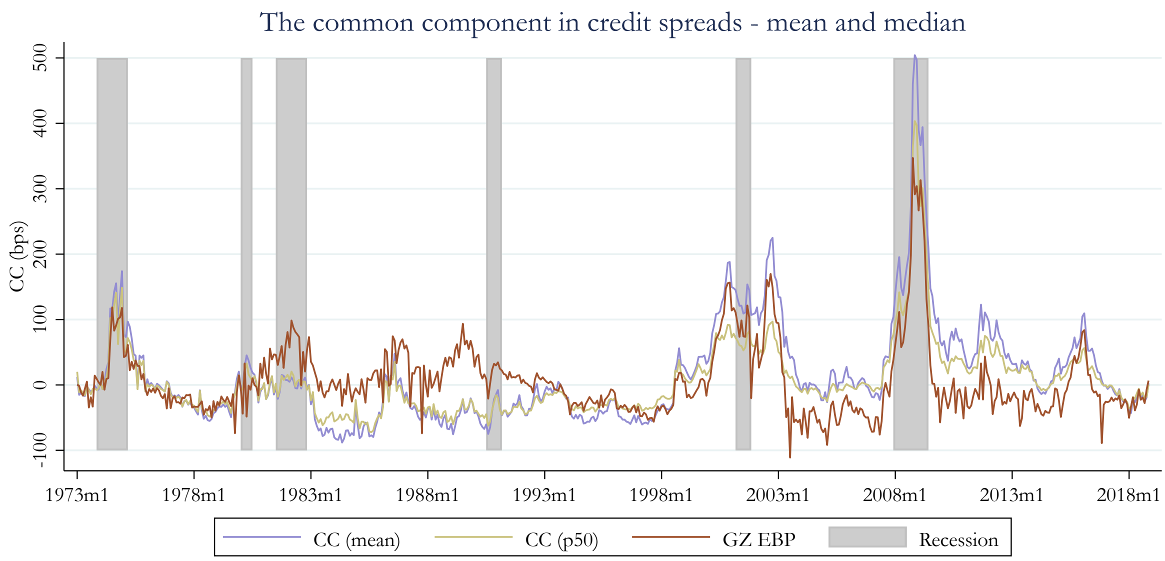

Figure 3.4. The common component of OAS (CC) and the EBP created by Gilchrist and Zakrajsek (2012). Data source for the EBP: the Federal Reserve website (see text for details).

Section 3 presented the procedure of translating the observed credit spreads of individual bonds into credit market indicators. It revealed that credit risk measures do not explain the majority of credit spread variation at the bond-level and, while the long-term level of the market credit spread is predominantly comprised of the idiosyncratic component, the common component accounts for the majority of the variation in OAS.

4 Constructing the term structure of the credit market indicators

Once the components of the credit spread are derived and the cross-section aggregation between issuers is decided on, the next step is assembling the term structure. In the case of Treasuries, the only maturities beyond 1-year, supplied by the sole issuer of the Treasury, are 2, 3, 5, 7, 10, 20 and 30-years. It follows that creating the yield curves merely implies gathering the securities in this order. In the case of the corporate credit market, there is a multitude of issuer firms suppling bonds of all monthly maturities across the thirty years spectrum – additionally, this intricate system is time variant, as bonds are issued and mature in every period. For this reason, the term structure construction is a comprehensive process, that has the goal of organising the system in a way which is robust both from the cross-section and time perspectives. It requires data analysis and involves discretionary decisions.

4.1 Methodology of term structure construction

As a first and high-level look at the data, bonds within each monthly term to maturity can be averaged in order to form the average yield curve over the sample period (January 1973 to December 2018). This curve is displayed below in Figure 4.1 and shows a stark upward sloping yield for bonds with maturities up to about 8 years (or 96 months). A pronounced change takes place with the subsequent rapid fall of yields up to about 11 years maturity, followed by a stabilisation maintained until just before the long-term end of the maturity spectrum. While this chart is illustrated to get a grasp of the dynamics of the data, it is crucial to note the underlying drivers of distortion of this curve, which need to be taken into account when creating the term structure of the data.

These drivers of distortion are predominantly due to the varying quantity of data across different maturities and time. Despite the vast size of the dataset, the market does not contain bonds of each maturity in most of the periods, and even when it does (or even for the contained maturities), the amount on bonds forming the aggregate can be very small in comparison to other maturities or periods, rendering the cumulative measure unreliable. For this reason, it becomes apparent that monthly maturities must be grouped into larger maturity baskets in order to form illustrative aggregate measures. This aspect is not detrimental to the analysis, since the focus of the study is on general longer versus shorter term dynamics and therefore information at the month-by-month level is not necessary. Moreover, given the diversity (both in terms of credit risk and lifespan) of the underlying securities forming the cumulative indicator, its curve is very noisy – allowing for bonds of a wider range of maturities to be combined into the same maturity basket can diminish this issue and smooth out the curve.

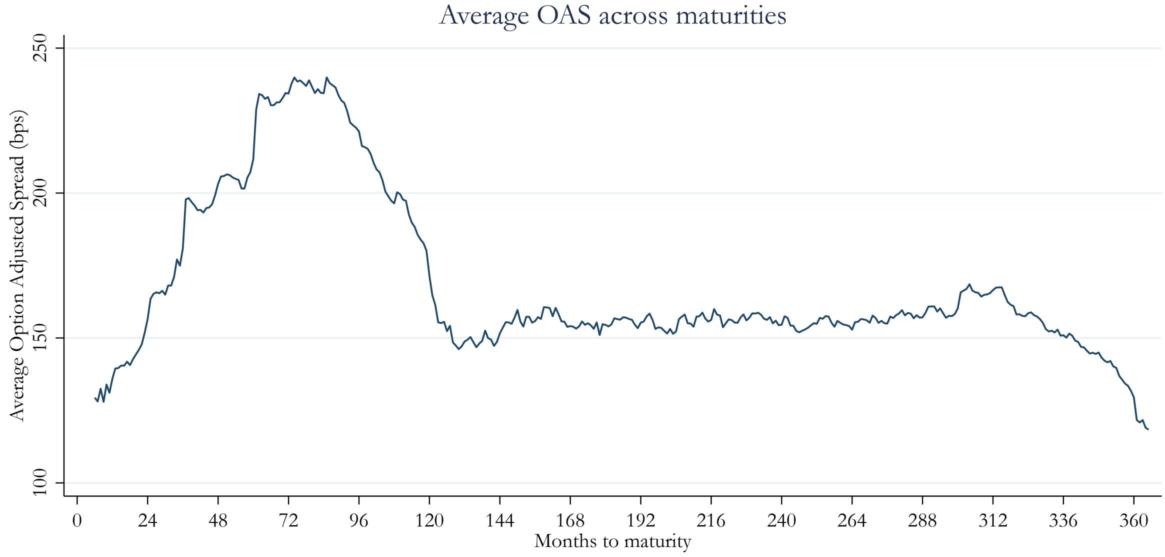

Figure 4.1: The sample average yield curve of the Option Adjusted Spread

Thus, on the one hand, forming larger baskets of maturity to group the data has the advantage of creating a more balanced and smoother yield curve. On the other hand, there is a tipping point in the size of such baskets after which they start to hide information and create distortions of their own. Furthermore, while these challenges arise when thinking about the size of maturity baskets, in overcoming them there are other dimensions to be considered as well – more specifically, the possibility of over-lapping the baskets in order to create a moving average to smoothen the curve; or the possibility to keep the basket size more granular at the shorter end of the spectrum and expanding it towards the longer end. While this is not difficult from a technical standpoint, the choice of the appropriate configuration of the term structure is challenging from a properness standpoint. More precisely, in having so much flexibility in construction, the main danger becomes basing decisions on the appearance of end results rather than robust arguments. This issue is particularly relevant when assigning meaning to economic periods in macro-finance, since finance research and macroeconomic research tend to delimitate differently between the short run and the long run. While for macroeconomists the long run can be long enough to outlive a generation[16], for financiers the long run often refers to 5 years or less – as highlighted in several finance models of the yield curve where the longest maturity is 5 years, such as Piazzesi and Ang (2001) or Cochrane and Piazzesi (2005). This is not surprising given the discrepancy in typical frequency and volatility in macroeconomic and financial data.

[16] "In the long-run we are all dead" (Keynes, 1923, p. 80)

With this in mind, a more in-depth look into maturity dynamics of the OAS data is undertaken in order to better examine its structure. Figure 4.2 displays the mean term to maturity of the underlying bonds throughout the sample time span, exposing a clear negative trend from the early 1970s until the early 2000s, followed by a slight positive trend thereafter. In order to disentangle the underlying movements behind this, the overall average needs to be decomposed; for the purpose of initial data investigation, monthly maturities are grouped into yearly baskets so that each basket spans 12 months ending in the label year (for example bonds in the 8-years basket mature anywhere between 7 years and 1 month and 8 years). Thus, Figure 4.3 shows a detailed view of the number of bonds of different maturities, revealing a number of relevant insights about the characteristics of the bond market.

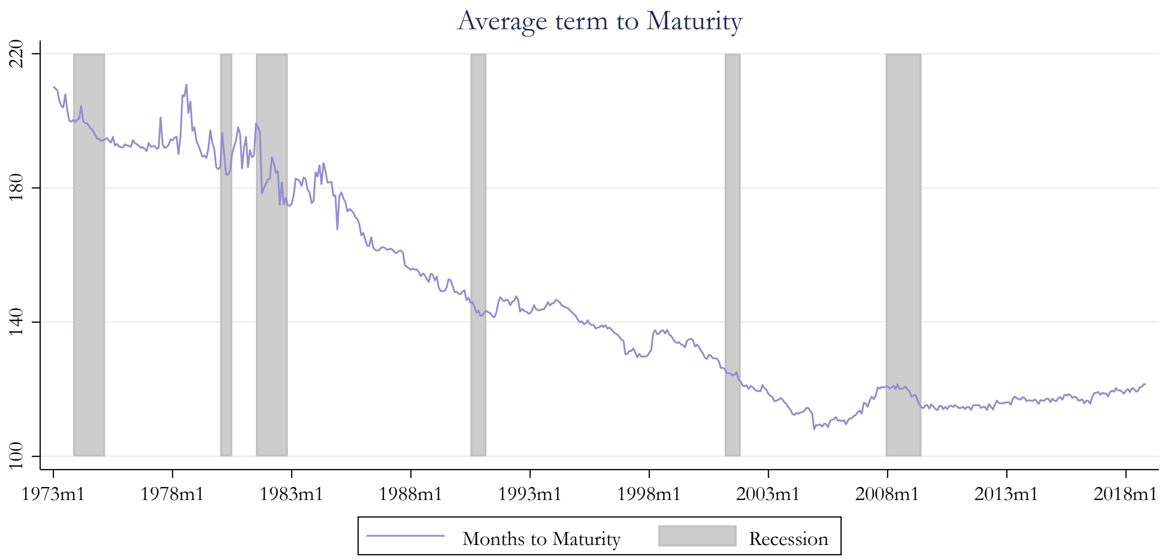

Figure 4.2: Average term to maturity each period

Firstly, the shift in average maturity with time is caused by a structural change whereby securities with a term to maturity longer than 10 years are more present in the market compared to shorter term securities until the mid 1980s, when this hierarchy permanently reverses. More precisely, there is a steadily increasing number of bonds of all maturities between 1 year and 10 years, but the number of longer-term bonds starts to decline drastically in the 1980s, reaching very limited numbers after the early 2000s (i.e. around 50 bonds in each yearly maturity group). Secondly, there is an apparent cohort effect present in bonds of longer maturities – most noticeable for high-teen maturities in the 1970s and for the longest maturities in the 1980s and 1990s. Solely examining the number of long term bonds in the market exposes the inaccuracy that would be contained in an index aggregating these bonds in the same way as their shorter-term counterparts, due to data limitations.

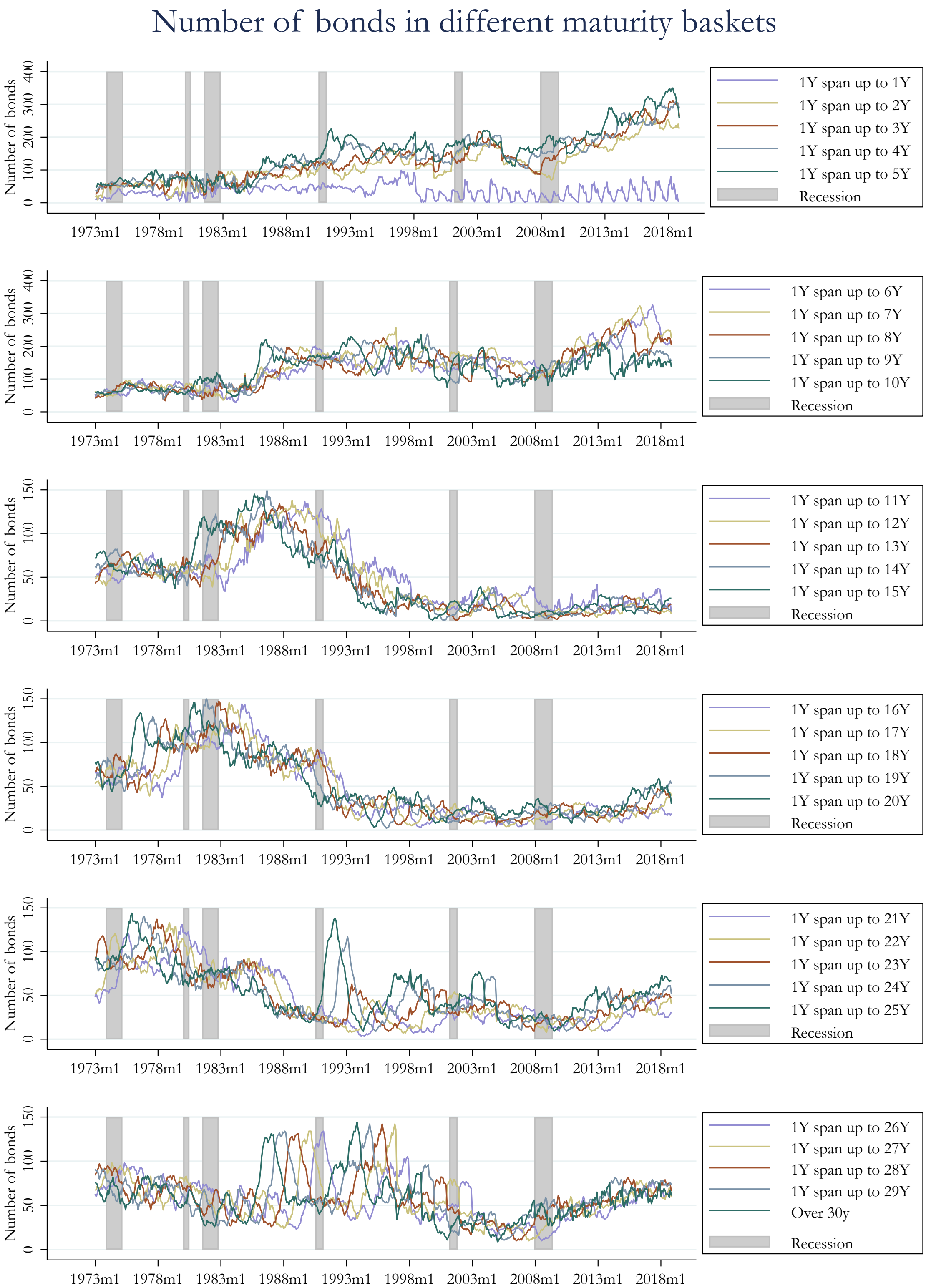

Figure 4.3: Number of bonds in different maturity baskets

Pooling together bonds of a wider range of maturities at the long end of the maturity spectrum also makes sense from a theoretical standpoint, since there is no general reason why two bonds of neighbouring yearly maturities, in more than ten years in the future, would be fundamentally different to each other. Thus, beyond the 10-year maturity mark, bonds are split into 10-year baskets: from 10 years and one month to 20 years maturity and above 20 years maturity.

At the opposite end of the maturity spectrum, a crucial aspect exposed by the first panel of Figure 4.3 is that the number of bonds with less than 1 year to maturity (that is, bonds with term to maturity between 6 months and 12 months) is also modest and after 1998 there are numerous periods with no such bonds in the market at all. Contrary to the case of long-term bonds, at short maturities smaller differences in terms are relatively more meaningful, so baskets need to be comparatively narrower; however, given this data limitation, baskets need to span longer than 1 year. Therefore, baskets spanning 2 years are created.

The reason why these particular spans are chosen at both ends is, put simply, because they are round numbers. More precisely, for shorter maturities where narrowness is desired, the next round span for a basket after 1 year is 2 years. A two-year span is seen as superior to one and a half years or other such choices in order to avoid data fitting – i.e. no trials are pursued with intermediary spans. Analogously, for longer maturities where broadness is welcomed, the largest span is chosen provided that it separates the longest maturities (which have a declining yield on average, according to Figure 4.1) from the preceding ones (with a flat curve).

Moving on to another dimension of constructing the term structure, the aspect of smoothing the curve arises. The most simple and flexible smoothing method in this case would be using a simple moving average through overlapping neighbouring maturity baskets. The advantage of using this would be reducing the noise in the data for better observation of patterns. However, this approach is discarded due to the analysis performed on the object after it is created, namely factor analysis, which requires unaltered correlation between indicators (i.e. between different maturities).

This being said, the term structure of the option adjusted credit spread up to 10 years to maturity is constructed by grouping bonds into non-overlapping baskets of maturity spanning 2 years each, and for longer maturities it is constructed by grouping bonds into non-overlapping baskets of maturity spanning 10-years each. The presence of bonds in the market according to their new split is illustrated in Figure 4.4. Unsurprisingly, there are many more long-term bonds until the 1990s, but their number converges to the amount of bonds in the baskets up to 10 years and all groups become similar in size by the new millennium.

The implementation of the term structure construction is depicted below in the case of the option adjusted credit spread and its components. To the knowledge of the author, these observations represent a novel finding in the literature, as they present the concrete term structures of corporate credit market indicators. Research of the reduced-form approach explaining corporate credit spreads (described in Section 2.3) has estimated their yield curves through fitted functional forms. However, the temporal development of the yield curves of credit spreads could not be examined until now, as this paper establishes the first term-structure construction procedure to robustly organise the market.

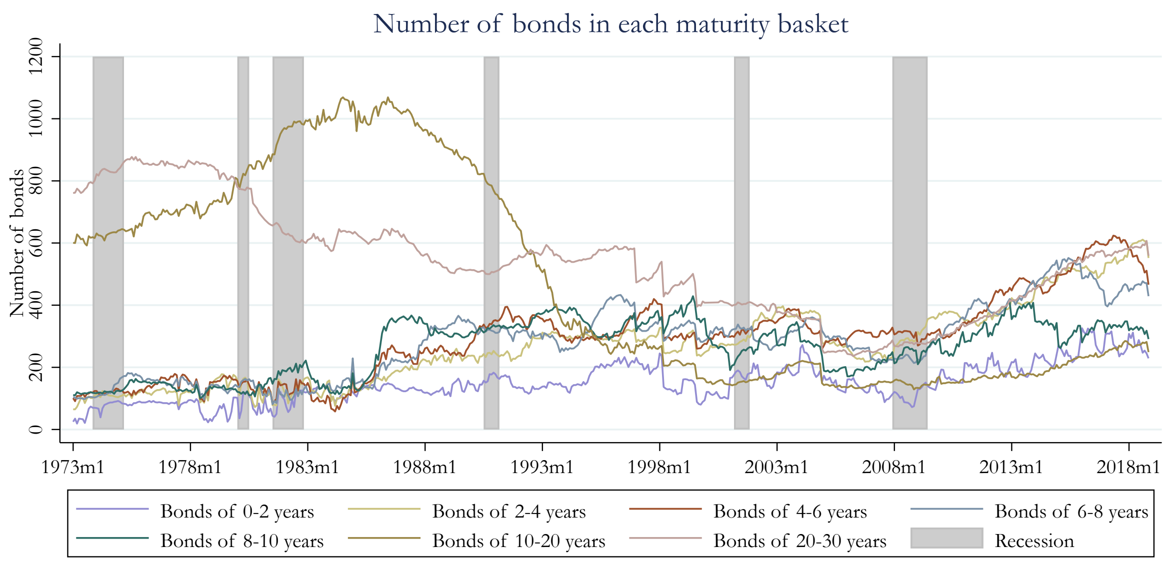

Figure 4.4: Number of bonds in each maturity basket

4.2 The observed term structures of the credit spread and its components

The results of the term structure construction in the case of the market OAS, its idiosyncratic component (IC) and its common component (CC) are presented in Figure 4.5. The figure depicts the time development of each measure aggregated separately for each maturity basket, allowing the visual inspection of discrepancies in rates dependent on the term to maturity. The image is telling of certain elements observed in the yield curves of Treasuries. Firstly, there is a clear level factor, which moves all spreads cyclically – more specifically spreads of all maturities fluctuate largely in the same direction, rising around recessionary periods. Secondly, there is a noticeable positive slope factor, especially after the mid 1990s, whereby credit spreads of shorter maturities are lower than their longer-term counterparts during the expansionary part of the cycles and converge to or surpass their longer-term counterparts around recessions. This dynamic is most noticeable in the case of the IC of bonds with term to maturity over ten years. Further, the IC of the credit spread generally appears more sensitive to the term to maturity of underlying bonds than the CC, hinting that the term to maturity is more connected to the default-risk premium than to the premium of exposure to the credit market.

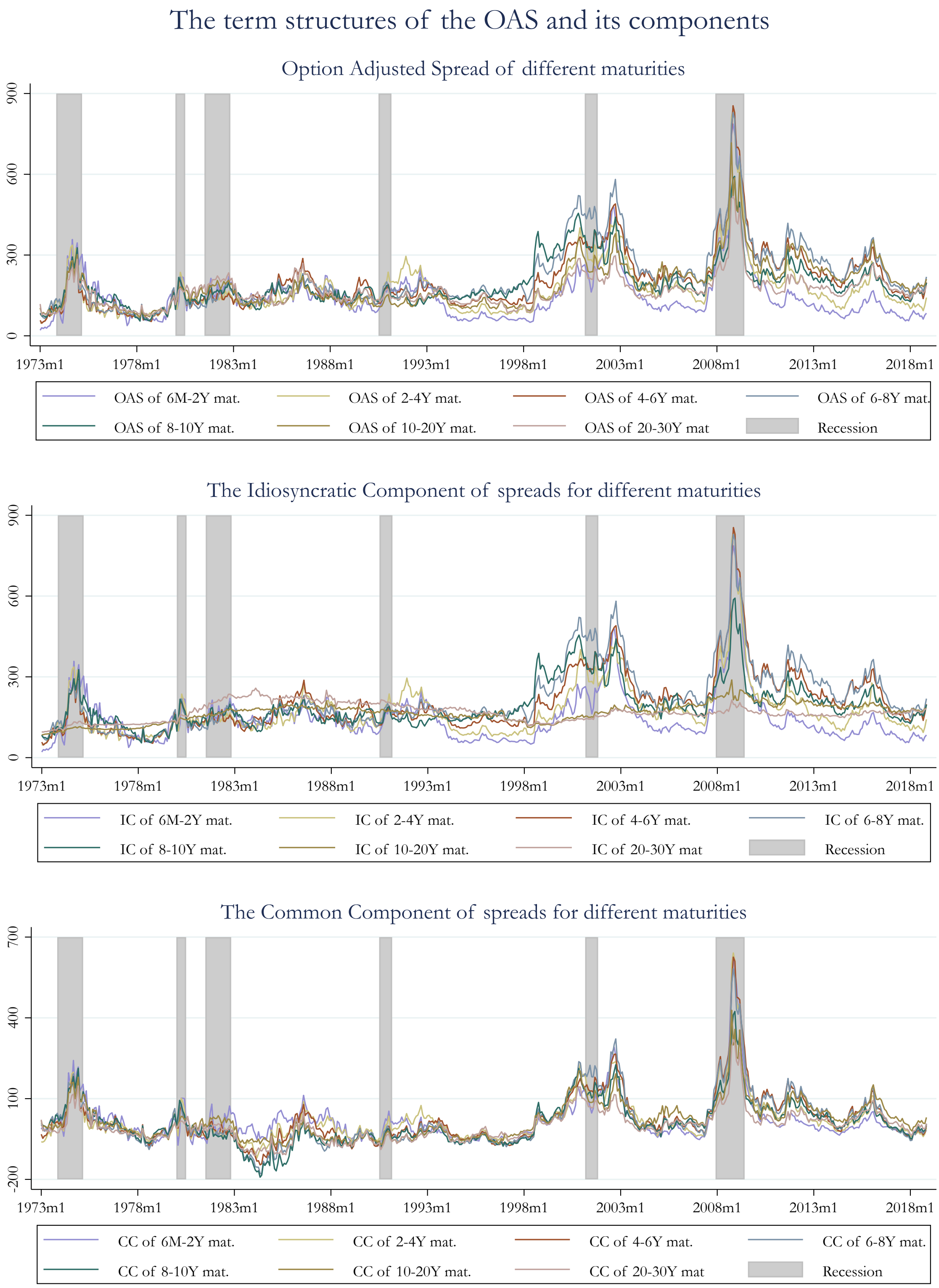

Figure 4.5: The observed term structures of the Option Adjusted Spread, the Idiosyncratic Component and the Common Component

In order to have a holistic look of the credit spreads term structures, the yield curves of the OAS are visually observed across the time period. As yields are expected to be affected by the economic conditions, recessionary and expansionary periods are examined separately. To observe expansionary periods, yearly averages of the OAS are taken for each maturity basket to create yearly yield curves spanning the whole period (1973-2018). Through this division, a few subtle patterns in the yields can be noted – firstly, yields only start having an upward slope after 1993 (as hinted by the time series in). The upward slope is more pronounced in the years which are not close to recession periods and in most cases OAS peaks around the 8-year maturity mark, slightly decreasing afterwards. Then, each recessionary period is looked at in detail, examining monthly yields for the 6 months prior- and post-recession, and the entire period during the recession. This investigation is depicted in Figure 4.6. As is indicated by the time series of the OAS, the yield curve starts to flatten in connection to recessions, but unlike the spread of treasury bonds, this flattening comes concomitantly with the recession, and if an inversion occurs, it is during and/or shortly after the recession. In interpreting the snapshot, it should be noted that the second and third recession periods are very close to each other – so close that the post- period of the former and the prior- period of the latter are consecutive months. This explains the similar flat shape of the yield curves between the two panels but also why a "normal" term structure does not have time to form.

Since the average OAS encompasses a wide range of securities with different characteristics, it is expected that the underlying yield curves are significantly different from each other and cannot show consistent patterns. Thus, to add a level of granularity to the data, the OAS is observed for different rating groups, in lines with research described in Section 2.3. Given that the initial rating index contains twenty-three categories (from AAA to D), it leaves groups with too few observations and numerous gaps across time and maturities[17]. For this reason, rating grouping is implemented, devised to maintain a roughly balanced size for each group[18]. In lines with the literature, there appears to be a consistent positive relationship between better ratings and maturity (in months), discovered through a positive correlation starting from 0.43 for the OAS in the safest rating group. The correlation disappears for middle-range ratings and turns slightly negative for rakings in the least-safe group.

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[17] An example is rating AAA which contains a grand total of 3.6 thousand observations throughout the period and maturities.

[18] Thus, the bonds are split into 7 rating groups (RG), in the following manner: RG1 contains bonds with ratings AAA to A1, RG2 through RG6 each cover 1 rating from A2 to BBB3, and RG7 covers all ratings from BB1 to D.

Figure 4.6: OAS Yield curves around recessions. Note: If the recession is spanning over more than 8 months, 2, 3 or 4 consecutive months are grouped together for easier visualisation.

5 Summarising term information: Factor analysis

The foundational aspect in using and interpreting the term structure of the credit market measures is summarizing the information contained in the distinct maturities in order to evaluate the overall indicator. For this reason, factor analysis (FA) is performed on the components of the option adjusted credit spread, as well as on the term structure of Treasury securities. In lines with the literature (as described in Section 2.1), the first three common factors are extracted as these allow the yield curve to move according to a long-term component (which is interpreted as the "level factor"), a short term component (which forms the "slope factor") and a medium-term component (which forms the "curvature factor") permitting the curves to be straight or hump-shaped. FA deduces each indicator (here, each maturity) to be a linear function of the underlying common factors. Thus, the coefficients of each factor in this function can be observed and are called pattern loadings, or factor loadings (Sharma, 1996). The values of these coefficients relative to each other describe the intensity with which the factors move maturities relative to each other. In Figure 5.1 the factor loadings are depicted for all maturity baskets of Treasury securities, the IC and the CC.

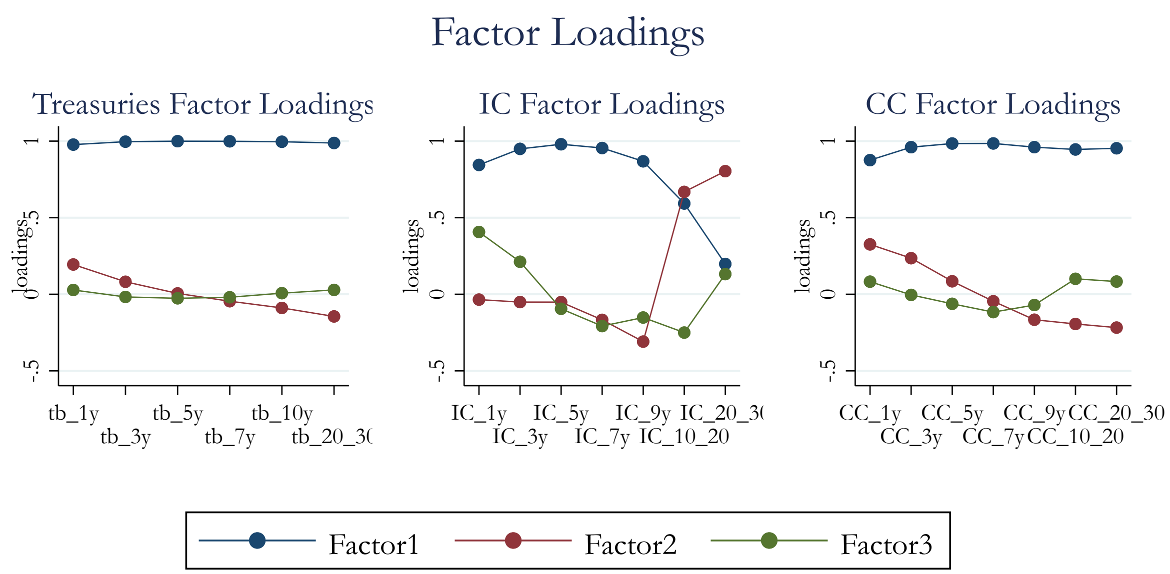

Figure 5.1: Factor loadings for Treasuries, IC and CC.

The first panel of the figure shows the pattern loadings for the Treasury yield curve[19], which is a fit starting point of analysis as it represents the basis of the standard level/slope/curvature interpretation of the factors. The first factor has virtually the same loadings for Treasury securities

[19] Market yield on U.S. Treasury securities; constant maturity, quoted on investment basis. The 20-year and 30-year Treasury bonds are averaged due to prolonged and distinct periods of missing observations.

of all maturities, suggesting it dictates the level of all maturities, in the long run. The 2nd factor linearly decreases, adding the short-term effect on the yields and thus creating a slope. The 3rd factor is tilted for medium-term bonds while mostly flat otherwise, singling out only those maturities.

Using this translation of the loadings results, the level, slope and curvature factors appear in the CC as well, with the long-term factor moving all maturities roughly by the same amount and with noticeable short- and medium-term factors. The factor loadings of the IC show a different and intriguing pattern. Firstly, the 1st factor weakens significantly for longer-term bonds, where the 2nd factor breaks and gains a stronger effect on bonds at this end of the spectrum than the 1st factor (very possibly relating to the fact that the next 2 maturity baskets cover a sizably longer timespan). Additionally, the 3rd factor moves downward until before the longest maturity. To this extent, it appears the term structure factors of the IC break the level-slope-curvature interpretation, as the 1st factor is most pronounced for short and medium-long term issues, the 2nd factor is most impactful for the longest extremity of the maturity spectrum and the 3rd factor displays a weak slope-like image.

To better understand the drivers of the term structure, it is important to restate that in the FA algorithm each first factor is constructed such that it explains the most possible variance between indicators. This means that the 1st factor explains the most variation in differing maturities and that out of the remaining variation, the 2nd factor explains more than the 3rd. To this end, the extent of variation explained in each case is vital in order to interpret the effect on yields of the loadings above. This is shown in Table 5.1, together with the Kaiser-Meyer-Olkin measure of sampling adequacy (required to be at least .5) to attest that indeed the series are sufficiently correlated to be considered for FA.

Table 5.1: Cumulative variation explained by common factors

	Cumulative variation explained in:		
	Treasuries	The IC	The CC
Factor 1	93.52%	75.15%	95.79%
Factor 2	98.52%	95.00%	100.06%
Factor 3	101.05%	100.93%	100.76%
KMO*	0.85	0.73	0.88

*Note: KMO shows the Kaiser-Meyer-Olkin measure of sampling adequacy, required to be above 0.5.

The table shows the expected outcome that the level factor explains the vast majority of variation in the Treasuries and the CC, with the slope factor inducing but a subtle change in indicators. This dynamic is less pronounced in the case of the IC, where the 2^{nd} factor has a relatively greater ability to capture variation. The significance of the difference in variation explained by the 1^{st} and 2^{nd} factors, is illustrated by the behaviour over time of the OAS and its components (noted in Figure 4.5): while different maturities do diverge to some extent around recessions (change captured in the slope factor), the overwhelming movement is that all spreads increase – change captured in the single level factor. For the IC, where the 2^{nd} factor is more relevant, divergences among maturities are also most noticeable. Lastly, in lines with the literature which often deems curvature insignificant, the 3^{rd} factor overexplains the variation in all cases, rendering itself superfluous.

The latent factors dynamics uncovers the fact that, within credit spreads, the idiosyncratic default-risk determined component is to some extent driven by the term to maturity of issued bonds, whereas the remainder market component is more robust with respect to maturity.

6 The term structure of credit spread components and economic activity

The portrayal of the term structures of the credit spread components and the subsequent factor analysis indicate the existence of a relationship between these financial measures and the real economy, through their countercyclical behaviour. In this section, this connection is examined. While this thesis does not intend to search for and capture the exact causal effect of these credit market indicators on the economy, it offers a primary investigation into the dynamics of the relationship. The manner in which this is achieved is by forming univariate forecasting regressions to assess the predictive power of the term structures of the IC and the CC on the growth rates of certain macroeconomic variables which are suggestive of economic activity.

The indispensable indicator in the context of economic prosperity is the growth rate of real gross domestic product (GDP). Notwithstanding this, the evolution of two of its main components – personal consumption expenditures (PCE) and gross private domestic investment (GPDI) – is also studied in order to extract information at the sectoral level[20]. Additionally, the growth rates of monthly indicators of the real economy are included in the analysis, comprising of industrial production, total private employment and the unemployment rate[21]. The specific approach of deriving the growth rates of interest is the following: where Y_t depicts a variable representing real activity at time t, the growth rate of Y from time $t-1$ to $t+h$ is captured by the equation: $\nabla^h Y_{t+h} \equiv \frac{c}{h+1} \ln\left(\frac{Y_{t+h}}{Y_{t-1}}\right)$. Here, $h \geq 0$ is the forecast horizon and c is a scaling constant that accounts for the frequency of the dependant variable in order to avoid erratic data (with $c = 1200$ in the case of monthly data and $c = 400$ for quarterly data)[22]. Given GDP and its constituents are measured quarterly, the forecasting regressors are in this case averaged over the three months of each quarter, with period t becoming one quarter. Growth rates over different horizons are specified in this way in order to allow for 'nowcasting' – for $h = 0$. Since the timely availability of financial data is emphasised as an influential element in the use of financial indicators to explain economic variables, nowcasting is the first assessment of the predictive power of the credit market term structures.

[20]Data on GDP and its constituents is taken from the Bureau of Economic Analysis (BEA), Table 1.1.6., where the series are in Billions of chained (2012) dollars, seasonally adjusted at annual rates: https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=3&isuri=1&nipa_table_list=6&categories=survey

[21] Data on total private employment and the unemployment rate is taken from BEA and data on industrial production is taken from the Federal Reserve: https://www.federalreserve.gov

[22] In the case of the unemployment rate, the growth rate formula does not involve logarithms.

As a first step of analysis, the pairwise correlations between the term structure factors and the growth rates of the economic indicators are considered. Table 9.1 in the Appendix displays these correlations, in the case of the growth rate or monthly and quarterly indicators (in Panel A and Panel B respectively). The first important aspect revealed by the table is that the 1st term structure factors of the IC and of the CC are all significantly correlated with the growth rate of each economic indicator. Secondly, the 1st factors behave in the direction indicated by the visual representations depicted in Sections 4.2: they present a countercyclical behaviour, which is translated into negative correlations with all growth rates (except the case of unemployment rate which is the reverse). The 2nd factors of the credit spread components, however, are not significantly correlated with any of the economic indicators.

This paper assesses the predictive power of the defined term structures of the two OAS components by estimating univariate forecasting regressions of the growth rates of each economic indicator on the term structure of the IC and of the CC. The manner in which the term structures are captured by the specification in this paper is through including the common factors that summarise them, derived in the previous section. As the 3rd factor is rendered inconsequential in explaining term structures, only the first two factors are considered for all objects. The term structure of Treasuries is also included as a control. This regression analysis partly resembles that of Gilchrist and Zakrajsek (2012), in that they estimate a univariate forecasting specification in order to evaluate the predictive power of credit spread components for economic activity. The fundamental difference between their configuration and the one presented here is that they use their estimates of aggregate predicted GZ spread and EBP, as a simple average of all bond-level values, across all maturities. Additionally, to control for the yield curve of government bonds, they use the difference between the 10-year bond and 3-month bill to account for the slope of the yield curve and the real federal funds rate (RFF) to account for the short-term interest rate. The RFF[23] is also controlled for in one version of the present specifications as it represents the instantaneous risk-free interest rate. However, it is not significantly different from zero in any of the cases.

Thus, the univariate forecasting specifications explain the growth rates of different economic indicators over different horizons using the afore mentioned regressors, augmented by p lags of the growth rates in order to account for autocorrelation (where p is determined through the Akaike

[23] The RFF in period t is created by deducting realised inflation from the nominal rate at period t, where realised inflation in period t is based on the Consumer Price Index (CPI) and is the log-difference between the index in t-1 and one year prior.

Information Criterion (AIC) and the autocorrelation function (ACF)). The forecasting regressions are estimated by ordinary least squares (OLS) and have the following form:

Equation 6.1: Effect of the term structure of each component of credit spreads on economic growth rates

$$\nabla^h Y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i \nabla^{\mathrm{h}} \mathrm{Y}_{t-i} + \sum_{j=1}^{2} \delta_j F_j IC_t + \sum_{j=1}^{2} \mu_j F_j CC_t + \sum_{j=1}^{2} \eta_j F_j Tr_t + \epsilon_{t+k}$$

The main independent variable determining the economic activity indicator are the term structures of the IC and the CC, contained in the first two latent factors for each respective component. Thus, $F_j IC_t$ is the jth factor of the IC at time t and $F_j CC_t$ is the jth factor of the CC at time t. The specification controls for the term structure of Treasuries in the same manner, with $F_j Tr_t$ being the jth factor of the Treasuries at time t. ϵ_{t+k} is the disturbance term, assumed to be normally distributed. For each of the examined economic indicators, δ_2 and μ_2 (the parameters for the 2nd factors of the credit spread components) are first constrained to be zero, in order to first examine the effects of the factor in each component that drives most of the variation. Since the 1st factors account for 75% of the variation in the IC and 96% in the CC, capturing the overall level of the maturity objects within components, they proxy the overall IC and CC. Further, adding the 2nd factors in the regressors is equivalent to assessing the effect of the term to maturity of the IC and CC. More precisely, the loadings of the IC 2nd factor, displayed in Figure 5.1, indicate that the effect of the IC slope on economic activity is based on the bonds of the longest maturities. At the same time, the figure reveals the economic effect of the CC slope is based on shorter-term bonds and is relatively weaker.

The results of the regressions showing results on the growth rates of monthly economic variables are displayed in Table 6.1, with panel A depicting the one-month contemporaneous growth rates. Focusing on this panel, it appears that the level factor of the IC cannot significantly explain changes in any growth rates, but its 2nd factor is negatively associated with the growth rate of industrial production. This suggests that in the case of contemporaneous industrial production, the slope of the term structure rather than the level of the IC is indicative of changes in the growth rate. More specifically, ceteris paribus, a 100 basis points increase in the IC 2nd factor – or the IC of the longest-term bonds – corresponds to a 13.2 basis points decrease in the growth rate of industrial production from the previous month. The CC shows a different image, as its 1st factor significantly explains all indicators, with a negative influence on the growth rate of industrial production and private employment and accelerating the rate of unemployment.

Table 6.1: Forecasting regressions of monthly economic indicators

Forecasting regressions of monthly economic indicators

	Industrial Production		Private Employment		Unemployment rate	
Panel A. Contemporaneous growth rates						
IC 1st Factor	-0.490	1.563	-0.328*	-0.0747	-4.861	-38.83
	(0.889)	(1.176)	(0.196)	(0.256)	(21.03)	(27.65)
IC 2nd Factor		-1.588***		-0.206		15.17
		(0.594)		(0.129)		(13.45)
CC 1st Factor	-2.498***	-5.034***	-0.435**	-0.746***	73.60***	106.4***
	(0.923)	(1.302)	(0.200)	(0.275)	(22.49)	(30.36)
CC 2nd Factor		-0.218		-0.0226		22.25*
		(0.551)		(0.125)		(12.78)
Tr 1st Factor	-1.220***	-1.231***	-0.305***	-0.303***	47.66***	41.83***
	(0.419)	(0.449)	(0.0912)	(0.0982)	(10.37)	(11.04)
Tr 2nd Factor	-0.659	-0.822*	-0.119	-0.133	13.97	23.24**
	(0.407)	(0.456)	(0.0948)	(0.110)	(9.646)	(10.82)
Observations	524	524	519	519	522	522
Adjusted R-squared	0.250	0.258	0.603	0.604	0.200	0.204
Panel B. Growth rates over the three months horizon						
	Industrial Production		Private Employment		Unemployment rate	
IC 1st Factor	-0.347	0.0575	-0.158***	-0.119	6.023	1.202
	(0.266)	(0.351)	(0.0564)	(0.0726)	(6.014)	(7.921)
IC 2nd Factor		-0.410**		-0.0438		1.549
		(0.180)		(0.0365)		(3.848)
CC 1st Factor	-0.363	-0.966**	-0.0189	-0.0775	14.98**	19.52**
	(0.280)	(0.402)	(0.0570)	(0.0788)	(6.613)	(8.936)
CC 2nd Factor		0.109		0.0140		4.238
		(0.164)		(0.0354)		(3.684)
Tr 1st Factor	-0.387***	-0.451***	-0.0854***	-0.0909***	15.56***	14.61***
	(0.130)	(0.139)	(0.0268)	(0.0287)	(3.178)	(3.324)
Tr 2nd Factor	-0.387***	-0.377***	-0.0954***	-0.0905***	9.026***	10.85***
	(0.124)	(0.139)	(0.0274)	(0.0317)	(2.811)	(3.193)
Observations	521	521	516	516	518	518
Adjusted R-squared	0.876	0.877	0.959	0.959	0.845	0.845

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Where h is the forecast horizon and h=0/h=3: Lags included: industrial production - 6/6; employment -11 /11; unemployment rate -8 /9. The constant is omitted

Nonetheless, the slope factor of the CC is not significantly different from zero. This is not surprising given the limited variation in the CC explained by the 2nd factor and also given that the commonality of this component extends to the maturity of underlying bonds. However, the effect of the CC level becomes stronger in conjuncture with the slope factors. In the case of industrial production for example, the growth rate decreases with 20.8 basis points, and 42 basis points respectively, for each 100 basis points increase in the CC level, all else equal.

Turning to panel B, which displays growth rates from the previous month to three months ahead, it is important to first emphasise that increasing the time span of the growth rate measurement with horizon together with the inclusion of several lags substantially increases the variation in data captured by the regression – this is revealed through the sizable improvement of the 'Adjusted R-squared' statistic. Moreover, coefficients between the same regressors across panels are not trivially comparable as adjustments for the scaling constant depend on horizon. To that end, the influence of the IC factors remains consistent with the contemporaneous case, with a 100 basis points increase in the longest-term IC corresponding to a 13.7 basis points fall in the industrial production growth rates over the three months ahead, all else equal. However, the level factor of the CC loses its predictive power when the regression is not augmented with the term structures, in the case of industrial production and completely in the case of private employment.

The results of the regressions using the quarterly data on GDP and its components are expressed in Table 6.2 and are consistent with the case of the monthly production and employment measures, for contemporaneous growth (panel A). When looking only at the levels of the credit spread components, the CC is the only driver of the GDP growth rate, with a negative impact. When the term structure factors are added however, both the level and slope of the IC show a significant effect, although in opposite directions. The only element that is not powerful in explaining changes in any economic indicator remains the slope of the CC. A similar picture is drawn in the GDP growth over the subsequent quarter (panel B), though to a lesser extent: the CC level factor becomes significant at the 5% level only in conjuncture with the slope factors, and the IC level factor remains inconsequential. Nonetheless, the negative impacts of the IC slope and the CC level remain robust for the longer horizon growth rate of the GDP. Another persistent feature across indicators and horizons is that the predictive power of the CC level strengthens with the addition of the slope factors.

Table 6.2: Forecasting regressions of quarterly economic indicators

Forecasting regressions of quarterly economic indicators

Panel A. Contemporaneous growth rates						
	GDP		PCE		GPDI	
IC 1st Factor	0.167	1.512**	-0.454	0.872	0.275	5.600
	(0.504)	(0.666)	(0.422)	(0.583)	(2.613)	(3.434)
IC 2nd Factor		-1.044***		-0.856***		-3.425**
		(0.332)		(0.303)		(1.682)
CC 1st Factor	-1.570***	-3.228***	-0.331	-1.894***	-7.106***	-12.81***
	(0.521)	(0.729)	(0.434)	(0.660)	(2.607)	(3.584)
CC 2nd Factor		-0.0245		-0.257		-1.648
		(0.308)		(0.253)		(1.618)
Tr 1st Factor	-0.488**	-0.526**	-0.230	-0.196	-3.416***	-3.045**
	(0.225)	(0.241)	(0.182)	(0.196)	(1.194)	(1.286)
Tr 2nd Factor	-0.198	-0.246	-0.332*	-0.429**	-1.494	-2.332*
	(0.229)	(0.252)	(0.189)	(0.209)	(1.197)	(1.327)
Observations	181	181	179	179	182	182
Adjusted R-squared	0.261	0.294	0.234	0.270	0.196	0.211
Panel B. Growth rates over the three months horizon						
	GDP		PCE		GPDI	
IC 1st Factor	-0.105	0.591	-0.335	0.288	-1.543	2.280
	(0.301)	(0.401)	(0.238)	(0.332)	(1.537)	(2.012)
IC 2nd Factor		-0.616***		-0.449**		-2.261**
		(0.202)		(0.175)		(0.995)
CC 1st Factor	-0.592*	-1.549***	0.0685	-0.723*	-3.136**	-7.257***
	(0.318)	(0.454)	(0.245)	(0.383)	(1.566)	(2.165)
CC 2nd Factor		0.127		-0.0529		-1.523
		(0.184)		(0.144)		(0.940)
Tr 1st Factor	-0.278**	-0.356**	-0.0731	-0.0855	-2.648***	-2.344***
	(0.136)	(0.146)	(0.103)	(0.112)	(0.715)	(0.759)
Tr 2nd Factor	-0.301**	-0.285*	-0.305***	-0.334***	-2.009***	-2.757***
	(0.138)	(0.152)	(0.108)	(0.121)	(0.707)	(0.781)
Observations	180	180	178	178	180	180
Adjusted R-squared	0.616	0.632	0.629	0.640	0.577	0.592

GDP= gross domestic product; PCE = personal consumption expenditure; GDPI = gross private domestic investment - all in chain (2012) dollars, seasonally adjusted. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Where h is the forecast horizon and h=0/h=3: Number of observations is x/y; Lags included: GDP - 2/2; PCE - 4/4; GPDI - 1/2. Regressions also include a constant, which is omitted.

Beyond understanding the relationship with GDP, it is insightful to examine dynamics at the level of its constituents, in order to understand the channels through which the corporate credit market affects the real economy. From the table, it is apparent that private domestic investment (GPDI) is more sensitive to the credit market than personal consumption (PCE). This result is in lines with expectations and confirms that the channel through which the credit market affects the real economy is predominantly the investment channel, as stated by Gilchrist and Zakrajsek (2012) among others. In the case of the GPDI, ceteris paribus, a 100 basis points increase in the CC level is associated with 59.2 basis points decrease in the contemporaneous growth rate from the previous quarter, when only levels are considered (where the rapport with the same PCE growth rate is immaterial), and with a 106.8 basis points decrease when slopes are added to the regression (in comparison with a 15.8 basis points fall in the same PCE rate). This dynamic holds for the IC slope as well and after extending the horizon by one quarter: for example, the growth rate of domestic investment from previous quarter to one quarter ahead on average decreases with 75.4 basis points for every 100 basis points increase in the IC slope, while the respective personal consumption rate decreases with 15 basis points.

In terms of the effect of the term structure of Treasuries, the general level of interest rates hinders economic activity with the exception of personal consumption (where it has the expected negative sign, nonetheless). The slope of the Treasury yield curve generally has a significant predictive power in all cases of the three-months horizon, in lines with the literature (Section 2.1), whereby flattening of the yield curve (equivalent with a decrease of the 2nd factor) signals economic weakness[24].

Lastly, Table 9.2 in the Appendix contains a comparison of the two regressions presented above for the industrial production growth rate over the three months horizon with the results of regressions including the actual IC and CC or including the indicators constructed by Gilchrist and Zakrajsek (2012). Since the regressors sizeably differ in scale, the table shows standardised coefficients before the coefficients in absolute terms, to compare the changes of the growth rate in standard deviations units caused by one standard deviation increase in each predictor, ceteris paribus. The predictive power of the overall IC and CC is directionally consistent with the predicted GZ spread and the EBP calculated here and in Gilchrist and Zakrajsek (2012) – showing a significantly negative impact of the common element in spreads. The effect of the idiosyncratic element is significantly different from zero only when in conjuncture with the term structure.

[24] Referring back to Figure 5.1, the slope factor represents the effect of short-term Treasuries over the long-term ones and thus it is defined as the negative standard slope of a curve.

Nonetheless, the standardised size of the effect is similar between the GZ predicted spread and the level factor of the IC. Moreover, in order to test the robustness of the results, the regressions are also performed on a subsample which spans periods from 1985 from 2018. Guided by Gilchrist and Zakrajsek (2012), this cut-off is chosen as it corresponds to a stabilisation of monetary policy and deregulation of financial markets. The results based on this subsample are displayed in the Appendix in Table 9.3 and in Table 9.4 and are vastly similar to the main results.

Overall, the results of the forecasting regressions show that the components of the OAS have a significantly negative association with economic activity. The idiosyncratic component of credit spreads creates a maturity variant impact, whereby the long-term factor represents the negative economic driver. In the same time, the common component of credit spreads has a maturity persistent impact which is, however, intensified by the addition of the slope regressors and surpasses the IC element in predictive power. In terms of impact channels, the credit market affects the GDP growth rate primarily through the private domestic investment channel.

It is important to restate, however, that the analysis in this section has an illustrative purpose, as opposed to a comprehensive assessment of the indicators, and serves as a preliminary investigation to be built upon. The main limitations of the present OLS specifications is that they do not account for endogeneity, in the context where omitted variable bias and reverse causality are possible. Moreover, in lines with the bilateral models explaining Treasury yield curves (discussed in Section 2.1), a vector autoregressive (VAR) model permitting bidirectional dynamics should be employed to dissect the relationship between the credit market and economic activity indicators. These advancements are reserved to future research.

7 Conclusion

This paper constructs the term structures of credit spread components observed in the U.S. corporate bond market between January 1973 and December 2018, in order to assess their predictive power over economic activity. The first prerequisite in doing so is extracting the two underlying components of the credit spreads: the idiosyncratic component (IC) and the common component (CC). Thus, the IC is linearly derived from firm characteristics that reflect its level of default risk and the portion of the spread that cannot be explained by this idiosyncratic driver is interpreted as the CC. The second prerequisite in constructing the term structure is the aggregation of bond-level data into market indicators, which is achieved through a simple average. With the scope of accurately representing the corporate bond market in the U.S., all issues of all firms are utilized, yielding a greater weight for the issuers with a higher number of bonds in the subsequent aggregates. The market credit spread thus obtained is countercyclical, rising during all recessionary periods throughout the timespan. The aggregate IC and CC uncover that the majority of the variation in credit spreads is due to market level factors, whereas idiosyncrasies appear to dictate the baseline level of the overall spreads. The fluctuation of the CC enforces the findings in the literature regarding a common factor driving credit spreads.

The construction of the term structure of the credit market indicators is the central part of this thesis. Given market heterogeneity, this is the process of organising bonds according to their term to maturity in a robust manner, without losing information content. More precisely, monthly maturities must be grouped into larger maturity baskets due to limitations of the amount of bonds of different maturities in the market in different periods. At the same time, there is a tipping point in the size of such baskets after which they start to hide information and create distortions of their own. Accounting for this aspect and other features, the term structure of the credit spread up to 10 years to maturity is constructed by grouping bonds into non-overlapping baskets of maturity spanning 2 years each, and for longer maturities it is constructed by grouping bonds into non-overlapping baskets of maturity spanning 10 years each.

The establishment of the term structure construction procedure represents a novel finding in the literature, to the knowledge of the author. Its relevance lies in allowing the examination of the temporal development of the yield curves of corporate credit market indicators. This examination reveals the presence of a level factor which moves all spreads countercyclically. Moreover, there is a slope factor, especially after the mid 1990s, whereby credit spreads of shorter maturities are lower than their longer-term counterparts during the expansionary part of the cycles and converge to or surpass their longer-term counterparts around recessions. This dynamic is most noticeable in the case of the IC of bonds with term to maturity over ten years. Further, the IC generally appears more sensitive to the term to maturity than the CC.

Beyond the visual evaluation, the term structures of the spread components are formally assessed through factor analysis. The level/slope/curvature configuration is present in the case of the CC, while the factor loadings of the IC diverge from it, in that the IC 1st factor weakens significantly for longer-term bonds, where the IC 2nd factor breaks and gains a stronger effect on bonds than the 1st factor. Further, the IC 2nd factor has a relatively greater than usual ability to capture variation (about 20%). The latent factors dynamics uncovers the fact that, within credit spreads, the default-risk determined component is partly driven by the term to maturity of issued bonds, whereas the remainder market component is more robust with respect to maturity.

Once the term structures of the IC and the CC are studied, their relationship with the real economy is assessed by estimating univariate forecasting regressions of the growth rates of several economic indicators. Thus, the growth rates from the previous period to the contemporaneous period or over a three months horizon are forecasted, in the case of real GDP and two of its components as well as in the case of monthly industrial production, private employment and the unemployment rate. The manner in which the term structures are captured by the forecast specifications is through including the latent factors that summarise them. The results of the forecasting regressions employed in this paper show that the components of the OAS have a significantly negative effect on economic activity. The idiosyncratic component of credit spreads creates a maturity variant impact, whereby its long-term fraction represents the negative economic driver. In the same time, the common component of credit spreads has a maturity persistent impact which is, however, intensified by the addition of the slope regressors and surpasses the IC element in predictive power. In terms of impact channels, the credit market affects the GDP growth rate primarily through private domestic investment rather than through personal consumption.

While this forecasting approach offers a primary investigation into the effects of the credit market rates on the real economy, these preliminary findings are encouraging for more in-depth research in this direction. In particular, the implementation of a vector autoregressive (VAR) model permitting bidirectional macro-finance dynamics could sizeably build upon the present analysis and potentially offer policy makers a tool to observe economic activity developments in real time.

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9 Appendix

Table 9.1: Pairwise correlations between term structure factors and growth rates of economic indicators

Pairwise correlations between term structure factors and growth rates of economic indicators

Panel A: Growth rates of monthly economic indicators

	Contemporaneous Indicators			Three months ahead		
	Industrial Production	Private Employ-ment	Unemploy-ment Rate	Industrial Production	Private Employ-ment	Unemploy-ment Rate
IC 1st Factor	-0.3403*	-0.5440*	0.2515*	-0.4623*	-0.5828*	0.3855*
IC 2nd Factor	0.0477	0.0367	-0.1039*	0.0655	0.0334	-0.1400*
CC 1st Factor	-0.3904*	-0.5583*	0.3165*	-0.5322*	-0.5969*	0.4761*
CC 2nd Factor	-0.0362	-0.0735	0.0696	-0.0224	-0.0544	0.076
Tr 1st Factor	0.0457	0.1036*	0.0659	0.0794	0.1396*	0.0816
Tr 2nd Factor	-0.0426	0.0959*	0.0429	0.0001	0.1669*	-0.0308

Contemporaneous indicators show the growth rate from the previous month to the present; Forecast horizon of three months show the cumulative growth rate from the previous month to 3 months ahead. *Significant at the 5% level.

Panel B: Growth rates of quarterly economic indicators

	Contemporaneous Indicators			Three months ahead		
	GDP	PCE	GPDI	GDP	PCE	GPDI
IC 1st Factor	-0.3885*	-0.3068*	-0.3232*	-0.4523*	-0.3806*	-0.3757*
IC 2nd Factor	0.0695	0.0138	0.0654	0.0731	-0.0024	0.0673
CC 1st Factor	-0.4758*	-0.3883*	-0.3858*	-0.5547*	-0.4769*	-0.4467*
CC 2nd Factor	-0.0285	-0.0479	-0.0821	0.0032	-0.0268	-0.0709
Tr 1st Factor	0.0859	0.0859	-0.0021	0.1123	0.115	-0.0037
Tr 2nd Factor	-0.0676	-0.1003	-0.0843	-0.0422	-0.0672	-0.0826

GDP= gross domestic product; PCE = personal consumption expenditure; GDPI = gross private domestic investment - all in chain (2012) dollars, seasonally adjusted. Contemporaneous indicators show the growth rate from the previous quarter to the present; Forecast horizon of three months show the cumulative growth rate from the previous quarter to 1 quarter ahead. *Significant at the 5% level.

Table 9.1 presents the pairwise correlations between the 1st and 2nd factors scores in period t and either the growth rate from $t-1$ to t in the case of contemporaneous indicators ($h=0$), where one period is either a month or a quarter. For the growth rate three months ahead, this refers to the growth rate over $h=3$ horizon in the case of monthly indicators and $h=1$ for quarterly indicators. The 3rd factor excluded as it is rendered inconsequential in explaining term structures.

Table 9.2: Forecasting regressions comparison

Different predictors of the Industrial Production over the three months horizon

	GZ Predicted spread and EBP	Overall IC and CC	IC and CC 1st Factors	IC and CC 1st and 2nd Factors
GZ Predicted spread	*-0.0409*			
	-0.00416			
GZ EBP	*-0.0712*			
	-0.00874***			
IC		*-0.0183*		
		-0.00476		
CC		*-0.0916*		
		-0.00806***		
IC 1st Factor			*-0.0495*	*0.00820*
			-0.347	0.0575
CC 1st Factor			*-0.0527*	*-0.140*
			-0.363	-0.966**
IC 2nd Factor				*-0.0543*
				-0.410**
CC 2nd Factor				*0.0144*
				0.109
Tr 1st Factor	*-0.0364*	*-0.0514*	*-0.0558*	*-0.0650*
	-0.251	-0.355***	-0.387***	-0.451***
Tr 2nd Factor	*-0.0539*	*-0.0547*	*-0.0550*	*-0.0536*
	-0.378***	-0.383***	-0.387***	-0.377***
Observations	541	541	521	521
Adjusted R-squared	0.8778	0.8779	0.876	0.877

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Numbers in *Italics* represent standardised coefficients and the numbers below show the coefficients in absolute terms. GZ regressors are calculated by Gilchrist and Zakrajsek (2012) (see text for details)

Table 9.3: Forecasting regressions of monthly economic indicators, 1985-2018 subsample

Forecasting regressions of monthly economic indicators, 1985-2018

	Industrial Production		Private Employment		Unemployment rate	
Panel A. Contemporaneous growth rates						
IC 1st Factor	-0.551	2.632	-0.167	0.177	17.21	-24.78
	(2.277)	(2.557)	(0.433)	(0.490)	(56.31)	(63.98)
IC 2nd Factor		-1.547***		-0.120		12.40
		(0.580)		(0.0970)		(13.62)
CC 1st Factor	-1.646	-5.562**	-0.322	-0.694	35.02	78.25
	(2.259)	(2.645)	(0.424)	(0.494)	(55.97)	(65.41)
CC 2nd Factor		0.0793		-0.0415		12.33
		(0.708)		(0.121)		(17.29)
Tr 1st Factor	-0.473	-1.224	-0.270**	-0.309*	42.23**	41.54*
	(0.724)	(0.918)	(0.130)	(0.165)	(17.98)	(22.56)
Tr 2nd Factor	-0.688	-0.606	-0.135	-0.150	19.09*	23.37*
	(0.440)	(0.525)	(0.0819)	(0.0951)	(10.73)	(12.72)
Observations	381	381	376	376	379	379
Adjusted R-squared	0.241	0.253	0.718	0.718	0.195	0.195
Panel B. Growth rates over the three months horizon						
	Industrial Production		Private Employment		Unemployment rate	
IC 1st Factor	-0.535	-0.0932	-0.0497	-0.00111	7.071	-1.251
	(0.674)	(0.752)	(0.118)	(0.133)	(15.69)	(17.81)
IC 2nd Factor		-0.462***		-0.0422		1.224
		(0.177)		(0.0278)		(3.888)
CC 1st Factor	0.163	-0.631	-0.0357	-0.112	9.707	17.40
	(0.667)	(0.783)	(0.115)	(0.134)	(15.65)	(18.34)
CC 2nd Factor		0.438**		0.0458		5.371
		(0.211)		(0.0348)		(4.961)
Tr 1st Factor	-0.0208	-0.501*	-0.0562	-0.106**	14.15***	11.93*
	(0.219)	(0.278)	(0.0375)	(0.0475)	(5.308)	(6.566)
Tr 2nd Factor	-0.151	0.0311	-0.0402*	-0.0218	6.063*	8.207**
	(0.135)	(0.160)	(0.0240)	(0.0278)	(3.148)	(3.741)
Observations	381	381	376	376	378	378
Adjusted R-squared	0.863	0.866	0.972	0.972	0.818	0.818

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Where h is the forecast horizon and h=0/h=3: Lags included: industrial production - 6/6; employment - 11/11; unemployment rate - 8/9. The constant is omitted

Table 9.4: Forecasting regressions of quarterly economic indicators on the 1985-2018 subsample

Forecasting regressions of quarterly economic indicators on the 1985-2018 subsample

Panel A. Contemporaneous growth rates						
	GDP		PCE		GPDI	
IC 1st Factor	-0.374	1.819	-1.123	0.447	-2.765	7.207
	(1.150)	(1.293)	(1.109)	(1.197)	(6.028)	(6.706)
IC 2nd Factor		-0.903***		-0.871***		-3.405**
		(0.293)		(0.272)		(1.503)
CC 1st Factor	-0.707	-3.266**	0.559	-1.482	-3.463	-13.97**
	(1.151)	(1.353)	(1.100)	(1.245)	(6.004)	(6.911)
CC 2nd Factor		0.0332		0.353		-1.818
		(0.343)		(0.302)		(1.839)
Tr 1st Factor	-0.131	-0.584	-0.0445	-0.608	-3.711*	-4.461*
	(0.354)	(0.462)	(0.328)	(0.424)	(1.893)	(2.493)
Tr 2nd Factor	-0.208	-0.102	-0.357*	-0.115	-2.054*	-2.568*
	(0.216)	(0.254)	(0.191)	(0.222)	(1.152)	(1.353)
Observations	134	134	132	132	135	135
Adjusted R-squared	0.321	0.366	0.339	0.380	0.262	0.303
Panel B. Growth rates over the three months horizon						
	GDP		PCE		GPDI	
IC 1st Factor	-0.431	0.765	-0.577	0.275	-3.788	2.721
	(0.685)	(0.759)	(0.636)	(0.698)	(3.516)	(3.825)
IC 2nd Factor		-0.710***		-0.499***		-2.902***
		(0.179)		(0.168)		(0.864)
CC 1st Factor	0.00786	-1.673**	0.428	-0.729	-0.0584	-7.836*
	(0.688)	(0.806)	(0.630)	(0.733)	(3.495)	(3.978)
CC 2nd Factor		0.465**		0.232		-0.00206
		(0.203)		(0.181)		(1.041)
Tr 1st Factor	0.0399	-0.619**	0.0901	-0.265	-2.320**	-4.057***
	(0.216)	(0.278)	(0.194)	(0.256)	(1.107)	(1.434)
Tr 2nd Factor	-0.152	0.0884	-0.155	-0.0203	-1.758**	-1.687**
	(0.133)	(0.153)	(0.116)	(0.134)	(0.673)	(0.780)
Observations	134	134	132	132	134	134
Adjusted R-squared	0.634	0.671	0.662	0.679	0.632	0.662

GDP= gross domestic product; PCE = personal consumption expenditure; GDPI = gross private domestic investment - all in chain (2012) dollars, seasonally adjusted. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Where h is the forecast horizon and h=0/h=3: Number of observations is x/y; Lags included: GDP - 2/2; PCE - 4/4; GPDI - 1/2. Regressions also include a constant, which is omitted.