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CLIMATE SCENARIOS AND FIRMS' FINANCIAL VULNERABILITY

by Maria Alessia Aiello*, Cristina Angelico*, Marco Invernizzi*
and Valentina Michelangeli*

Abstract

We assess the impact of alternative climate scenarios on the probability of default (PD) of Italian banks' loan portfolios. We employ a top-down stress-testing approach to simulate firm-level PDs. We rely both on the latest long- and short-term scenarios developed by the Network for Greening the Financial System (NGFS), focusing on a 6-year horizon up to 2030 in line with the EU Fit-for-55 target. To better capture sector-specific dynamics, we complement the framework with sectoral PD models. Our findings suggest that climate risks, in particular those related to the transition towards a more sustainable economy, have, on average, a modest impact on corporate PDs, albeit with some heterogeneity across sectors. In the near term, ambitious and orderly transition pathways are associated with slightly higher, yet still limited, credit risks. The near-term costs are expected to be more than offset in the long run by the reduced accumulation of future physical climate risks.

JEL Classification: Q43, Q58, G21.

Keywords: climate stress test, banks' credit risk, NGFS scenarios.

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1 Introduction[1]

Climate change and related policies could be a source of systemic financial risk. Physical risks — such as floods, droughts, and heatwaves — can materially diminish asset values and disrupt production, while transition risks — stemming from energy shocks or abrupt climate policy shifts, stranded assets, market repricing or technological and preferences changes— pose substantial threats to corporate balance sheets via additional energy costs, asset revaluations and the need for additional investments. Conventional risk assessment frameworks often overlook these novel risks and transmission channels, providing an incomplete picture of the financial system's or individual intermediaries' ability to withstand adverse shocks (Acharya et al., 2023). To address this gap, climate stress testing has emerged as a forward-looking tool that enables regulators and financial institutions to simulate potential losses across various climate scenarios, complementing existing micro- and macroprudential frameworks and risk assessment practices, and providing critical insights into capital adequacy and risk management (Alogoskoufis et al., 2021).

Early contributions, such as (Battiston et al., 2017), investigated financial institutions' exposures to climate-policy-relevant sector. Subsequent work has refined these approaches by integrating firm-level balance sheet data with macro-financial variables, allowing for a more granular assessment of financial vulnerabilities, PDs and credit losses under different climate pathways (e.g., Allen et al., 2020, Faiella et al., 2022, Aiello and Angelico, 2023). A major advance in the field has been the introduction of a set of long-term scenarios by the Network for Greening the Financial System (NGFS). These scenarios provide consistent projections of key climate and energy-related variables — such as damages from physical risks, carbon prices, energy consumption and prices — that allow for capturing the evolution of physical and transition risks over alternative possible futures that vary in the degree of ambition and timeliness of the climate and energy policies (NGFS, 2024). Importantly, they also provide projections for a wide range of macroeconomic variables, including GDP, inflation, and interest rates, for a large number of countries that are required to assess financial risks. Their development has facilitated cross-country comparisons and methodological alignment across supervisory authorities and financial institutions (e.g., Alogoskoufis et al., 2021; BOE, 2021;

[1]We thank Alessio Anzuini, Enrico Bernardini, Marcello Bofondi, Francesco Cannata, Alessio De Vincenzo, Ivan Faiella, Giacomo Manzelli, and Patrizio Pagano for their valuable comments. We are also grateful to Francesca Ada Rinaldi, Davide Valvasson, and Ivan Quaglia for their invaluable assistance in preparing the dataset during the initial stages of this research.

Emambakhsh et al., 2023). In addition to the long-term scenarios, in 2025 the NGFS also released the first vintage of short-term scenarios, that cover five years and have the explicit objective of enabling the assessment of the near-term effects of climate policies, or the lack thereof, on financial stability and economic resilience (NGFS, 2025).

Building on the literature and leveraging the latest long and short-term NGFS scenarios, we assess the impact of alternative climate scenarios on the probability of default (PD) of Italian banks' loan portfolios. In particular, we focus on credit risk to non-financial corporations. Our research extends through 2030, aligns with the EU's Fit-for-55 objectives, and projects firm PDs under alternative climate scenarios.

To this end, we develop a novel top-down stress-testing approach to capture climate-related financial risks. Namely, we define sectoral PD models capturing both transition and aggregate (both acute and chronic) physical risks via several macrofinancial variables that are available in the NGFS scenarios. We consider a five-year horizon and recursively project annual PDs one year ahead. Our setting also accounts for the energy-expenditure channel at the firm level, thereby incorporating how changes in energy prices and consumption affect firm profitability and risk profiles, according to the firm-specific energy mix. This approach represents a distinguishing feature relative to the existing literature since it bypasses reliance on CO2 and GHG emissions data, which are often characterized by data gaps, low quality, and are unavailable to smaller and non-listed firms (Di Virgilio et al. (2024); Papadopoulos (2022); Bingler et al. (2022)). Precisely, given the lack of granular data, we build on Faiella and Mistretta (2015) to estimate firm-level energy expenditure for a broad sample of Italian non-financial corporations.[2]

The ability of our projections to capture transition and physical risks depends on the interplay between the granularity of our modeling framework and that of the NGFS forward-looking variables. Transition risk is well captured along both dimensions. This is driven by economy-wide policy and market shocks—such as carbon pricing, regulatory changes, and shifts in energy technologies—that propagate through observable macro-financial variables, including GDP and energy prices. These are precisely the variables featured in our model and projected under the NGFS scenarios. At the

[2]Recent European climate stress test exercises (Emambakhsh et al., 2023; European Central Bank, 2024) assessed the impact of transition pathways on firms' balance sheets and probabilities of default in a top-down fashion. These approaches differ from our paper since they estimate direct (brown) energy and electricity consumption at the company level for each energy source by combining firm-level emissions with information on country-sector energy mix and energy-to-emissions conversion factors.

same time, the impact of transition shocks is heterogeneous across firms and sectors. Our firm-level data—covering energy costs and balance-sheet variables—combined with sectoral models, allow us to capture this heterogeneity. The picture is more nuanced for physical risk. Chronic physical risks—such as gradual changes in temperature and precipitation—are incorporated via the long-term NGFS projections of macroeconomic variables at the national level. Similarly, acute physical risks—such as floods or heatwaves—enter our framework only through their aggregate macroeconomic footprint, as the short term scenarios translate discrete climate shocks into national-level trajectories. Firm-level, location-specific exposure to climate hazards is therefore not captured—deliberately so, as this would require detailed asset-level geolocation data and lies outside the scope of this work, which focuses on the systemic and cyclical dimensions of climate risk. A complementary and growing strand of the literature instead aims at assessing granular physical risks in Italy (i.e., Cugliari et al. (2026), Clò et al. (2024), Loberto and Russo (2024), and Meucci and Rinaldi (2022)).

More precisely, we adopt a two-step approach. In the first stage, we estimate firm-level EBITDA as a function of lagged EBITDA, real GDP, and firm-specific energy expenditures. This step allows us to assess the impact of rising energy prices on firms' EBITDA, while accounting for their potential adjustment in energy consumption and strategies in response to higher energy costs, and the cyclical dynamics. In the second stage, we estimate the PD as a function of the forecasted EBITDA from the first stage, the aggregate interest lending rate to non-financial corporations, and additional firm-level variables. We estimate the model using granular historical default and balance-sheet data on the universe of non-financial corporations within Italian banks' portfolios from 2013 to 2019. We stop in 2019 in order to avoid to capture the Covid and European energy crisis. We then evaluate its performance out-of-sample using several alternative rolling windows, test its robustness to the inclusion of additional variables and verify its ability in projecting firms' PDs over time and across different sectors. The model performance benefits from the inclusion of both micro- and macro-variables, and it is confirmed by the alternative robustness checks. Then, to project PDs up to 2030 under the alternative scenarios, we combine the model estimated up to 2023 with NGFS forward-looking data.

We find that higher energy expenditures, projected by the NGFS scenarios, have only a limited impact on firms' EBITDA and as a consequence on the PDs. In line with the evidence for households in Colabella et al. (2025), this contained effect reflects the fact that firms may adjust their energy

consumption and corporate strategies in response to higher energy prices, potentially passing higher costs on to their clients and thereby dampening the impact of energy prices on EBITDA and financial vulnerability. As a result, PDs are only marginally affected through the energy-expenditure channel and are instead primarily driven by broader macroeconomic conditions. In particular, lending rates driving debt-servicing costs account for the rise in PDs in the scenarios assuming ambitious transition pathways (e.g., Net Zero by 2050), which entail weaker GDP growth and higher interest rates relative to the others. Nevertheless, PDs are only slightly higher under scenarios that assume an orderly and ambitious decarbonisation pathway, and near-term costs remain contained especially considering that mitigation policies— while initially costly—significantly reduce long-term GDP losses due to climate change, relative to disorderly or delayed transitions (Aiello et al., 2024). The results should therefore not be interpreted as implying that the transition is detrimental in terms of overall credit risk. Rather, they indicate limited but heterogeneous short-term effects on corporate PDs, which are expected to be more than offset by long-term benefits. Ambitious decarbonisation pathways—such as the Net Zero 2050 and Highway to Paris scenarios—entail moderate short-term adjustment pressures for firms, while over the longer term mitigation policies are expected to enhance financial stability by reducing the build-up of physical climate risks.

The exercise reveals the resilience to credit risk for the Italian banking sector up to 2030, while also highlighting sectoral heterogeneity in firms' vulnerability to transition and physical shocks; sectors more exposed to climate risks are Mining and Construction. These findings are relevant for supervisory assessment of climate-related financial risks and contribute to the ongoing policy debate on climate risk. At the same time, it contributes to the growing literature on climate stress testing by providing a practical example of how NGFS short- and long-term scenarios can be applied to the Italian context, illustrating both their strengths and limitations, and estimating the resilience of the Italian banking system as a whole under such scenarios. Further, it provides insights on the role of the energy expenditure channel relative to macroeconomic variables in projecting firms' PDs.

The modeling features outlined above motivate our choice to rely on the latest NGFS long-term scenarios (NGFS, 2024). To our knowledge, the NGFS long-term scenarios are the only widely available set providing consistent projections for Italy on energy prices, energy mixes and consumption, as well as macrofinancial variables, under alternative assumptions about the ambition and timing of global climate and energy policies. We are also among the first to extend the analysis

by exploiting the NGFS short-term scenarios, which are specifically designed for stress testing exercises over cyclical horizons and allow us to capture the macroeconomic footprint of transition risks and acute physical events within the 6-year stress testing window. However, as they do not include detailed information on energy prices and consumption, we assume these variables remain constant. The two sets of scenarios are thus complementary: together, they allow us to cover both the structural, policy-driven dimension of climate risk and its shorter-term, shock-driven manifestations. That said, the framework remains flexible and can be adapted to other scenarios under specific assumptions.

The main results from the two set of scenarios remain broadly unchanged: risks to the banking sector arising from corporate defaults appear to be contained, despite heterogeneity across sectors. An early and ambitious climate policy implies relatively limited losses in the near term, especially if compared to the likely substantial benefits in terms of avoided GDP damages over the longer horizon (Aiello et al. (2024)).

Notably, our analysis is not affected by the ongoing and active debate among both policymakers and academics regarding the most appropriate modeling approach to estimate damages from physical risks related to climate change, and particularly the critiques (Schötz (2025); Bearpark et al. (2025)) surrounding the damage function adopted by (Kotz et al., 2024) and in the NGFS Phase V scenarios since we focus on a short/medium-term horizon, where physical risks are not yet dominant and confirm this outcome by disentangling physical from transition risks.[3]

We also note that NGFS scenarios for the long- and short-term horizons were developed in 2024 and 2025, respectively, and became available only in late 2025. As a consequence, our results do not fully capture the most recent macroeconomic developments, the latest climate policy measures, or the recent surge in energy prices. The main contribution of this work is therefore to develop a flexible stress-testing framework that can serve as a reference for the ongoing monitoring of climate-related financial risks in Italy and, with comparable data, for similar exercises in other countries. The framework is designed so that projections can be easily updated as new data and scenarios become available, making it a practical tool for supervisory and policy use. A natural future extension would be to link the firm-level PD projections to bank-level capital impact assessments, by computing

[3]Kotz et al. (2024) has been retracted by *Nature* following the identification of data issues and concerns related to the estimation methodology.

losses in terms of the CET1 ratio for the Italian banking sector.

The paper is organised as follows. Section 2 describes the data. Section 3 presents the stress testing framework and its performance. Section 4 shows the PDs projections under alternative NGFS scenarios. Section 5 concludes.

2 Data

Our empirical analysis draws on micro- and macro-level datasets covering 2013–2023 at annual frequency, complemented by NGFS scenario projections for 2025–2030. Our choice to use annual data is consistent with the scenario projections, which are not available at higher frequencies. The final sample comprises all Italian limited liability companies available in Cerved for which credit register, balance sheet, employment and sectoral energy data can be matched, yielding a representative dataset of about 904,446 firms across all major sectors of the economy that we observe over multiple years.

Firm-level credit and balance sheet data. We use annual observations on credit exposures from the Italian Credit Register, which provides granular information on banks' lending to individual firms, including the amount and status of the loans (at the bank-firm level). These credit data are matched with firm-level balance sheets from Cerved, supplemented with employment data from the National Institute of Social Security (INPS).

Energy expenditure. Energy expenditure is a key variable we use to capture the impact of climate and energy policies on firms' revenues, and, consequently, their financial vulnerability. Notably, it reflects several potential drivers of transition risks, such as the adoption of a carbon tax, a ban on a specific type of carbon-intensive technology (e.g. burning coal for producing electricity or driving internal combustion engine cars), or the subsidisation of low-carbon sources (renewables) or technologies (i.e. Carbon Capture and Storage). Unfortunately, firm-level energy expenditure data are neither available from official sources nor from private data providers in Italy, posing challenges to the possibilities of studying the effects of energy price shocks on firms' decisions and performance. To overcome this limitation and estimate energy expenditure at the firm-level, we follow Faiella et al. (2022) and Faiella and Mistretta (2015). Starting from the aggregated official information about energy consumption sources provided by the EUROSTAT Physical Energy Flow Accounts

(PEFA), which report annual energy use by source and economic sector, distinguishing different energy sources and sectors, we compute the per-worker energy consumption by using data on the total workers in the sector provided in the national accounts. We then impute firm-level data on energy consumption, exploiting the firm's number of employees sourced from INPS. At the time of analysis, the available data on energy consumption ended in 2022. Finally, we calculate the firm-level energy expenditure by multiplying the energy consumption of each source by the historical energy price data from the European Commission's Weekly Oil Bulletin, which covers multiple energy sources (e.g., electricity, natural gas, oil products).

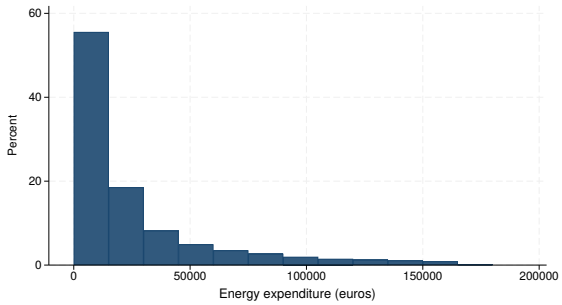
This approach has the key advantage of providing firm-level data on annual energy expenditures, which enables us to capture and exploit the considerable heterogeneity across firms in our analysis (Figure 1, panel a). Such heterogeneity emerges within and across sectors (panel b). Heterogeneity across sectors derives from differences in the energy mix (panel c), which must be considered as the impact of an energy price shock can substantially differ depending on the degree of reliance on the alternative energy sources. Variation across time, instead, derives both from changes in the energy mix and prices (panel d). Despite these advantages, we acknowledge important limitations. First, the within-sector variability is driven solely by the number of employees, implying that all firms are assumed to share the same energy mix and work–energy ratio within each sector. Second, the methodology assumes homogeneous energy prices across firms. At this stage, the lack of more granular data prevents us from relaxing these assumptions.

Macroeconomic data. For the period 2013–2024, we incorporate annual macroeconomic indicators, that are in lie with those available from the Banca d'Italia Macroeconomic Projection Exercise (BMPE). These include GDP, inflation and the interest rate applied to loans to non-financial corporations.

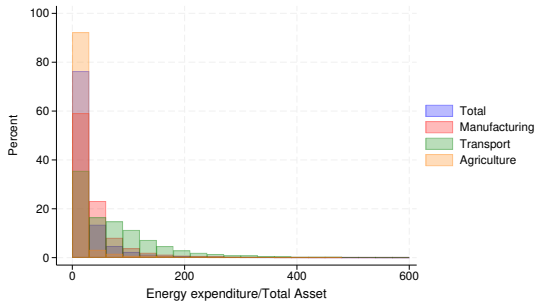
Scenario projections. From 2025 to 2030, macroeconomic and climate variables are sourced from both the latest NGFS long-term scenarios (Phase V, NGFS (2024)) and the first release of NGFS short-term ones (NGFS (2025)).

Figure 1: Energy expenditure

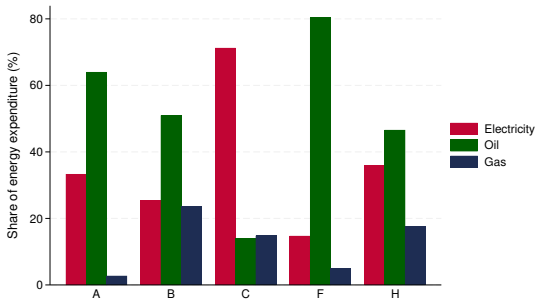
(a) Firm-level data



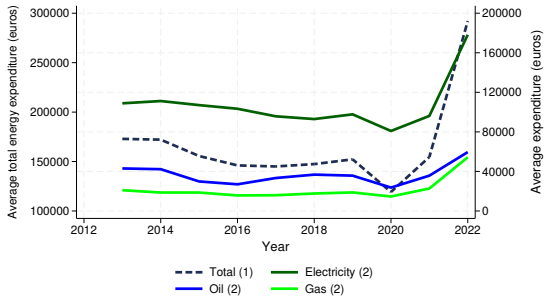
(b) Across and within sector heterogeneity



(c) Sectoral energy mix



(d) Variation over time



Note: The figures in panels a)-c) display firm-level energy expenditure at the end of 2019. Panel a) shows the distribution of the firm-level energy expenditure in our sample. Panel b) compares the distribution of the energy expenditure/total asset ratio for the entire sample with that of specific sectors. Panel c) plots the share of energy expenditure for different sources: electricity oil and gas. The sectors are reported at NACE 1-digit codes and A is Agriculture, B is Mining and quarrying, C is Manufacturing, F is Construction and H is Transporting and storage. Panel d) shows how the average energy expenditure varied over time, distinguishing for the different sources.

3 Stress testing framework

3.1 Empirical strategy

To evaluate the resilience of the Italian banking system under alternative climate–energy scenarios, with a focus on credit risks from corporate lending, we develop a framework to project how the PD of individual firms within banks' portfolios varies across scenarios. Importantly, the definition of the framework is guided by the objective of capturing energy price risks and, more broadly, transition risks and potential aggregate physical damages resulting from climate change, using a parsimonious and tractable model suitable for out-of-sample projections. Additionally, the selection of variables

of interest is conditioned by the variables available in the NGFS scenarios, which we can therefore project over time. As for physical risks, we consider only aggregate damages and macroeconomic effects due to global warming and acute events, while we do not account for more granular impacts which lie outside the scope of this work, which focuses on the systemic and cyclical dimension of climate risk rather than its idiosyncratic, asset-level component.

More in detail, we adopt a two-step approach. First, we estimate the profitability as a function of its lagged value, total energy expenditure at the firm level, and Real GDP, which captures both physical and transition risks more broadly (eq. 1). The intuition is that, holding all other firms' characteristics constant in the medium term and considering past profitability and current economic conditions, an increase (or decrease) in energy expenditure could induce a decrease (or increase) in the firm's EBITDA. In contrast, a growing (or decreasing) Real GDP could translate into higher (or lower) profitability.

$$EBITDA_{i,t} = \alpha_0 + \alpha_1 EBITDA_{i,t-1} + \alpha_2 E_{i,t} + \beta_2 RealGDP_t + \gamma_i + \mu_{20} + \mu_{21} + \epsilon_{i,t} \qquad (1)$$

where $EBITDA_{i,t}$ is profitability of the firm i and time t, $E_{i,t}$ is its total energy expenditure, computed as described in section 2, $RealGDP_t$ is the real GDP growth rate in the same year and γ_i is a firm fixed effect to control for time-invariant firm characteristics such as location, size, sector, and structural efficiency.[4] We augment the baseline specification with indicator variables for 2020 and 2021, which proxy for the COVID-19 shock. These dummies absorb unobserved, time-specific factors affecting all units during the pandemic, thereby mitigating potential omitted variable bias. Standard errors are clustered at firm level to account for serial correlation and heteroskedasticity within firms. In alternative specifications, estimated to evaluate the robustness of the results, we differentiate expenditure by source or account separately for energy prices and consumption.

Second, we estimate the firm's PD for next year using the fitted values of profitability obtained in eq. 1, other firm-level micro variables and the average interest rate on firms' lending as a proxy of the credit market conditions (eq. 2).

$$PD_{i,t+1} = \omega_0 + \omega_1 \widehat{EBITDA}_{i,t} + \omega_2 X_{i,t} + \omega_3 Z_t + \gamma_s + \gamma_d + \mu_{20} + \mu_{21} + \epsilon_{i,t} \qquad (2)$$

[4]Including the lagged real GDP growth rate or energy expenditure does not significantly change the results.

where $PD_{i,t+1}$ is a dummy indicator equal to 1 if firm i is in default in the next year $t+1$ and 0 otherwise. $X_{i,t}$ is a vector of firm-level variables that include interest expenses, cash to total asset ratio and equity to total asset ratio.[5] In the baseline specification, Z_t includes the aggregate interest rate on firms' lending as a proxy for credit market conditions, while in the alternative specification, used as a robustness check, it also includes the inflation rate and the lagged real GDP growth rate. This specification enables us to capture the effect of a change in a firm's profitability on its PD, given the other firms' features, while isolating the effect of credit market conditions on the PDs. The model includes sectoral (γ_s) and size (γ_d) fixed effects to control for time-invariant firm characteristics that can be assumed to remain constant over the short projection horizon. Since our ultimate goal is to project the PDs under alternative scenarios and to have a parsimonious model suitable for out-of-sample projections, we refrain from including firm fixed effects in the equation 2, as these would eliminate useful cross-sectional variation and capture only within-firm deviations around firm-specific means, thereby hindering the projection of profitability levels in out-of-sample scenarios.

The baseline specification is selected to capture the relevant transmission channels of climate risks in a parsimonious framework that can be projected forward under the NGFS scenario; nevertheless, alternative specifications have been evaluated — including additional lags and macro variables — and yield very similar in-sample and out-of-sample RMSEs. The results are discussed in the next session.

3.2 Estimates: historical performance

As a first step, we estimate the model in-sample for the period 2013-2019. We stop before 2020 to avoid taking into account the effects of the COVID-19 pandemic or the 2022 energy crisis and the related supporting measures.

The in-sample estimates of equation (1) are presented in column (1) of Tables 1. The positive and highly significant coefficient for the past EBITDA indicates a strong persistence in firm operating profitability. The positive coefficient for real GDP growth reflects the cyclicality of firms' profitability, which tends to increase during periods of positive growth. By contrast, energy expenditure is

[5]For the model projections to 2030, we maintain the last available data for interest expenses, cash to total asset ratio and equity to total asset ratio. The increase in interest expenses due to changes in monetary policy is captured by the aggregate interest rate on business loans.

negatively correlated with firms' profitability, implying that energy cost pressures compress operating margins. The magnitude of the estimated coefficient suggests an overall modest effect on profitability, consistent with the fact that energy expenditure represents only a fraction of the firm's overall costs (in median, less than 13 per cent of the EBITDA). The estimated coefficient for energy expenditure also captures offsetting effects: on the one hand, higher energy consumption—and thus expenditure—may reflect increased production; on the other hand, firms tend to adjust their energy use, both in quantity and in the composition of energy sources, in response to rising energy prices (consistent with Colabella et al. (2025)) and other cost factors, while potentially passing part of the higher costs on to consumers. A negative relationship between profitability and energy expenditure is also confirmed when considering the three energy sources separately (see Table A1 in the Appendix). Nevertheless, the coefficients on energy expenditure and GDP growth are both relatively small reflecting the high persistence of the EBITDA, which dominates the dynamics and absorbs much of the explanatory power.

Column (2) of Table 1 shows that a higher profitability today is associated with a lower PD next year, in addition to and beyond other firms' characteristics. The positive and significant coefficient for interest expenses is consistent with the financial distress channel, so a higher debt service burden increases insolvency risk. Similarly, the coefficient for the interest rate indicates that worsening credit conditions are associated with higher future PDs.

Table 1: Empirical framework: in-sample estimates

	(1)	(2)	(3)	(4)	(5)
	Baseline framework		Energy price channel		
	$EBITDA_{i,t}$	$PD_{i,t+1}$	$EBITDA_{i,t}$	$EBITDA_{i,t}$	$EBITDA_{i,t}$
$\text{EBITDA}_{i,t-1}$	0.361***		0.359***	0.361***	0.356***
	(0.005)		(0.005)	(0.005)	(0.005)
$\text{Energy expenditure}_{i,t}$	-0.001**				
	(0.001)				
Real GDP_t	0.007***				
	(0.000)				
$\text{Gas consumption}_{i,t}$			-0.094*		
			(0.054)		
Gas price_t			-0.014***		
			(0.000)		
$\text{Oil consumption}_{i,t}$				-0.064*	
				(0.054)	
Oil price_t				-0.004***	
				(0.000)	
$\text{Power consumption}_{i,t}$					0.051
					(0.051)
Power price_t					-0.005***
					(0.000)
$\hat{EBITDA}_{i,t}$		-0.006***			
		(0.001)			
$\text{Int. Expenses}_{i,t}$		0.000***			
		(0.000)			
$\text{Cash-Asset Ratio}_{i,t}$		-0.053***			
		(0.001)			
$\text{Equity-Asset Ratio}_{i,t}$		-0.077***			
		(0.001)			
Interest rate_t		0.013***			
		(0.000)			
Observations	1,366,229	1,797,143	1,366,229	1,366,229	1,366,229
R^2	0.901	0.020	0.901	0.901	0.901
Adjusted R^2	0.875	0.020	0.876	0.876	0.876
Firm FE	YES	NO	YES	YES	YES
Sector FE	NO	YES	NO	NO	NO
Year FE	NO	YES	NO	NO	NO

Note: The Table displays the estimates of equation 1, in column (1) and equation 2, in column (2). Columns (3)-(5) instead show the link between firm's profitability, energy consumption and prices by energy sources. All the regressions include the constant. The regressions are estimated on the entire sample of firms over the period between 2013 and 2019. Standard errors in parentheses are clustered at firm level.

Notably, the estimated coefficients are very similar when we replace the estimated EBITDA with the historical one, indicating that potential measurement errors in the estimated measure are not a major concern for our analysis.

The first-stage equation is estimated using a fixed-effects (FE) specification and includes the

lagged dependent variable to capture the well-documented persistence of firm profitability. However, the inclusion of the lagged dependent variable raises concerns about the presence of the Nickell bias, which may be non-negligible. Standard dynamic panel estimators (Arellano–Bond and Blundell–Bond GMM) prove unreliable in this setting due to the high persistence of EBITDA, which renders lagged values weak instruments, as confirmed by AR(2) and Hansen diagnostics across all specifications and sub-samples.[6] We therefore retain the FE estimator, noting that the Nickell bias induces a downward bias in the persistence coefficient. Conversely, the GMM estimator tends to overestimate the coefficient due to the weakness of the instruments. As a result, the true value is plausibly intermediate, although neither approach is able to identify it precisely. Crucially, the estimated coefficients of the default probability equation and the projected path of default probabilities are virtually identical across FE and GMM specifications, suggesting that these biases do not materially affect the quantities of interest for the stress-testing exercise (see Figure A3). The close alignment of the predictions further suggests that the main drivers of default probability dynamics are the macroeconomic variables included in equation 2, conditional on firm characteristics, while the channels operating through EBITDA — including energy costs — play a relatively limited role, as its variation is largely driven by firm-specific persistence.

In Columns (3) to (5) of Tables 1, we isolate the effect of energy prices and consumption for different sources on the profitability of firms: an increase in energy prices - for a given consumption level - is associated with reductions in EBITDA. The three energy sources (Oil, Power, and Gas) are considered separately because their prices are highly correlated with each other and with real GDP, which is why they are excluded from the baseline specification.

In summary, the estimates in Table 1 confirm that our economic framework can gauge the transition and aggregate physical risks, leveraging on both micro and macro-level data. The main result is that PDs are marginally affected by the energy expenditure channel and they are mainly impacted by macroeconomic variables.

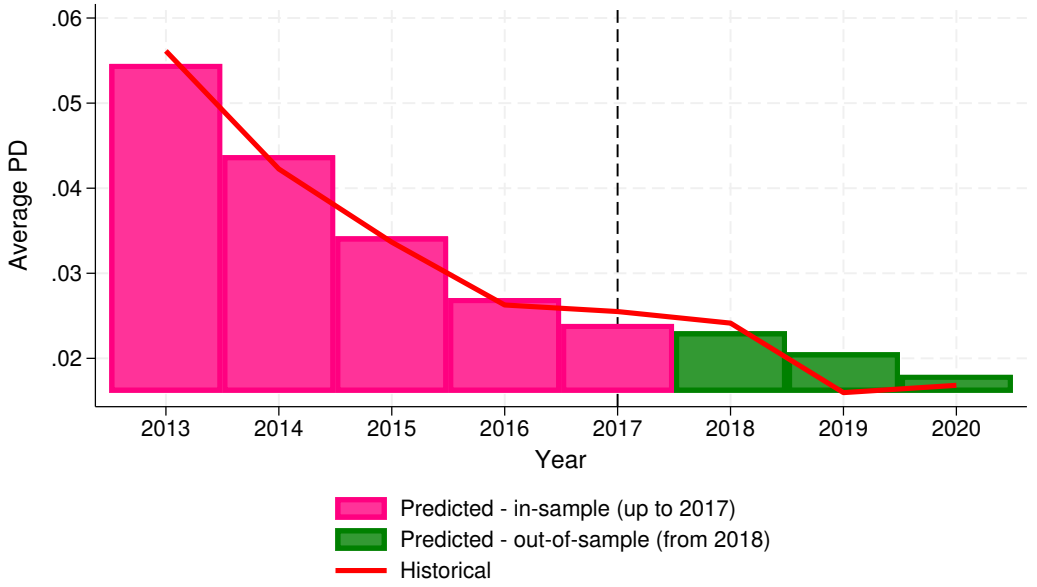
[6]GMM estimators yield a coefficient on the lagged dependent variable close to 0.9, but the AR(2) and Hansen tests reject the validity of the instruments across all tested specifications, including those with a reduced number of instruments via the collapse option. This appears to reflect a structural limitation that cannot be resolved through alternative lag choices, since, given the high persistence of EBITDA, autocorrelation propagates beyond the second order. Robustness checks on progressively more balanced sub-samples confirm that this issue is structural rather than driven by panel composition. The relevance of the other variables declines when moving from FE to GMM, reflecting the dominance of persistence in GMM specifications.

3.3 Out-of-sample performance

We estimate the model using data up to the end of 2017 and assess its predictive accuracy both in-sample and out-of-sample during the period 2018–2020. Historical default rates start above 5 percent in 2013 and decline steadily and substantially in the following years, reflecting the gradual economic recovery after the European sovereign debt crisis. For the years 2018–2020, the PDs predicted out-of-sample track historical defaults quite closely, suggesting that the model captures the direction and magnitude of default rate changes well over the short horizon, thanks to the inclusion of macro variables and firm fundamentals in the equation of PD (Figure 3). Similar results are obtained when changing the in- and out- of sample windows, as shown in Figure 4. These figures suggest that the model appears to not systematically over- or underestimate risk during the validation period, supporting the model's reliability for scenario-based projections.

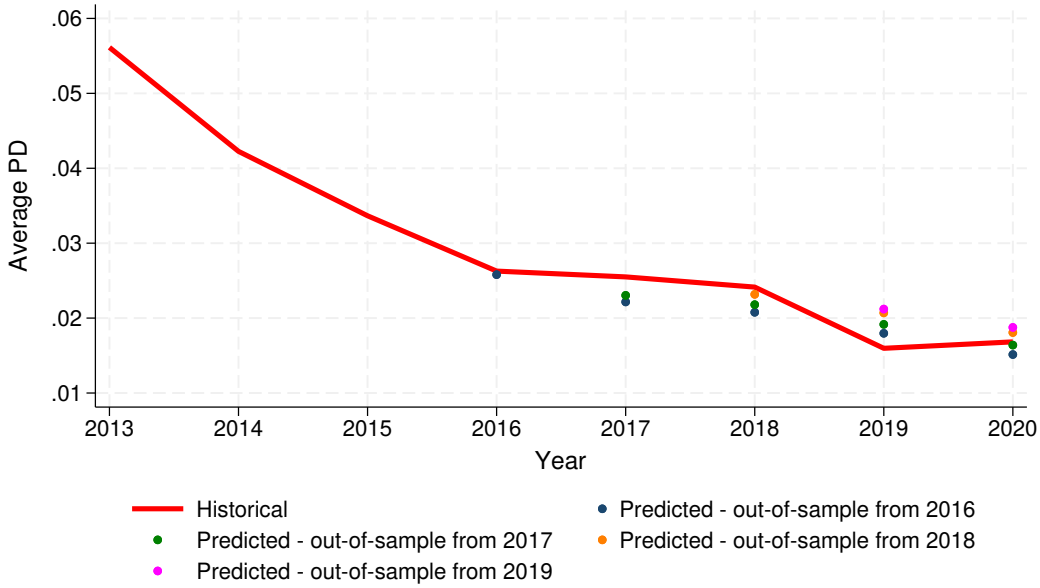
We also run additional robustness checks to confirm that the in and out-of sample performance of the model does not change substantially when varying the specifications in equations 1 and 2, by including additional macroeconomic variables such as the lagged real GDP growth and the inflation are and micro variables (i.e. the value added); these tests confirm the key role of macroeconomic dynamics in explaining and forecasting the dynamics of the PD (Figure A1 in the Appendix).

Figure 3: In- and out-of sample performance



Note: The figure displays both historical and estimated annual PDs for the period between 2013 and 2020. The red line indicates the historical data. The pink bars represent in-sample values obtained estimating equations 1 and 2 on all the firms in the sample and data up to 2017, while the green bars show out-of-sample projections for the period between 2018 and 2020.

Figure 4: Out-of sample performance with rolling windows



Note: The figure displays both historical and estimated annual PDs for the period between 2013 and 2020. The red line indicates the historical data. The coloured dots indicate the PDs predicted out-of-sample obtained using the equations 1 and 2 for all firms in the sample over different in-sample time windows.

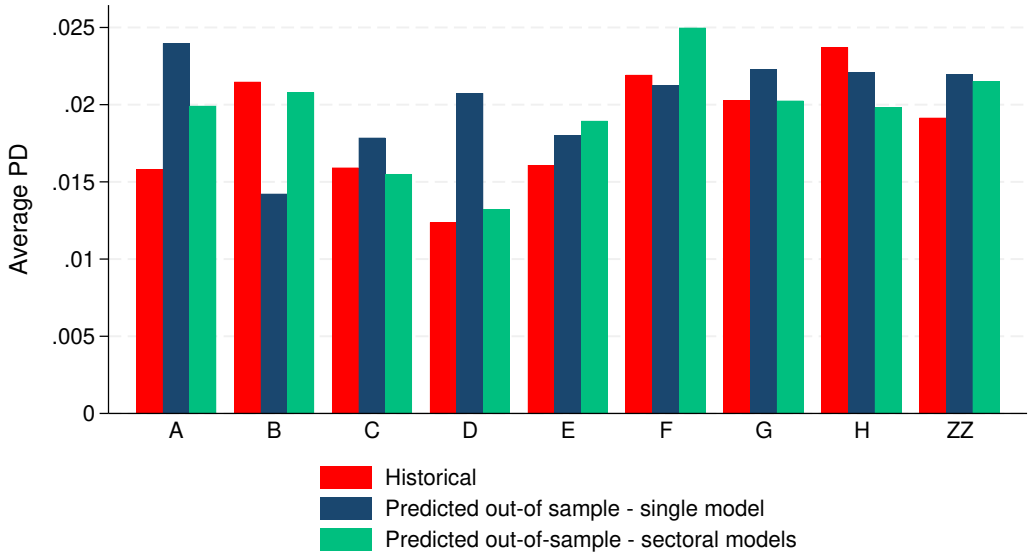
Robustness tests also indicate that extended models, which differentiate energy consumption by source or separately account for consumption and prices, exhibit very similar predictive power for aggregate PDs both in and out of sample (Figure A2 in the Appendix) .

3.3.1 Sectoral models

To better capture sectoral heterogeneity and the heterogeneous role that energy costs play in firms' profitability across different sectors of economic activity, we re-estimate the model separately for the main sectors, including Agriculture, Electricity, Mining, Manufacturing, Construction, and Transport. The aggregate probability obtained with the sectoral models is in line with that obtained with a single model estimated on all firms in the sample (see Figure A4 in the Appendix). Besides, Figure 5 shows that, while the model estimated on the entire sample of firms predicts the PDs across sectors fairly well (blue bars in the figure), the sectoral models help improve the predictions for specific sectors (green bars), such as Agriculture, Mining, Manufacturing, Electricity, and Wholesale and retail trade. These sectors account for a large share of the sample and, for several of them, energy expenditures represent a key transmission channel of climate and energy shocks.[7] Sectoral models allow for a more accurate depiction of this channel and of sector-specific cyclical dynamics, including heterogeneous sensitivities to interest rates—related to differences in debt burdens—and to aggregate GDP and the business cycle. Similar figures are obtained using the Arellano–Bond and Blundell–Bond GMM estimators (Figure A5 in the Appendix).

[7]For firms in the Agricultural sector, indeed, we observe a strong negative relationship between energy expenditure and profitability, consistent with evidence showing that energy demand in this sector is inelastic (Faiella et al. (2022)) meaning that it does not react to price hikes so that higher energy prices are therefore reflected in additional costs and lower profitability. Firms in the Electricity and Mining sectors, instead, exhibit a high ratio of energy expenditure to total assets, but may also benefit from rising energy prices, particularly when they operate on the production or distribution side of the energy market. In such cases, higher prices can translate into increased revenues, potentially offsetting the impact of higher energy expenditures. This distinguishes them from other sectors, where energy costs typically represent a net burden.

Figure 5: Out-of-sample performance of sectoral models



Note: The red bars display the historical average annual PDs for the period between 2018 and 2020 for different sectors. The blue bars show the values predicted out-of-sample for the same time period obtained by estimating equations 1 and 2 on the entire sample of firms, while the green bars report the results from estimating the equations separately for each sector. All models are estimated over the period 2013-2017. The sectors are classified according to NACE 1-digit codes: A is Agriculture, B is Mining and quarrying, C is Manufacturing, D is Electricity, gas and steam, E is Water supply and waste management, F is Construction, G is Wholesale and retail trade, H is Transporting and storage, and ZZ includes all the remaining ones.

4 PDs projections under alternative climate scenarios

4.1 NGFS long-term scenarios

4.1.1 Forward-looking macroeconomic variables

The NGFS scenarios provide forward-looking climate and macroeconomic pathways designed to support central banks, supervisors, and financial institutions in assessing climate-related risks and transition dynamics. The latest release (Phase V, NGFS (2024)) includes seven scenarios that differ in the timing and ambition of climate policies (see Figure A6 in the Appendix). We focus on five scenarios most relevant for stress testing.[8]

The Current Policies and Fragmented World scenarios assume limited (already implemented)

[8]We exclude from this analysis the Low demand and Below 2° scenarios, since they assume an orderly transition by 2050, in line with the narrative of the Net Zero 2050.

or uncoordinated policy action, leading to rising emissions and elevated long-term physical risks. The Delayed Transition scenario postpones climate action until 2030, followed by abrupt policy tightening, resulting in higher transition risks in the medium term. By contrast, Net Zero 2050 assumes immediate and coordinated action to achieve carbon neutrality by mid-century, entailing short-term transition costs but significantly mitigating long-term physical risks. The Nationally Determined Contributions (NDCs) scenario reflects pledged but not fully implemented policies, leading to limited emissions reductions and severe physical risks over the long run. For highly ambitious countries, such as European ones including Italy, the NDCs and Net Zero 2050 scenarios are almost equivalent in the medium term. This is because transition risks are the same across both scenarios, and physical damages remain limited over shorter time horizons.

NGFS scenarios provide projections for key macroeconomic and energy variables—such as GDP, interest rates, prices, and energy consumption—allowing us to model transition and physical risk shocks for Italy over the 2025–2030 horizon.[9] Importantly, they also allow us to disentangle the effects of transition and aggregate physical risks on macroeconomic outcomes.

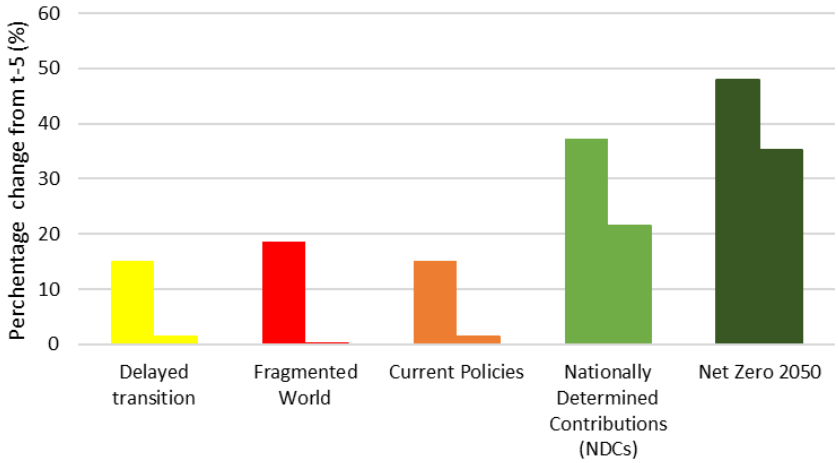
Starting from the projection of energy prices for the different sources and the energy consumption, we recover the percentage change of five years in energy expenditure in 2025 and 2030 for industry and the other sectors under alternative scenarios. As shown in Figure 6, in all scenarios, energy expenditure increases substantially in 2025 relative to 2020, reflecting the observed upsurge in energy prices in 2022. Besides, it further increases up to 2030 in the most climate ambitious scenarios, i.e. the Net Zero by 2050 and NDCs, due to the implementation of the energy and climate-related policies that lead to an increase in fossil-fuels prices and more, in general, in energy prices in the short-term.

Macroeconomic variables are broadly similar across all NGFS scenarios, though they are consistently more pessimistic in the ones with more ambitious decarbonization pathways (Figure 7). The limited differences observed stem from the medium-term horizon of our analysis, while they would be substantially larger over longer horizons. On the one hand, physical damages from climate change remain small and broadly comparable across scenarios, since the effects of policy ambition—or the absence of policies—on physical risks materialize mostly in the long term rather than within

[9]We use data from REMIND-MAgPIE downscaled for Italy to recover the shocks of interest. Data on final energy consumption and prices are very similar in the integrated run that accounts for physical risk.

the horizon considered. On the other hand, transition risks differ across scenarios, being higher under more ambitious pathways (e.g., Net Zero by 2050). Yet these differences remain limited, as Italy is already committed to ambitious decarbonization trajectories, which are embedded in the Current Policy scenarios. Moreover, the Current Policy and Delayed Transition scenarios display no differences by 2030, as the latter assumes no additional measures before that date.

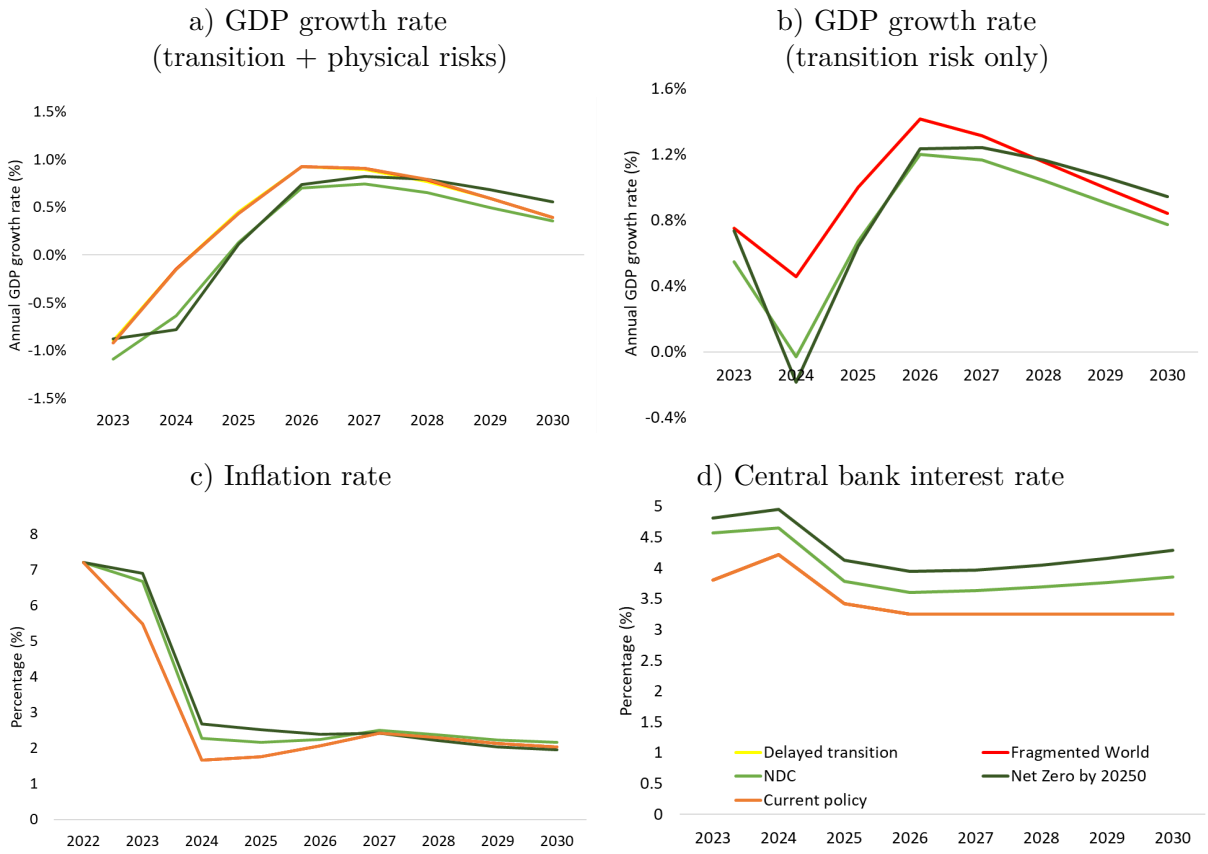
Figure 6: NGFS forward-looking energy expenditure for industry: 5-years percentage change in 2025 and 2030



Note: The Figure displays the 5-year percentage change in the energy expenditure for industry, based on the NGFS data for Italy. For each scenario, the first bar reports the 2025 values while the right bar refers to the 2030 ones. Industry includes all the firms within the Manufacturing and Mining and quarrying sectors. A similar figure is available for the "other sectors" as a whole.

Specifically, the annual GDP growth rate ranges between -1 and +1 per cent (panel a). The pathways for the scenarios that assume no new climate policies in the short term (i.e., Current Policy, Fragmented World, and Delayed Transition) are very similar (almost overlapping) and driven by the chronic physical risk on top of the baseline dynamics (i.e., GDP in the absence of physical or transition risks). In the first few years, the GDP growth rate is, instead, lower in the scenarios assuming ambitious mitigation policies (i.e. Net Zero by 2050 and NDCs) due to the short-term costs of the transition and then recovers from 2026 onward, as shown in panel b), which displays the GDP pathways assuming no physical risk (transition risk only). The inflation rate stabilises around 2 per cent from 2024 (panel b).

Figure 7: NGFS forward-looking macroeconomic variables



Note: The figures display the NGFS (NIGEM-Remind) data for Italy for the following variables in the alternative scenarios. Panel a) and b) display the annual GDP growth rate, accounting both for chronic physical and transition risks (panel a) and for transition risk only (panel b). Panel c) displays the inflation rate, while panel d) the central bank interest rate.

The central bank interest rate is approximately 4 per cent in 2025 (panel c). For both of these variables, the dynamics are driven by the transition risk.[10] Notably, the high interest rate going forward mirrors the high interest rates observed in 2024 when the NGFS scenarios were published, relying on the most updated available data.[11]

These figures show that NGFS long term scenarios are not designed as macro-adverse scenarios, such as those used in traditional stress tests and previous climate exercises. Instead, they describe alternative plausible futures that may materialize depending on the timing and ambition of the climate policies implemented.

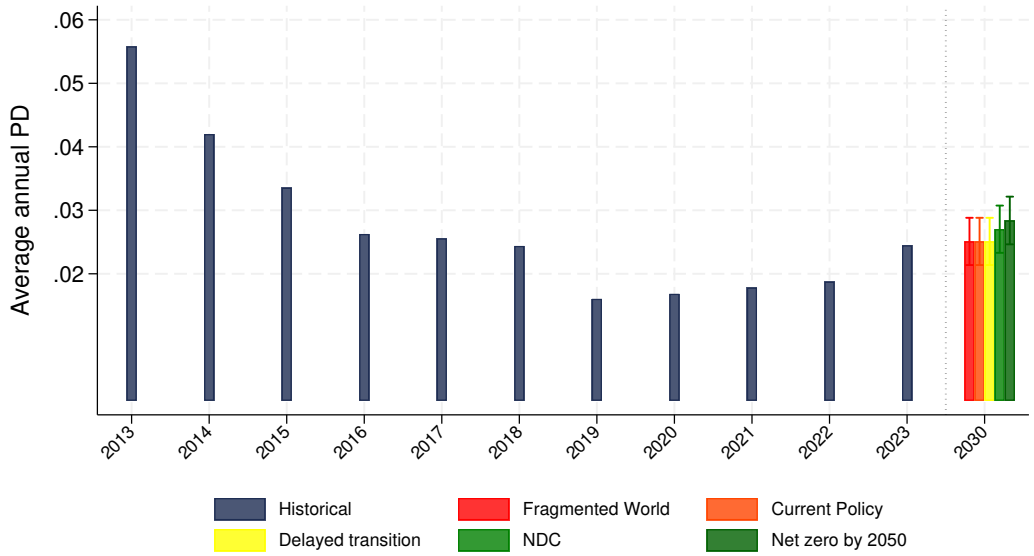
[10]The inflation rate is almost not affected by the physical risk in the short to medium term. Additionally, the NGFS scenarios assume that monetary policy does not react to physical risk.

[11]The interest rate is about 3 per cent in the baseline scenario that assumes no transition or physical risks.

4.1.2 Results

Exploiting the empirical framework defined in Section 3 and the NGFS scenarios, we project the PDs up to 2030. The projected PDs slightly differ across scenarios, but remain broadly in line with the 2023 levels and significantly below the high historical values observed in 2012 during the sovereign debt crisis (Figure 8).

Figure 8: Average PDs in 2030 by the alternative NGFS scenarios in 2030



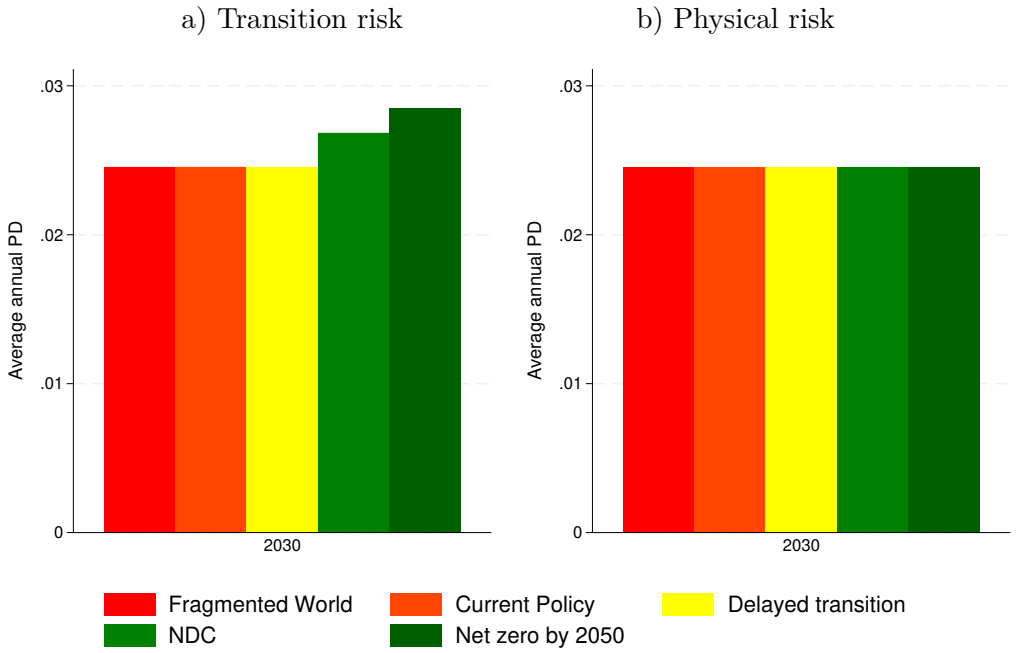
Note: The figures display historical PDs between 2013 and 2023 and the projected PDs in 2030 under the alternative NGFS scenarios. The predictions are obtained by estimating the model (equations 1-2) on the entire sample of firms for the period between 2013 and 2023. It is assumed that energy expenditure in 2023 remains constant and equal to the level observed in 2022. Confidence intervals are computed at 95%.

The Net Zero 2050 pathway is associated with the highest increase in default risk, signaling a short-term impact of an ambitious transition on corporate vulnerabilities. Such costs are still very contained considering that the PDs do not reach 3 per cent in 2030. Conversely, the Current Policy, Fragmented World, and Delayed Transition scenarios show no increase in aggregate PDs.

If we then disentangle the physical (chronic following the NGFS terminology) from the transition risk component, it is clear that the variation in PDs across scenarios is driven by the transition risk, which is higher in the scenarios that assume ambitious decarbonization pathways (i.e., NDCs and Net Zero by 2050) (Figure 9, panel a). As for physical risks, no differences across scenarios are observed as such risks are not influenced by mitigation policies in the near term, given that climate

effects materialize only in the long run (Figure 9, panel b).

Figure 9: PDs in 2030: physical vs. transition risk



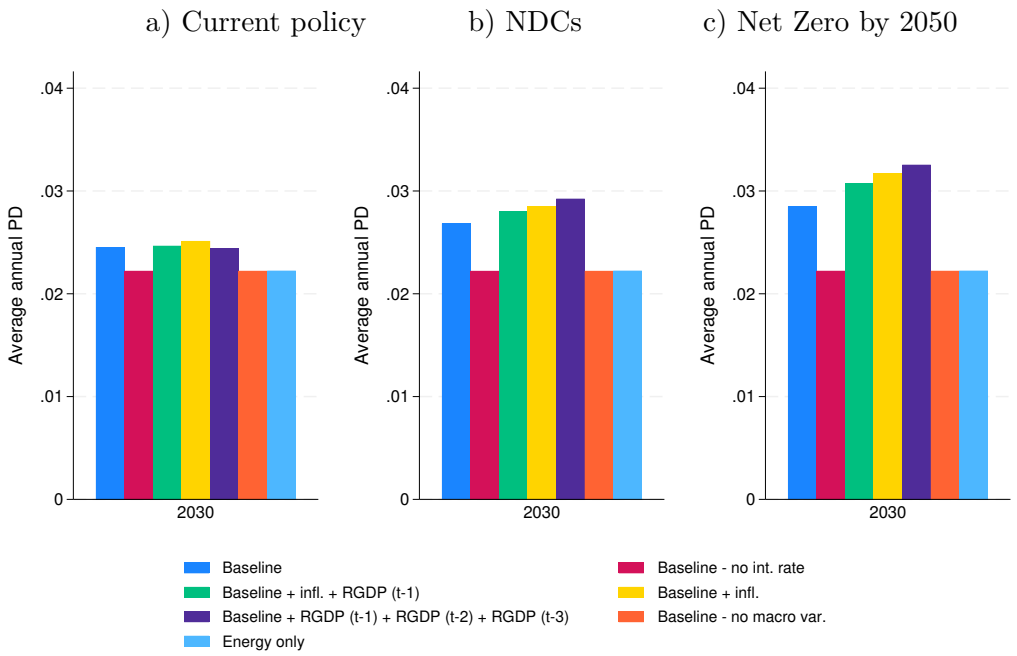
Note: The figures display the projected PDs in 2030 under the alternative NGFS scenarios, considering separately transition (panel a) and physical risks (panel b). The predictions are obtained by estimating the model (equations 1-2) on the entire sample of firms for the period between 2013 and 2023. It is assumed that energy expenditure in 2023 remains constant and equal to the level observed in 2022. In the first panel, the Current Policy scenario is equal to the baseline.

Besides, this analysis confirms that the PDs under the Current Policy and similar scenarios are unaffected by either physical or transition risks. Instead, they reflect baseline trajectories that assume the absence of both risk types, which explains why they remain constant in Figure 9. Therefore, from this point onward, we focus only on a subset of scenarios, given the similarities among the Current Policy, Fragmented World, and Disorderly Transition pathways.

We then conduct several tests to identify the main drivers of the projected PDs and to assess the robustness of our results. Across all scenarios, the PDs are primarily driven by the interest rate or, when included, by other macroeconomic variables. When the effect of the interest rate is removed, the projected PDs decline to around 2 percent and remain nearly constant across scenarios (Figure 10, pink bars). Similar outcomes are observed when all macroeconomic variables are excluded (orange bars), or when only the energy expenditure channel is isolated and all others are disregarded (light blue bars).

These findings suggest that, consistent with the limited impact of energy expenditure on firms' profitability, the effect of energy price shocks on firms' financial vulnerability is modest—likely reflecting their capacity to adjust energy consumption, reduce other costs, or pass on higher costs to consumers. By contrast, when the specification includes the inflation rate (and the lagged real GDP growth rate), the aggregate PDs in 2030 are slightly higher, especially in the Net Zero by 2050 scenarios, though the increase remains modest and the PDs are just above 3 percent (yellow, green and purple bars). This result confirms the role of the macroeconomic variables in the PD's projections and reflects the elevated inflation projected in the NGFS scenarios compared with most of the historical values in our sample.

Figure 10: PDs in 2030: alternative specifications

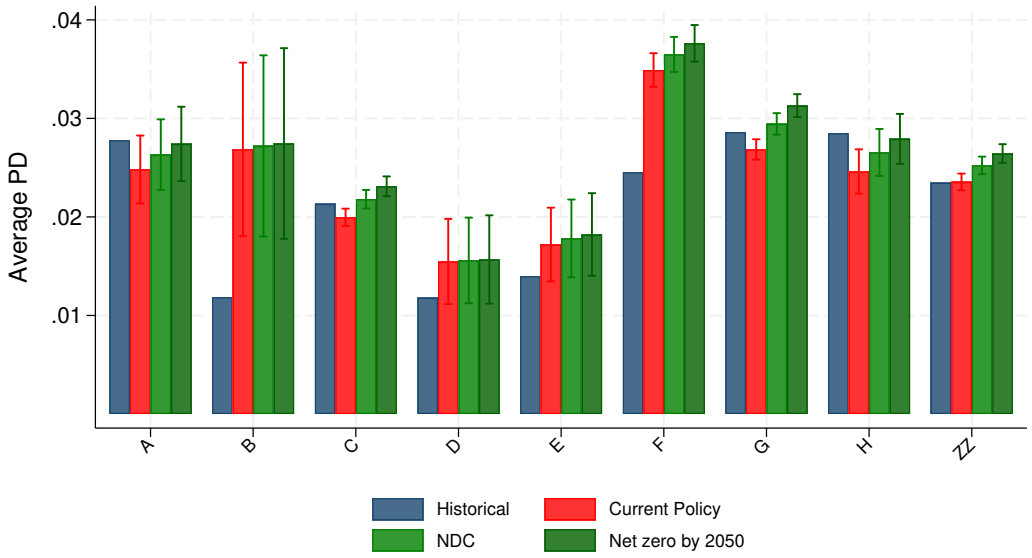


Note: The figures display the projected aggregate PDs in 2030 under the alternative NGFS scenarios, based on different specifications of equation 2. The equations are estimated on the full sample of firms over the period 2013-2023. It is assumed that energy expenditure in 2023 remains constant and equal to the level observed in 2022. The blue bars show results from the baseline model discussed in Section 3; the red bars from a model that excludes the interest rate; the green bars from a model that includes also the inflation rate and the lagged real GDP growth rate; the yellow bars from a model that adds the inflation rate; the purple bars from a model that inludes three lags of the real GDP growth rate; the orange bars from a model that excludes all the macro variables; the light blue bars with a model that excludes all the macro variables in equation 2 and accounts only for the energy expenditure channel in equation 1.

Finally, we estimate equations 1 and 2 separately for each sector, as described in Section 3, to capture sectoral heterogeneity. The aggregate results are broadly consistent with those obtained

from the baseline model estimated on the full sample of firms, although slightly lower. Nevertheless, aggregate figures mask a wide sectoral heterogeneity (Figure 11). Across all sectors, PDs reach their highest levels under the Net Zero scenario. When compared to the historical level of 2023, the largest increases in PDs are observed in the Mining and Construction sectors. For these sectors, PDs also rise under the Current Policies scenario, suggesting that the main drivers of the increase are baseline macroeconomic dynamics rather than climate-related risks.

Figure 11: Average PD by Sector and NGFS scenarios in 2030



Note: The figure displays the projected sectoral PDs in 2030 under the alternative NGFS scenarios and the historical values in 2023. The predictions are obtained by estimating the model (equations 1-2) on the entire sample of firms for the period between 2013 and 2023. It is assumed that energy expenditure in 2023 remains constant and equal to the level observed in 2022. The figure displays the sectoral results obtained estimating the model separately for each sector. The sectors are classified according to NACE 1-digit codes: A is Agriculture, B is Mining and quarrying, C is Manufacturing, D is Electricity, gas and steam, E is Water supply and waste management, F is Construction, G is Wholesale and retail trade, H is Transporting and storage, and Other (ZZ) includes all the remaining ones. Confidence intervals are computed at 95%.

4.2 NGFS short-term scenarios

4.3 Forward-looking macroeconomic variables

The NGFS short-term climate scenarios provide a framework for assessing climate risks over a six-year horizon, integrating transition policies, physical shocks, and macro-financial feedback effects (NGFS (2025)). We focus on four narratives: Highway to Paris, Sudden Wake-Up Call, Disasters

and Policy Stagnation, and Diverging Realities, which differ in the timing and intensity of transition and physical risks.

Highway to Paris (HWTP) assumes an orderly, coordinated transition consistent with net-zero emissions by 2050, with moderate macroeconomic impacts and contained inflationary pressures. By contrast, Sudden Wake-Up Call (SWUC) features delayed policy action until 2027, followed by abrupt tightening, leading to a negative supply shock, asset repricing, and increased credit risk.

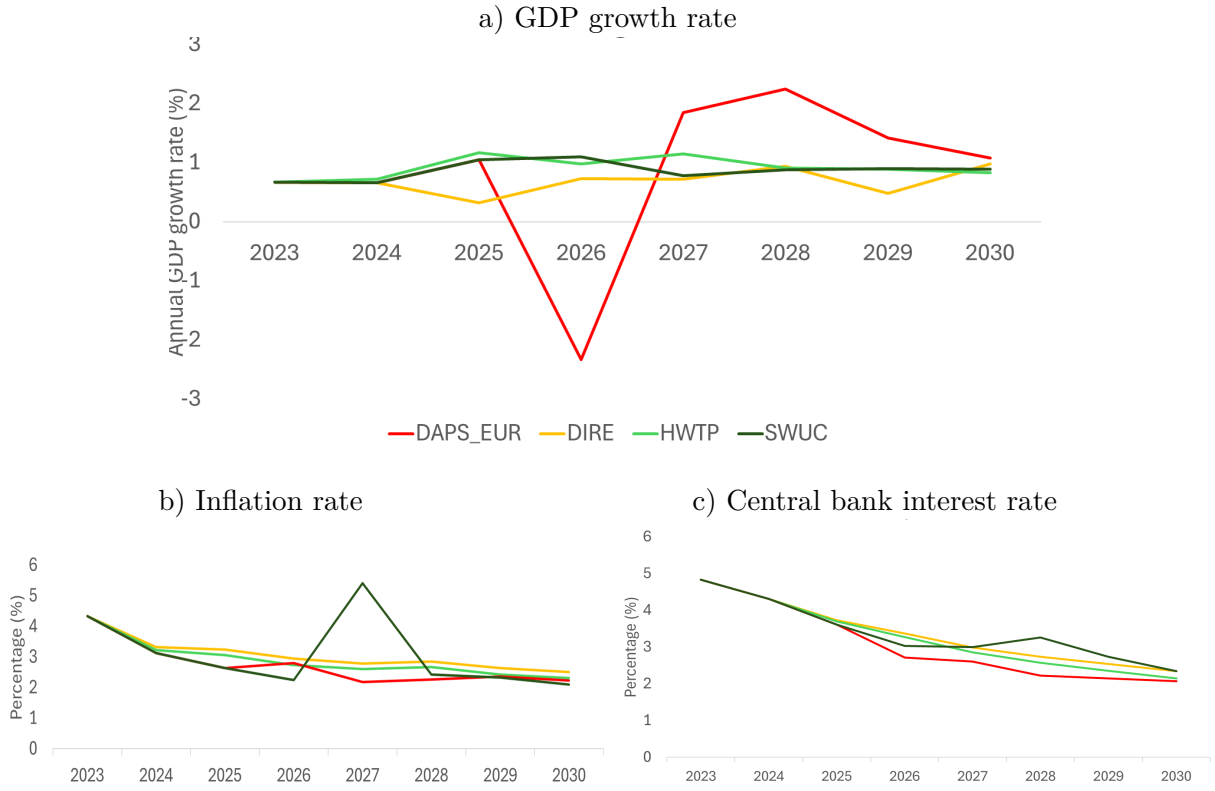
Disasters and Policy Stagnation (DAPS) isolates acute physical risks under weak policy action, with repeated extreme weather events causing significant regional output losses and global spillovers. Two consecutive years of extreme weather events occur in each region: droughts, heatwaves, and wildfires in 2026, followed by storms and floods in 2027. Diverging Realities (DIRE) combines transition and physical risks, with advanced economies following orderly transitions while emerging and developing economies experience repeated weather events from 2025 to 2030, leading to supply-chain disruptions in critical raw materials, energy technologies, and essential commodities and higher global inflation.

Overall, the scenarios illustrate distinct macroeconomic patterns: orderly transitions generate gradual adjustments, delayed action amplifies instability, while acute physical shocks and global fragmentation increase systemic risks.

Macroeconomic dynamics for Italy broadly follow global ones. The annual GDP growth rate ranges between 0.5 and 1.2 per cent (Figure 12, panel a) across all scenarios, with the exception of the DAPS which envisages a significant reduction in GDP growth in 2026 due to severe dry climate events affecting all European countries, including Italy. Still, this decline is followed by a rapid recovery already in 2027, driven by reconstruction spending (e.g. increased investment), which more than offsets the damages caused by wet climate events (i.e. floods) assumed to occur in 2027. All other scenarios display very similar GDP trajectories.

Inflation dynamics are also broadly similar across scenarios, with a gradual decline from the elevated levels observed in 2023. The only exception occurs in 2027 under the SWUC scenario, when inflation temporarily rises at the onset of the abrupt transition. This increase is subsequently reabsorbed following the monetary policy response. Consistently, the central bank policy rate exhibits a declining trend up to 2030 in all scenarios, except for a temporary increase in the SWUC scenario after the inflation shock and the associated monetary policy reaction (panel c).

Figure 12: NGFS short- term scenarios: macroeconomic variables

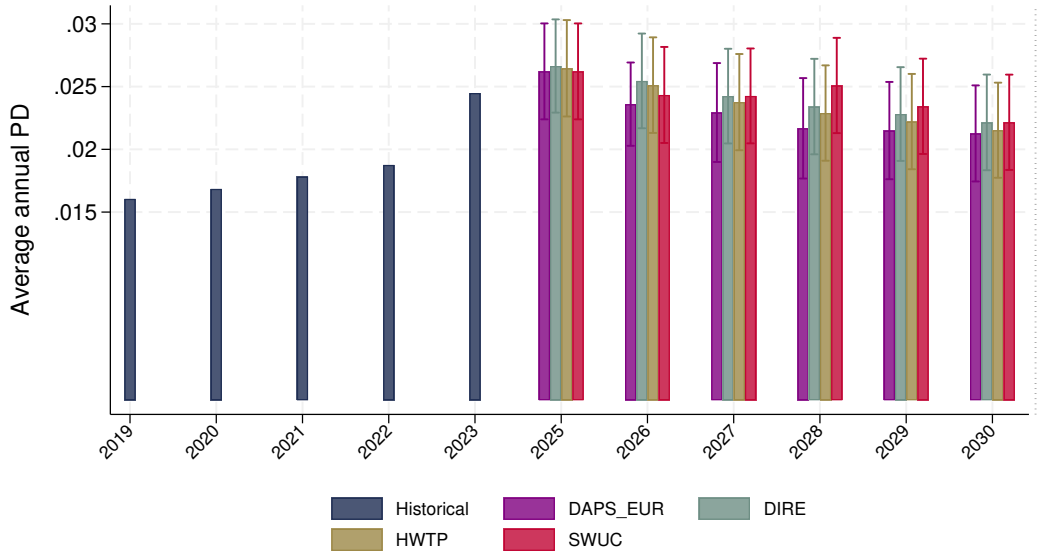


Note: The figures display the NGFS data for Italy for the following variables in the alternative short-term scenarios. Panel a) displays the annual GDP growth rate; panel b) shows the interest rate and panel c) the central bank interest rate.

4.3.1 Results

Results for the short-term scenarios are presented in Figure 13. Also in this case, the primary driver of aggregate PD dynamics is the policy rate. The DAPS scenario is characterized by the lowest policy rate throughout the horizon, which translates into the lowest aggregate average PD. This result holds despite the drop in GDP growth observed in 2026 due to the occurrence of acute climate events, given the fast recovery, the prompt monetary policy reaction, and the limited impact of short-term GDP fluctuations on PDs.

Figure 13: PDs by the alternative NGFS scenarios



Note: The figures display historical PDs between 2019 and 2023 and the projected PDS from 2025 to 2030 under the alternative NGFS scenarios with confidence intervals. The predictions are obtained by estimating the model (equations 1-2) on the entire sample of firms for the period between 2013 and 2023. It is assumed that energy expenditure in 2023 remains constant and equal to the level observed in 2022.

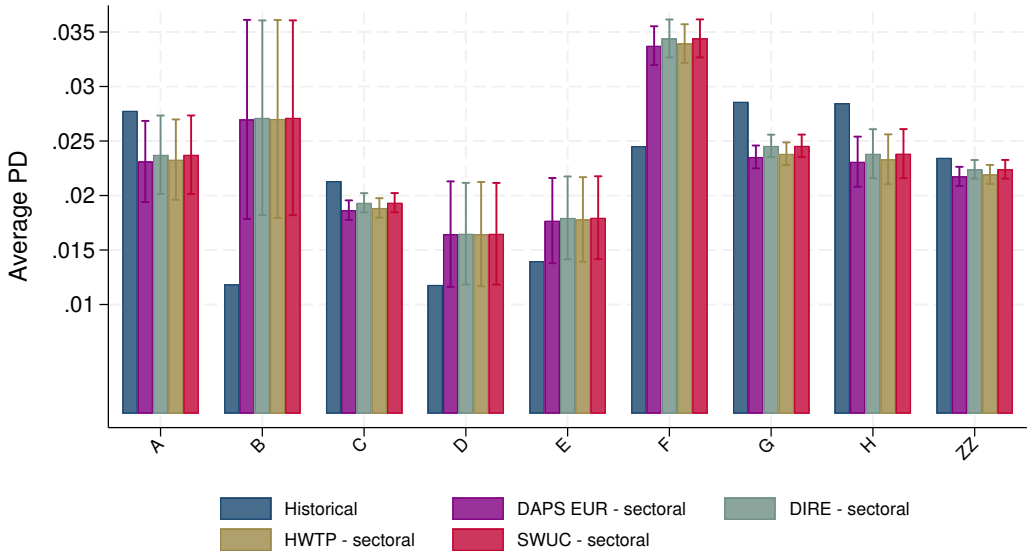
By contrast, from 2028 onward, the SWUC scenario exhibits the highest policy rate, corresponding to the highest aggregate PD.

Despite these differences, average PDs are similar across scenarios and there are no significant differences, suggesting that even in the case of an early transition, the cost in terms of default losses would not be burdensome for banks. More generally, in all scenarios, the policy rate declines between its peak in 2025 and its level in 2030, contributing to an overall reduction in PDs over the period.

These results are confirmed when considering alternative specifications of the model, including the inflation rate and the lagged real GDP growth rate. Robustness results are reported in the Appendix.

We now turn to sector-level PD estimates, obtained using the sectoral models. The results are reported in Figure 14.

Figure 14: Average PDs by Sectors and NGFS scenarios in 2030



Note: The figure displays the projected sectoral PDs in 2030 under the alternative NGFS scenarios and the historical values in 2023 with confidence intervals. The sectors are classified according to NACE 1-digit codes: A is Agriculture, B is Mining and quarrying, C is Manufacturing, D is Electricity, gas and steam, E is Water supply and waste management, F is Construction, G is Wholesale and retail trade, H is Transporting and storage, Other (ZZ) includes all the remaining ones.

Aggregate figures obtained with the sectoral models are well aligned with those discussed above. In contrast to the aggregate results, however, sectoral patterns reveal some heterogeneity across sectors. In 2030, several sectors (B, D, E, and F) exhibit average PDs exceeding their 2023 historical levels; these are the most sectors that are more sensitive to the variations in the cycle and in particular to the interest rate (possibly because of their financial structure).[12] Consistent with the evidence from PDs based on long-term scenarios, the largest increase by 2030 is observed in sectors B and F. In the the others (A, C, G, H, and ZZ), instead, the PDs remain below historical values, thereby driving the overall aggregate decline. Within each sector, instead, differences are limited across scenarios and insignificant.

[12]Regarding uncertainty, sector B exhibits the widest confidence interval, likely reflecting the relatively small number of firms in this sector.

5 Conclusions

Our model for Italian banks' PDs, grounded in both the long-term and the short-term NGFS scenarios, provides novel insights into the distribution of credit risks across firms and sectors over possible climate scenarios for Italy.

The analysis suggests that near-term transition costs are modest. Ambitious decarbonization pathways—such as those embedded in the Net Zero 2050 and High Way to Paris scenarios—do impose initial adjustment burdens on firms, but these remain contained. Over the long time horizon, thus, mitigation policies would strengthen financial stability by curbing the accumulation of long-term physical risks.

Moreover, our analysis highlights the inherent complexity of assessing climate-related risks for the banking sector by offering a concrete illustration of how the energy expenditure channel and macroeconomic dynamics affect firms' vulnerabilities, and how NGFS (short and long term) scenarios can be operationalized in the Italian context, thereby shedding light on their practical applicability as well as on their main strengths and limitations.

At the same time, several methodological challenges remain open and call for further investigation. These include, among others, the explicit incorporation of firms' adaptation and mitigation strategies, the modeling of second-round effects propagated through supply chains and financial linkages, and a more detailed assessment of physical damages associated with acute climate-related events.

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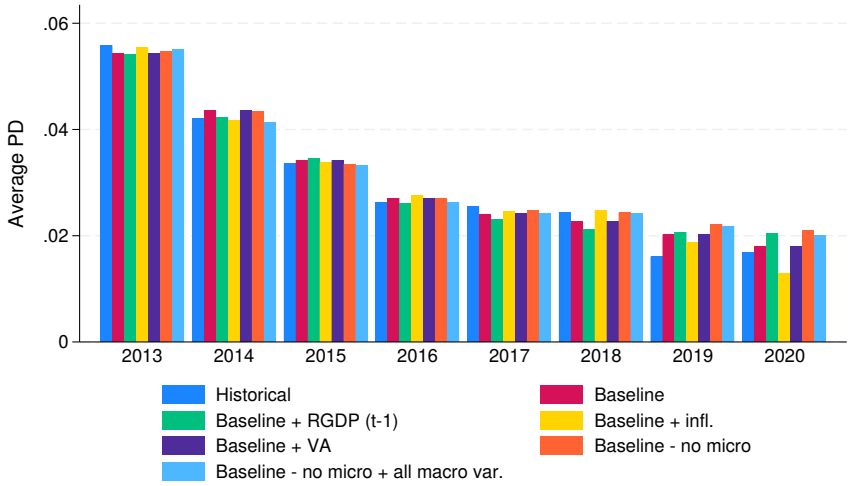
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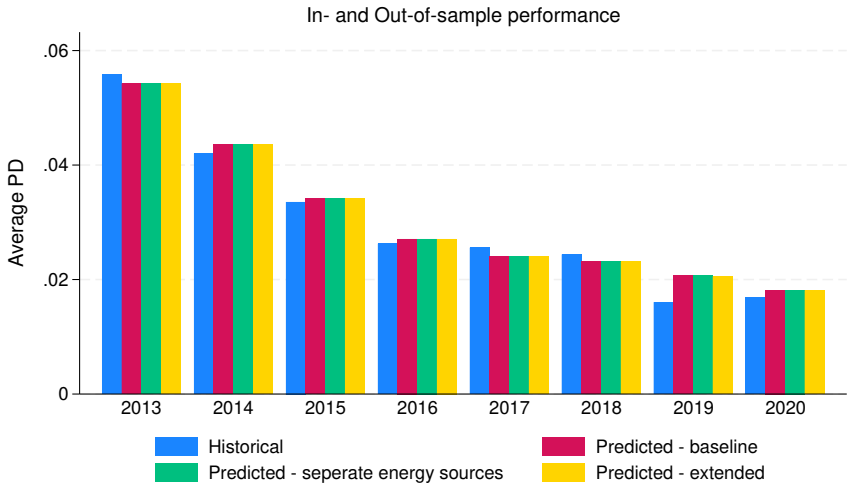
Appendix A

Figure A1: Model performance: robustness checks



Note: The figure displays both historical (blue bar) and estimated annual PDs for the period between 2013 and 2020. The estimated data are in-sample up to 2017 and out-of-sample for the period between 2018 and 2020. The red bars indicate the results of the baseline model discussed in Section 3; while the other modify equation 2. The green bars consider a model that adds the lagged Real GDP in equation 2; the yellow bars a model that adds the inflation rate; the purple bars a model that adds the value added; the orange bars a model that excludes all the micro variable, except the EBITDA; the light blue bars a model that adds the lagged real GDP and inflation, while exluding the firm-level variables (except the EBITDA).

Figure A2: Model performance: baseline vs. extented model



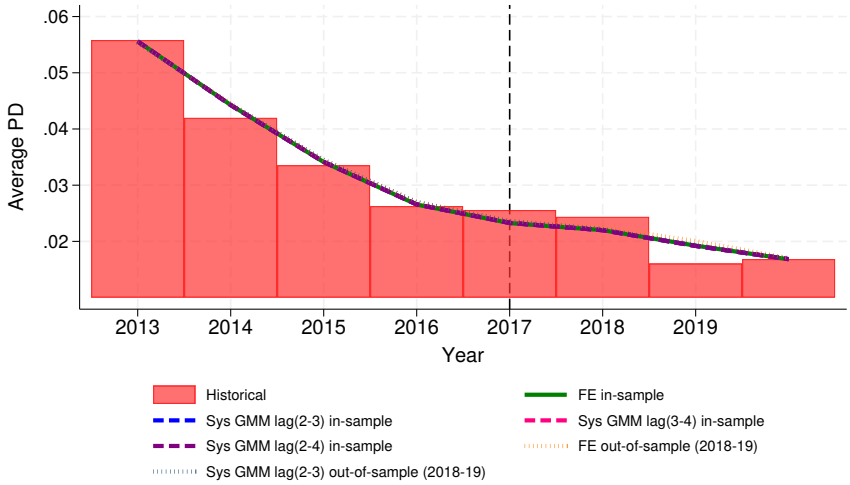
Note: The figure displays both historical (blue bar) and estimated annual PDs for the period between 2013 and 2020. The red bars indicates PDs predicted estimating the baseline model (in equations 1 and 2), while the green bars estimating with a similar model that in equation 1 differentiates energy expenditure by sources (Oil, Power and Gas) and the yellow bars with the extended version of the model that in equation 1 include seperately energy consumption and prices by sources. All the models are estimated on the period between 2013 and 2017. The values plotted are predicted in-sample up to 2017 and out-of-sample from 2018 to 2020.

Table A1: Energy expenditure channel by source

	(1)	(2)	(3)
		$EBITDA_{i,t}$	
$EBITDA_{i,t-1}$	0.361***	0.361***	0.361***
	(0.005)	(0.005)	(0.005)
Gas $expenditure_{i,t-1}$	-0.017**		
	(0.007)		
Oil $expenditure_{i,t-1}$		-0.007**	
		(0.003)	
Power $expenditure_{i,t-1}$			-0.000
			(0.001)
Real GDPt	0.007***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)
Observations	1366229	1366229	1366229
R^2	0.901	0.901	0.901
Adjusted R^2	0.875	0.875	0.875
Firm FE	YES	YES	YES

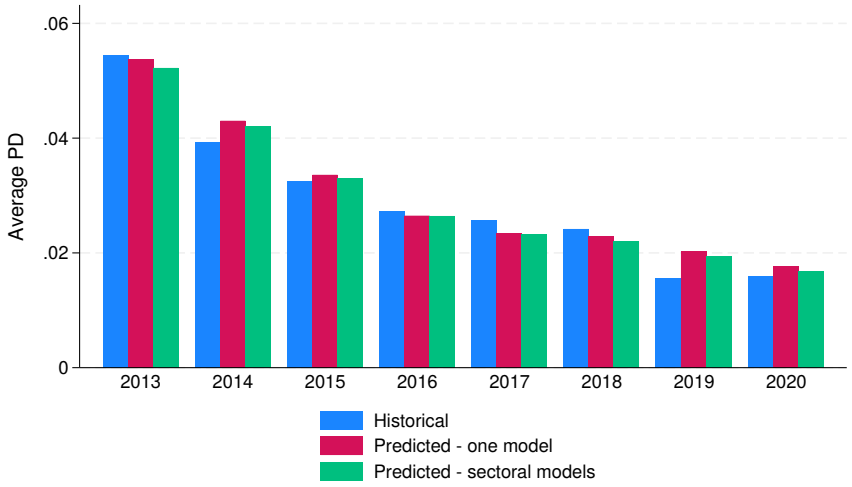
Note: The Table displays the link between firm's profitability and energy expenditure by sources. All the regressions include the constant. The regressions are estimated on the entire sample of firms over the period between 2013 and 2019. Standard errors in parentheses are clustered at firm level.

Figure A3: Model performance: FE vs Blundell-Bond GMM



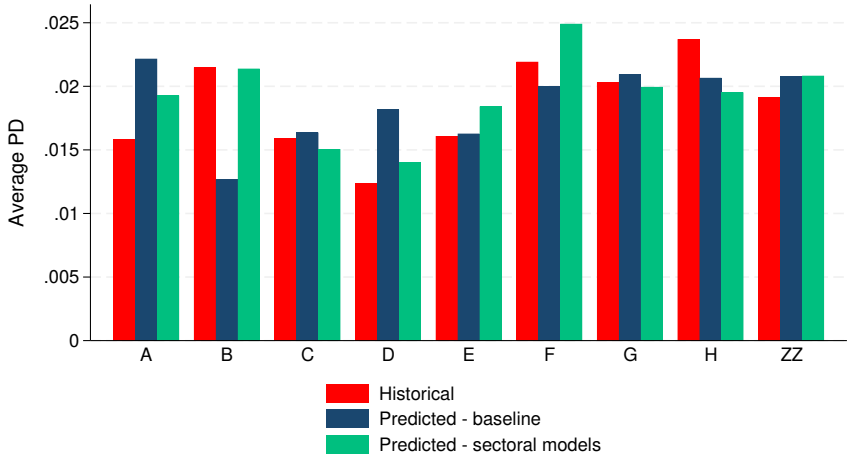
Note: The figure displays the average historical and predicted PD over the estimation period. The GMM estimators use different lags of the dependent variable as instruments. The vertical dashed line indicates the end of the in-sample period (2017) and the beginning of the out-of-sample period (2018–2019). The near-perfect overlap across all specifications confirms that the choice of estimator does not materially affect the predicted path of default probabilities. Similar results are obtained when using the Arellano-Bond GMM estimators.

Figure A4: Model performance: single vs. sectoral model



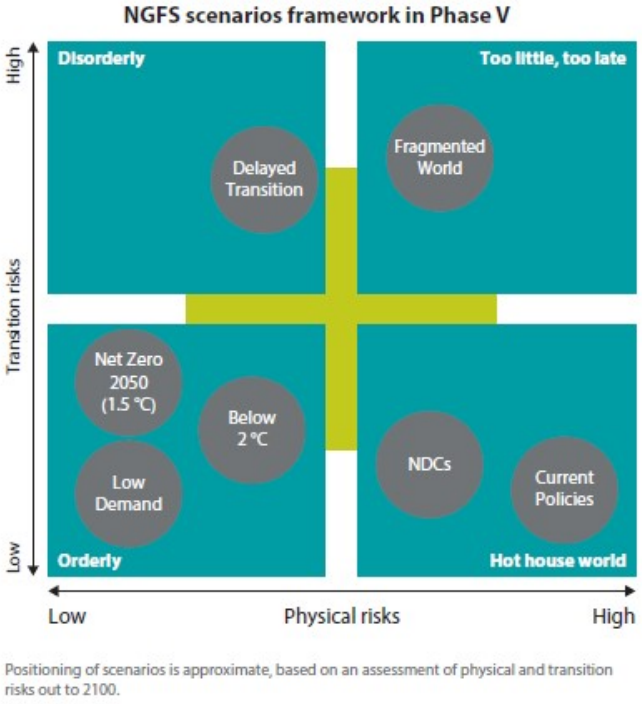
Note: The figure displays both historical (blue bar) and estimated annual PDs for the period between 2013 and 2020. The red bars indicates PDs predicted estimating one model (equations 1 and 2) on the entire sample of firms, while the green bars estimating the model separately for each sector on the period between 2013 and 2017. The values plotted are predicted in-sample up to 2017 and out-of-sample from 2018 to 2020.

Figure A5: Out-of-sample performance of sectoral models: GMM



Note: The red bars in the figure display the historical average annual PDs for the period 2018–2020 across sectors. The blue bars show the out-of-sample predicted values for the same period, obtained by estimating equations 1 and 2 via fixed effects on the pooled sample of firms. The green bars report the out-of-sample predicted values obtained from the same set of equations, with the EBITDA equation re-estimated separately for each sector using the Blundell-Bond two-step System GMM estimator (with lags 2–3 of the lagged dependent variable as GMM instruments for the first-differenced equation and lag 1 for the levels equation, collapsed). All estimates use data up to 2017 as the in-sample period.

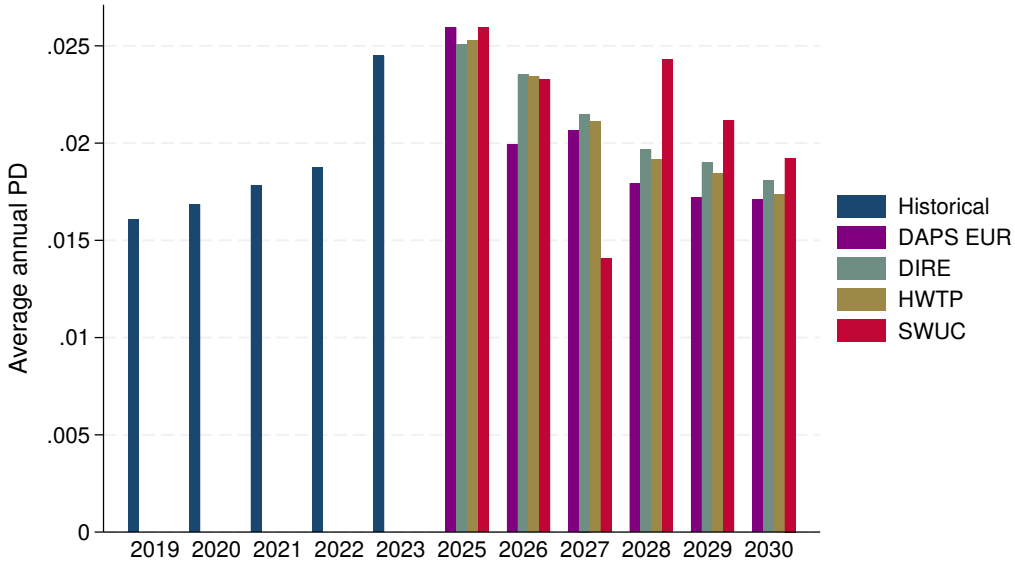
Figure A6: Phase V NGFS long-term scenario framework



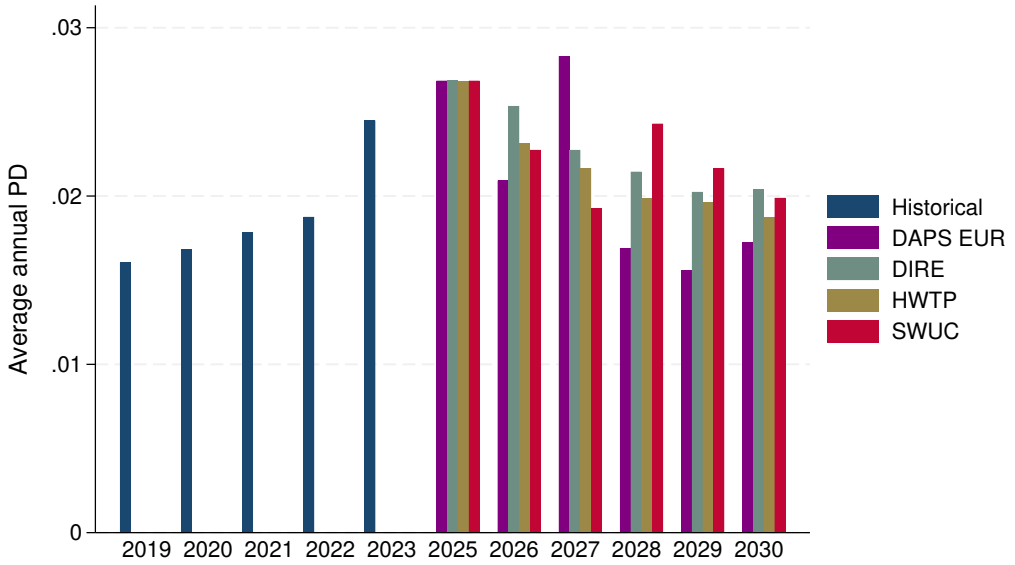
Positioning of scenarios is approximate, based on an assessment of physical and transition risks out to 2100.

Figure A7: Average PD by NGFS scenarios: alternative specifications

a) Inflation rate



b) Inflation rate and RGDP (t-1)



Note: The figures display historical PDs between 2019 and 2023 and the projected PDS from 2025 to 2030 under the alternative NGFS scenarios. The predictions are obtained by estimating the model (equations 1-2) on the entire sample of firms for the period between 2013 and 2023. Equation 2 includes the inflation rate in panel a) and also the lag of the RGDP in panel b). It is assumed that energy expenditure in 2023 remains constant and equal to the level observed in 2022.