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Bond financing conditions, economic activity and the financial accelerator

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Abstract

This paper studies how bond financing conditions affect economic activity in the United Kingdom, both in aggregate and across firms. At the aggregate level, we show that our proxy for bond financing conditions – the excess bond premium (EBP) – outperforms traditional business cycle indicators in predicting macroeconomic outcomes. EBP shocks have economically significant effects, with investment – especially in capital-intensive assets and industries – being more strongly affected. At the firm level, we show that highly leveraged and bond-reliant firms are particularly exposed to such shocks to market-based credit conditions, providing novel evidence on the financial accelerator.

Key words: Bond financing conditions, business cycle, external financing, firm leverage and investment.

JEL classification: D22, D25, E22, E32, E44.

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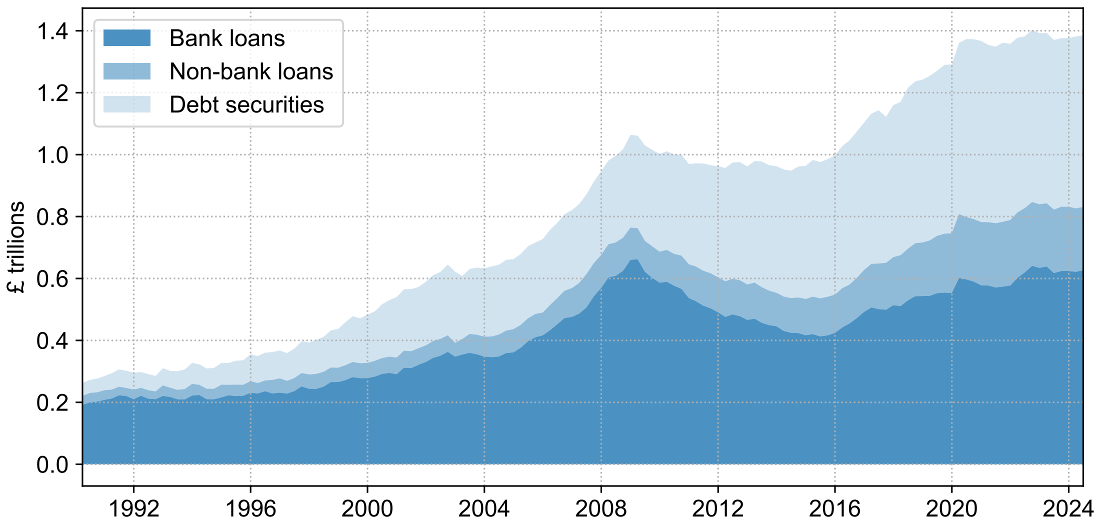
1 Introduction

In recent decades, corporate bond markets have become increasingly important as a source of external finance for firms in advanced economies (Berg et al., 2021; Darmouni and Papoutsi, 2022). In the United Kingdom, the share of external finance raised by private non-financial corporations through the issuance of debt securities – mostly corporate bonds – increased from around 15% in the early 1990s to over 40% by the mid-2020s (Figure 1). At the end of this period, these firms raised almost as much finance through bonds as bank loans.

Figure 1: Composition of UK corporate debt



Notes: The chart shows the composition of UK private non-financial corporate debt during 1990Q1–2024Q2. 'Non-bank loans' includes finance leasing and peer-to-peer lending as well as direct and syndicated loans from non-bank financial institutions. 'Debt securities' is mainly (>90%) corporate bonds but also includes commercial paper.

This raises the important question of whether financing conditions in corporate bond markets have come to affect economic activity in a similar manner to credit conditions for bank loans (Bernanke and Gertler, 1995; Jiménez et al., 2012; Barnett and Thomas, 2014; Saunders et al., 2025). Focusing on the UK, we address this issue in two ways. First, we investigate in the time series the extent to which bond financing conditions influence aggregate economic activity. Second, we study in the cross section of firms how the effects of bond financing conditions on corporate activity vary with leverage and the share of bond debt within it.

A pre-requisite for this analysis is, of course, a measure of bond financing conditions. For this, we adopt the Excess Bond Premium (EBP) of Gilchrist and Zakrajšek (2012), computing the metric for the UK private non-financial corporate sector. The EBP is the residual part of corporate bond spreads that is not accounted for by characteristics of the bonds or their obligors. As such, it more likely reflects investor characteristics, being lower when investors have greater appetite and capacity to extend finance to companies and vice versa.[1]

Equipped with our EBP measure, we first investigate the effects of bond financing conditions on key macroeconomic outcomes in the UK, such as investment, employment and output. We find that the EBP is better at forecasting these outcomes at multiple horizons than both the fitted component of spreads and traditional business cycle indicators. Moreover, we find that changes in bond financing conditions have economically meaningful effects on aggregate activity. For instance, a one-standard-deviation shock to the EBP lowers investment, as measured by gross fixed capital formation (GFCF), by almost 4 percentage points after 1.5 years. These results are similar to findings of Gilchrist and Zakrajšek (2012) for the United States and Bleaney et al. (2016) for several large European economies. In addition, we show that certain components of GFCF are especially sensitive to the EBP. In particular, GFCF in capital-intensive assets (machinery and equipment) and industries (manufacturing and other production industries) decline by as much 6 and 10 percentage points, respectively, following the same shock. Conversely, public sector GFCF is countercyclical, being strong when the EBP is higher (and hence private sector GFCF is weaker) and vice versa, thus stabilising overall investment in the economy.

We then turn to study the effects of bond financing conditions on firm-level activity. Guided by the financial accelerator mechanism (Bernanke et al., 1999), empirical studies have consistently shown that financially constrained or more-leveraged firms react more when bank credit conditions are tighter (Gertler and Gilchrist, 1994; Giroud and Mueller, 2017; Kalemli-Özcan et al., 2022; Melcangi, 2024; Anderson and Cesa-Bianchi, 2024). We present similar findings for bond financing conditions. Building on Gilchrist and Zakrajšek (2007), who show at the firm level that higher bond spreads reduce investment, we find that EBP shocks have heterogeneous effects on corporate investment, with firms with higher leverage and higher contributions of bond financing to that leverage being more affected. Thus, we contribute to the financial accelerator literature by presenting

[1] Collin-Dufresne et al. (2001) and Mueller (2009) offer a similar decomposition of corporate bond spreads and consistent rationale.

novel evidence on the amplifying role of market-based financing, depending both on its level and composition. In contrast, while sales and profits decline on average across all firms after an EBP shock, we find less heterogeneity in the responses of these income measures. These results are consistent with the effect of bond financing conditions on investment operating directly through firms' heterogeneous capital structures, while income is affected indirectly through the broader effects of bond financing conditions on aggregate activity, which is the same for all firms.

Our findings have implications for policy. First, bond financing conditions provide a helpful signal of the economic outlook, which policymakers may wish to consider alongside other information when setting cyclical policies. Second, our evidence of amplified effects of EBP shocks on investment by more-leveraged firms when they are more reliant on bond financing highlights the value of diversified sources of finance for the structural resilience of firms and, hence, the overall economy. These policy considerations will become increasingly relevant should the importance of market-based finance continue to grow.

The paper proceeds as follows. In Section 2, we describe our data sources. In Section 3, we construct a time series of the EBP for UK firms as a proxy for bond financing conditions. In Section 4, we investigate how shocks to our EBP metric affects economic activity in aggregate. In Section 5, we study how the same shocks affect the activity of individual firms, taking into account their different debt exposures. Section 6 concludes.

2 Data

In this section, we describe the different data sources used in our analysis. First, we detail the data on corporate bonds and their obligors, which we use to estimate the EBP. This includes an account of how we map bonds to obligors. Second, we outline the data on macroeconomic and sectoral activity that we use to study the impact of the EBP on aggregate economic outcomes. Third, we describe the firm-level dataset employed to explore the cross-sectional impact of the EBP on corporate activity.

2.1 Corporate bonds and their obligors

We construct a matched sample of data on corporate bonds and their obligors by (i) collecting corporate bond data from the ICE Index Platform, (ii) mapping ICE obligor identifiers to London Stock Exchange Group (LSEG) company identifiers in its Datastream and Eikon databases, (iii) gathering financial data on obligors from Datastream and Eikon and (iv) merging the bond and obligor datasets, and applying some data-cleaning filters.

Corporate bond data. From the ICE Index Platform, we combine data on particular investment-grade corporate bonds in the Global Corporate Index (G0BC) and sub-investment grade corporate bonds in the Global High Yield Index (HW00) to construct a whole-market index at month ends from December 1997 to June 2024.[2,3] Specifically, we collect data on UK non-financial fixed-coupon (including zero-coupon), senior-unsecured, non-convertible bonds without sinking funds.[4,5] This results in a sample of corporate bonds without any complex features, whose spreads are more straightforward to model.

The key variable we collect is the option-adjusted spread (OAS). This is the constant amount by which the government yield curve must be shifted up for the resulting discount rates to reduce a bond's expected future cashflows such that they sum to its price. This is essentially the same concept as the 'GZ spread' in Gilchrist and Zakrajšek (2012). Moreover, for bonds that are callable (issuer may buy back the bond prior to maturity) or putable (holders may force such a buyback), the OAS accounts for any termination of cashflows due to exercise of the call and put options. This obviates the need to control for the value of call and put options in our subsequent analysis of spreads.[6] However, we do collect

[2] December 1997 was the first month when both indices were available. The investment-grade index was launched a year earlier.

[3] To be included in these indices, bonds must have at least one year remaining until maturity and an outstanding amount of at least GBP100/EUR250/USD250 million. These criteria help to ensure that the constituent bonds are traded regularly, resulting in spreads that are less affected by illiquidity premiums and that better reflect the *current* financial condition of obligors.

[4] Non-financial obligors were identified as those with 'financial' as their level-2 industry or 'REITs' (real estate investment trusts) as their level-4 industry. UK obligors were identified as those with 'UK' for either their domicile or 'country of risk' (which, for non-financial companies, means the location of their headquarters).

[5] Senior-unsecured bonds are not secured against any specific assets of the obligor but have a senior claim on its remaining assets relative to any subordinated debt. Convertible bonds may be converted into equity securities at the option of the bondholder. And bonds with sinking funds have escrow accounts into which the obligor regularly deposits funds to help redeem or facilitate early buy back of the bond.

[6] In contrast, Gilchrist and Zakrajšek (2012) strip out the effects on spreads of call options (the

data on bond age, coupon rates, outstanding amounts, credit ratings, modified duration, currency, and obligor industry for use as control variables.[7]

Mapping obligor identifiers. Each bond-month observation in the ICE data identifies the ultimate obligor of the bond at the time of observation via a ticker symbol. We need a mapping from these tickers to company identifiers in LSEG's Datastream and Eikon databases in order to collect financial data on the obligors. However, as far as we are aware, no such mapping exists. We therefore construct our own.

This process involves three steps. First, based on the International Securities Identification Number (ISIN) of bonds in the ICE data, we collect LSEG identifiers for the issuers of the bonds at their *origin*. Second, we obtain from LSEG a *current* list of bonds for which each company in our sample is the obligor and look up any company tickers associated with these bonds in the ICE data. The first step provides an accurate mapping if the original issuer was not *later* subject to a merger or acquisition and the second step provides an accurate mapping if the current obligor was not *previously* subject to such corporate action. If these two steps agree, we infer that the obligor was not subject to a merger or acquisition during our sample period, and we accept the suggested mapping. Otherwise, we proceed to the third step, which is to confirm any suggested mappings from the first two steps, as well as to fill any blanks by manually checking corporate histories on company websites. Further details on the procedure and its results are reported in Appendix A.

Financial data on obligors. Having obtained Datastream and Eikon identifiers for our bond obligors, we gather the data necessary to compute the distance to default (DD) for these firms. This includes data on company market capitalisations and related equity returns, as well as short and long-term liabilities. To cover as many companies for as much of our sample period as possible, we draw on both Datastream and Eikon. We detail the series collected from each source and the algorithm used to choose between them, where necessary, in Appendix B.

main option type in their data) by controlling for interest-rate metrics such as volatility, which are key determinants of the option value.

[7] Age is derived from the issue date of the bond; outstanding amounts are collected in sterling; credit ratings are averages across all rating agencies that rated the bond; modified duration is a risk metric that measures the sensitivity of the bond's price to a change in its yield; and issuer industry is ICE's level-3 industry classification, which features 15 non-financial industries.

We also collect further company-level variables for use in robustness analyses from LSEG Datastream. This includes a 10-category industry classification of our non-financial obligors, which we use as an alternative to the 15-category classification in the ICE dataset. It also includes data on the geographic breakdown of company revenues, as we experiment by computing an alternate EBP for a smaller sample of 'UK-focused' obligors that generate at least 70% of their revenues in the UK.

Filtering. After merging our data on bonds and their obligors, we apply some data-cleaning filters to the combined dataset. First, we drop all observations without an OAS and corresponding DD, as well as a small number of observations with negative bond age. Following Gilchrist and Zakrajšek (2012), we also drop observations with a bond outstanding amount below £1 million, an OAS below 5 basis points or above 3,500 basis points, or with a residual maturity of less than 1 year or more than 30 years.[8] Finally, we focus our sample on bonds denominated in GBP, EUR or USD and UK-listed companies.[9] These filters have only a small effect on our sample size (see Appendix C). Table 1 presents descriptive statistics for the resulting data sample.

Table 1: Summary statistics on corporate bonds and their obligors

Variables	Mean	SD	Min	P25	P50	P75	Max	Obs
OAS (basis points)	153.9	169.3	5	81	117	171	3500	97,931
Coupon (%)	4.8	2.3	0.0	3.0	5.0	6.2	13.2	97931
Outstanding (£ mn)	501.8	332.5	50.8	290.8	423.9	626.3	3135.4	97,931
Duration (years)	6.0	3.8	0.9	3.2	5.2	7.9	22.6	97,931
Age (years)	4.7	4.4	0.0	1.6	3.5	6.4	29.2	97,931
Original maturity (years)	13.0	8.4	1.5	7.0	10.0	15.0	40.0	97,931
Residual maturity (years)	8.3	6.9	1.0	3.5	6.0	9.8	30.0	97,931
Firms per month	56.9	7.3	36	52	59	62	69	319
Bonds per month	307.0	113.6	82	220	288	398	503	319
Bonds per firm-month	5.4	6.8	1	2	3	6	58	18,164

Notes: The sample comprises 1680 bonds, matched to 149 UK private non-financial corporations, that were outstanding during 1997Q4-2024Q2.

[8] Strictly speaking, the outstanding amount threshold in Gilchrist and Zakrajšek (2012) is \$1 million, whereas ours is £1 million.

[9] We earlier limited the sample to UK companies defined in terms of domicile or headquarters, so the additional restriction of having a UK listing only removes a few obligors.

2.2 Aggregate activity

Most of the macroeconomic data in our sample is sourced from the UK Office for National Statistics (ONS). This includes real gross domestic product (GDP); its investment component, gross fixed capital formation (GFCF), which reflects investment in tangible and intangible fixed assets; and its consumption component, which captures the expenditure of households and non-profit institutions serving households. It also includes the (all items) consumer prices index and the unemployment rate (amongst people aged 16+). In addition, we source data on S&P Global's Composite Purchasing Managers' Index (PMI). The PMI is designed to show whether the economy is expanding (PMI > 50) or contracting (PMI < 50) based on surveys of purchasing managers in the manufacturing and service sectors.[10]

The ONS also makes available more-granular data on GFCF, allowing us to study the effect of the EBP on different components of investment. It provides a sectoral split into GFCF by private corporations, public corporations and the government. Moreover, GFCF by private corporations is further decomposed, including into business investment by manufacturing, other production and non-financial service industries. A split of GFCF is also available by asset type, which we group into machinery and equipment, buildings and intellectual property.[11]

2.3 Firm-level activity

In order to analyse the impact of shocks to bond financing conditions on firm-level outcomes, we use firm-level data from Compustat, specifically the *Compustat Global – Fundamentals Quarterly* database, maintained by S&P Global Market Intelligence. This is a comprehensive database containing standardised financial statement information for publicly traded companies, including quarterly data on company fundamentals for firms outside of North America.

We retrieve identifying information on firms, their balance sheets and other financial information for the obligors of the bonds in our corporate bond sample. Using this sample again is helpful as one of our key explanatory variables is the

[10]We use the average of three monthly PMI observations to obtain a quarterly measure.

[11]We group 'transport equipment' and 'information, communication and technology equipment and other machinery and equipment' into 'machinery and equipment'. We group 'dwellings' and 'other buildings and structures and transfer costs' into 'buildings'. And we retain 'intellectual property' as a group.

bond share of external debt, which we calculate as the sum of the outstanding amount of each obligor's corporate bonds (from Section 2.1) divided by its total debt. This approach allows us to distinguish between different sources of external financing at the firm level even though Compustat only contains information on total debt.

After combining the Compustat data with the EBP and a set of indicators calculated from the corporate bond data, we end up with a dataset for 1997Q4-2024Q2 and 5,067 observations for a sample of 131 firms.

3 The Excess Bond Premium

In this section, we construct a time series of the EBP for UK private non-financial corporations. We describe our methodology in Section 3.1 and expand on the construction of a key input variable – the obligor distance to default (DD) – in Section 3.2. These two sections follow closely Gilchrist and Zakrajšek (2012). Our results are presented in Section 3.3. Here, we demonstrate that our EBP metric is robust by showing that it remains largely unaffected by several reasonable adjustments in the variables considered.

3.1 Methodology

Our aim is to isolate the effect on corporate bonds spreads of key obligor (sell-side) characteristics in the expectation that the remainder will largely reflect investor (buy-side) characteristics and, thus, bond financing conditions. For this to be more effective, we also control for the effect of various bond-specific characteristics. Thus, we estimate the following regression specification:

$$\ln S_{i,t}[k] = \beta DD_{i,t} + \gamma' \mathbb{Z}_{i,t}[k] + \epsilon_{i,t}[k], \tag{1}$$

where $\ln S_{i,t}[k]$ is the natural logarithm of the OAS on bond k (which has obligor i) at time t; $DD_{i,t}$ is firm i's distance to default at the same time and $\mathbb{Z}$ is a vector of bond-specific characteristics such as age, coupon rate, outstanding amount, credit rating, modified duration, currency and obligor industry.

Assuming $\epsilon_{i,t}[k]$ is normally distributed, the predicted OAS for bond k of firm i

at time t is given by:

$$\hat{S}_{i,t}[k] = \exp\left(\hat{\beta}DD_{i,t} + \hat{\gamma}'\mathbb{Z}_{i,t}[k] + \frac{\hat{\sigma}^2}{2}\right), \tag{2}$$

where $\hat{\beta}$ and $\hat{\gamma}$ denote the ordinary least squares (OLS) estimates of the corresponding parameters and $\hat{\sigma}^2$ is the estimated variance of $\epsilon_{i,t}[k]$ from Equation 1.

Averaging across bonds and firms at time t, we define the EBP – our summary measure of bond financing conditions – as:

$$EBP_t = \frac{1}{N_t}\sum_i\sum_k S_{i,t}[k] - \frac{1}{N_t}\sum_i\sum_k \hat{S}_{i,t}[k], \tag{3}$$

where the first and second terms are the average OAS of bonds in our sample (the 'index' spread) and the fitted component of the index spread, respectively. Thus, the EBP is the residual part of the index spread not accounted for by obligor DDs and bond characteristics.

3.2 Distance to default

An obligor's DD is a measure of its probability of default. Specifically, it measures the distance between the market value of the obligor's assets and the liabilities it has due at a particular horizon relative to the volatility of its asset market value over that horizon.

To calculate a firm's DD on a given date, we first require estimates of its asset market value and volatility at that time. To help derive these variables, we use a Merton model, which equates the market value of a firm's equity to the value of a call option on the market value of its assets with a strike price equal to the face value of its debt (Merton, 1974):

$$E = V\mathcal{N}(d_1) - e^{-rT}D\mathcal{N}(d_2), \tag{4}$$

where

$$d_1 = \frac{\ln(V/D) + (r + \frac{1}{2}\sigma_V^2)T}{\sigma_V\sqrt{T}}, \tag{5}$$

$$d_2 = d_1 - \sigma_V\sqrt{T}. \tag{6}$$

In Equations (4)-(6), E is the equity market value (i.e., market capitalisation) of the firm, V is its asset market value, σ_V is the volatility of its assets, D is the face value of its debt, T is the horizon and r is the risk-free interest rate over that horizon. $\mathcal{N}(.)$ denotes the cumulative standard normal distribution function.

We use an iterative procedure to find values of V and σ_V that are consistent with these equations. Thus, for each observation date, we make an initial assumption that $\sigma_V = 0.1$ and solve for values of V for the 252 business days (i.e., one year) up to and including that observation date. To do this, we input values for T, r, D and E. We use a horizon of one year for T and one-year government bond yields in the currency of the firm's equity for r.[12] Assuming that half of the firm's long-term debt (LD) falls due after one year as well as all of its current liabilities (CL), we set $D = \frac{1}{2}LD + CL$. These values are fixed for all 252 business days. In addition, we input daily market capitalisation data for E for each of those days.[13] We then solve for V on each day and set the standard deviation of the 252 inferred values of V as a new estimate of σ_V. We repeat the steps in this paragraph until σ_V converges to a steady value.

Finally, we compute the DD for a particular firm-date as:

$$DD = \frac{\ln(V/D) + (\mu - \frac{1}{2}\sigma_V^2)T}{\sigma_V \sqrt{T}}, \tag{7}$$

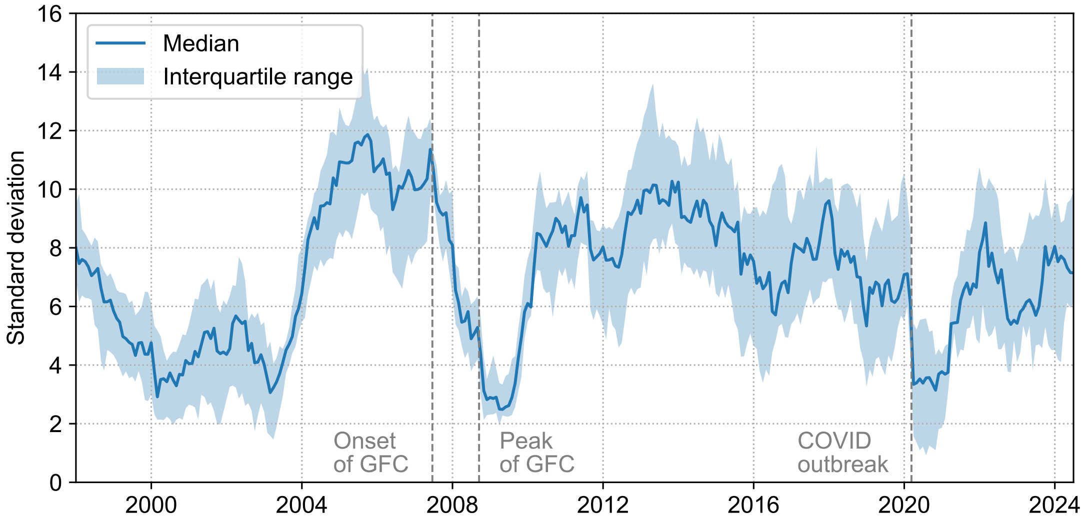
where μ is the drift in the market value of the firm's assets, computed as the growth between the first and last of the 252 estimates of V at which our algorithm converges.

Figure 2 shows the median and interquartile range of our DD estimates for the firms in our sample. As might be expected, the DD falls when the economy weakens, declining to some of the lowest levels during the recessions that followed the 2007-08 Global Financial Crisis (GFC) and the start of the COVID pandemic in March 2020.

[12] This is GBP for more than 90% of the firms in our sample.

[13] For these daily observations, we begin with end-quarter data on company market capitalisation from LSEG Datastream/Eikon (see Appendix B) for the same date for which we are solving for V and σ_V. We then scale these values by daily equity prices indexed to the same end-quarter date. Compared with using a time series of company market capitalisation, this approach avoids occasional large changes in market capitalisation due to mergers, acquisitions and other corporate actions. However, such *backward-looking* volatility would be misrepresentative of the *forward-looking* prospects of the firm that we wish to capture in σ_V.

Figure 2: Distance to default



Notes: The chart shows the median and interquartile range of distance-to-default estimates for the 149 UK private non-financial corporations in our sample that had bonds outstanding during 1997Q4-2024Q2.

3.3 Results

Equipped with our DD estimates, we proceed to estimate the model in Equation (1). We estimate several specifications of this model, experimenting with different versions of our DD variable and different controls. Specifically, we substitute the DD variable computed in Section 3.2 with one that follows the same construction but using two-year instead of one-year histories of V and one that computes σ_V using exponentially weighted averaging instead of simple averaging. Table 2 presents the results.

Across the specifications, we find the anticipated negative relationship between DD and spreads, which is consistently highly statistically significant. We also find that riskier bonds, i.e., with higher duration, have higher spreads, as do bonds with higher coupons.[14] However, we find no consistent evidence that older bonds or bonds with smaller amounts outstanding – both potential indicators of lower liquidity – have higher spreads.

Column (1) is essentially the specification in Gilchrist and Zakrajšek (2012), except that we include additional currency fixed effects as we have bonds denominated

[14]This may reflect higher higher tax rates for income than capital gains or higher loss-given-default expectations, as all bond holders receive the same fraction of principal in a corporate recovery but could lose different coupon amounts.

Table 2: Explaining corporate bonds spreads

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Constant	3.89***	3.82***	4.00***	4.14***	3.94***	4.02***	4.97***
DD	-0.05***	-0.05***	-0.05***	-0.06***	—	—	-0.08***
DD (2 year)	—	—	—	—	-0.05***	—	—
DD (EWMA)	—	—	—	—	—	-0.05***	—
log(Age)	0.01	0.01	-0.00	0.01	-0.01	-0.00	-0.00
log(Outstanding)	0.03*	0.04**	0.01	0.02	0.01	0.01	-0.05
log(Duration)	0.34***	0.34***	0.33***	0.35***	0.33***	0.33***	0.29***
Coupon	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.06***
FEs: Currencies	Y	Y	Y	Y	Y	Y	Y
FEs: Ratings	Y	Y	Y	Y	Y	Y	N
FEs: Industries	Y	Y	N	N	N	N	N
FEs: Firms	N	N	Y	N	N	N	N
FEs: Ratings	Y	Y	Y	Y	N	Y	Y
Adjusted R^2	0.64	0.64	0.63	0.67	0.61	0.64	0.34
Observations	97,909	97,909	97,909	97,909	97,546	97,909	97,909

Notes: Based on sample of 1680 bonds, matched to 149 UK private non-financial obligors, that were outstanding during 1997Q4-2024Q2. DD, DD (2 year) and DD (EWMA) respectively denote our baseline estimate of the obligor's distance to default and two alternative estimates, as described in Section 3.2. FEs denote fixed effects, where for industries we use two classifications: one from ICE and one from Datastream (DS). ***/**/* denotes statistical significance at the 1%/5%/10% level (based on standard errors clustered at the firm-date level).

in multiple currencies in our sample.[15] In column (2), we substitute fixed effects based on the 15-category ICE industries for fixed effects based on the 10-category Datastream industries. This has little effect on the results. Similarly, substituting industry fixed effects for more-granular firm fixed effects, as in column (3), or dropping industry/firm fixed effects from the specification, as in column (4), has little effect on the results. This suggests that firm-level effects on spreads are already well-captured by our firm-specific DD variable, steering us towards column (4) as our preferred specification.

In columns (5) and (6), we substitute our baseline DD measure with $T = 1$ and σ_V set equal to the simple volatility of V in its computation algorithm (see Section 3.2) for ones with $T = 2$ and σ_V set equal to the exponentially weighted moving average (EWMA) volatility of V, respectively. This has little effect on the results. Finally, in column (7), we drop the rating fixed effects. Without rating effects, the sensitivity of spreads to DD increases, suggesting that the information content of ratings and DD overlap to some extent. However, the adjusted R^2

[15]It also replaces the 'ln(coupon rate)' variable with the simple 'coupon rate'. This allows us to keep zero-coupon bonds in the sample, while for other bonds the numerical value of the variable is hardly changed given typical values of coupon rates.

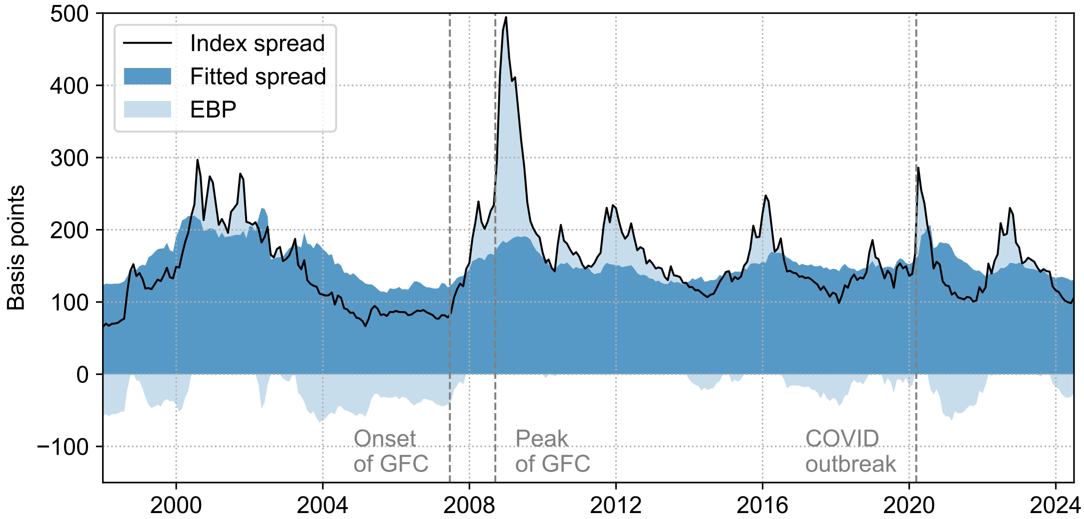
falls significantly, suggesting that ratings capture some 'soft' information that is pertinent to credit spreads and not reflected in the 'hard' data from which DD is computed. Given that, we retain rating fixed effects and settle on column (4) as our preferred specification.

Given our preferred specification for the model in Equation (1), we proceed to decompose spreads into the fitted spread and the EBP using Equations (2) and (3). The results are shown in the top panel of Figure 3. The fitted spread accounts for the largest portion of the index spread and is relatively stable over time. In contrast, the EBP is a much more volatile component, accounting for major movements in the index spread. For the majority of the sample period until the onset of the GFC, the EBP was historically low. We interpret this as bond financing conditions being favourable in the latter years of the *Great Moderation*, a period in which UK macroeconomic volatility was historically low. Then, during the GFC, the EBP increased significantly, reflecting a marked tightening of conditions in non-bank credit markets. A second peak of the EBP occurred after the start of the COVID pandemic. However, it quickly reverted, as a swift policy response helped to ensure supply of credit to firms through both bank and non-bank channels.

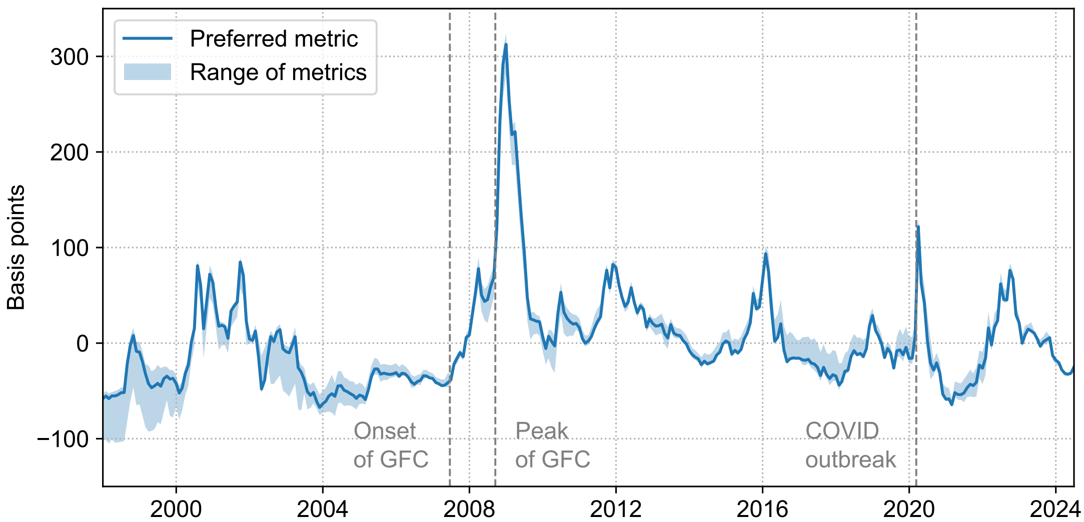
In the bottom panel of Figure 3, we plot the EBP for our preferred specification along with the range of the other specifications in Table 2. The close similarity of the time series within this range shows that our EBP metric is robust, remaining relatively invariant to reasonable variations in its derivation.

Figure 3: Components of corporate bond spreads

(a) Fitted spread and the EBP



(b) Preferred and alternative estimates of the EBP



Notes: The top chart shows an index of UK private non-financial corporate bond spreads and how it decomposes into the fitted spread and excess bond premium (EBP) on the basis of equations (1)-(3). The bottom chart reproduces the preferred EBP metric shown in the top chart, placing it within a range of alternative estimates based on the alternative regression specifications in Table 2.

4 The EBP and aggregate economic activity

In this section, we assess how shocks to the EBP affect measures of economic activity for the whole economy and particular economic sectors. We begin by comparing the ability of corporate bonds spreads and their components to forecast key macroeconomic indicators over a range of horizons. Finding superior performance when spreads are decomposed, with the EBP being the key component, we subsequently generate impulse response functions showing how a wider range of macroeconomic and sectoral indicators react to EBP shocks. Here, we find that EBP shocks affect capital formation more strongly than other macroeconomic activity measures, so we drill into these effects at the sector level. First, we contrast the effects on capital formation in the public and private sectors, finding that private investment is procyclical while public investment is countercyclical. Second, we study the response of investment in different industries and asset types, finding a stronger impact in industries and assets that are more capital intensive.

4.1 Macroeconomic forecasts

We forecast the effects of corporate bond spreads, as a whole or decomposed into their fitted-spread and EBP components, on key quarterly macroeconomic indicators using the following regression specifications:

$$\frac{4}{h+1}\Delta Y_{t+h,t-1} = \alpha + \beta^h \,\mathrm{OAS}_t + \boldsymbol{\delta^T X_t} + \sum_{l=1}^{4} \phi_l \Delta Y_{t-l,t-l-1} + \epsilon_t, \tag{8}$$

$$\frac{4}{h+1}\Delta Y_{t+h,t-1} = \alpha + \beta^h \,\mathrm{EBP}_t + \gamma^h \,\mathrm{FS}_t + \boldsymbol{\delta^T X_t} + \sum_{l=1}^{4} \phi_l \Delta Y_{t-l,t-l-1} + \epsilon_t. \tag{9}$$

The dependent variable in these regressions is the change in macroeconomic indicator Y between quarter $t-1$ and $t+h$, where h is the forecast horizon. The scale factor $4/(h+1)$ annualises this change, aiding comparability over different forecast horizons. For non-stationary variables, like gross domestic product (GDP) and gross fixed capital formation (GFCF), we use the natural logarithm of the variable so that ΔY measures its growth. Our key independent variables of interest include either the option-adjusted spread (OAS) (as in equation (8)) or the fitted spread (FS) and the excess bond premium (EBP) (as in equation

(9)). We also include a set of control variables, $\boldsymbol{X}$, which comprise the term spread, the real policy rate and two time-dummy variables which are equal to one in 2020 Q1 (COVID pandemic) or 2020 Q2 (COVID policy response), and zero otherwise. Finally, we include four lags of ΔY on the right-hand side to help account for any autocorrelation of the dependent variable, which would otherwise carry through to the residuals, ϵ_t, potentially undermining our standard error estimates. Moreover, we use Huber-White standard errors to correct for any remaining autocorrelation or heteroskedasticity of the residuals. To aid interpretability of the coefficient estimates, the independent variables other than the constant and the two time-dummy variables are standardised.

Table 3 shows our regression results for 1, 4 and 8-quarter forecast horizons. The negative coefficients on OAS for GDP and GFCF and positive coefficients on the unemployment rate imply that higher credit spreads weaken economic activity. Moreover, the larger coefficients on the EBP (which are statistically significant) than on fitted spreads (which are not statistically significant) imply that these effects are driven by bond financing conditions rather than default risk or other risk factors priced into credit spreads. This contrasts with results in Gilchrist and Zakrajšek (2012) suggesting that both components have independent effects on macroeconomic activity in the United States. Nevertheless, decomposing credit spreads into fitted spreads and the EBP still increases our adjusted R^2, meaning that it improves our ability to explain variation in our macroeconomic forecasts (even after adjusting for having an increased number of predictors).

Table 3: Forecast regressions of key macroeconomic indicators using corporate bond spreads and their components

Horizon	**1 quarter**		**4 quarters**		**8 quarters**	
	Panel A: Gross Domestic Product					
Constant	1.64***	1.62***	1.61***	1.58***	1.45***	1.43***
OAS	-1.94***	—	-1.19***	—	-0.51*	—
EBP	—	-2.71***	—	-1.71***	—	-0.94***
Fitted	—	0.82*	—	0.58*	—	0.56*
Term spread	0.08	0.32	0.55	0.75	0.68	0.81
Real policy rate	0.36	-0.30	0.68	0.26	0.82	0.50
2020Q1	-5.14***	-5.10***	-0.80***	-0.77***	0.01	0.03
2020Q2	-1.71***	-1.91***	-0.14	-0.26**	0.06	-0.03
Adjusted R^2	0.81	0.86	0.25	0.31	0.14	0.23
Observations	101	101	98	98	94	94
	Panel B: Gross Fixed Capital Formation					
Constant	2.02**	2.00**	2.00**	1.94**	1.74**	1.72**
OAS	-4.13***	—	-2.51***	—	-1.16**	—
EBP	—	-4.40***	—	-3.03***	—	-1.60***
Fitted	—	-0.12	—	0.48	—	0.56
Term spread	0.00	0.23	1.39	1.66*	1.63*	1.77*
Real policy rate	-0.33	-0.94	0.41	-0.16	0.73	0.27
2020Q1	-5.14***	-5.11***	-0.58***	-0.54***	0.13	0.15
2020Q2	-1.61***	-1.79***	0.13	-0.03	0.28	0.16
Adjusted R^2	0.54	0.55	0.18	0.24	0.08	0.13
Observations	101	101	98	98	94	94
	Panel C: Unemployment Rate					
Constant	-0.07	-0.07	-0.07	-0.06	-0.05	-0.05
OAS	0.29**	—	0.26**	—	0.12	—
EBP	—	0.38***	—	0.37***	—	0.21**
Fitted	—	-0.09	—	-0.12	—	-0.12*
Term spread	-0.15	-0.18*	-0.22*	-0.26**	-0.25**	-0.28**
Real policy rate	-0.04	0.05	-0.03	0.06	-0.01	0.07
2020Q1	0.04**	0.03**	0.08***	0.07***	-0.02	-0.02
2020Q2	0.12***	0.15***	0.01	0.03*	-0.04*	-0.02
Adjusted R^2	0.36	0.41	0.23	0.33	0.19	0.29
Observations	101	101	98	98	94	94

Notes: Regressions as specified in equations (8) and (9), with $Y = log(\text{GDP})$ in Panel A, $Y = log(\text{GFCF})$ in Panel B and $Y =$ Unemployment Rate in Panel C. For brevity, lagged dependent variables are omitted from all panels. ***/**/** denotes statistical significance at the 1%/5%/10% level (based on Huber-White standard errors). The sample period is 1998Q1–2024Q2, with 1, 4 or 8 observations lost at the end depending on the forecast horizon.

4.2 Impulse response functions

Having found the EBP to be the key component of credit spreads for predicting headline measures of macroeconomic activity, we next use a slightly modified version of our forecasting regression based on credit spread components (i.e., equation (9)) to generate impulse response functions showing how a wider range of macroeconomic and sectoral indicators react to EBP shocks. One change is to drop the $4/(h+1)$ scale factor to make it easier to see how the response of Y cumulates as the forecast horizon, h, lengthens. We also drop the fitted spread as an independent variable given its statistical insignificance throughout Table 3.[16] This gives:

$$\Delta Y_{t+h,t-1} = \alpha + \beta^h \, \mathrm{EBP}_t + \boldsymbol{\delta}^{\boldsymbol{T}} \boldsymbol{X_t} + \sum_{l=1}^{4} \phi_l \Delta Y_{t-l,t-l-1} + \epsilon_t. \tag{10}$$

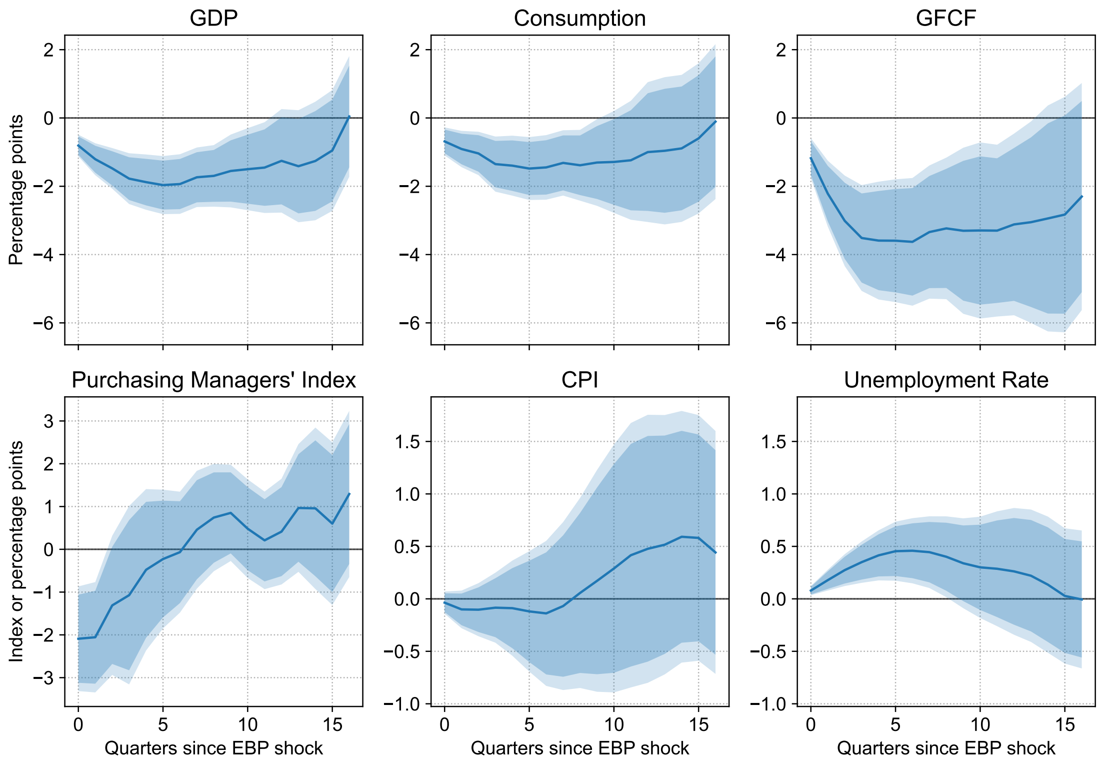
Following the local-projections approach of Jorda (2005), we estimate Equation (10) for increasing values of h, each time recording the estimate of β^h. As the EBP variable is standardised, this shows the expected cumulative effect on Y of a one-standard-deviation shock to the EBP, which is 53 basis points. The standard errors of β^h allow us to place confidence intervals around these expectations.

Macroeconomic indicators. Figure 4 shows our estimated impulse responses for a selection of key macroeconomic indicators. In expectation, a one-standard-deviation shock to the EBP lowers GDP by as much as 2.0 percentage points, consumption by as much as 1.2 percentage points and GFCF by as much as 3.8 percentage points. The larger and more persistent effect on GFCF than consumption, with overall GDP in between, seems intuitive as GFCF is driven by firms while consumption is driven by households and we would expect firms to be more sensitive to bond financing conditions. These peak effects occur about 1.5 years after the EBP shock. That is also the case for the unemployment rate, where the peak effect is an increase of 0.5 percentage points. In contrast, the peak effect on the Purchasing Manager's Index (PMI) is immediate, perhaps because it is a survey-based indicator and expectations for the economy adjust more quickly than economic activity itself. Finally, EBP shocks have no significant effects on the price level. So, all the effects of EBP shocks are real effects.[17]

[16] The impulse response functions presented in this section remain largely unchanged if we retain this variable.

[17] Appendix D provides equivalent results from a vector autoregression (VAR) model, which

Figure 4: Impulse responses of macroeconomic indicators to an EBP shock

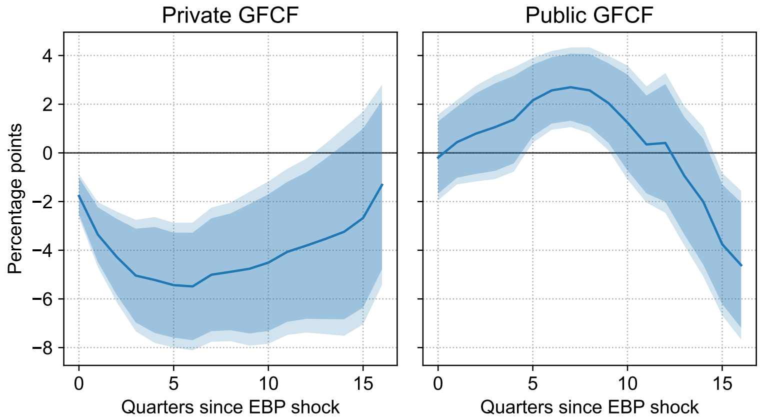


Notes: The shock is a one-standard-deviation (53 basis points) increase in the EBP, which corresponds to a deterioration in bond financing conditions. The responses were estimated using the model in Equation (10). From top-left to bottom-right, Y in that model is given by: log(GDP), log(consumption), log(GFCF), the Purchasing Managers' Index (PMI), log(CPI) and the unemployment rate. The response of the PMI is in index points, while that of all other variables is in percentage points. The dark blue and light blue areas show 90% and the 95% confidence intervals, respectively.

GFCF by sector. Having identified the EBP as a particularly important driver of capital formation, we next drill into sectoral components of GFCF. First, we estimate separate impulse response functions for GFCF by the public and private sectors. Here, private-sector GFCF is capital formation by private corporations while public-sector GFCF is capital formation by public corporations as well as central and local government. Figure 5 shows the results. While private-sector GFCF declines in response to tighter bond financing conditions, again with a peak effect after about 1.5 years, public-sector GFCF responds in the opposite direction. Such countercyclical behaviour helps stabilise overall capital formation in the economy. Over a longer time horizon, however, public-sector GFCF declines, perhaps because some financial consolidation is required after the countercyclical expansion.

serve as robustness for our local-projection findings and a benchmark for previous studies.

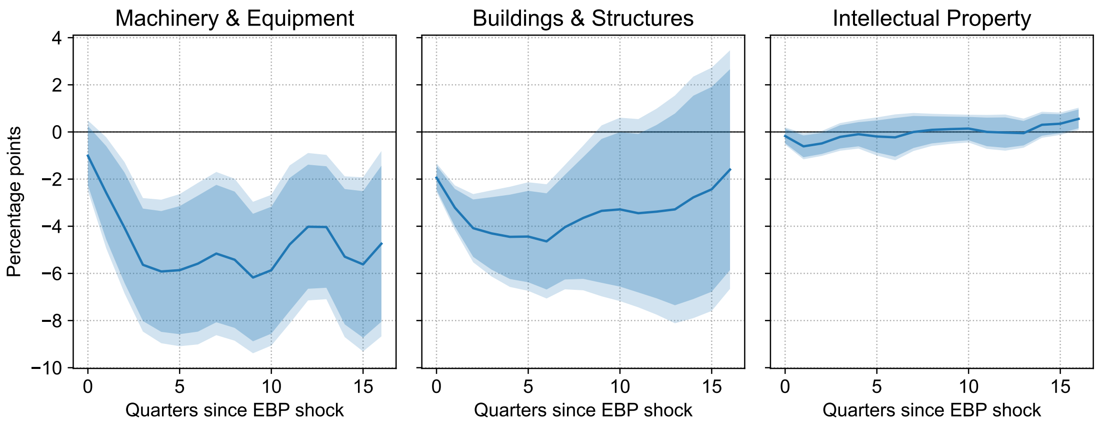
Figure 5: Impulse responses of private and public GFCF to an EBP shock



Notes: The shock is a one-standard-deviation (53 basis points) increase in the EBP, which corresponds to a deterioration in bond financing conditions. The responses were estimated using the model in Equation (10). In that model, both Y variables are in logarithmic form, with private GFCF corresponding to real gross fixed capital formation by private-sector corporations and public GFCF to real gross fixed capital formation by the government and public-sector corporations. The dark blue and light blue areas show 90% and the 95% confidence intervals, respectively.

GFCF by asset. UK national statistics also provide a breakdown of GFCF by asset type. So, as a second exercise to understand the effects of EBP shocks more granularly, we estimate individual impulse response functions for machinery and equipment GFCF, buildings and structures GFCF, and intellectual property GFCF. Figure 6 shows the results, which contrast sharply. Investment in machinery and equipment and buildings and structures, which are intensive in physical capital, are pulled down by a one-standard-deviation positive EBP shock by as much as 6.0 and 4.3 percentage points, respectively. In contrast, there is no discernible effect on intellectual property investment, which is intensive in human capital rather than physical capital.

Figure 6: Impulse responses of GFCF asset components to an EBP shock

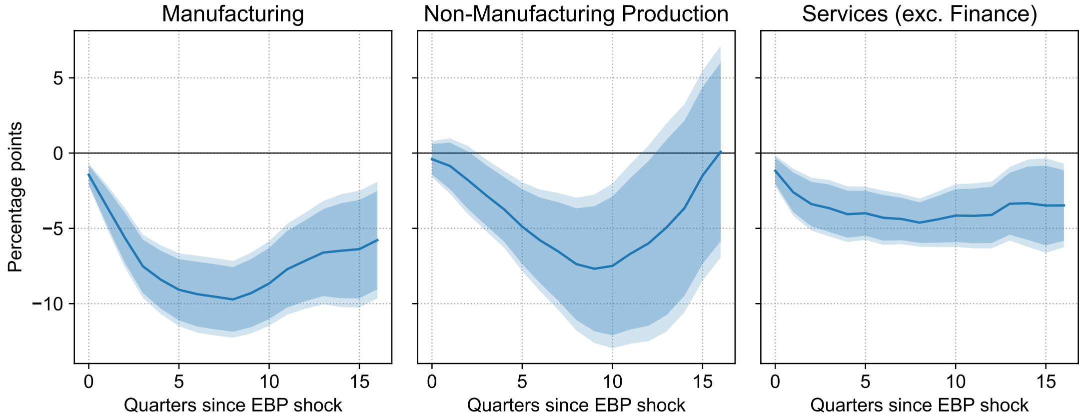


Notes: The shock is a one-standard-deviation (53 basis points) increase in the EBP, which corresponds to a deterioration in bond financing conditions. The responses were estimated using the model in Equation (10). In that model, Y is log(asset component), where 'asset component' is the part of real gross fixed capital formation attributable to machinery and equipment (left panel), business dwellings and other buildings and structures (centre panel) and intellectual property products (right panel). The dark blue and light blue areas show 90% and the 95% confidence intervals, respectively.

Business investment by industry. Finally, we study business investment by private corporations, which accounts for more than half of total GFCF and is available by industry. Figure 7 show individual impulse response functions for investment by manufacturers, non-manufacturing producers (which includes extraction industries and utilities) and non-financial service providers.[18] A one-standard-deviation positive EBP shock reduces investment by manufacturers by as much as 9.5 percentage points and investment by non-manufacturing producers by as much as 7.8 percentage points, with these peak effects occurring after around 2 years. Non-financial services investment is much less affected. These results again suggest that investment that is more intensive in physical capital is more sensitive to bond financing conditions.

[18]We exclude financial service providers as we constructed our EBP from non-financial corporate bonds spreads to reflect bond financing conditions for the *non-financial sector*, which we now relate to investment by different industries in the *non-financial sector*.

Figure 7: Impulse responses of industry components of private business investment to an EBP shock



Notes: The shock is a one-standard-deviation (53 basis points) increase in the EBP, which corresponds to a deterioration in bond financing conditions. The responses were estimated using the model in Equation (10). In that model, Y is $log(\text{sector component})$, where 'sector component' is the part of real private-sector business investment (which is a majority component of real gross fixed capital formation) attributable to manufacturing (left panel), non-manufacturing production (i.e. primary industries, extraction and utilities) (centre panel) and non-financial services (right panel). The dark blue and light blue areas show 90% and the 95% confidence intervals, respectively.

5 The EBP and firm-level activity

In this section, we assess how shocks to bond financing conditions affect firm-level outcomes. By affecting the cost and availability of external financing, shocks to the EBP are expected to affect firms' investment and capital structure decisions, and thus their balance sheets. This is especially so for firms that rely on corporate bond financing, which are expected to be more sensitive to changes in financing conditions in bond markets. We begin with a baseline study of the average effects in our cross section of firms and then investigate whether there are heterogeneous effects for firms with different levels of leverage and shares of bond debt within that leverage.

5.1 Baseline effects

We estimate the impact of an EBP shock on firm-level outcomes for each horizon $h = 1, ..., 16$, using the following specification:

$$\ln\left(\frac{Y_{i,t+h}}{Y_{i,t-1}}\right) = \alpha + \delta_i + \beta^h \, \mathrm{EBP}_t + \sum_{l=1}^{4} \gamma_l \ln\left(\frac{Y_{i,t-l}}{Y_{i,t-l-1}}\right) + \epsilon_{i,t}, \tag{11}$$

where $\ln\left(Y_{i,t+h}/Y_{i,t-1}\right)$ is the log cumulative change in a given firm-level variable Y between $t-1$ and $t+h$ and EBP_t is the excess bond premium at time t, which is standardised to aid interpretability of its coefficient. We also include lagged values of the firm-level variable subject to analysis to account for any autocorrelation of the endogenous variable, as well as firm fixed effects, δ_i, to control for time-invariant firm-specific characteristics, thus ensuring that we obtain the within-firm variation as a consequence of the shock. We cluster standard errors at the firm level to account for potential autocorrelation and heteroskedasticity within firms.

For the dependent variable, Y, we consider several outcomes recorded in firms' financial statements, both in their balance sheets, i.e., financial positions at the end of reporting periods, and income statements, i.e., financial performance during reporting periods. In terms of financial positions, we examine the effect of shocks to the EBP on investment and assets, while for financial performance we study the impact of EBP shocks on firms' income.

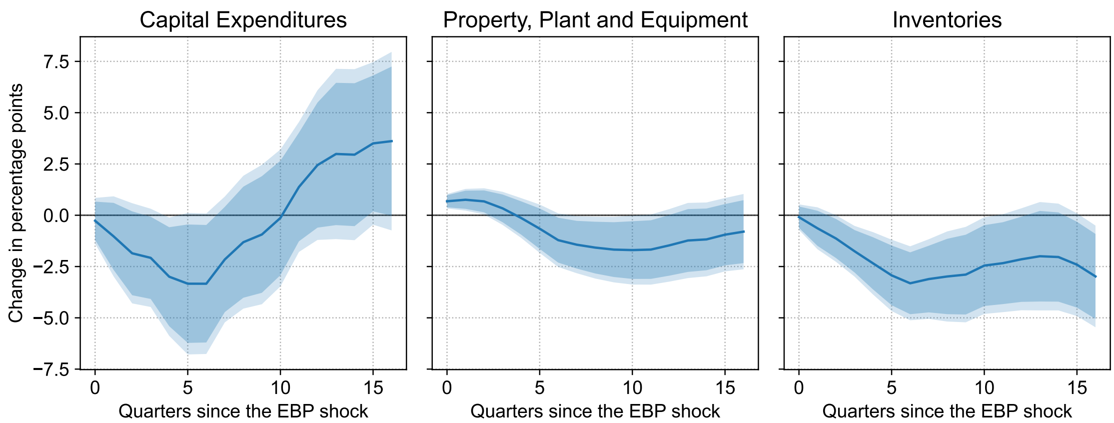
Investment. The results on firms' investment responses are presented in Figure 8. Here we consider three variables: capital expenditures, which correspond to investment in long-term assets; property, plant and equipment (PPE), which is the stock generated by cumulating the flow of capital expenditures, minus depreciation and any sale of assets; and inventories, with investment in inventories corresponding to investment in current assets, which are expected to be sold within one year.

Following a positive EBP shock – representing a deterioration in bond financing conditions – firm-level capital expenditures decline with a three-quarter lag. The cumulative reduction in capital expenditures reaches 3.3 percentage points six quarters after the initial shock before beginning to recover. This decline is statistically significant at the 10% level and, for four quarters following the shock, at the 5% level as well. This means that firms scale back their investment when bond financing conditions worsen. This is consistent with the finding in Section 4.2 that private business investment falls in manufacturing and non-manufacturing production.

Property, plant, and equipment (PPE) experiences a gradual cumulative decline from the sixth to eleventh quarters post-shock, reaching a trough of 1.7 percentage points, after a slight increase immediately following the shock, persisting for two quarters.

More pronouncedly, firms also reduce their investment in inventories, which decline with a two-quarter lag and reach a peak cumulative reduction of 3.3 percentage points six quarters after the shock. This result is in line with our prior expectations, given that firms may rely on external financing to fund their working capital needs, prompting them to reduce inventories when the cost of that finance rises. This may also reflect liquidity constraints or the fact that worsening bond financing conditions provide a signal of economic slowdown. In any case, inventories fall by much less than capital expenditures, which may reflect the fact that inventories are less often financed through bond issuance and more often by bank credit lines or commercial paper issuance.

Figure 8: Impulse responses of firm-level investment to an EBP shock



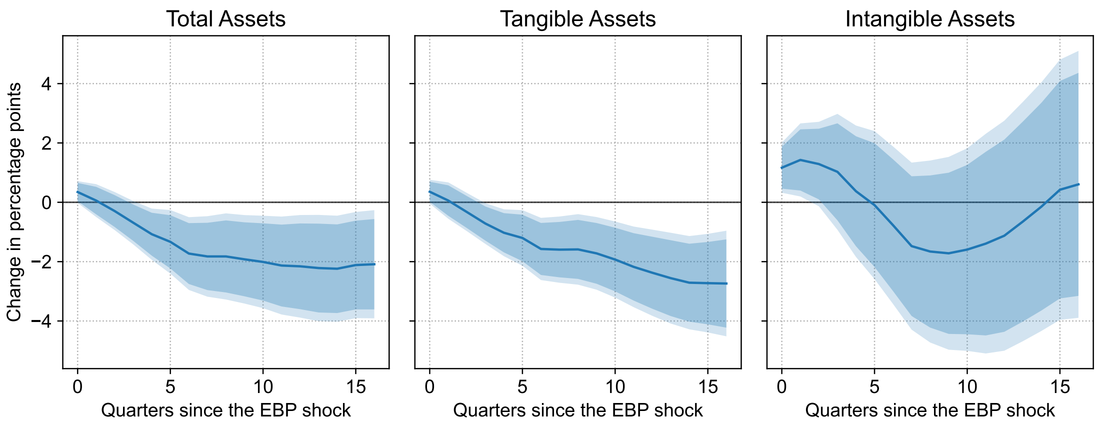
Notes: The shock is a one-standard-deviation (53 basis points) increase in the EBP, which corresponds to a deterioration in bond financing conditions. The responses were estimated using the regression specified in Equation (11). The dark blue and the light blue areas correspond to the 90% and the 95% confidence intervals, respectively.

Assets. Figure 9 shows the results for firms' assets. Here we consider total assets, tangible assets and intangible assets. Tangible assets include manufacturing equipment and machinery, raw materials and other assets with physical substance. Intangible assets include intellectual property, patents or other assets such as software licenses.

Total assets respond three quarters after the EBP shock, falling by, at most, 2.2 percentage points, with the fall persisting for the remainder of the horizon being considered. When decomposed into tangible and intangible assets, this decline is almost fully driven by tangibles, which fall by a similar magnitude and trajectory as total assets. This likely reflects investment in tangible assets being more reliant on debt financing since firms can pledge these assets as collateral (Almeida and Campello, 2007).

Conversely, intangible investment shows a brief immediate increase, rising by 1.4 percentage points one quarter after the shock. This effect dissipates by the second quarter, after which the response of intangible investment becomes statistically insignificant. One possible explanation for this pattern is that, when bond financing conditions deteriorate, the increased cost of tangible investment reduces the relative opportunity cost of intangible investment.

Figure 9: Impulse response of firm-level assets to an EBP shock



Notes: The shock is a one-standard-deviation (53 basis points) increase in the EBP, which corresponds to a deterioration in bond financing conditions. The responses were estimated using the regression specified in Equation (11). The dark blue and the light blue areas correspond to the 90% and the 95% confidence intervals, respectively.

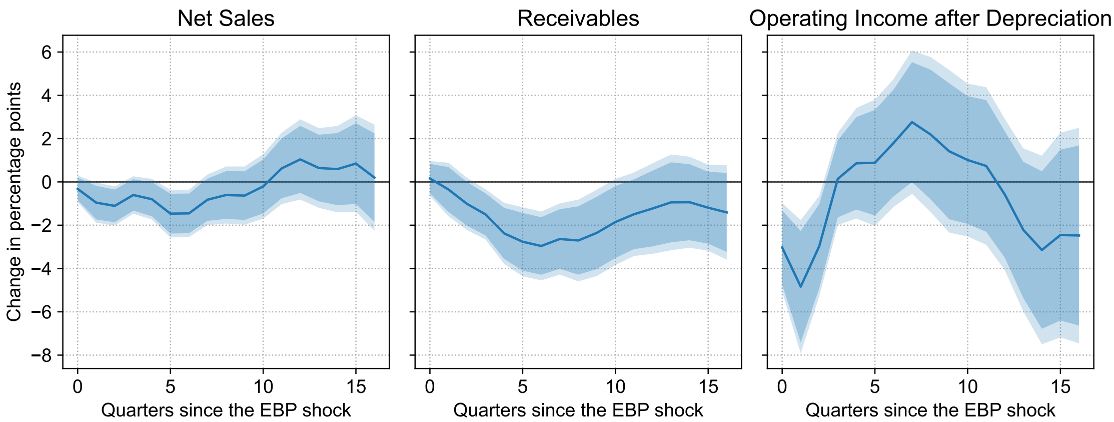
Income. Finally, Figure 10 shows the response of different dimensions of firms' income to worsening of bond financing conditions. Here we consider three variables: net sales, which correspond to the total revenue from sales minus any returned items; receivables, which correspond to the amount owed for goods and services sold on credit (and which is a sub-component of net sales); and operating income, which is the profit for the reporting period, i.e., net sales minus operating costs.

In the first panel, we see that a one-standard-deviation increase in the EBP leads net sales to fall by 1 percentage points one quarter after the shock, with the cumulative decline remaining between that level and 1.5 percentage points for an additional six quarters before recovering.

Receivables fall further, by a peak of 3.0 percentage points six quarters after the shock, recovering after roughly two and a half years. The fact that receivables fall more sharply than net sales could be due to firms being less willing to give credit for goods and services – or only willing to give it at higher interest cost – if their own cost of credit has increased due to worse bond financing conditions.

Finally, operating income after depreciation falls more sharply, declining by roughly 4.8 percentage points one quarter after the shock. This effect is more short-lived, lasting for only six months after the shock. Since operating income falls by more than net sales and it reflects net sales minus operating costs, one possible explanation for this behaviour is that firms take remedial action after the shock by cutting the cost of goods sold or other administrative expenses, which deepens the effect of the shock on operating income after depreciation.

Figure 10: Impulse response of firm-level income to an EBP shock



Notes: The shock is a one-standard-deviation (53 basis points) increase in the EBP, which corresponds to a deterioration in bond financing conditions. The responses were estimated using the regression specified in Equation (11). The dark blue and the light blue areas correspond to the 90% and the 95% confidence intervals, respectively.

5.2 The role of the level and composition of leverage

We expect highly leveraged firms to exhibit greater sensitivity to EBP shocks than their less leveraged counterparts. Moreover, this effect should particularly pronounced for firms with a substantial proportion of bond debt relative to bank debt, as they are more exposed to fluctuations in bond financing conditions. This is especially relevant in light of our findings in Section 4, which demonstrated that shocks to bond financing conditions have significant effects on macroeconomic outcomes. Should these aggregate effects be driven primarily by firms that are not only highly leveraged but also heavily reliant on bond financing, this would constitute evidence of an amplified financial accelerator mechanism.

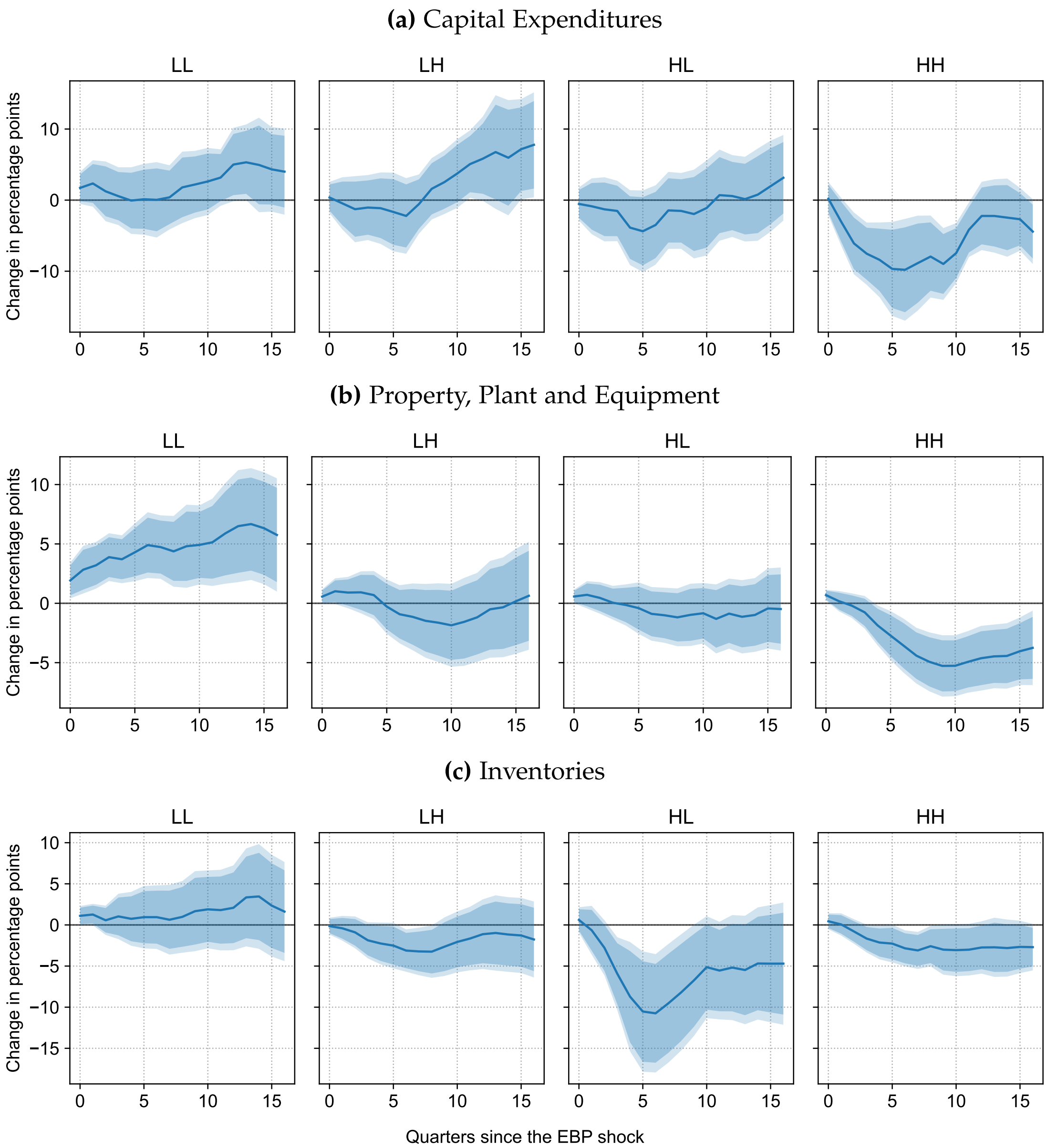
To examine this, we re-estimate the model in Equation (11) for four different groups: (i) below both median leverage and median bond debt (we will henceforth call this group 'LL', which stands for 'low debt, low bond debt'), (ii) below median leverage but above median bond debt (LH), (iii) above median leverage but below median bond debt (HL), and (iv) above both median leverage and median bond debt (HH). Leverage corresponds to long-term debt over total assets, while bond debt is measured as each obligor's outstanding bond debt relative to its total long-term debt. Medians are computed quarterly to avoid systematic classification biases, i.e., more recent observations being classified as above median given the upward trend in bond financing over time. To ensure that the results are not driven by outliers, we winsorise observations below the 5th percentile and above the 95th percentile, meaning that those observations are recoded with the value of the 5th percentile and the 95th percentile, respectively.

Investment. Figure 11 presents the results for the four different groups for the same investment-related variables previously discussed, highlighting the differences masked by aggregation. The baseline result – that, on average, capital expenditures decline by over 3 percentage points after the shock – is driven by firms with both above-median leverage and an above-median proportion of bond debt (HH). Highly leveraged and bond reliant firms respond more quickly to the shock, with their capital expenditure falling by a cumulative 9.0 percentage points around after two years of the shock. By contrast, firms in the remaining groups do not exhibit a statistically significant response to the shock.

PPE, which is the stock-counterpart to capital expenditures, also accounting for depreciation, actually increases for the low leverage and low bond debt group (LL). This result is robust to several specifications and different samples.[19] This could be a result of the reallocation of funds towards these firms, although that is not observed through an increase in their capital expenditures. Low leverage and high bond debt firms (LH), as well as high leverage and low bond debt

[19]This result remains in the sample without winsorising and for the winsorised samples recoding both the top and bottom 1% and 5% observations.

Figure 11: Impulse response of firm-level investment to an EBP shock by leverage and bond share



Notes: The shock is a one-standard-deviation (53 basis points) increase in the EBP, which corresponds to a deterioration in bond financing conditions. The figures presented contain the local projections that result from estimating the regression specified in Equation (11) separately for four different groups, according to their degree of leverage and bond debt.

firms (HL), do not respond in a statistically significant manner. High leverage and high debt firms (HH) decrease their PPE by a maximum of 5 percentage points, which is likely a result of the strong impact of the shock on the capital expenditures of these firms.

While inventories decline shortly after the EBP shock for firms on average, we see that low leverage and low bond debt firms (LL) do not respond in a statistically significant manner to the shock. Having either higher leverage or a higher proportion of bond debt (LH, HL and HH) translates into a stronger decline in inventories, but firms with above-median leverage and below-median bond debt experience further declines beyond the baseline result, reaching a trough of 10.7 percentage points six quarters after a one-standard-deviation increase in the EBP.

Assets. The resulting estimates from decomposing the response of assets by leverage and bond debt are presented in Figure 12. Looking at total assets, we see that low leverage and low bond debt firms (LL) actually increase their assets after the shock, whereas low leverage and high bond debt firms (LH and HL) do not respond in a statistically significant manner to the shock. The seemingly counterintuitive increase in assets for the first group may stem from several factors. One possible explanation is a reduction in competition from bond-dependent competitors, which become capital-constrained and consequently scale back operations, sell assets, or delay projects. This may create market opportunities that financially unconstrained firms can exploit, leveraging an internal funding advantage.

Income. Figure 13 contains the heterogeneous results of the previously considered income variables by level and composition of leverage.

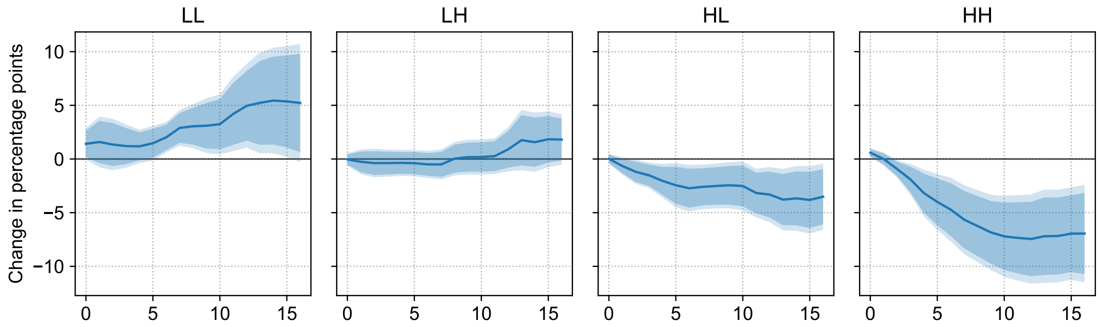
Despite the decline shown in the baseline results in Figure 10, the distributional effects on different income variables – particularly net sales and operating income – are more muted, with wider confidence bands indicating greater uncertainty.

For the most part, net sales do not respond, falling only for high-leverage firms following an EBP shock. For HL firms, net sales decline by around 4.7 percentage point following the shock, whereas for HH firms, the effect is less pronounced and short-lived, reaching a cumulative decline of 2.5 percentage points.

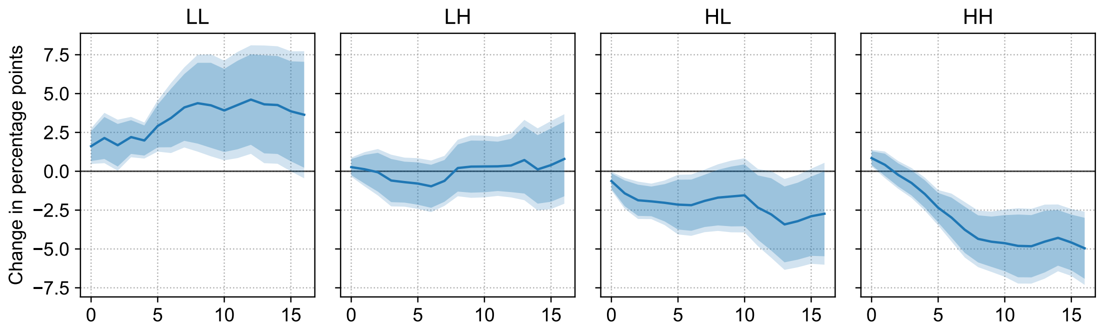
On the other hand, receivables show a clear decline for both high leverage groups (HL and HH) and no statistically significant result for low leverage groups (LL and LH). Looking at the average estimate in Figure 10, receivables drop by a maximum of 3.0 percentage points six quarters after the shock. However, disaggregating by leverage reveals substantial variation: the high leverage and low bond debt group (HL) experiences a decline of approximately 5.6 percentage points, whilst the high leverage and high bond debt group (HH) sees a decline of 6.7 percentage points. This means that, similarly to investment and assets, a deterioration in bond financing conditions affects mostly bond-reliant firms and,

Figure 12: Impulse response of firm-level assets to an EBP shock by leverage and bond share

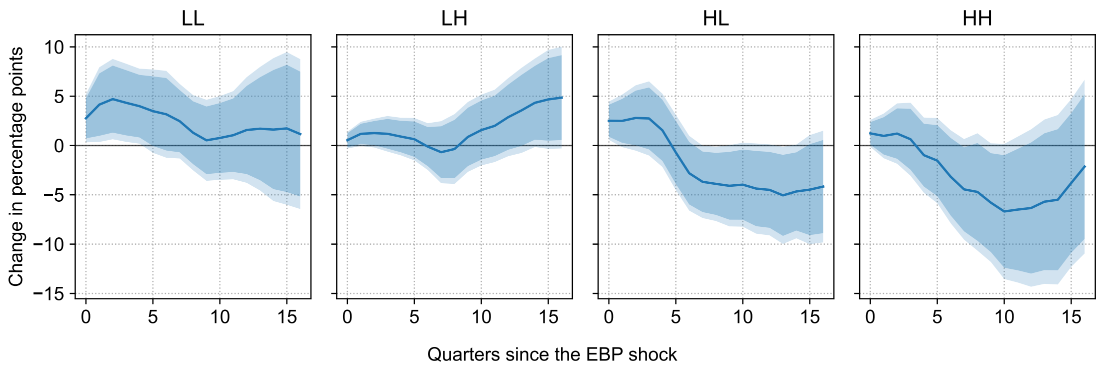
(a) Total Assets



(b) Tangible Assets



(c) Intangible Assets



Notes: The shock is a one-standard-deviation (53 basis points) increase in the EBP, which corresponds to a deterioration in bond financing conditions. The figures presented contain the local projections that result from estimating the regression specified in Equation (11) separately for four different groups, according to their degree of leverage and bond debt.

more severely, bond-reliant firms with high leverage ratios, further highlighting the incremental impact of leverage. Since receivables correspond to the amount owed for goods and services sold on credit, one possible explanation could be that firms with more bond debt give less generous credit when their own (bond) financing conditions worsen.

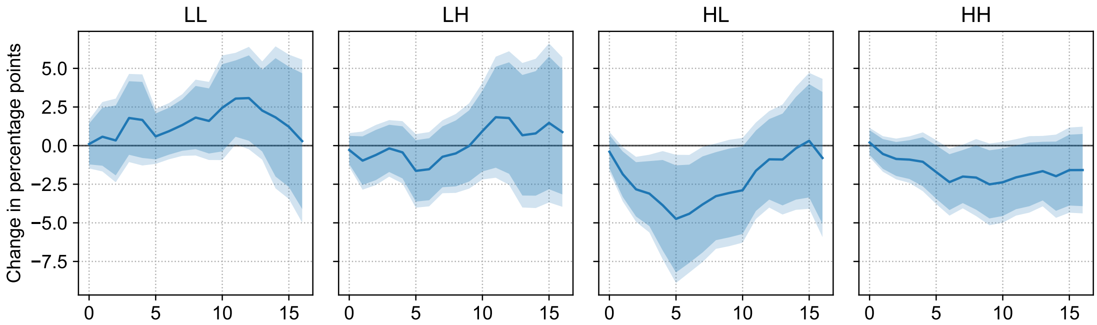
Finally, operating income after depreciation exhibits a more muted and short-lived response across all groups. However, both low bond debt groups (LL and HL) experience statistically significant drops in operating income during the two quarters following the shock – declining by 5.7 and 7.2 percentage points, respectively – before recovering quickly thereafter.

The reduced heterogeneity in income responses across groups, especially when compared to the differential effects observed for investment and assets, suggests that all firms are indirectly affected through general equilibrium effects arising from the broader economic slowdown, irrespective of their leverage. This is consistent with the results observed for macroeconomic indicators in Figure 4, where we see a broader deterioration in GDP and consumption that is likely to affect the income of the population of firms.

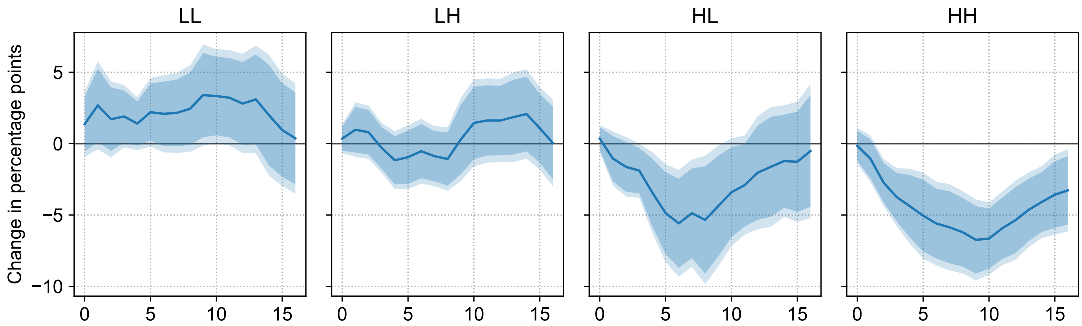
The differences across groups are notably less pronounced for income variables – particularly net sales and operating income – than for investment or assets. Despite some variation between groups, these relatively more muted differential effects may reflect that all firms are indirectly affected through general equilibrium effects arising from the broader economic slowdown, irrespective of their leverage. This is consistent with the results observed for macroeconomic indicators in Figure 4, where we see a broad deterioration in GDP and consumption that is likely to affect the income of the population of firms.

Figure 13: Impulse response of firm-level income to an EBP shock by leverage and bond share

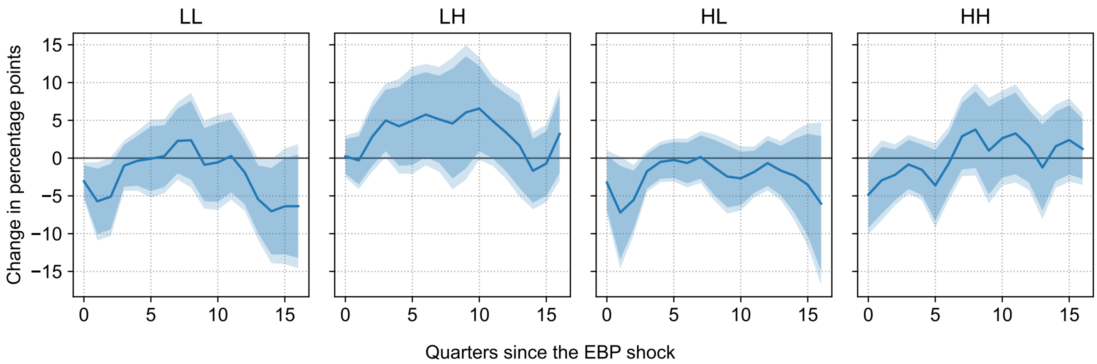
(a) Net Sales



(b) Receivables



(c) Operating Income after Depreciation



Notes: The shock is a one-standard-deviation (53 basis points) increase in the EBP, which corresponds to a deterioration in bond financing conditions. The figures presented contain the local projections that result from estimating the regression specified in Equation (11) separately for four different groups, according to their degree of leverage and bond debt.

6 Conclusion

In this paper, we have studied the effects of bond financing conditions on economic activity in the UK, both in aggregate and at the firm level.

At the aggregate level, we find that our proxy for bond financing conditions – the excess bond premium (EBP) – outperforms traditional business cycle indicators, such as the real policy rate and the yield curve term spread, in predicting key measures of economic activity. It also outperforms the fitted component of corporate bond spreads that reflects key characteristics of the bonds and their obligors, to which the EBP is the complementary residual. As such, it seems plausible that the EBP reflects variation in investors' demand for bonds.

Moreover, we find that the effects of bond financing conditions on aggregate activity are economically significant. A one-standard-deviation (53 basis points) positive shock to the EBP, which represents a deterioration in bond financing conditions, lowers capital formation by as much as 3.8 percentage points, increases the unemployment rate by as much as 0.5 percentage points and lowers GDP by as much as 2.0 percentage points, with these peak effects occurring around 1.5 years after the shock. We find even larger effects on capital formation for assets (machinery and equipment) or industries (manufacturing and other production industries) that are capital intensive. However, we find an offsetting countercyclical effect for public sector capital formation, which stabilises overall investment in the economy.

Across individual firms, we find that various measures of investment decline to a greater extent after a tightening of bond financing conditions for firms with higher leverage and a higher share of bond debt in that leverage. For instance, following a one-standard-deviation positive shock to the EBP, capital expenditure plunges by as much as 9.0 percentage points at firms with above-median leverage and bond shares. In contrast, we find less heterogeneity in different measures of income. But sales, receivables and profits all fall, on average, across firms following a positive EBP shock. This suggests that firm-level investment is affected directly by bond financing conditions – with the impact depending on individual firms' leverage and reliance on bond financing – while firm-level income is affected indirectly through the impact of bond financing conditions on macroeconomic activity, which affects all firms irrespective of their leverage.

Our findings have implications for policy and research. First, bond financing conditions provide a helpful signal of the economic outlook, which policymakers may wish to consider alongside other information when setting cyclical policies. Indeed, building on our evidence that bond financing conditions affect economic activity, research into the *drivers* of these conditions would be valuable. Second, our finding of amplified effects of EBP shocks on investment by more-leveraged firms when they are more reliant on bond financing highlights the value of diversified sources of finance for the structural resilience of firms and, hence, the overall economy. Reflecting that, further research would be worthwhile on the substitutability of bond and bank financing when conditions are shocked in either of these markets. These considerations will become increasingly relevant should the importance of market-based finance continue to grow.

References

H. Almeida and M. Campello. Financial constraints, asset tangibility, and corporate investment. *The Review of Financial Studies*, 20(5):1429–1460, 2007.

G. Anderson and A. Cesa-Bianchi. Crossing the credit channel: credit spreads and firm heterogeneity. *American Economic Journal: Macroeconomics*, 16(3): 417–446, 2024.

A. Barnett and R. Thomas. Has weak lending and activity in the UK been driven by credit supply shocks? *The Manchester School*, 82:60–89, 2014.

T. Berg, A. Saunders, and S. Steffen. Trends in corporate borrowing. *Annual Review of Financial Economics*, 13(2):321–340, 2021.

B. Bernanke and M. Gertler. Inside the black box: the credit channel of monetary policu transmission. *Journal of Economic Perspectives*, 9(4):27–48, 1995.

B. S. Bernanke, M. Gertler, and S. Gilchrist. The financial accelerator in a quantitative business cycle framework. *Handbook of Macroeconomics*, 1:1341–1393, 1999.

M. Bleaney, P. Mizen, and V. Veleanu. Bond spreads and economic activity in eight european economies. *The Economic Journal*, 126(598):2257–2291, 2016.

P. Collin-Dufresne, R. Goldstein, and S. Martin. The determinants of credit spread changes. *Journal of Finance*, 56:2177–2207, 2001.

O. Darmouni and M. Papoutsi. The rise of bond financing in europe. *ECB Working Paper*, (2663), 2022.

M. Gertler and S. Gilchrist. Monetary policy, business cycles, and the behavior of small manufacturing firms. *Quarterly Journal of Economics*, 109(2):309–340, 1994.

S. Gilchrist and E. Zakrajšek. Investment and the cost of capital: New evidence from the corporate bond market. *NBER Working Paper*, (13174), 2007.

S. Gilchrist and E. Zakrajšek. Credit spreads and business cycle fluctuations. *American Economic Review*, 102(4):1692–1720, 2012.

X. Giroud and H. M. Mueller. Firm leverage, consumer demand, and employment losses during the great recession. *Quarterly Journal of Economics*, 132(1):271–316, 2017.

G. Jiménez, S. Ongena, J.-L. Peydró, and J. Saurina. Credit supply and monetary policy: identifying the bank balance-sheet channel with loan applications. *Journal of Finance*, 102(5):2301–2326, 2012.

O. Jorda. Estimation and inference of impulse responses by local projections. *American Economic Review*, 95:161–182, 2005.

Kalemli-Özcan, L. Laeven, and D. Moreno. Debt overhang, rollover risk, and corporate investment: Evidence from the european crisis. *Journal of the European Economic Association*, 20(6):2353—-2395, 2022.

D. Melcangi. Firms' precautionary savings and employment during a credit crisis. *American Economic Journal: Macroeconomics*, 16(1):356–386, 2024.

R. C. Merton. On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, 29(2):449–470, 1974.

P. Mueller. Credit spreads and real activity. *SSRN*, (1105728), 2009.

A. Saunders, A. Spina, S. Steffen, and D. Streitz. Corporate loan spreads and economic activity. *The Review of Financial Studies*, 38(2):507–546, 2025.

Bond financing conditions and economic activity

Appendix

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Appendix A Obligor identifier mapping

To link data on corporate bonds (sourced from ICE) to financial data on their obligors (sourced from LSEG's Datastream and Eikon databases), we require a mapping between company identifiers in these datasets. As far as we are aware, no such mapping exists, so we create our own.

We start from the 'ticker' in the ICE corporate bond dataset, which is a short alphabetic code. This is complemented by a fuller 'description' (or name) of the obligor, but we focus on the ticker for two reasons. First, the ticker only changes when there is a substantive change in the obligor. For instance, when National Express Group rebranded as Mobico Group, the firm's ticker remained NEXLN, while its description changed to reflect the new name. Second, the ticker identifies the *ultimate* obligor of the bond, whereas the description may refer to a subsidiary. For instance, the ticker for BAE Systems (Finance) Ltd is BALN, which is the same as for its parent company, BAE Systems PLC, which is ultimately responsible for repayment of the bond. This feature is especially helpful when the ultimate obligor changes because of a merger or acquisition but the name of the subsidiary is unaffected. For instance, when Grand Metropolitan merged with Guinness to form Diageo, the description for bonds issued by Grand Metropolitan Investment Corporation continued to reflect that name while the ticker was updated from GMET to DIAG.

To help match ICE tickers of ultimate bond obligors to Datastream and Eikon company identifiers, we exploit bond ISINs, which are commonly available across the three databases. First, we look up in Datastream the Primary Equity Quote (PEQ) for the issuer of bonds with ISINs that are already associated with a particular ticker in the ICE data. The PEQ is a six-digit alphanumeric code identifying the primary equity security of a listed company and, hence, the company itself. While this only works for listed companies, our sample is in any case restricted to such firms because our required distance-to-default (DD) variable needs equity prices as an input. Even for listed companies, however, results from this procedure are patchy, with many null returns. Hence, we also take a second approach. In particular, we request via Eikon a list of bond ISINs for which UK companies are the present obligors (or were the final obligors for matured bonds).[20] Such requests are only available on a current basis and we

[20]We form a comprehensive list of UK companies by merging the constituents of several Datastream equity indices: UK companies that are currently active (FGBALL) and no longer active (DEADGB), UK companies covered by the Worldscope financial information service

made our request at the end of June 2024. We record the tickers of any obligors in the ICE data associated with the input ISINs which were, in turn, associated with a particular company in the Eikon database. Although less frequent, this second approach also produces some null returns.

Where these two approaches agree, which occurs when bond issuers were not subsequently involved in mergers or acquisitions, we accept the affirmed mapping of ICE tickers to Datastream/Eikon ID.[21] Otherwise, the first approach suggests a mapping that should be accurate wherever the bond issuer was not *later* subject to a merger or acquisition. Similarly, the second approach suggests a mapping that should be accurate wherever the recent bond obligor was not *previously* subject to a merger or acquisition. We verify these suggested mappings, as well as fill any gaps, by checking corporate histories on company websites. The resulting mapping is shown in Table A.1.

(WSCOPEUK), current membership of the FTSE All Share index (LFTALLSH) as well as historical membership at the end of each year going back to 1997 (LFTALLSH12YY, where YY denotes the year), and all UK listed companies identified through Datastream's 'Navigator' user interface. This gives a six-digit Datastream ID for each company (which matches the PEQ in the case of listed companies). Finally, we map these Datastream IDs to Eikon IDs by requesting the Equity ISIN associated with each Datastream ID and the Eikon 'RIC' (Reuters Identity Code) associated with each Equity ISIN.

[21] There is often more than one ICE ticker mapped to a Datastream/Eikon identifier as ICE updated it's symbology part way through our sample period to reflect not only the name of the company but where it is listed. For instance, earlier in the sample Diageo has DIAG for its ticker but later in the sample it has DGELN (DGE for Diageo and LN for London).

Table A.1: Obligor identifiers

Company	ICE	Datastream	Eikon
Afren	AFRLN	30398Q	AFRE.L^H15
Alliance Boots	ABLN, BOOT	901192	AB.L^G07
Allied Domecq	ALYON	900232	ALLD.L^G05
Anglo American	AALLN	903076	AAL.L
Antofagasta	ANTOLN	926288	ANTO.L
Asda Group	ASSD, ASSDLN	900793	ASSD.L^J99
Ashtead Group	AHTLN	906045	AHT.L
Associated British Foods	ABFLN	900825	ABF.L
Assura	AGRFIN	28065X	N/A
Aston Martin Lagonda	ASTONM	9339MD	AML.L
AstraZeneca	AZN, ZEN	319608	AZN.L
Atlantic Telecom	ATNLN	135132	ATN.L^J01
BAA	BAA	953553	BAA.L^H06
BAE Systems	BALN, BAPLC	901419	BAES.L
BG Group	BGGRP, BRIGF	911488	BG.L^B16
BHP Group	BHP	906169	BHP.AX
BOC Group	BOC, BOCLN	900451	BOC.L^I06
BP	BP, BPLN	900995	BP.L
BPB	BPB, BPBLN	900358	BPB.L^A06
BT Group	BRITEL	900888	BT.L
Babcock International	BABLN	900552	BAB.L
Berkeley Group	BKGLN	974117	BKGH.L
Big Food Group	BIGFD	900610	BFP.L^B05
Bitish Energy Group	BGY	29905D	BGY.L^B09
British Airways	BAB	914447	BAY.L^A11
British American Tobacco	BAT, BATSLN	901295	BATS.L
British Land	BLNDLN	901587	N/A
Bunzl	BNZLLN	901067	BNZL.L
Burberry Group	BRBYLN	25968K	BRBY.L
Burmah Castrol	BMAH	900996	BMAH.L^I00
Cable & Wireless Communications	CWCLN, CWLN, CWZLN	901634	CWC.L^E16
Cadbury	CBRY, CBRYLN	900286	CBRY.L^C10
Canary Wharf Group	CWHARF	697097	CWG.L^F04
Carlton Communications	CCMLN	901604	CCM.L^A04
Carnival	CCL, CCLLN	265148	CCL.L
Centrica	CENTRI, CNALN	888276	CNA.L
Colt Telecom	COLTEL	414348	N/A
Compass Group	CPGLN, GCPLN	255049	CPG.L
Convatec Group	CTECLN	2643R5	CTEC.L
Corus Group	CORUS	953191	CS.L^D07
Daily Mail and General Trust	DMGOLN, DMGTLN	910716	DMGOa.L^A22
Debenhams	DEBLN	35793C	DEB.L^D19
Delphi Technologies	DELJER, DLPH	9217FM	DLPH.K^J20
Derwent London	DLNLN	926373	N/A
Diageo	DGELN, DIAG	900251	DGE.L
Dixons Retail	DIX, DSGILN, DXNSLN	900906	DXNS.L^H14
Drax Group	AES, DRXLN	32545E	DRX.L
EI Group	EIGLN, ENTINN, ETILN	137668	EIGE.L^C20
EMAP	EMALN, EMAP	910283	EMA.L^C08
Eastern Electricity	EASELE, TXU	928847	N/A
EasyJet	EZJLN	280641	EZJ.L
Endeavour Mining	EDVLN	2581JD	EDV.L
Energean	ENOGLN	9279XW	ENOG.L
Energis	EGSLN	671363	EGS.L^I02

Table A.1: Obligor identifiers (cont.)

Company	ICE	Datastream	Eikon
Enodis	ENO	900767	ENO.L^J08
Enquest	ENQLN	69033U	ENQ.L
Enterprise Oil	ENTOIL	974355	ETP.L^F02
Evraz	EVRAZ	77863Q	EVRE.L
Experian	EXPNLN	410124	EXPN.L
FKI	FKI	911384	FKI.L^G08
Ferguson Enterprises	FERGLN	900764	FERG.L
First Group	FGPLN	135229	FGP.L
Fresnillo	FRES, FRESLN	53414Q	FRES.L
G4S	GFSLN, GFSPLN	871674	GFS.L^E21
GKN	GKNLN	900754	GKN.L^E18
Gallaher Group	GLHLN	897328	GLH.L^D07
GlaxoSmithKline	GLXO, GSK	900479	GSK.L
Glencore	GLENLN	77128V	GLEN.L
Globalworth REIT	GWILN	89560H	GWI.L
Go-Ahead Group	GOGLN	135565	GOG.L^J22
Grainger	GRILN	931261	GRI.L
Granada Media	GAA, GAALN	296968	GME.L^B01
Grand Metropolitan	GMET	900841	GMET.L^L97
Great Universal Stores	GUSLN	901200	N/A
Haleon	HALEON, HLNLN	26781Y	HLN.L
Hammerson	HAMRSN, HMSOLN	901596	N/A
Hanson	HANSON	901932	HNS.L^H07
Harbour	HBRLN	900997	HBR.L
Helios Towers	HLSTWR	95197F	HTWS.L
Hikma Pharmaceuticals	HIKLN	32273L	HIK.L
Hyder	HYRLN	904438	HYR.L^J00
ITV	ITVLN	931524	ITV.L
Imperical Brands	IMBLN, IMPTOB, IMTLN	882240	IMB.L
Imperical Chemical Industries	ICI	900455	ICI.L^A08
Inchcape	INCHLN	901029	INCH.L
Informa	INFLN, INFO	679154	INF.L
Inmarsat	INMARS, ISATLN	30877H	ISA.L^L19
Innogy	IOGLN, LADLN	263812	IOG.L^G02
Intercontinental Hotels Group	IHGLN	26923V	IHG.L
International Airlines Group	IAGLN	74190D	ICAG.L
International Distribution Services	IDSLN, RMGLN	91073H	IDSI.L^F25
International Game Technology	IGT	9437JT	BRSL.K
International Power	IPRLN, RWE	928901	IPR.L^G12
Invensys	ISYSLN	905110	ISYS.L^A14
Kelda Group	KEL, YW	904486	KEL.L^B08
Kier Group	KIELN	882977	KIE.L
Kingfisher	KGFLN, KINGFI	940281	KGF.L
Land Securities Group	LAND	901598	N/A
Lasmo	LSMA	901206	LSMR.L^D01
Linde	LIN	9373MH	LIN.O
London Electricity	LONELE	928855	LON.L^D97
London Merchant Securities	LMSO, LMSOLN	901554	LMSO.L^B07
Marks & Spencer Group	MARSPE, MKS	901207	MKS.L
Matalan	MATFIN, MTNLN	679666	MTN.L^L06
Melrose Industries	MROLN	27922U	MRON.L
Merlin Entertainments	MERLLN	86990F	MERL.L^K19
Mobico Group	MCGLN, NEXLN	301917	MCG.L
Mondi	MNDILN	50629V	MNDI.L

Table A.1: Obligor identifiers (cont.)

Company	ICE	Datastream	Eikon
Morrison (WM) Supermarkets	MRWLN	905576	MRW.L^J21
NTL	NLI, NTLD, NTLI	545464	NTLDQ.OB^A03
National Grid	NATGRI, NGGLN	870181	NG.L
New Look	NEWLOK, NLKFIN	681341	NEW.L^D04
Next	NXT, NXTLN	901203	NXT.L
Northern Electricity	NTE	928859	NTE.L^D97
Northumbrian Water Group	NUW, NWGLN	27057U	NWG.L^J11
O2	OOMLN	257686	OOM.L^C06
Ocado Group	OCDOLN	69832L	OCDO.L
Orange	ORALN	870800	ORA.L^B00
Pearson	PSON	914021	PSON.L
Pentair	PNR	906585	PNR
Petra Diamonds	PDLLN	888928	PDL.L
Petrofac	PFCLN	31946M	PFC.L
Petropavlovsk	POGLN	257965	POG.L^G22
Pilkington	PILKIN	917163	PILK.L^F06
Pinewood Group	PINEFI	28874M	PWS.L^J16
Playtech	PTECLN	32975D	PTEC.L
Powergen	PWG, PWGLN	928903	PWG.L^G02
Premier Foods	PFDLN	28961T	PFD.L
RELX	REED, REEDLN, RELLN	901080	REL.L
RSL Communications	RSLC, RSLCOM	878916	RSLCF.PK^E16
Rank Group	RNK	900918	RNK.L
Reckitt Benckiser Group	RBLN, RKTLN	900484	RKT.L
Rentokil Initial	RENTKL, RTOLN	906480	RTO.L
Reuters Group	RTRGRP	51917K	N/A
Rexam	REXAM, REXLN	901065	REX.L^G16
Rio Tinto	RIOLN, RTZ	901714	RIO.L
Rolls-Royce Holdings	ROLLS	940793	RR.L
SABMiller	MILLER, SABLN	695504	SAB.L^J16
SEGRO	SGROLN, SLOU	901614	N/A
SIG	SHILN	946054	SHI.L
Safeway	AYL	904998	SFW.L^C04
Sage Group	SGELN	904649	SGE.L
Sainsbury (J)	SBRY	926002	SBRY.L
Scottish & Newcastle	SCOTNB, SCTNLN	900261	SCTN.L^D08
Scottish Power	SCOTPO, SCTPWR	928741	SPW.L^F07
Severn Trent	SEVTRE, SVTLN	904373	SVT.L
Shell	RDANA, RDNA, RDSALN, SUO	902178	SHEL.AS
Six Continents	BASS, SXCLN	900242	SXC.VX^I03
Sky	BSY, SKYLN	135116	SKYB.L^K18
Smith & Nephew	SNLN	900487	SN.L
Smith (DS)	SMDSLN	910685	SMDS.L^B25
SmithKline Beecham	SBH	900517	BHAM.L^A03
Smiths Group	SMIN, SMINLN	900943	SMIN.L
Southern Electric	SOUELE	928877	SEL.L^B99
Southern Water	SOWLN, SWSFIN	904378	WASN.L^G93
Stagecoach Group	SGCLN	319410	SGC.L^F22
Summit Germany	SMTGLN, SMTPLN	35975K	SGL.L^F09
Synthomer	YULCLN	905310	SYNTS.L
TI Fluid Systems	TIFSLN	9181DG	TIFS.L^D25
TI Group	TILN	900762	TIGL.L^G93
TalkTalk Telecom Group	TALKLN	69056U	TALK.L^C21
Tate & Lyle	TATELN, TATELY	900819	TATE.L

Table A.1: Obligor identifiers (cont.)

Company	ICE	Datastream	Eikon
Telent	MNILN, MONILN, MONLIN	26958F	TLNT.L^A08
Telewest Communications	TWT	135090	TWT.L^G04
Tesco	TSCO, TSCOLN	900803	TSCO.L
Thames Water	THWA	904393	WATH.L^G93
Thomas Cook Group	TCGLN	30059W	TCG.L^I19
Tomkins	TOMKIN, TOMKLN	911258	TOMK.L^I10
Travis Perkins	TPKLN	931669	TPK.L
Tullow Oil	TLWLN	506343	TLW.L
UBM	UBMLN	901106	UBM.L^F18
Unilever	CONOPC, ULVR, ULVRLN, UNANA	900789	ULVR.L
Unite Group	UTGLN	698466	N/A
United Utilities Group	NORWEB, NRWLN, NWENET, NWWLN, UU	904367	UU.L
Valaris	VAL	992520	VALPQ.PK^D21
Vedanta Resources	VEDLN	28212P	VED.D^K18
Victoria	VCPLN	905329	VCP.L
Virgin Media	VMED, VMDTEF	29202N	VMED.O^F13
Viridian Group	VRDLN	319743	VIRDF.PK^L06
Vodafone Group	VOD, VODFON	953133	VOD.L
WPP	WPPGRP, WPPLN	926119	WPP.L
Weir Group	WEIRLN	900699	WEIR.L
Wessex Water	WESWAT, YTLPMK	904474	WSXWF.PK^H09
Whitbread	WTBLN	900271	WTB.L
William Hill	WMH	258107	WMH.L^D21
Workspace Group	WKPLN	745481	N/A
Xstrata	XTALN	15322M	XTA.L^E13
Yorkshire Electricity	YKE, YORPOW	928888	YKE.L^E97

Appendix B Financial data on obligors

To compute distances to default (DDs) for corporate bond obligors, we require data on their market capitalisations and short and long-term liabilities. To cover as many obligors for as long as possible, we combine data on these variables from LSEG's Datastream and Eikon datasets. This appendix details our approach.

First, we gather data from the two datasets. For market capitalisation, we collect both company-level data ('MVC' in Datastream or 'TR.CompanyMarketCap' in Eikon) and issue-level data ('MV' in Datastream or 'TR.IssueMarketCap' in Eikon). Company-level data is preferred but we frequently accept issue-level data in its absence as listed companies often have only a single equity issue, the value of which is then by definition equal to the market capitalisation of the company. Additionally, we collect data on current liabilities ('WC03101' in Datastream or 'TR.F.TotCurrLiab' in Eikon), which are due within 12 months, and long-term debt ('WC03251' in Datastream or 'TR.F.DebtLTTot' in Eikon), which is not due for at least a year. We ensure that all variables for a given firm are in the same currency, specifically the currency of its primary equity issue (which is usually GBP for the firms in our sample). And we create monthly time series for all of the variables, either by sampling them at month ends (for market capitalisation) or forward filling the last observed values to those dates (for current liabilities and long-term debt).

Next, we choose between the two data sources for current liabilities and long-term debt. Initially, we take the Datastream data as our preferred series. However, this switches to Eikon data if it provides a longer historical time series and the two series agree fully during their period of overlap. If the agreement during the period of overlap is not perfect but sufficiently high and there is at least 30 months of overlapping data available to make such an assessment, we splice the earlier Eikon data onto the Datastream series from first date of perfect agreement. A 'sufficiently high' degree of overlap means that for at least 70% of the overlap period the difference between the two series on a given date as a percentage of the average of their values is less than the average standard deviation of the monthly percentage changes in the two series.

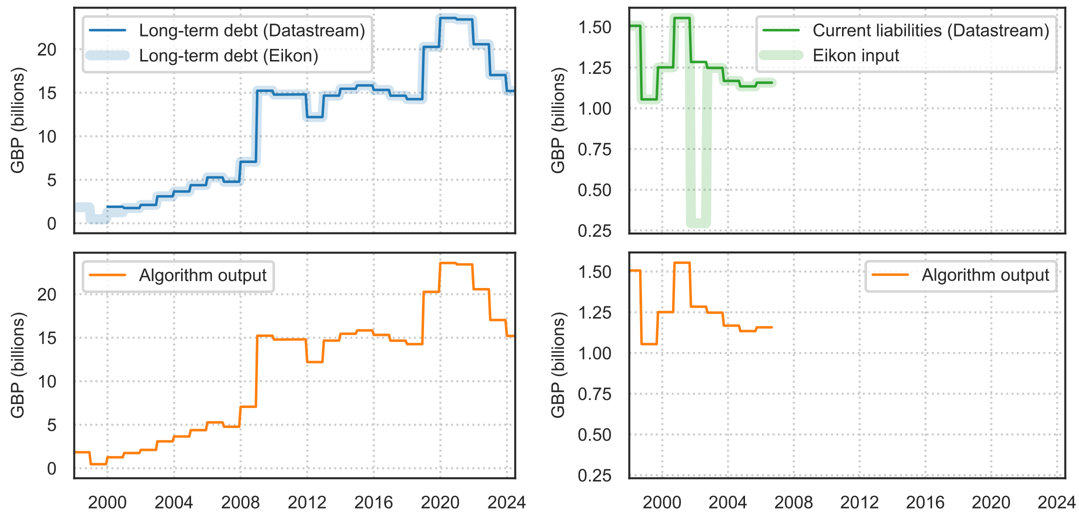
For market capitalisation, we use the same algorithm but augmented to help remove spurious-looking volatility or occasional spikes from the data. Thus, we also switch from the initially preferred series to the alternative series if either (i) the standard deviation of monthly percentage changes in the former is more than 105% of that of the latter or (ii) the preferred series at least doubles in some months and halves in other months and these changes are at least ten times greater than the corresponding changes in the alternative series. In each of these cases, we also require that there is a high degree of overlap between the alternative series and the initially preferred series as defined above.

We apply this augmented algorithm first to Datastream versus Eikon *company* market capitalisation, then to Datastream versus Eikon *issue* market capitalisation and finally to the output of the first application versus the output of the second application. This ordering means we would only use issue market capitalisation in preference to company market capitalisation if it resulted in a longer or less-volatile/spike-free data series and the issue market capitalisation agreed with the company market capitalisation to a high degree.

Finally, we plot all the preferred series suggested by our algorithm against the candidate series from which they were derived to judge whether it had made the correct decisions. Figures B.1 and B.2 show a selection of these plots, illustrating some of the most common data enhancements and corrections. We made further manual adjustments only in a few cases.

Figure B.1: Algorithm for selecting obligor data on liabilities

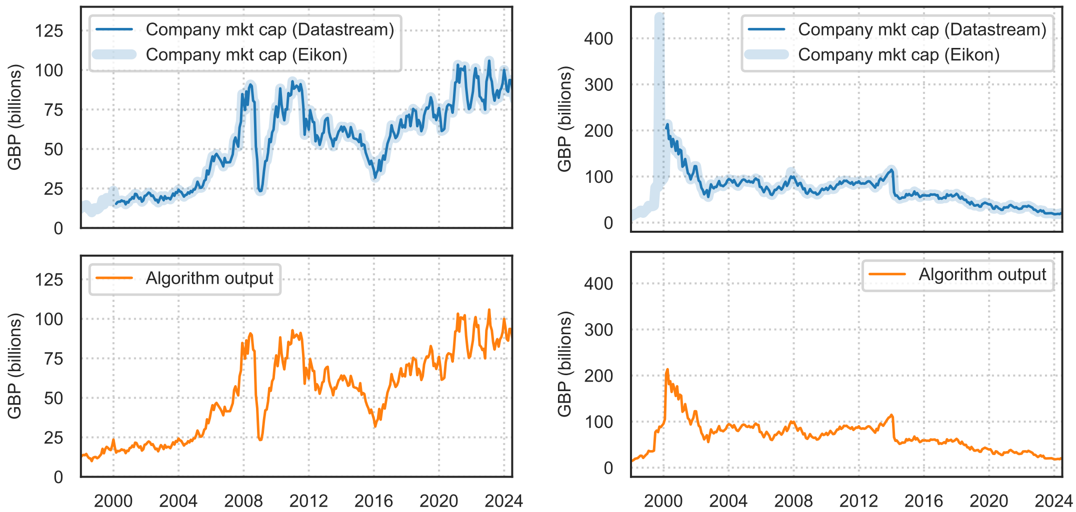
(a) Extend history (GlaxoSmithKline) **(b)** Remove spike (BOC Group)



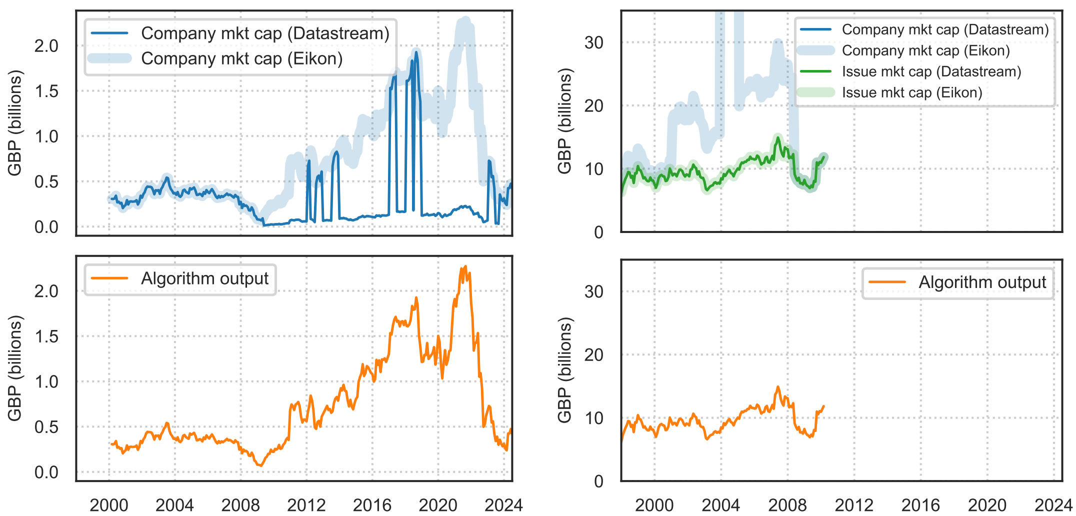
Notes: This figure shows selected inputs to (top panels) and outputs from (bottom panels) of our algorithm for choosing between LSEG Datastream and Eikon datasets for our data on obligor liabilities. In most cases, the datasets provided identical data. So, it was only in a minority of cases, such as those shown above, that the algorithm was needed.

Figure B.2: Algorithm for selecting obligor data on market capitalisation

(a) Extend history (Rio Tinto) **(b)** Remove spike (Vodafone)



(c) Excess volatility (Synthomer) **(d)** More stable issue data (Cadbury)



Notes: This figure shows selected inputs to (top panels) and outputs from (bottom panels) our algorithm for choosing between LSEG Datastream and Eikon datasets for our data on obligor market capitalisations. In most cases, the datasets provided identical data. So, it was only in a minority of cases, such as those shown above, that the algorithm was needed.

Appendix C Corporate bond data filters

The table below shows how our initial sample of UK non-financial corporate bonds from the ICE index platform is affected by our subsequent filtering.

Table C.2: Corporate bond data filters

	Bonds	**Obligors**	**Observations**
Initial sample of UK non-financial corporate bonds	2,227	188	122,500
Filter bond types			
Retain only bonds with fixed-rate (including zero) coupons	2,133	188	120,493
Retain only senior-unsecured bonds	1,948	174	111,228
Exclude convertible bonds	1,944	174	111,163
Exclude bonds with sinking funds	1,943	174	111,114
Filter for essential data on bonds and matched obligors			
Retain only observations with both an OAS and a DD	1,777	153	101,814
Data-quality filters			
Exclude bonds with negative age	1,764	153	101,631
Exclude bonds with outstanding < £1 million	1,764	153	101,631
Retain only bonds with OAS between 5-3500 basis points	1,763	153	101,295
Retain only bonds with residual maturity between 1-30 years	1,754	153	100,168
Retain non-UK-listed obligors only when incorporated in UK	1,723	149	99,717
Retain only major currencies (GBP, EUR and USD)	1,680	149	97,931

Notes: The table shows how the corporate bond data sample size is affected by filtering. The sample observations span 1997Q4-2024Q2. The number of bonds and obligors are the unique numbers that feature during the sample period. The numbers in any given quarter are lower (see Table 1).

Appendix D EBP and economic activity: A VAR approach

We further implement a standard vector autoregression (VAR) model. This complementary approach serves the purposes of testing the robustness of our empirical findings using the local projections framework and benchmarking our results with previous studies.

We assess the macroeconomic impact of a shock to bond financing conditions following the recursive ordering VAR model specification of Gilchrist and Zakrajšek (2012). Such identification approach assumes that a shock to bond financing conditions affects economic activity and inflation with a lag, while financial markets respond contemporaneously. The model includes the log-difference of private consumption, private gross-fixed capital formation, GDP and inflation, along with the excess bond premium, equity market excess returns, the 10-year gilt yield and the Bank of England policy rate in nominal terms.

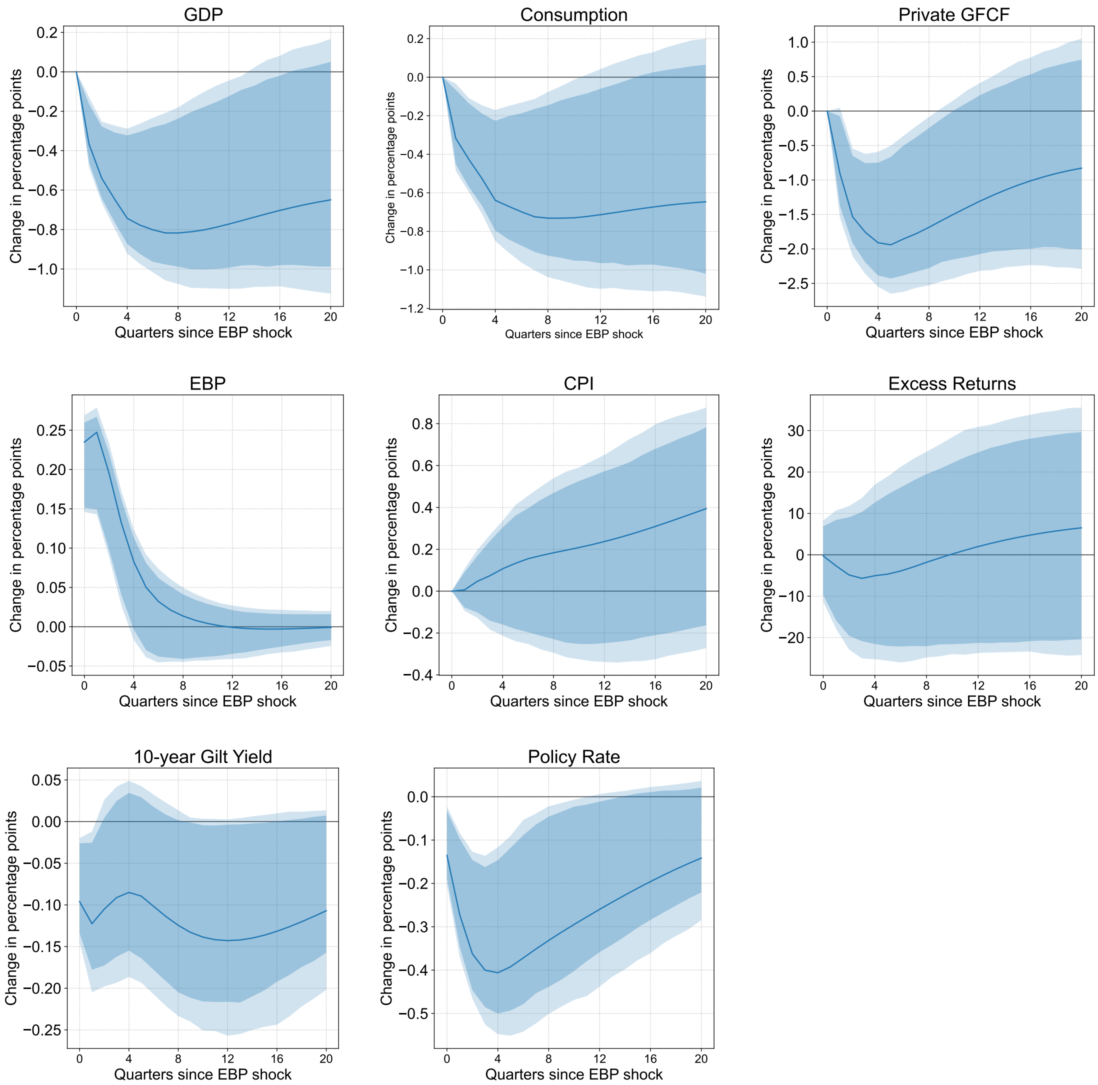
The VAR model is estimated using the whole sample period, including two lags of each endogenous variable informed by the Akaike Information Criterion (AIC). To account for the extraordinary impact of the COVID-19 pandemic, the VAR specification is augmented with two exogenous dummy variables corresponding to the first and second quarters of 2020. The dummies capture the onset of the pandemic shock and the policy response to it, respectively, isolating the effects of extreme macro-financial volatility and avoiding attributing the pandemic-driven shock to structural credit market dynamics.

Figure D.3 shows the impulse response functions for a one-standard deviation shock to the EBP, offering insights into the transmission of bond financing conditions shocks on the broader economy. A positive innovation to the excess bond premium –interpreted as a tightening in credit market conditions that is not justified by macroeconomic fundamentals– produces rather pronounced and persistent adverse effects.

A one standard deviation shock leads to a deterioration in real activity, including a cumulative decline of around 0.8% in real GDP and private consumption over a 2-year horizon and a 2% drop in private investment after one year. These findings align with the financial accelerator framework of Bernanke et al. (1999), in which worsening credit conditions amplify the real effects of macroeconomic disturbances by raising the external finance premium and thereby depressing investment and consumption.

The estimated responses also suggest a countercyclical policy reaction, as the Bank policy rate declines in response to bond premium shocks, reflecting an accommodative monetary stance. Nonetheless, despite this monetary easing, broader financial conditions remain tight. Equity markets experience losses and bond financing conditions continue to deteriorate over a 1-year horizon. This could reflect limitations in the modelling approach as it does not capture the effect of unconventional monetary policy in stabilising the economy following financial shocks. Relative to the results for the US in Gilchrist and Zakrajšek (2012), UK estimates suggest a more muted and less persistent macroeconomic response overall.

Figure D.3: VAR impulse responses to an EBP shock



Notes: The impulse responses correspond to the response of each variable to a one standard deviation shock to the EBP, where an increase in the EBP corresponds to worsening financing conditions. The blue areas show bootstrapped 95% confidence intervals based on 2,000 replications.