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The impact of macroeconomic and monetary policy shocks on credit risk in the euro area corporate sector

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Abstract

We analyse the impact of macroeconomic and monetary policy shocks on corporate credit risk as measured by firms' probabilities of default (PDs) for the four largest euro area countries. We estimate the impact of shocks on one-year PDs using local projections (LP). For the period 2014-19, we find that aggregate shocks significantly affect the dynamics of credit risk. An adverse supply shock leads to a deterioration of firms' riskiness 10 per cent above the average PD. Contractionary monetary policy shocks exert similar, but delayed effects. Firms' responses to shocks vary depending on their characteristics and degree of financial constraints. Smaller firms are affected to a larger degree. Firms' outstanding indebtedness and debt repayment capacity are an important transmission channel for aggregate shocks, but the accumulation of cash reserves helps building resilience.

Keywords: Corporate credit risk; probabilities of default; structural demand and supply shocks; monetary policy shocks, local projections.

JEL classification: C23, C55, E43, E52, G33.

Non-technical summary

The Covid-19 pandemic, price spikes in energy and commodity markets, and monetary policy tightening reignited the attention on the consequences of economy-wide shocks for the solvency of non-financial firms. Significant business and supply chain disruptions during the pandemic, together with a decline in demand, have led to a deep economic contraction. In this context, firms made substantial effort to build cash buffers which, coupled with massive support from the monetary, fiscal, and supervisory authorities, helped to avert a liquidity crisis, preventing corporate defaults. The energy and commodity crisis triggered by the Russian invasion of Ukraine challenged again the corporate sector. Production and input costs increased, particularly in energy-intensive sectors, exerting pressure on profit margins. Persistently high energy costs may trigger losses, depleting firms' equity and increasing debt burdens, resulting in higher bankruptcy risk. Finally, increasing global inflation triggered monetary policy tightening which translated into increasing financing costs with implications for firm liquidity and solvency.

Against this background, this paper analyses the transmission of macroeconomic and monetary policy shocks to corporate credit risk, as measured by firms' probabilities of default (PDs). We employ the macroeconomic shocks (*i.e.,* demand and supply shocks) computed by Gonçalves and Koester (2022) and monetary policy shocks from Altavilla *et al.* (2019). The former assume that supply shocks affect activity and inflation in opposite directions while demand shocks drive inflation and economic activity in the same direction. The latter estimate monetary policy surprises based on high frequency changes in the yields of various risk-free and risky assets following a monetary policy announcement. We include these shocks in a panel local projection model (Jordà, 2005) to estimate their dynamic impact on euro area non-financial companies' (NFC) probabilities of default. We conducted the empirical analysis at four levels of aggregation: country, country-size of firm, country-sector of firm and firm-level. The source of firms' PDs is Moody's RiskCalc and we focus on the four largest euro area countries: Germany, France, Spain, and Italy. The sample spans the period from the first quarter of 2014 to the fourth quarter of 2019 and includes listed and unlisted NFCs.

Our contribution to the literature is twofold. First, to the best of our knowledge, we are the first ones to study the impact of market-wide economic and funding shocks on a measure of credit risk for unlisted firms whose characteristics and access to financing differ from their listed counterparts (Anderson and Cesa-Bianchi, 2022; Palazzo and Yamarthy, 2022). Second, we shed light on the timing, magnitude, and heterogeneity across the spectrum of firms of the effects of aggregate shocks on corporate credit risk. We document differences in the response of firms' PDs depending on their *ex-ante* financial conditions, thus helping policy makers to understand both the transmission channels of shocks and to design measures aimed at reducing the vulnerability of corporates to shocks.

The main results of our analysis are the following. First, country-level PDs increase markedly following both contractionary supply and monetary policy shocks. The magnitude of the increase is economically significant, accounting for about 10 percent of the average PD in our sample. The response peaks one year after the shock. In contrast, the effect of expansionary demand shocks (*i.e.*, shocks associated with an increase in both economic activity and inflation) are smaller in magnitude and less significant. Second, the transmission of shocks depends on firms' characteristics. Smaller firms (which are typically financially constrained and reliant on bank lending) are twice more affected. Economic sectors such as construction, real estate, transport, and trade are particularly exposed to demand and supply shocks, while most economic sectors are affected by shocks to monetary conditions. Third, estimations based on firm-level PDs confirm our country-level results. Moreover, we highlight the role of financial frictions in the transmission of shocks with fragile companies (*i.e.*, highly indebted or with a limited debt repayment capacity) being more affected. Importantly, cash reserves provide a partial hedge against shocks which is even more beneficial for highly leveraged companies.

1. Introduction

The pandemic of 2020, the energy price spikes in 2022 and monetary policy tightening reignited attention on the consequences of economy-wide shocks for the solvency of non-financial firms. Significant business and supply chain disruptions during the pandemic, together with a decline in demand, have led to a deep economic contraction. The increase of corporate indebtedness in combination with weaker corporate profitability prospects raised widespread concerns about the vulnerability of the corporate sector. In this context, firms made substantial effort to build cash buffers which, coupled with massive support from the monetary, fiscal, and supervisory authorities, helped to avert a liquidity crisis, thereby preventing corporate defaults.[2] The energy and commodity price spikes triggered by the invasion of Ukraine challenged again the corporate sector. Production and input costs increased, particularly in energy-intensive sectors, squeezing again profit margins. Persistently high energy costs may trigger losses, depleting firms' equity and increasing debt burdens, resulting in higher bankruptcy risk. Higher prices for consumers have hit purchasing power, affecting aggregate demand. Finally, increasing global inflation triggered monetary policy tightening which translated into increasing financing costs, with implications for firms' liquidity and solvency.

Against this background, in this paper we ask the following two questions. First, how do aggregate shocks impact corporate credit risk? As policy makers design policies to shield corporates from the consequences of adverse shocks, it is of paramount importance to understand how, when and to what extent such shocks propagate to the corporate sector. Second, what role firms' characteristics play in the transmission of such shocks? In this regard, we intend to shed light on the timing, magnitude, and heterogeneity across the spectrum of firms of the effects of aggregate shocks on corporate credit risk. We answer these questions by analysing the transmission of macroeconomic and monetary policy shocks to corporate credit risk, as measured by firms' probabilities of default (PDs). We employ the macroeconomic shocks (*i.e.,* demand and supply shocks) computed by Gonçalves and Koester (2022). The authors decompose changes in individual components of the HICP index (*e.g.*, food and beverages, clothing, housing, etc.) into supply and demand shocks based on the direction of shifts in economic activity and inflation (if they move in the same -opposite- direction, the change is classified as demand –supply- driven). For monetary policy shocks, we rely on high frequency changes in the yields of various risk-free and risky assets following a monetary policy announcement (Altavilla *et al.*, 2019). We include these exogenous shocks in a panel local projection model (Jordà, 2005) to estimate their dynamic impact on euro area non-financial companies' (NFC) probabilities of default eight-quarters ahead. We conduct the empirical analysis at four levels of aggregation: country, country-size of the firm, country-economic sector, and firm level. The source of firms' PDs is Moody's RiskCalc and we focus on the four largest euro area countries: Germany, France, Spain, and Italy. The sample spans the period from the first quarter of 2014 to the fourth quarter of 2019.

The literature on the response of corporate riskiness to aggregate shocks in economic, financial, and monetary conditions is ample and dates to the seminal theoretical works of Bernanke and Gertler (1995), Mishkin (1995) and Bernanke *et al.* (1999). Under information asymmetries, monetary and real shocks affect the cost of credit via the values of the assets and the cash flows of potential borrowers (their creditworthiness) and via the amount of credit provided by banks. A number of papers documented the empirical relevance of macroeconomic and monetary policy

[2] These measures have prevented financing and rollover risks from materialising, improved access to credit, kept debt servicing costs at low levels and extended the maturity of outstanding debt. See de Bondt *et al.* (2021).

shocks in explaining corporate defaults since the publication of these studies. Pesaran *et al.* (2006), Bonfim (2009), Lando and Nielsen (2010) and Jacobson *et al.* (2011) focused on macroeconomic shocks. Pesaran *et al.* (2006) employ listed firms with a credit rating from either Moody's or S&P. Lando and Nielsen (2010) and Jacobson *et al.* (2011) focus on actual defaults in the USA and in Sweden, respectively. Gertler and Karadi (2015), Kim and Other (2019), Palazzo and Yamarthy (2022) and Anderson and Cesa-Bianchi (2022) studied the impact of monetary policy shocks on corporate credit spreads or credit default swaps employed as proxies for firms' credit risk. Except Kim and Other (2019), the studies focus on the USA. Other studies have highlighted the role of firm heterogeneity in the propagation of shocks. While Palazzo and Yamarthy (2022) employed credit spreads on listed bonds as a measure of credit risk, other papers have studied the role of firm heterogeneity in affecting the transmission of shocks on firms' stock prices and activity ratios, such as investments, cash holdings, inventories and sales growth (Ippolito *et al.*, 2018; Jeenas, 2019; Durante *et al.*, 2022).

Our contribution to this literature is fourfold. First, to the best of our knowledge, we are the first ones to study the impact of shocks on credit risk for both listed and, in particular, unlisted firms in the euro area, whose characteristics and access to financing differ substantially from their listed counterparts (Anderson and Cesa-Bianchi, 2022; Palazzo and Yamarthy, 2022). Second, we employ corporate's probability of default as our measure of credit risk, by contrast to the existing literature that has employed less accurate proxies of credit risk such as credit-default-swaps or credit spreads or has focused on stock prices and economic outcomes (investments, cash holdings, inventories, and sales growth, etc.). Third, we expand over the existing literature by encompassing different macroeconomic shocks, namely demand, supply and monetary policy. Fourth, we shed light on the timing, magnitude, and heterogeneity across the spectrum of firms of the effects of aggregate shocks on corporate credit risk. We highlight the role of financial frictions by documenting different responses of firms' PDs depending on their *ex-ante* financial conditions, thus helping policy makers to understand both the transmission channels of shocks and to design measures aimed at reducing the vulnerability of corporates to shocks.

The main results of our analysis are the following. First, for the whole euro area we show that weighted average country-level PDs increase markedly following both contractionary supply and monetary policy shocks. The magnitude of the increase is economically significant, accounting for about 10 percent of the average PD in our sample. The response peaks one year after the shock. In contrast, the effect of expansionary demand shocks (*i.e.*, shocks associated with an increase in both economic activity and inflation) are smaller in magnitude and less significant. Second, smaller firms, which are typically financially constrained and more reliant on bank lending, are twice as much more affected. Economic sectors such as construction, real estate, transport, and trade are particularly exposed to demand and supply shocks, while most economic sectors are affected by shocks to monetary conditions. Third, estimations based on firm-level PDs confirm our main country-level results. Moreover, we find that shocks propagate more strongly amongst financially constrained and fragile corporations (*i.e.*, highly indebted or with a limited debt repayment capacity). Importantly, cash reserves provide a partial hedge against shocks which is even more beneficial for highly leveraged companies: notably, following a shock, cash buffers can be used to repay outstanding debt, avoid default and limit refinancing.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 sets out the modelling framework and Section 4 presents and describes the data. Section 5 discusses the results at various levels of aggregation (country, size, sector, and firms). Section 6 concludes.

2. Related literature

The literature on the response of firms to aggregate shocks in economic, financial, and monetary conditions is ample. A first strand dates to the seminal work of Bernanke *et al.* (1999) and studies the impact of the macro-economy, alongside firm-specific factors, in affecting corporate defaults. Since then, a number of papers have documented the empirical relevance of macroeconomic variables (such as GDP, inflation, and interest rates) in explaining corporate defaults that "horse-race" the explanatory power of models obtained with and without macroeconomic factors (Bonfim, 2009; Lando and Nielsen, 2010; and Jacobson *et al.,* 2011). Pesaran *et al.* (2006) link credit risk to different macroeconomic shocks and found that equity price shocks have the most significant effect on credit risk, followed by oil price shocks.

A second strand of literature investigates the impact for the corporate sector of shocks to real economic outcomes. The literature studied the transmission of monetary policy shocks to firms' balance sheets and their financial conditions since the seminal contributions of Bernanke and Gertler (1995) and Mishkin (1995) on the credit channel. The idea is that contractionary monetary policy shocks increase the cost of external financing (due to borrowers' default risk and information asymmetries) and reduce credit availability for the economy.[3] The former affects firms' balance sheets directly via increasing interest payments on outstanding debt or floating-rate debt and lower firms' collateral value (through decreased asset-prices). It also affects firms indirectly by reducing aggregate demand and firms' revenues. The combined effect of lower revenues relative to costs erodes the firms' net worth and their credit-standing over time.

More recently, Gertler and Karadi (2015) employed monetary policy shocks identified using high frequency surprises around Federal Open Market Committee (FOMC) meetings and find that corporate credit spreads increase when monetary policy is tightened due to credit constraints faced by private borrowers.[4] Palazzo and Yamarthy (2022) find that firms' credit risk (proxied by credit default swaps) increases following a contractionary monetary policy shock during FOMC announcement days. Evidence also suggests heterogeneity in the response to shocks. Palazzo and Yamarthy (2022) find that riskier firms (e*x-ante*) display a stronger sensitivity to shocks. Anderson and Cesa-Bianchi (2022) document that the impact on credit risk (measured by credit spreads on listed bonds) is stronger for highly leveraged firms.

Kim and Other (2019) focus on listed firms' corporate bond spreads in the euro area. In contrast with predictions from the credit channel of monetary policy, their study shows that monetary policy easing is associated with an increase in credit risk in a low interest rate environment. However, this effect is relevant in the short-run only and it disappears when shocks entail changes in the path of future policy rates (long-run expectations). The authors argue that this is due to the negative news for economic prospects conveyed to market participants when interest rates decline.

The third strand of literature that relates to our paper focuses on the role of heterogeneity in the cross section of firms for the transmission of shocks. For the main euro area countries, Durante *et al.* (2022) investigate the transmission of monetary policy shocks to firms' investment decisions. The authors show that investments decline after a contractionary shock, but the response of

[3] The credit channel of monetary policy predicts a contraction in the supply of bank loans due to a drain in the amount of funds (mostly deposits) available to banks. If loan supply contracts, borrowers will be credit rationed (resulting in higher financing costs), reducing real economic activity.

[4] Conventional theoretical models of monetary policy transmission are based on frictionless financial markets and predict that the response of the cost of credit for private borrowers should depend entirely on the expected path of the central bank short-term interest rate.

investments differs depending on firms' financial constraints (proxied by age) and the economic sector. Financially constrained (*i.e.*, younger) firms and those in the durable goods sector respond more strongly to monetary policy shocks. Ippolito *et al.* (2018) examine the response of firms' stock prices, cash holdings, inventories, and fixed capital investments to monetary policy shocks. In all cases they find a larger sensitivity to shocks for financially constrained firms. The authors argue that the transmission of shocks operates mostly through existing floating-rate loans that become more expensive when monetary policy is tightened. Jeenas (2019) investigate how NFCs' activity ratios (fixed capital, inventory, and sales growth) respond to high frequency empirically identified monetary policy shocks. Financially constrained firms (highly leveraged or with a low cash balance) experience negative activity ratios following a shock, with the greater disparities occurring 8 to 12 quarters after the shock. It is however the low cash balance that explains the more pronounced contraction in activity ratios, also because these firms record the largest increase in the cost of debt servicing.

Against this background, we contribute to the literature by estimating the causal impact of macroeconomic shocks (*i.e.*, independent from the economic cycle and the information set available at time *t*) on the probability of default of NFCs. This contrasts with the existing literature that has used credit-default-swaps as proxies for credit risk. Importantly, we extend over the existing literature by encompassing different macroeconomic shocks, namely demand, supply and monetary policy. We also expand the sample of firms to include both listed and unlisted firms. We shed light on the potential channels through which aggregate shocks translate into vulnerabilities for several types of firms. We focus primarily on the role of financial constraints as an amplification mechanism of firms' riskiness and show that credit risk worsens after a monetary policy shock for both highly leveraged and low debt service capacity firms. Hence, we provide evidence in favour of the balance-sheet channel of monetary policy, using a novel, large set of firm-level data on PDs estimated using both balance-sheet and market information. Sectors more exposed to cyclical fluctuations are more severely impaired by adverse economic shocks.

3. Modelling the dynamics of credit risk

We employ local projections (LP) to investigate the response of firms' PDs to macroeconomic shocks. We obtain demand and supply shocks from Gonçalves and Koester (2022), and monetary policy shocks from Altavilla *et al.* (2019) (see Sub-sections 4.2 and 4.3 below). We then estimate the impact of shocks using a panel dataset by aggregating firm's PDs at various levels: country, country-firm-size, country-firm-sector and firm-level observations. Using different aggregation levels allows us to nail down the role played by heterogeneous countries and firms. We apply weights to individual firms' PDs to restore the proportions of SMEs and large firms in our sample with those in the population for each country.

Our benchmark LP model is as follows:

$$PD_{i,\,t+h} - PD_{i,\,t-1} = \alpha_{country,h} + \alpha_{size,h} + \alpha_{sector,h} + \sum_{j=1}^{J} \beta_{j,h} * shock_{t} * D_{j,t-1} + \gamma_h X_{country,t-1} + \varepsilon_{i,t+h} \tag{1}$$

where: *i* is the level of aggregation (country, firm sizes within a country, sectors within a country, and firms), *h*=0,1,…8 indicates quarters following a shock, $X_{country,t-1}$ is a set of time varying macroeconomic variables observed at time (quarter) *t-1* in each country, $shock_t$ denotes the type of aggregate shock at time *t* (demand, supply and monetary) and D_j is a dummy variable taking the value one for each country, size, sector or firms' group. Depending on the aggregation, we perform estimations using country, size, and/or economic-sector fixed effects to capture time-invariant, unobservable factors ($\alpha_{country,size,sector}$). Standard errors are clustered at the individual level (country, firm-size, and sector) and robust. We construct impulse responses based on the estimated β_h coefficients at each horizon.[5] When including an exogenous shock in a LP model, controls are often omitted. However, we decided to include them as they are likely to improve efficiency (see Stock and Watson, 2018; and Plagborg-Møller and Wolf, 2021). In Sub-section 5.2.2, we extend Equation (1) to include interaction terms and account for the role played by firm's characteristics in shaping the response of credit risk to shocks.

4. Data

4.1. Probabilities of default

Our sample spans the 2014-19 period and includes listed and unlisted NFCs from the largest four euro area countries (Germany, France, Spain, and Italy) for which financial information is available in the Orbis database (the main database containing firm-level balance sheet data). Including unlisted firms in the sample is important because their characteristics and access to financing differ from their listed counterparts (Anderson and Cesa-Bianchi, 2022; Palazzo and Yamarthy, 2022). We use probabilities of default (PDs) at a one-year horizon for active NFCs to measure credit risk. Firms under a bankruptcy or liquidation procedure were excluded, as well as firms in the financial and public administration sectors. We draw on Moody's Analytics RiskCalc PDs as our benchmark for firms' credit risk in euro area countries.[6] There are two types of PDs available in Moody's RiskCalc: credit cycle adjusted (CCA) and financial statements-only (FSO). We employ credit cycle adjusted (CCA) PDs, which are available at a quarterly frequency, while FSO are available annually. The CCA PDs also provide a more comprehensive and timelier picture of firms' risk.

Moody's estimates the CCA PDs using FSO's PDs as a starting point, adjusted for the stage of the credit cycle. To that end, Moody's uses quarterly macroeconomic and sectoral data (the average distance-to-default of listed firms in the industry) to compute an adjustment factor: a positive level for this factor indicates risks above the historical average and the FSO's PDs are adjusted upwards. This adjustment allows PDs to closely track the business and financial cycle, therefore resembling a "point-in-time" assessment of credit risk.

Importantly, Moody's RiskCalc uses actual defaults as an input by to compute the FSO's PDs and according to Moody's, their models are good at predicting actual defaults, both in-sample and out of sample and across industry, size, and different time periods. Such PDs are used by banks for a variety of applications, including in risk management, as an input or threshold on the banks' internal rating models (*e.g.*, for credit approval and underwriting, loan pricing, allowance for loan and lease losses, credit administration, risk reporting and portfolio management) and as an input or benchmark in regulatory capital calculations. Therefore, understanding how PDs react to shocks is important from a financial stability perspective against the backdrop of the possible multifaceted impact on banks.

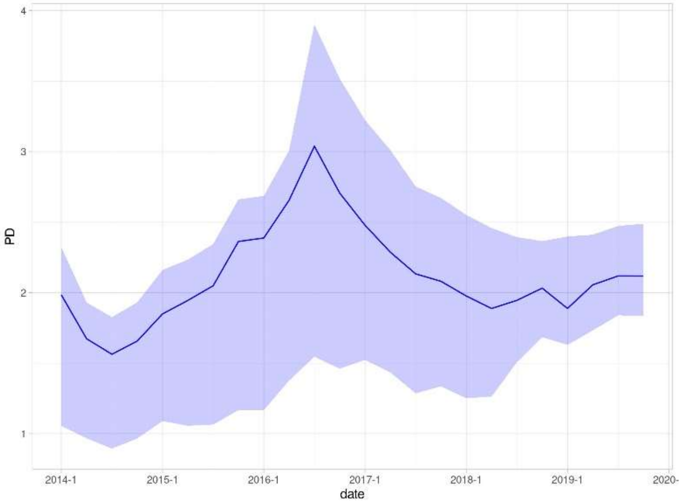
[5] We follow Jeenas (2019) and Jordà *et al.* (2015) and regress the cumulative difference between PDs over the right-hand side variables.

[6] Palazzo and Yamarthy (2022) use annualized, physical probabilities of default across multiple maturities from Moody's to compute a credit default swap (CDS) rate's expected loss component.

Firms' coverage by firm size is heterogeneous across countries. It is limited in the case of Germany, while it is larger in the case of Spain, France, and Italy (Table 1). To overcome representativeness issues, we apply weights to firms' PDs to restore the proportions of SMEs and large firms in our sample with those reported in the national statistics for the population of firms.[7] This approach allows us to obtain estimates that may hold for the population of firms in each country. Figure 1 reports the median PD and its interquartile range for our sample of euro area countries over the period 2014-19. The median PD hovered around 2% over the sample, being lower in 2014 and then increasing in the 2016-17 period.

Figure 1: Probability of default of euro area firms

(%)



Notes: The Figure reports the median RiskCalc 1-year PDs for NFCs in France, Germany, Italy, and Spain. The shaded area marks the 1st and 3rd quantile of the distribution of PDs. The expected default frequencies of the firms available in our sample are reproportioned to the population of firms in each country using the employment shares by micro, SMEs, and large firms as weights (Table A.1 in the Appendix). Firms under a bankruptcy or liquidation procedure were excluded, as well as firms in the financial and public administration sectors.
Source: Data from Moody's Analytics RiskCalc and Eurostat and author's calculations.

Table 1: Country coverage by firms' size and PD distribution

				PDs			
Country	**N Firms**	**SMEs**	**Assets**	**25th**	**50th**	**75th**	**w.a.**
	(units)	*(percent)*	*(billion)*	*(percent)*	*(percent)*	*(percent)*	*(percent)*
DE	1,881	38.50	2.87	0.30	0.48	0.91	0.76
ES	937,151	22.57	4.81	0.43	1.12	3.50	3.66
FR	1,065,144	16.90	8.69	0.26	0.66	2.33	1.84
IT	1,048,630	27.75	5.39	0.55	1.41	2.81	2.18

Notes: The sample PD quartiles are computed from the (unweighted) distribution of PDs while the weighted average PDs use firms' employment shares in the economy as weights. The countries are: DE = Germany, ES = Spain, FR = France, IT = Italy.
Source: Data from Moody's Analytics RiskCalc and author's calculations.

[7] The reproportioned PDs are obtained as weighed average PDs at the size-class level (*i.e.*, using individual firm's assets over each size class total assets as weights) multiplied by a measure of economic importance of each class in the population of firms. We follow the approach in the ECB Survey on the Access to Finance of Enterprises (ECB, 2022) and use the share of employed people in each firm size-class as a measure of economic importance (sourced from Eurostat's Structural Business Statistics, see Table A.1 in the Appendix).

4.2. Demand and supply shocks

We obtain aggregate demand and supply shocks for the euro area from Gonçalves and Koester (2022), who rely on Shapiro (2022). This approach assumes that supply shocks affect activity and inflation in opposite directions while demand shocks drive inflation and economic activity in the same direction. In more detail, the authors attribute forecasting errors from the modelling of consumer prices and economic activity to supply factors when the errors in prices and activity have different sign. When they have the same sign, the authors attribute the forecasting errors to demand factors. When errors are not statistically significant, the unexpected changes in prices and activity are classified as ambiguous. Therefore, we exclude them from the analysis. Figure A.1 in the Appendix displays the time series of the shocks. Descriptive statistics are presented in Table 2. Gonçalves and Koester (2022) find that the increase in euro area inflation starting in the third quarter of 2021 was initially mainly supply-driven, but the importance of demand factors has gradually increased over time. These results are broadly in line with expectations.

Table 2: Shocks

(basis points)

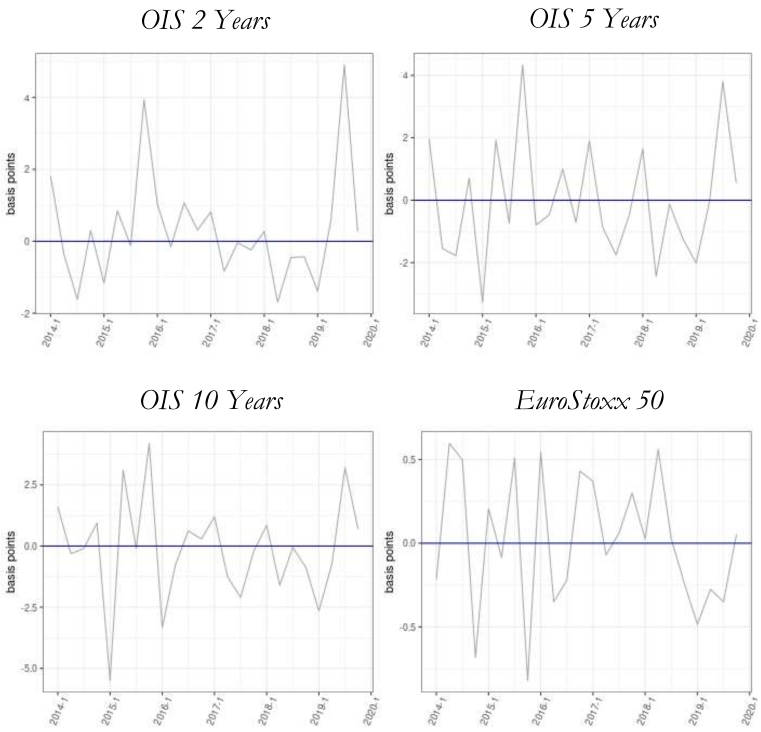
Variable	mean	standard deviation
demand shocks	0.37	0.08
supply shocks	0.31	0.12
mon. policy shocks OIS 2 years	0.31	1.52
mon. policy shocks OIS 5 years	- 0.02	1.85
mon. policy shocks OIS 10 years	- 0.14	2.03
mon. policy shocks Euro Stoxx 50	0.01	0.39

Note: The Table presents descriptive statistics for the macroeconomic and monetary policy shocks obtained by averaging daily observations at each quarter.
Source: Gonçalves and Koester (2022) and Altavilla *et al.* (2019) and author's calculations.

4.3. Monetary policy shocks

We employ exogenous changes in euro area monetary conditions using high-frequency monetary policy surprises from Altavilla *et al.* (2019) drawn from the publicly available Euro Area Monetary Policy Event-Study Database (EA-MPD). These series are available at daily frequency and for different asset classes (*i.e.*, overnight index swap -OIS- rate of different maturities, sovereign bonds, equity indices and exchange rates). They report the basis points change for these assets around monetary policy announcements (*i.e.*, from before the press release to after the press conference of Governing Council meetings, the so-called monetary event window). We compute quarterly shocks as the average of daily shocks in each quarter.

Figure 2: Monetary policy shocks
(basis points)



Note: The Figure reports quarterly averages of monetary policy shocks. Daily shocks are aggregated to quarterly frequency by taking simple averages over the daily shocks within the quarter. Benchmark assets are the OIS 2, 5, and 10 years and the Euro Stoxx 50.
Source: Data from Altavilla *et al.* (2019) and author's calculations.

We assess the impact of monetary policy shocks by using different series (Figure 2 and Table 2). These include shocks to the term structure of euro area risk free rates (OIS 2, 5 and 10 years) and to a euro area large firms stock market index (Euro Stoxx 50). As documented in Altavilla *et al.* (2019), measuring shocks from changes in asset prices or yields for different benchmark assets is important to capture the multifaceted effects of policy announcements. In fact, changes in interest rates influence short-term maturities of the curve, forward guidance reaches its peak at intermediate maturities and quantitative easing measures exert maximum impact on long maturities and equity indices. Moreover, changes in stock prices also influence liability costs via changes in the cost of equity.

4.4. Macro and financial controls

We include a set of macroeconomic and financial control variables in Equation (1), as it is common in the modelling of aggregate default rate series (Cathcart *et al.*, 2020). As mentioned before, including control variables is likely to improve efficiency (see Stock and Watson, 2018; and Plagborg-Møller and Wolf, 2021). We include the first lag of the annual real GDP growth rate, the quarterly change in the unemployment rate, the 2-year government bond yield, the 5-year sovereign CDS spread plus a measure of the firms' cost of funding which is the corporate bond yield. The source of these variables is the ECB Statistical Data Warehouse. Table 3 provides descriptive statistics.

Table 3: Descriptive statistics for the control variables
(percent)

Country	Percentile	GDP growth	Gov. yield short term	Gov. CDS spread	Unemploy. rate	Corporate bond yield
	25th	0.81	-0.69	10.56	3.17	3.27
DE	50th	1.67	-0.60	13.39	3.64	3.66
	75th	2.28	-0.26	17.96	4.06	4.20
	25th	1.75	-0.40	41.00	14.46	3.75
ES	50th	2.53	-0.22	66.97	16.33	4.40
	75th	3.47	0.12	84.96	20.28	5.38
	25th	0.83	-0.63	20.13	8.11	3.29
FR	50th	1.33	-0.51	25.91	9.06	3.89
	75th	2.37	-0.19	38.01	10.17	4.71
	25th	0.07	-0.14	101.72	9.75	2.79
IT	50th	0.84	0.03	131.55	10.82	3.55
	75th	1.62	0.41	163.93	11.72	3.96

Note: The Table presents descriptive statistics for the set of macroeconomic and financial controls included in Equation (1). All controls are lagged. The countries are: DE = Germany, ES = Spain, FR = France, IT = Italy.
Source: Data from ECB Statistical Data Warehouse and author's calculations.

5. Results

This section presents the cumulative impulse response functions and discusses the effect of macroeconomic and monetary policy shocks on credit risk over an eight-quarter horizon. First, we present the results for a country panel dataset (Sub-section 5.1). The impact per firms' heterogeneity is presented in Sub-section 5.2. In particular, Sub-section 5.2.1 presents the results for size and economic sectors. Thereafter, we study the heterogeneity of responses to shocks depending on firms' characteristics focusing on firms' financial constraints using standard proxies such as a firms' age, leverage, and debt servicing capacity (Sub-section 5.2.2).

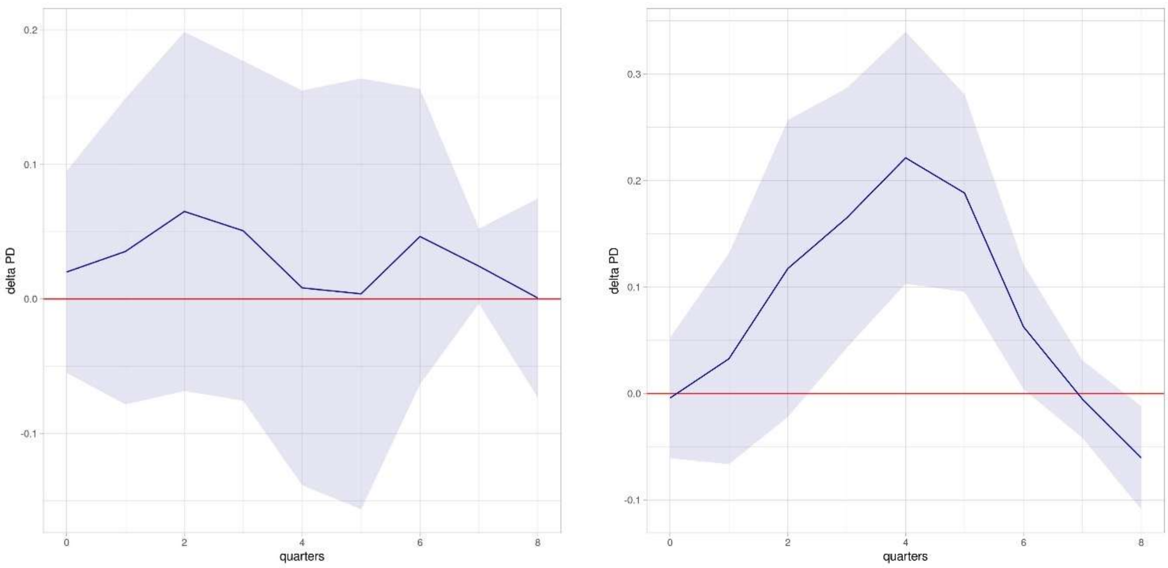
5.1. The response of credit risk at the euro area level

We apply Equation (1) to a country-panel dataset assuming $\beta_{j,h} = \beta_h \forall j$. We aggregate default probabilities at the country level (*i=4*) employing the weighs which allows us to obtain estimates that may hold for the population of firms in each country. Cumulative impulse response functions (*i.e.*, the estimated coefficients) for demand and supply shocks are plot in Figure 3 using fixed effects at the country level ($\alpha_{1,\text{country},h}$). We set $\alpha_{2,\text{size},h}=\alpha_{3,\text{sector},h} = 0$. The estimated coefficients are rescaled to provide the magnitude of the impact on PDs, in percentage points, of a one standard deviation change in the level of individual shocks.

Figure 3: Response of PDs to demand and supply shocks

(response to a one standard-deviation shock, %)

Panel A: demand shock *Panel B: supply shock*



Notes: The Figure reports the cumulative impulse response functions (IRFs) employing the panel local projection model in Equation (1). The response of PDs is rescaled to a one standard deviation of individual shocks. Estimates are obtained for the main EA countries using one year lagged control variables: annual real GDP growth rate, 2-year government bond yield, 5-year government CDS spread, corporate bond yield and change in unemployment rate. The model also includes country fixed effects. Standard errors are clustered. Weighted average PDs at the country level are obtained using employment shares as weights (see Equation A.1).
Source: Data from Moody's Analytics RiskCalc, Gonçalves and Koester (2022), Altavilla *et al.* (2019) and ECB Statistical Data Warehouse and author's calculations.

The transmission of macroeconomic shocks to euro area corporate credit risk is heterogeneous between shocks. The response to expansionary demand shocks (*i.e.*, those associated with unexpected increases in economic activity and inflation) is not statistically significant. By contrast, the response of firms' PDs to adverse supply shocks (*i.e.*, those associated with a contraction in economic activity and a rise in inflation) is statistically significant and economically substantial. Euro area PDs peak at slightly above 0.2 percentage points four quarters after the shock following a one-standard deviation adverse supply shock. The response is important, accounting for about 10 percent of the mean pooled PD for euro area NFCs.

Figure 4 presents the response of PDs to the monetary policy shocks from Altavilla *et al.* (2019). The Figure reports estimates for shocks to different asset classes: the term structure of risk-free OIS rates (2, 5 and 10 years) and a major euro area stock index (the Eurostoxx 50). The use of different assets classes characterizes the changing nature of market reactions to policy decisions (Wright, 2019) and disentangles the effects of different information announcements (raising policy rates, the announcement of forward guidance and quantitative easing; see Altavilla *et al.*, 2019).

Consistent with the credit channel narrative that predicts that negative monetary policy shocks increase the cost of outstanding financial liabilities and worsen prospective firms' solvency positions, we find that unexpected increases in risk-free rates along the yield curve lead to a rise in firms' PDs (Panel A in Figure 4). The magnitude of this effect is larger when for shocks to short-term rates: it peaks at about 0.17 percentage points four quarters after a one-standard deviation shock to OIS 2 years, compared with 0.13 and 0.10 for the OIS 5 and 10 years, respectively. The greater sensitivity to shorter maturity rates could be due to: the prevalence of variable rate and shorter maturity indebtedness in the corporate sector, a feature that makes the cost of debt service more sensitive to unexpected changes in financing conditions (Ippolito *et al.*, 2018).[8] When monetary policy announcements lead to an unexpected increase in equity returns, featuring a scenario where market participants react positively to a policy decision perhaps in association with the easing of financing conditions or the improvement in the economic outlook, NFCs' prospective credit worthiness ameliorate decisively by about 0.12 percentage points four quarters after a one-standard deviation shock. The positive impact on PDs persists longer and peaks at 0.21 percentage points with a delay of about seven quarters. Pesaran et *al.* (2006) documented a strong effect of stock market fluctuations on corporate credit risk. However, here we elicit the link between monetary policy shocks, stock market fluctuations and credit risk.[9]

Overall, the results regarding the negative effect of tighter monetary conditions on credit risk point to the role of debt (new and outstanding loans) for the propagation of such shocks.

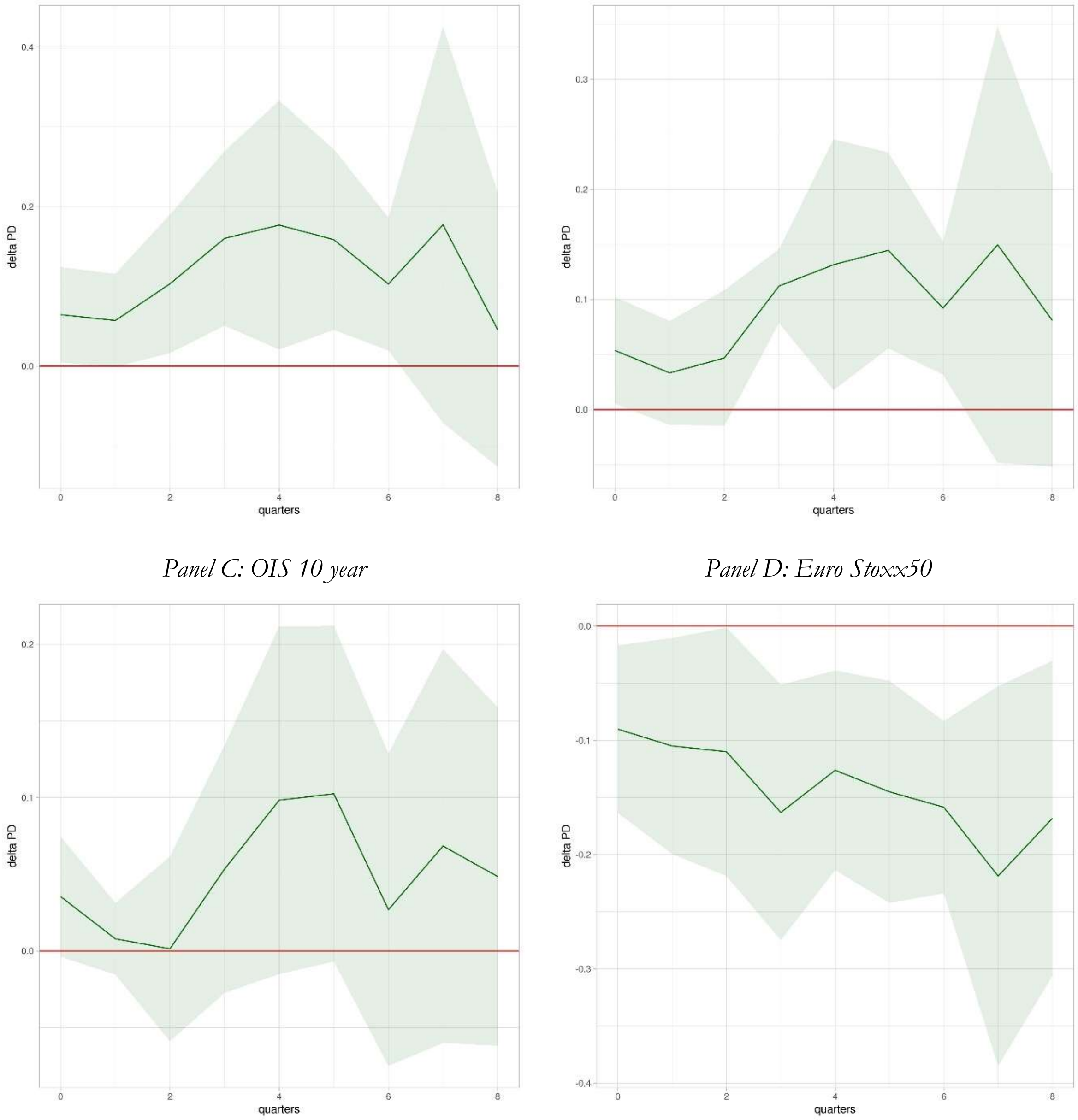
[8] The floating rate channel hypothesis (Ippolito *et al.*, 2018) suggests that monetary policy shocks can affect firms' financial strength by draining internal cash resources due to increasing cost for debt servicing of existent loans (and not only for the new loans as predicated by the credit channel hypothesis). We argue that this is a particularly relevant channel as most corporate loans from banks feature floating interest rates.

[9] The prominent effect of changes in short-term rates related to monetary policy announcements is confirmed when using shocks to domestic sovereign bond yields from Altavilla *et al.* (2019). The magnitude of the effect is however smaller, but we observe a similar pattern along the maturity term structure as with the OIS rates. Results are available from the authors upon request.

Figure 4: Response of PDs to monetary policy shocks

(response to a one standard-deviation shock, %)

Panel A: OIS 2 year *Panel B: OIS 5 year*



Notes: The Figure reports the cumulative impulse response functions (IRFs) employing the panel local projection model in Equation (1). The response of PDs is rescaled to a one standard deviation of individual shocks. Estimates are obtained for the main EA countries using one year lagged control variables: annual real GDP growth rate, 2-year government bond yield, 5-year government CDS spread, corporate bond yield and change in unemployment rate. The model also includes country fixed effects. Standard errors are clustered. Weighted average PDs at the country level are obtained using employment shares as weights (see Equation A.1).

Source: Data from Moody's Analytics RiskCalc, Altavilla *et al.* (2019) and ECB Statistical Data Warehouse and author's calculations.

5.2. Exploring firms' heterogeneity

5.2.1. Firm size and economic sectors

In this section, we examine the role of heterogeneity by estimating the dynamic reaction of firms' PDs according to size and economic sector. We estimate Equation (1) on weighted average PDs, using firms' assets in the same group (*i.e.*, size, or sectoral group within each country) as weights, leading to a country-size and country-sector panel datasets. We focus on three firm sizes (micro, SMEs, and large firms) and eight economic sectors. The dummy variable D_j in Equation (1) takes the value one for each of the elements in these two groups, where $j=3$ and 8, respectively. Firms are classified by size using the European Commission's thresholds on asset values (less than EUR 2 million for micro, between EUR 2 and 43 million for SMEs and more than EUR 43 for large firms). See Table A.2 in the Appendix for more details regarding the classification of sectors. In the first regression we set $\alpha_{3,sector,h} = 0$, while in the second one we set $\alpha_{2,size,h}=0$.

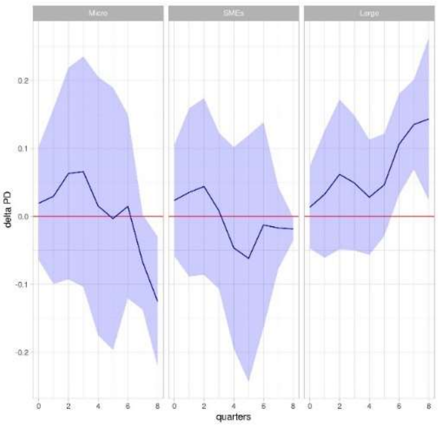
Figure 5 presents the response of PDs by firm size to a one standard deviation shock. As in the case of the country level aggregation, the shocks have significant effects on firms' credit risk. Additionally, we uncover significant differences depending on firms' sizes. Demand and supply shocks hit more decisively smaller firms, probably due to their lower capacity to adapt to rapid cyclical changes (*i.e.*, lower export share or capacity to adapt to technological shocks; panels A and B in Figure 5). A one-standard deviation contractionary supply shock increases micro firms' PDs by twice as much as for their larger counterparts (about 0.26 percentage points compared with 0.12 percentage points) four quarters after the shock. Interestingly though, in association with expansionary demand shocks, the credit risk standing of larger firms does not benefit as their smaller counterparts.

Consistent with these findings, our results also suggest that monetary policy shocks are transmitted more markedly to smaller firms, which tend to be financially constrained (panels C to E in Figure 5). A one-standard deviation tightening monetary policy shock (measured using OIS 2-year yields) entails a 0.26 percentage point increase in the credit risk of micro firms. This is a three-fold increase with respect to the impact on the large ones (0.09 percentage points). This result is also observed along shocks to the yield curve. As observed when presenting the aggregate euro area results in Subsection 5.1, the impact of the shorter end of the yield curve is stronger that than one of longer maturities. This result applies to all firm sizes.

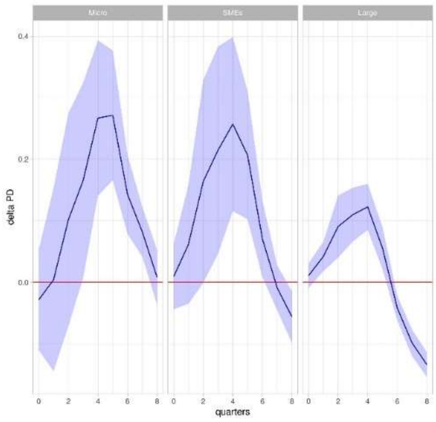
Figure 5: Response of PDs to shocks by firm size

(response to a one standard-deviation shock, %)

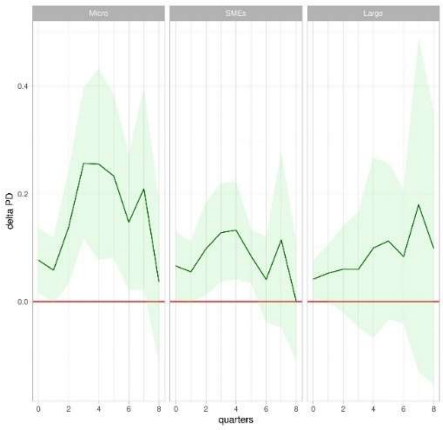
Panel A: demand shock



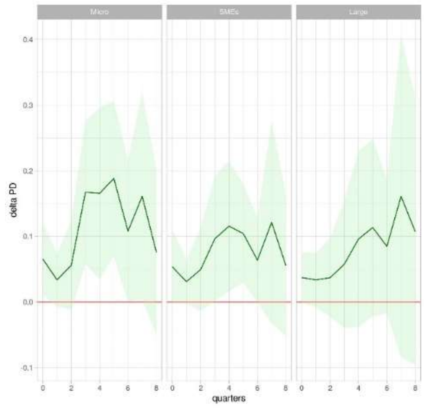
Panel B: supply shock



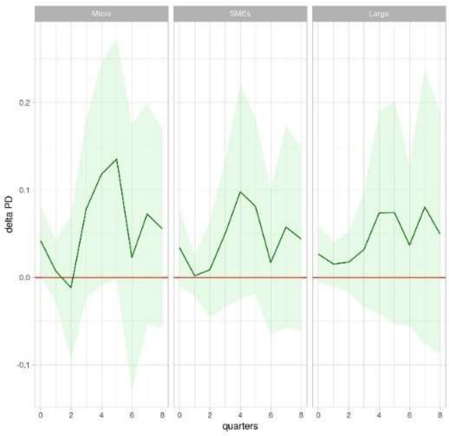
Panel C: monetary policy shock OIS 2y



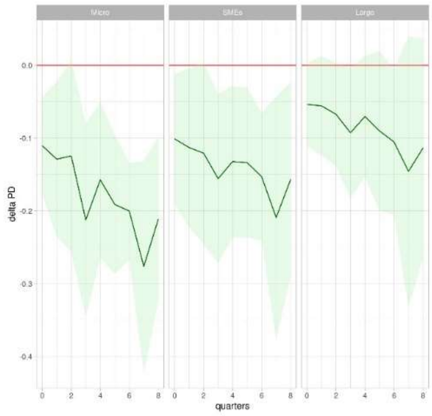
Panel D: monetary policy shock OIS 5y



Panel E: monetary policy shock OIS 10y



Panel F: monetary policy shock Euro Stoxx 50



Notes: The Figure reports the cumulative impulse response functions (IRFs) employing the panel local projection model in Equation (1). The response of PDs is rescaled to a one standard deviation of individual shocks. Estimates are obtained for the main EA countries using one year lagged control variables: annual real GDP growth rate, 2-year government bond yield, 5-year government CDS spread, corporate bond yield and change in unemployment rate. The model includes country and firm size fixed effects. Standard errors are clustered. Country-size classes weighted average PDs are obtained using a firm's total assets over total assets of the size class as weights.

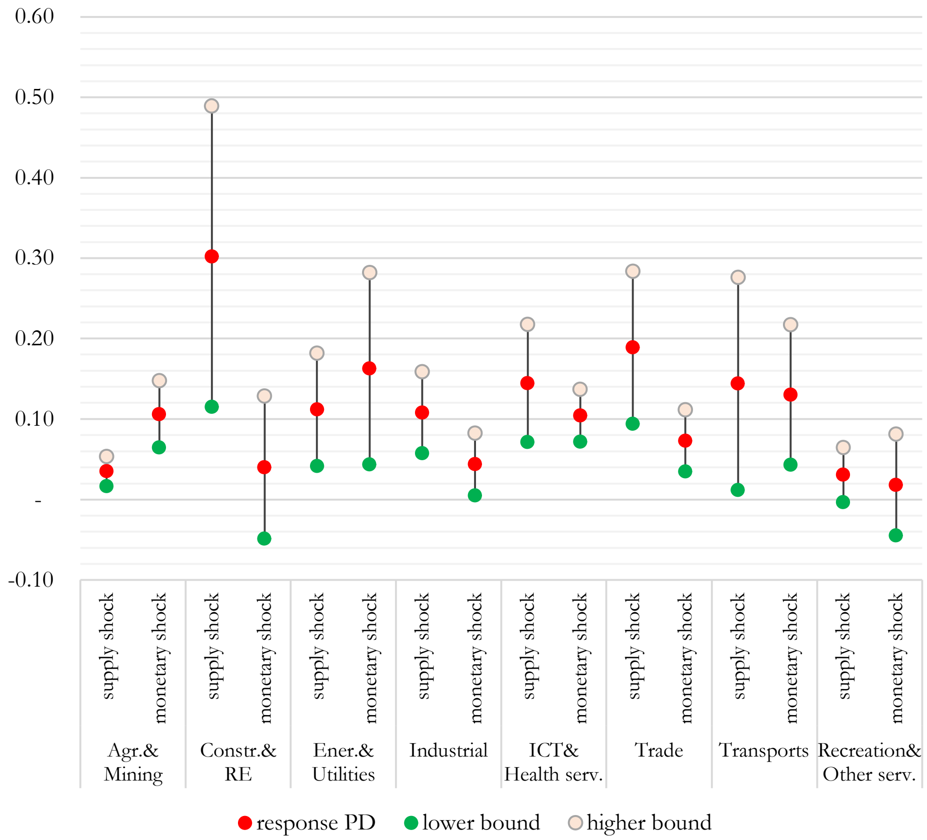
Source: Data from Moody's Analytics RiskCalc, Gonçalves and Koester (2022), Altavilla *et al.* (2019), ECB Statistical Data Warehouse and author's calculations.

Figure 7 reports the response of PDs at the sectoral level to supply and monetary policy shocks (for the OIS 2-year rate). Selected $\beta_{i,h}$ coefficients for the horizon $h = 4$ were multiplied by one standard deviation of individual shocks. We estimate the model using country-sectors fixed effects. Figure A.2 in the Appendix reports the full structure of impulse response functions.

The transmission of macroeconomic shocks is remarkably uneven across economic sectors. Sectors where the estimated impact of supply shocks is large are construction and real estate, trade, transport, and ICT. These sectors are strongly linked to the economic cycle and these firms occupy key roles in supply chains. Regarding the monetary policy shock, in most cases the impact is similar. However, for energy, utilities and transport, the impact is stronger.

Figure 7: Response of firms' PDs by sectors to selected shocks

(response to a one standard-deviation shock, %)



Notes: The Figure reports the response of PDs to individual shocks estimated from the panel local projection model in Equation (1). The response of PDs four quarters after is rescaled to a one standard deviation of individual shocks. Estimates are obtained for the main EA countries using one year lagged control variables: annual real GDP growth rate, 2-year government bond yield, 5-year government CDS spread, corporate bond yield and change in unemployment rate. The model includes country and sector fixed effects. Standard errors are clustered. Country-sector weighted average PDs are obtained using a firm's total assets over total assets of the size class as weights. The lower and upper bounds represent the 90 percent confidence interval of the response of the PD. Firms are assigned to economic sectors using the statistical classification of economic activities in the European Community (NACE classification): (A, B) agriculture and mining, (C) industrial, (D, E) energy and utility, (F, L) construction and real estate (G) trade, (H) transportation (I, R, S) tourism, recreation other services (J, M, N, Q, P) information, scientific and health services. Robust standard errors in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Source: Data from Moody's Analytics RiskCalc, Gonçalves and Koester (2022), Altavilla *et al.* (2019), ECB Statistical Data Warehouse and author's calculations.

5.2.2. Firm level results

In this section, we use individual firms' PDs matched with balance sheet information to estimate how the propagation of macroeconomic and monetary policy shocks to firms' PDs differs depending on their characteristics. We perform regressions on a stratified sample of euro area corporates controlling for firms' observable and unobservable time-invariant characteristics, as well as time-varying balance-sheet items. We provide results on the effect of different shocks using our main Equation (1), with *i* being the index for individual firm PDs. To account for the different role played by firms' characteristics we augment Equation (1) as follows:

$$PD_{i,\,t+h} - PD_{i,\,t-1} = \alpha_{country,h} + \alpha_{size,h} + \alpha_{sector,h} + \beta_{1,\,h} * shock_t + \beta_{2,\,h} * shock_t * D_{i,\,t-1} + \gamma_h X_{country,t-1} + \varepsilon_{i,t+h} \qquad (2)$$

where D_i is a dummy variable used to approximate financial constraints of firm *i* (low debt servicing capacity or young age and high leverage) or the availability of hedges against financial constraints (high cash buffers).

We define financially constrained firms as those with leverage or debt service ratio above the 75th percentile of the distribution, computed for each year at a granular sectoral classification (NACE 4-digits). Similarly, firms with high cash buffer are those whose cash to total assets ratio exceed the 75th percentile of the year-sector distribution. Due to the large size of the dataset, we perform regressions using a sample of firms for each country, stratified by size classes, and using fixed effects at the country, firm-size class and sectors.[10]

Firstly, we replicate country-level estimates by imposing $\beta_{2,\,h} = 0$ in Equation (2); Table 3 presents the results for two horizons: *h= 4* and *8*. The dynamic effect of expansionary demand shocks on firm-level PDs is highly volatile and insignificant. Adverse supply shocks lead to a significant deterioration in firms' credit risk in the short run. Contractionary monetary policy shocks also impair firms' creditworthiness for several quarters. These results are consistent with our previous findings obtained using a less computationally intensive procedure based on country-level weighted average PDs.

[10] For each individual country, the size of the panel exceeds 20 million observations (more than 400.000 firms-quarter from 2014 to 2019).

Table 3: Firm level IRFs

Variable	h = 4	h = 8
demand_shock_hicp	-0.0022 (0.0034)	0.0078 (0.0029)
supply_shock_hicp	0.0206 *** (0.0007)	0.00
mon_policy_shock_OIS_2y	0.0012 ** (0.0002)	0.0004 ** (0.0001)
mon_policy_shock_OIS_5y	0.0008 *** (0.0000)	0.0006 *** (0.0001)
mon_policy_shock_OIS_10y	0.0005 *** (0.0000)	0.0003 *** (0.0000)
mon_policy_shock_STOXX50	-0.0039 ** (0.0004)	-0.0046 ** (0.0006)
Fixed-Effects:	---------------------	---------------------
countryisocode	*Yes*	*Yes*
size	*Yes*	*Yes*
nacerev2corecode4digits	*Yes*	*Yes*
S.E.: Clustered	by: coun. & size & nace.	by: coun. & size & nace.
Observations	2,127,965	1,601,526

Notes: The Table provides estimates of the of the panel local projection model in Equation (2). Estimates are obtained from a sample of about 100.000 firms for each country (except for Germany) using one year lagged control variables: annual real GDP growth rate, 2-year government bond yield, 5-year government CDS spread, corporate bond yield and change in unemployment rate. The model includes country, firm size class and sectoral fixed effects. Standard errors are clustered. Robust standard errors in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.
Source: Data from Moody's Analytics RiskCalc, Gonçalves and Koester (2022), Altavilla *et al.* (2019), ECB Statistical Data Warehouse and author's calculations.

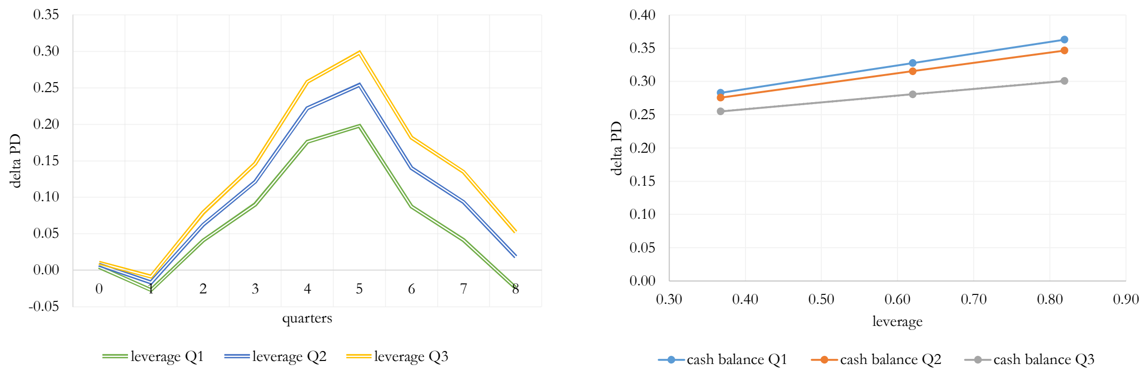
Secondly, we assess the role of financial constrains in the transmission of shocks using a set of proxy variables: *i*) Young age: young firms being less than ten years old since foundation (Durante *et al.*, 2020); *ii*) High leverage: leverage ratio (liabilities to total liabilities plus shareholder funds) above the 75th percentile threshold of the distribution computed for each year at a granular sectoral classification (NACE 4-digits); and *iii*) Low debt servicing capacity: debt service ratio (interest expenses to earnings before interest taxes, amortisation and depreciation, EBITDA) above the 75th percentile threshold of the distribution, as before. We also look at potential hedges against financial constraints such as high cash holdings (ratio of cash items to total assets above the 75th percentile threshold of the distribution, as before). Younger, highly leveraged, cash poor and companies with a high debt-servicing ratio are financially constrained.

We focus on the role of leverage and cash holdings (Figure 8 and Figure 9) using both features either as continuous indicator and as dummy variables. The results for the full set of proxies for financial constraints are reported in the Appendix (Table A.3 to Table A.6).

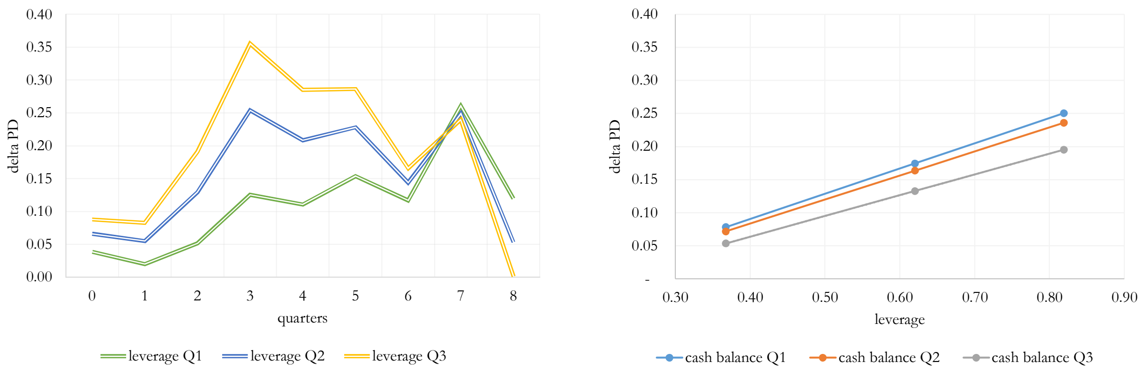
Supply shocks lead to a deterioration in credit risk which is stronger for more leveraged firms: for highly leveraged firms (3rd quartile of the distribution) the estimated increase in PDs, 4 quarters after the shock, is about 1 and half times stronger with respect to less leveraged firms (1st quartile of the distribution; 0.26 and 0.18 p.p.) (Figure 8 – Panel A, left hand side Figure). Holding constant corporate indebtedness, the availability of cash reserves reduces the negative impact of shocks: high cash balances (third quantile of the distribution) benefit more highly leveraged firms (as it is apparent from the lower slope of the grey line in Figure 8 – Panel A, right hand side Figure). Monetary policy shocks (OIS 2-year rate) have an impact on PDs that is increasing in firms' leverage: highly leveraged firms are two and half times more responsive than firms with less leverage (0.29 and 0.11 p.p.) (Figure 8 – Panel B, left hand side Figure). However, while cash buffers still provide a hedge against monetary shocks, the relative advantage between high and low debt firms is reversed with respect to that provided for supply shocks: high cash balance is more beneficial for low leverage firms. This different role played by cash holdings could reconcile with previous findings in Bottero and Schiaffi (2022). The authors show that when the yield curve steepens in response to a monetary policy tightening, holding cash becomes costlier (the trade-off between cash holdings and returns from investments increases) and those borrowers that maintain higher cash buffers obtain better financing terms from their lenders (which attribute higher value to firms' cash holdings). The lower marginal advantage from holding cash for highly leveraged firms that we find could be because these firms have already exploited much of the benefits.

Figure 8: The role of leverage and cash holdings

Panel A: supply shock – leverage and cash holdings



Panel B: monetary policy shock – leverage and cash holdings

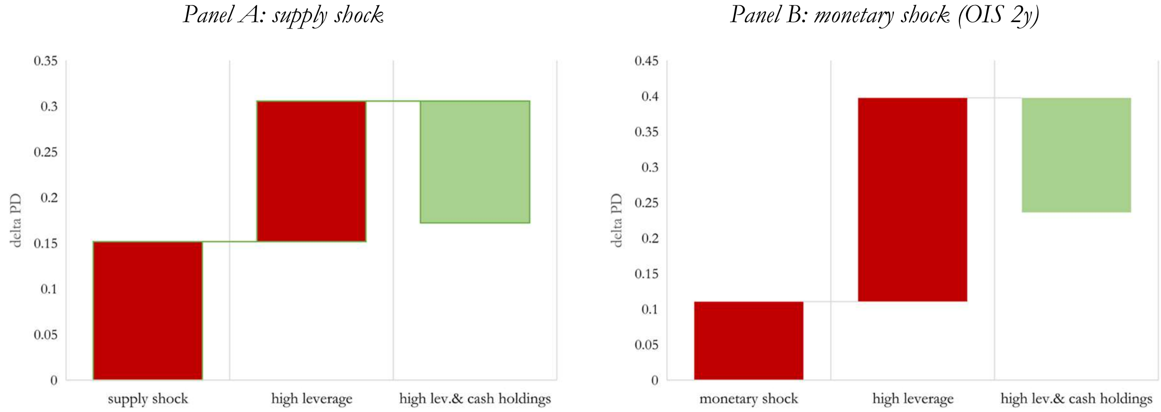


Notes: The Figure reports the response of PDs to individual shocks estimated from the panel local projection model in Equation (2) using firms' leverage and cash holdings in *t-1* as regressors. The left-hand panel illustrates the dynamic response of PDs, rescaled to a one standard deviation of individual shocks, for firms with leverage equalling the 1st to 3rd quantile of the distribution. The right-hand panel shows the response of PDs 4 quarts after the shock for firms in different quartiles of leverage and cash balance. Estimates are obtained for the main EA countries using one year lagged control variables: annual real GDP growth rate, 2-year government bond yield, 5-year government CDS spread, corporate bond yield and change in unemployment rate. The model includes country, firms' size, and sector fixed effects. Standard errors are clustered.
Source: Data from Moody's Analytics RiskCalc, Gonçalves and Koester (2022), Altavilla *et al.* (2019), ECB Statistical Data Warehouse and author's calculations.

In Figure 9 we single out the impact of shocks for the sub-group of fragile firms which are most likely to face financial constrains (*i.e.*, those with leverage above the third quartile). For financially constrained firms we estimate a one-fold (three-fold) increase in PDs following a one standard deviation supply (monetary) shock four quarters after.

Figure 9: The role of leverage in the response of firms' PDs to shocks

(response to a one standard-deviation shock, %)



Notes: The Figure reports the response of PDs to individual shocks estimated from the panel local projection model in Equation (2) with $D_{1,2} = 1$ for high leverage firms or high cash firms. The response of PDs four quarters after is rescaled to a one standard deviation of individual shocks. Estimates are obtained for the main EA countries using one year lagged control variables: annual real GDP growth rate, 2-year government bond yield, 5-year government CDS spread, corporate bond yield and change in unemployment rate. The model includes country, firms' size, and sector fixed effects. Standard errors are clustered. Source: Data from Moody's Analytics RiskCalc, Gonçalves and Koester (2022), Altavilla *et al.* (2019), ECB Statistical Data Warehouse and author's calculations.

The availability of cash buffers to credit constrained firms builds resilience against such shocks. We explore this hedging channel of cash holdings by augmenting Equation (2) with a third interaction term to capture the response to shocks of financially constrained, but cash rich firms ($\beta_{3,h}$*$shock_t$* $D_{i,t-1}$* $D_{i,t-1}$). Estimates indicate that highly leveraged firms can shield large increases in credit risk by as much as one third if their cash balance stands out from their industry peers, at least in the case of adverse supply shocks.

Our results for the dynamic response of corporate credit risk to monetary shocks are overall consistent with previous studies on the role of financial constraints. More opaque or riskier firms react more strongly (Ippolito *et al.*, 2018; Durante *et al.*, 2022; Palazzo and Yamarthy, 2022), but liquid asset holdings may partially shield exposure to negative shocks (Jeenas, 2019).

6. Conclusion

This paper investigates the impact of macroeconomic shocks, stemming from unanticipated changes in demand, supply, and monetary conditions, on credit risk of non-financial firms in four large euro area economies, namely Germany, Spain, France, and Italy.

We focus also on unlisted limited liabilities companies and use individual firm PDs to measure their riskiness. As policy makers design policies to shield corporates from the consequences of adverse shocks, it is of paramount importance to understand how, when and to what extent such shocks propagate to the corporate sector.

We find that supply shocks exert severe effects on firms' credit risk. Differences amongst firms' size classes and economic sectors emerge, due to their different capacity to shield the effects of shocks as well as to their degree of exposure to aggregate fluctuations.

Monetary policy shocks also affect the credit risk of euro area corporates. Fragile firms characterized by higher indebtedness and lower debt servicing capacity appear more sensitive to shocks, but cash buffers can help mitigate the impact on PDs.

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1. Appendix

To re-proportion sample average PDs (weighted by firms' assets) available in Moody's to the population of firms in each country, the share of employment of each firm size class (available in the Eurostat, Structural Business Statistics) is used as weight. In formula:

$$PD^{wa} = \left\{ \sum_{size\ class} \left[\sum_{i}^{n} PD_{i,size\ class} * \frac{assets_i}{assets_{size\ class}}) \right] * emply\ share^{pop}_{size\ class} \right\} \tag{A.1}$$

Table A.1: Share of persons employed by firms' size class

	total	micro	SMEs	large
Germany	1.00	0.19	0.43	0.37
Spain	1.00	0.38	0.34	0.28
France	1.00	0.25	0.30	0.47
Italy	1.00	0.44	0.33	0.21
median	1.00	0.32	0.33	0.32

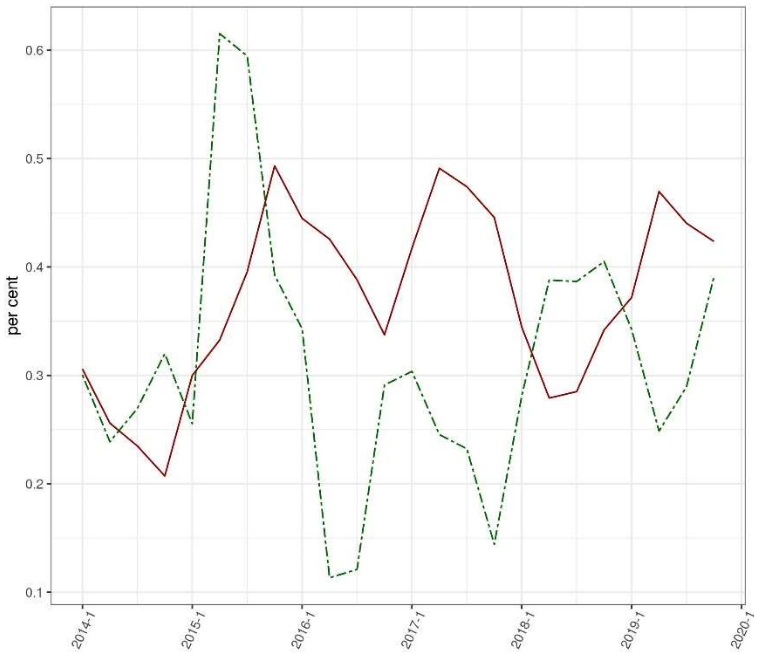
Source: Eurostat.
Note: The median share of persons employed in the non-financial business economy for the years 2014-2019 (Eurostat, Structural Business Statistics Data). The data is broken down by firms' size classes with micro firms having 0 to 9 persons employed, SMEs from 10 to 250 and large firms more than 250.

Table A.2: Mapping of NACE codes into eight sectors

Code	Economic Area	Mappinng in 8 economic aggregates
A	Agriculture, Forestry and Fishing	agricolture and mining
B	Mining and Quarrying	agricolture and mining
C	Manufacturing	industrial
D	Electricity, Gas, Steam and Air Conditioning Supply	energy and utility
E	Water Supply; Sewerage, Waste Management and Remediation Activities	energy and utility
F	Construction	construction and real estate
G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	trade
H	Transportation and Storage	transportation
I	Accommodation and Food Service Activities	turism, recreation other services
J	Information and Communication	information, scientific and health services
K	Financial and Insurance Activities	excluded
L	Real Estate Activities	construction and real estate
M	Professional, Scientific and Technical Activities	information, scientific and health services
N	Administrative and Support Service Activities	information, scientific and health services
O	Public Administration and Defence; Compulsory Social Security	excluded
P	Education	information, scientific and health services
Q	Human Health and Social Work Activities	information, scientific and health services
R	Arts, Entertainment and Recreation	turism, recreation other services
S	Other Service Activities	turism, recreation other services
T	Activities of Households as Employers	excluded
U	Activities of Extraterritorial Organisations and Bodies	excluded

Note: Statistical classification of economic activities in the European Community Rev. 2 (2008): Level 1 Codes.

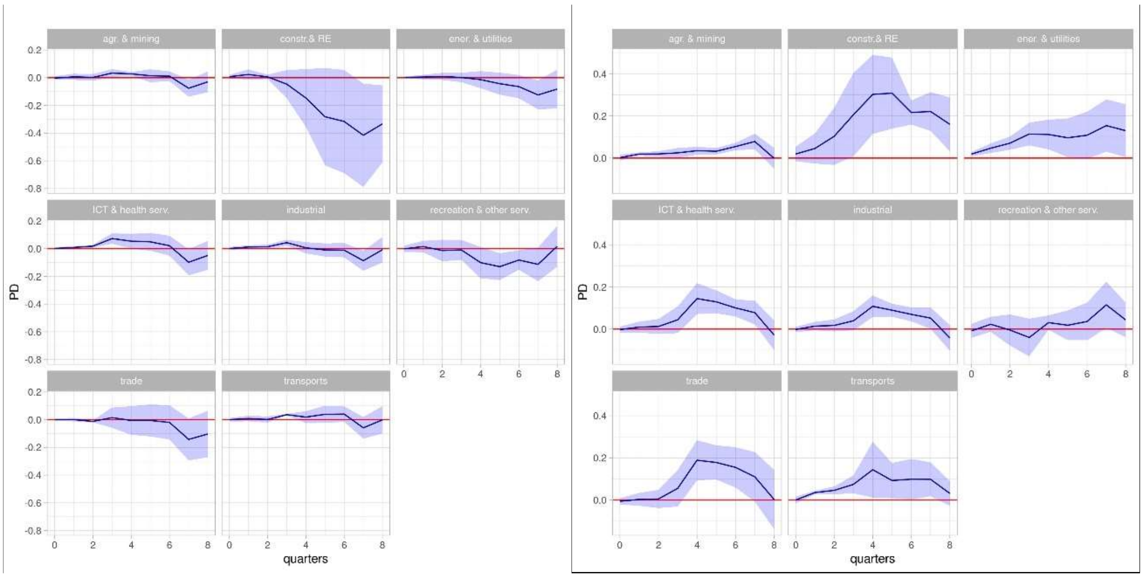
Figure A.1: Macroeconomic shocks



Note: The Figure reports quarterly averages of demand and supply shocks from Gonçalves and Koester (2022). Daily shocks are aggregated to quarterly frequency by taking simple averages over the daily shocks within the quarter. The red solid line indicates demand-side shock, and the green dotted line the supply-side shock.

Figure A.2: IRF by sectoral aggregates (1/2)

Panel A: demand shock *Panel B: supply shock*

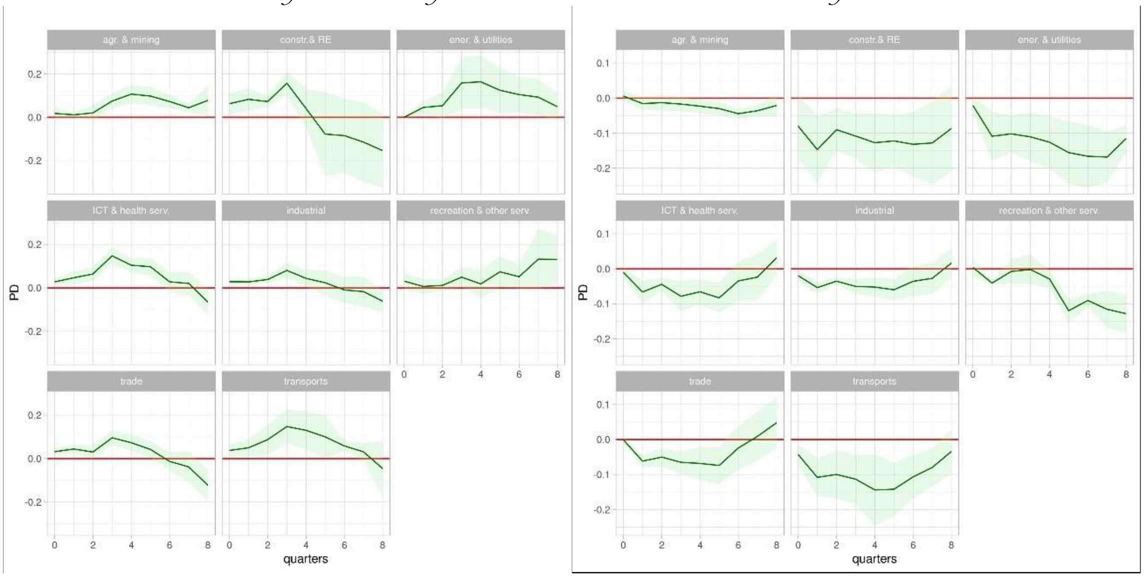


Source: The probabilities of default of non-financial firms in euro area countries are from Moody's and the macro-financial control variables are from the ECB Statistical Data.

Note: Cumulative impulse response functions from panel local projection models in Equation (2). The response of PDs is rescaled to a one standard deviation of individual shocks. Estimates are obtained for all countries using 1 year lagged control variables (real GDP growth rate, 2-year government bond yield, 5-year government CDS spread, corporate bond yield, and change in unemployment rate), country-sector fixed effects and clustered robust standard errors. Country-sector average PDs are obtained using a firm's total assets over the total assets of sectors as weights. Firms are assigned to economic sectors using NACE letters: (A, B) agriculture and mining, (C) industrial, (D, E) energy and utility, (F, L) construction and real estate (G) trade, (H) transportation (I, R, S) tourism, recreation other services (J, M, N, Q, P) information, scientific and health services. Confidence intervals at 90 per cent are displayed in the grey shaded area. Demand, supply, and financial stocks were obtained from BVAR model with sign restrictions as described in Section 3 while monetary policy shocks to OIS 2, 5, 10 years and the Euro Stoxx 50 are from Altavilla *et al.* (2019). Daily shocks were cumulated at the quarterly frequency as simple averages.

Figure A.2: IRF by sectoral aggregates (2/2)

Panel C: monetary shock OIS 2y *Panel D: monetary shock Euro Stoxx 50*



Source: The probabilities of default of non-financial firms in euro area countries are from Moody's and the macro-financial control variables are from the ECB Statistical Data.

Note: Cumulative impulse response functions from panel local projection models in Equation (2). The response of PDs is rescaled to a one standard deviation of individual shocks. Estimates are obtained for all countries using 1 year lagged control variables (real GDP growth rate, 2-year government bond yield, 5-year government CDS spread, corporate bond yield, and change in unemployment rate), country-sector fixed effects and clustered robust standard errors. Country-sector average PDs are obtained using a firm's total assets over the total assets of sectors as weights. Firms are assigned to economic sectors using NACE letters: (A, B) agriculture and mining, (C) industrial, (D, E) energy and utility, (F, L) construction and real estate (G) trade, (H) transportation (I, R, S) tourism, recreation other services (J, M, N, Q, P) information, scientific and health services. Confidence intervals at 90 per cent are displayed in the grey shaded area. Demand, supply, and financial stocks were obtained from BVAR model with sign restrictions as described in Section 3 while monetary policy shocks to OIS 2, 5, 10 years and the Euro Stoxx 50 are from Altavilla *et al.* (2019). Daily shocks were cumulated at the quarterly frequency as simple averages.

Table A.3 The role of firm characteristics: age

Variable	h = 4	h = 8
demand_shock_hicp	-0.0032 (0.0030)	0.0072 * (0.0024)
demand_shock_hicp x d_young	0.0032 ** (0.0006)	0.0025 (0.0011)
supply_shock_hicp	0.0199 *** (0.0006)	-0.0038 ** (0.0008)
supply_shock_hicp x d_young	0.0027 ** (0.0003)	0.0040 ** (0.0007)
mon_policy_shock_OIS_2y	0.0009 *** (0.0000)	0.0004 *** (0.0000)
mon_policy_shock_OIS_2y x d_young	0.0011 * (0.0003)	0.0002 (0.0003)
mon_policy_shock_OIS_5y	0.0007 *** (0.0001)	0.0006 *** (0.0000)
mon_policy_shock_OIS_5y x d_young	0.0003 (0.0000)	-2.68e-5 (0.0001)
mon_policy_shock_OIS_10y	0.0005 *** (0.0000)	0.0003 *** (3.29e-6)
mon_policy_shock_OIS_10y x d_young	-0.0000 (0.0000)	-0.0000 (0.0000)
mon_policy_shock_STOXX50	-0.0037 *** (0.0004)	-0.0044 ** (0.0005)
mon_policy_shock_STOXX50 x d_young	-0.0006 (0.0002)	-0.0007 (0.0004)
Fixed-Effects:	---------------------	---------------------
countryisocode	*Yes*	*Yes*
size	*Yes*	*Yes*
nacerev2corecode4digits	*Yes*	*Yes*
S.E.: Clustered	by: coun. & size & nace.	by: coun. & size & nace.
Observations	2,123,259	1,597,916

Notes: The Table provides estimates of the of the panel local projection model in Equation (2). Estimates are obtained from a sample of about 100.000 firms for each country using one year lagged control variables: annual real GDP growth rate, 2-year government bond yield, 5-year government CDS spread, corporate bond yield and change in unemployment rate. The model includes country, firm size class and sectoral fixed effects. Standard errors are clustered. Robust standard errors in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.
Source: Data from Moody's Analytics RiskCalc, Altavilla *et al.* (2019) and ECB Statistical Data Warehouse and author's calculations.

Table A.4: The role of firm characteristics: leverage

Variable	h = 4	h = 8
demand_shock_hicp	0.0048 (0.0067)	0.0036 (0.0019)
demand_shock_hicp x d_leverage	0.0075 *** (0.0004)	0.0063 ** (0.0013)
supply_shock_hicp	0.0125 *** (0.0009)	-0.0056 *** (0.0004)
supply_shock_hicp x d_leverage	0.0111 *** (0.0003)	0.0127 ** (0.0013)
mon_policy_shock_OIS_2y	0.0007 *** (0.0000)	0.0007 *** (0.0000)
mon_policy_shock_OIS_2y x d_leverage	0.0017 ** (0.0004)	0.0001 ** (0.0001)
mon_policy_shock_OIS_5y	0.0005 *** (0.0000)	0.0007 *** (0.0000)
mon_policy_shock_OIS_5y x d_leverage	0.0005 (0.0002)	-0.0007 ** (0.0000)
mon_policy_shock_OIS_10y	0.0004 ** (0.0000)	0.0004 *** (0.0000)
mon_policy_shock_OIS_10y x d_leverage	0.0002 (0.0001)	-0.0004 ** (0.0000)
mon_policy_shock_STOXX50	-0.0025 *** (0.0001)	-0.0035 *** (0.0003)
mon_policy_shock_STOXX50 x d_leverage	-0.0027 ** (0.0006)	-0.0018 (0.0007)
Fixed-Effects:	---------------------	---------------------
countryisocode	*Yes*	*Yes*
size	*Yes*	*Yes*
nacerev2corecode4digits	*Yes*	*Yes*
S.E.: Clustered	by: coun. & size & nace.	by: coun. & size & nace.
Observations	1,484,003	1,141,839

Notes: The Table provides estimates of the of the panel local projection model in Equation (2). Estimates are obtained from a sample of about 100.000 firms for each country using one year lagged control variables: annual real GDP growth rate, 2-year government bond yield, 5-year government CDS spread, corporate bond yield and change in unemployment rate. The model includes country, firm size class and sectoral fixed effects. Standard errors are clustered. Robust standard errors in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.
Source: Data from Moody's Analytics RiskCalc, Altavilla *et al.* (2019) and ECB Statistical Data Warehouse and author's calculations.

Table A.5 The role of firm characteristics: interest expenses to EBITDA

Variable	h = 4	h = 8
demand_shock_hicp	-0.0022 (0.0057)	-0.0052 ** (0.0011)
demand_shock_hicp x d_ie_ebitda	0.0245 ** (0.0049)	0.0519 * (0.0157)
supply_shock_hicp	0.0106 *** (0.0002)	-0.0194 ** (0.0032)
supply_shock_hicp x d_ie_ebitda	0.0343 ** (0.0044)	0.0657 * (0.0172)
mon_policy_shock_OIS_2y	0.0010 ** (0.0001)	0.0006 * (0.0001)
mon_policy_shock_OIS_2y x d_ie_ebitda	0.0018 (0.0009)	-9.88e-5 (0.0009)
mon_policy_shock_OIS_5y	0.0009 *** (0.0001)	0.0012 *** (0.0001)
mon_policy_shock_OIS_5y x d_ie_ebitda	2.93e-5 (0.0002)	-0.0025 ** (0.0003)
mon_policy_shock_OIS_10y	0.0005 *** (0.0001)	0.0007 ** (0.0001)
mon_policy_shock_OIS_10y x d_ie_ebitda	0.0004 (0.0002)	-0.0015 ** (0.0003)
mon_policy_shock_STOXX50	-0.0030 ** (0.0005)	-0.0060 ** (0.0012)
mon_policy_shock_STOXX50 x d_ie_ebitda	-0.0039 ** (0.0005)	0.0064 * (0.0021)
Fixed-Effects:	---------------------	---------------------
countryisocode	*Yes*	*Yes*
size	*Yes*	*Yes*
nacerev2corecode4digits	*Yes*	*Yes*
S.E.: Clustered	by: coun. & size & nace.	by: coun. & size & nace.
Observations	1,353,119	1,044,712

Notes: The Table provides estimates of the of the panel local projection model in Equation (2). Estimates are obtained from a sample of about 100.000 firms for each country using one year lagged control variables: annual real GDP growth rate, 2-year government bond yield, 5-year government CDS spread, corporate bond yield and change in unemployment rate. The model includes country, firm size class and sectoral fixed effects. Standard errors are clustered. Robust standard errors in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.
Source: Data from Moody's Analytics RiskCalc, Altavilla *et al.* (2019) and ECB Statistical Data Warehouse and author's calculations.

Table A.6 The role of firm characteristics: leverage and cash holdings

Variable	h = 4	h = 8
demand_shock_hicp	0.0058 (0.0075)	0.0037 (0.0018)
demand_shock_hicp x d_leverage	0.0085 *** (0.0006)	0.0080 ** (0.0014)
demand_shock_hicp x d_leverage x d_cash_assets	-0.0074 *** (0.0006)	-0.0135 *** (0.0006)
supply_shock_hicp	0.0122 *** (0.0009)	-0.0056 *** (0.0004)
supply_shock_hicp x d_leverage	0.0124 *** (0.0004)	0.0150 ** (0.0017)
supply_shock_hicp x d_leverage x d_cash_assets	-0.0108 *** (0.0002)	-0.0188 *** (0.0005)
mon_policy_shock_OIS_2y	0.0007 ** (0.0001)	0.0006 *** (0.0004)
mon_policy_shock_OIS_2y x d_leverage	0.0019 * (0.0005)	-0.0007 (0.0003)
mon_policy_shock_OIS_2y x d_leverage x d_cash_assets	-0.0010 (0.0005)	0.0002 (0.0003)
mon_policy_shock_OIS_5y	0.0005 *** (0.0003)	0.0007 *** (0.0003)
mon_policy_shock_OIS_5y x d_leverage	0.0005 (0.0002)	-0.0008** (0.0001)
mon_policy_shock_OIS_5y x d_leverage x d_cash_assets	-0.0002 (0.0002)	0.0008 ** (0.0001)
mon_policy_shock_OIS_10y	0.0003 ** (0.0001)	0.0004 *** (0.0000)
mon_policy_shock_OIS_10y x d_leverage	0.0002 (0.0001)	-0.0004 ** (0.0001)
mon_policy_shock_OIS_10y x d_leverage x d_cash_assets	-0.0002 (0.0007)	0.0005 *** (0.0001)
mon_policy_shock_STOXX50	-0.0025 *** (0.0001)	-0.0035 *** (0.0002)
mon_policy_shock_STOXX50 x d_leverage	-0.0028 ** (0.0006)	-0.0017 (0.0008)
mon_policy_shock_STOXX50 x d_leverage x d_cash_assets	0.0010 (0.0004)	-0.0000 (0.0005)
Fixed-Effects:	---------------------	---------------------
countryisocode	*Yes*	*Yes*
size	*Yes*	*Yes*
nacerev2corecode4digits	*Yes*	*Yes*
S.E.: Clustered	by: coun. & size & nace.	by: coun. & size & nace.
Observations	1,437,109	1,108,035

Notes: The Table provides estimates of the of the panel local projection model in Equation (2). Estimates are obtained from a [random drawn of (100.000) firms for Italy] using one year lagged control variables: annual real GDP growth rate, 2-year government bond yield, 5-year government CDS spread, corporate bond yield and change in unemployment rate. The model includes country, firm size class and sectoral fixed effects. Standard errors are clustered. Robust standard errors in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.
Source: Data from Moody's Analytics RiskCalc, Altavilla *et al.* (2019) and ECB Statistical Data Warehouse and author's calculations.

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The views expressed do not necessarily represent the views of BdI and the ECB. All remaining errors are our responsibility.

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