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Chronicle of a death foretold: does higher volatility anticipate corporate default?

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Abstract

We test whether a simple measure of corporate insolvency based on equity return volatility – and denoted as Distance to Insolvency (DI) – delivers better predictions of corporate default than the widely-used Expected Default Frequency (EDF) measure computed by Moody's. We look at the predictive power that current DIs and EDFs have for future defaults, both at a firm-level and at an aggregate level. At the granular level, both DIs and EDFs anticipate corporate defaults, but the DI contains information over and above the EDF, especially at longer forecasting horizons. At an aggregate level the DI shows superior forecasting power compared to the EDF, for horizons between three and twelve months. We illustrate the predictive power of the DI measure by examining how corporate defaults would have evolved during Covid-19 had the ECB not implemented the pandemic emergency purchase programme (PEPP).

Key words: Default probability, equity volatility, Distance to Insolvency, Expected Default Frequency.

JEL classification: C53, C58, G33.

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1 Introduction

Economists are interested in corporate defaults because such events, especially when they occur simultaneously for many firms and over a short interval of time, can lead to a significant deterioration in future economic growth. Weaker economic activity relates primarily to the financial turbulence and the loss in business confidence that corporate defaults tend to generate. As a matter of fact, there is an ample literature that explores the predictive content of corporate credit spreads (a common default-risk indicator) for economic activity.[1] Furthermore, both academics and practitioners have been actively developing indicators and models aimed at measuring firms' financial fragility as well as forecasting corporate defaults. A seminal work in the literature is Altman (1968), who developed the Z-score, an indicator that uses multiple corporate income and balance sheet information to measure the financial health of a company. The Z-score became widely popular and it is, with various modifications since its original development, a standard measure reported by industry analysts. Another important indicator is the Distance-to-Default measure which underpins the Merton's model (Merton (1974)), popularized by Moody's in their proprietary product Expected Default Frequency (EDF). Up to date, both Z-scores and EDFs are routinely employed by investors and academics to study credit market developments and assess the financial soundness of firms.

More recently, Atkeson et al. (2017) proposed a new indicator of a firm's financial soundness, the so-called Distance to Insolvency (DI). This measure is also based on Merton's Distance-to-Default (DD) model, but the authors propose a set of simplifications which make it very easy to compute, basically boiling it down to the inverse of the volatility of a firm's equity return. An additional advantage of this measure is that the DI is not dependent on any modelling choices and as such it is easy to be used and compared across firms, time and studies.

This paper examines the default forecasting ability of the DI measure comparing it to the other two aforementioned widely used measures, with a special focus on the EDF.[2] The purpose of the paper is to show whether such a simplified measure of default risk has better forecasting performance for future defaults than more complex indicators which rest upon an extra set of assumptions. In the remainder of the paper we identify defaults as cases in which firms lose almost all their market value in a few months. We provide further motivation for this choice in

[1] See for example, Gilchrist and Zakrajšek (2012).

[2] The EDF is a daily measure with also very broad coverage. In later sections we also provide comparisons with the Altman Z-score, which is only available at a lower quarterly frequency.

the next sections.

Our findings show that, at the granular level, both the EDF and the DI are relevant measures to forecast defaults. However, the EDF loses its forecasting power once we look at horizons beyond 3 months, while the DI preserves its forecasting properties at longer horizons. Furthermore, also when dealing with aggregate data, the DI indicator performs better than the EDF for predictive horizons beyond 3 months. In both analyses we control for relevant covariates, i.e. the comparison between EDF and DI also takes into account other variables which have been reported by the literature to have a role in predicting either defaults or negative economic out-turns more generally. Finally, to show the use of the DI indicator in macro-financial applications, we present a counterfactual exercise that considers the level at which corporate defaults in the euro area would have settled if the ECB had not implemented the Pandemic Emergency Purchase Program (PEPP). We show that the ECB intervention reduced defaults during the crisis, relative to a counterfactual scenario, by mitigating financial shocks (as captured by the DI) on euro area non-financial firms.

As mentioned before, our paper is linked to a large literature that focuses on the prediction of corporate bankruptcies. This literature varies in the preferred indicator used to predict bankruptcies as well as in the methodology used to estimate the likelihood of such events. For example, Beaver (1966), Altman (1968), Ohlson (1980) and Campbell et al. (2008) use accounting variables to estimate the probability of bankruptcy in a static model. Despite its longevity, Altman's Z-score is arguably still the most widely used measure of firms' financial distress and a benchmark to evaluate the ability of any other measure. Another strand of the literature examines the predictions of the Merton model. The first authors to carry out a detailed examination of the performance of the model were practitioners employed by either KMV or Moody's. A number of papers including Sobehart and Keenan (1999, 2002a,b) and Kealhofer and Kurbat (2001) analyze Merton DD models and argue that the Merton DD-like model originally developed by the KMV corporation captures both the information in traditional agency ratings and in the accounting variables typically used to derive these ratings. An academic literature has also recently developed that critically assesses the model. Hillegeist et al. (2004) examine whether the Z-score developed by Altman effectively summarises publicly available information about the probability of bankruptcy. Based on over 500 bankruptcies between 1979 and 1997, they conclude that reliance on accounting-based measures of bankruptcies is not appropriate and that information from the Merton's model has relatively more explanatory power for subsequent default events. However, they also find that the Z-score has significant incremental information and therefore the information derived from the Merton's model is not a sufficient statistic. Bharath and Shumway (2008) examine the predictive power of the Merton model in a way that we follow in our paper. More specifically, they compare the DD model to a naive model whose functional form is the same as in Merton's model but without solving for an implied probability of default. Overall they find that the naive model performs slightly better than the original DD model in hazard models as well as in out of sample forecasts.

Finally, as our default measure is inherently linked to equity returns, our paper is also related to some research in the asset pricing literature focused on the distress puzzle. This anomaly relates to the observation that firms with high credit risk forecast low expected equity returns, even when accounting for risk adjustments (Dichev (1998), Griffin and Lemmon (2002)). This stands in contrast to the standard rational framework. Some advocates of this puzzle, such as Campbell et al. (2008), Shleifer and Vishny (1997) and Gao et al. (2018), also show that this anomaly is concentrated in small and scarcely liquid stocks.

The rest of this paper is organized as follows. The next section describes the data and concepts used through the paper. Section 3 shows results of forecast accuracy based on Cumulative Accuracy Paths, while Section 4 extends the analysis to an econometric framework through the use of hazard models. Section 5 looks at the role of DI vs EDF in a macro setting and also discusses the policy relevance of the DI measure. Finally, Section 6 concludes.

2 Data and Definitions

Our analysis uses all listed non-financial firms in euro area countries, as available in Refinitiv Eikon, between 1999 and 2020. This amounts to an unbalanced panel of 7,490 firms. Out of these, 929 firms defaulted at some point according to our default definition, which will be explained in detail further below. We retrieve daily equity price data for each of the 7,490 firms from Thomson Reuters Datastream. We also collect other financial market variables as well as selected information for the panel of firms which are illustrated in detail throughout the analysis in the following subsections and whose summary statistics are reported in Table I.

2.1 A Default Proxy

As the aim of this paper is to forecast corporate defaults, we need to try to accurately measure and define this event. This task is not straightforward since the moment in which a company defaults is subject to various alternative definitions. It can be identified with the time when the firm is late or misses payments on a debt obligation, or with the moment in which a firm officially declares bankruptcy. The former case, however, might only be a temporary setback which the firm can subsequently successfully deal with, while the latter usually takes place a long time after the firm has actually ended up in serious financial trouble. In general, papers studying corporate defaults make use of proprietary databases compiled by rating agencies or specialised firms (e.g. Moody's Default and Recovery database or the Altman default database). While the resources invested in compiling these databases makes them the best available measure of defaults, there is necessarily a certain degree of subjectivity in defining the default event. In this paper we take a new and alternative approach and use equity price data in order to build a proxy default measure.

We proxy defaults through strongly negative equity returns (i.e. returns lower than minus 80%) over a 3 months horizon. Historically, such strong equity price declines have usually been associated with deep financial distress of the respective company leading to a subsequent default. While this development does not necessarily imply that the firm has defaulted on its debt, it is a clear indication of the financial distress experienced around or ahead of a default event. If a firm in our sample experiences a default as defined above, we remove it from the sample. Thus, in our exercise, firms cannot experience more than a single default by construction. Also, it is worth noting that more than 75% of firms that defaulted according to our measure were delisted at some point afterwards, which highlights the high correlation of our measure to bankruptcy.

Comparing the aggregate measure of default based on our definition to historical default rates obtained from S&P Ratings suggests broadly similar dynamics (see Fig 1).[3] In general, our return-based default proxy tends to lead spikes in actual defaults, which is consistent with the forward-looking nature of our market-based indicator. Furthermore, we also check the specific balance sheet characteristics of the firms at the time of default in our sample. We split the firms into deciles according to the Altman Z-score, profitability (EBIT/total sales), size (log of assets) and leverage (1-book equity/total assets) and we count the number of observed defaults in each

[3]We thank Nick Kraemer from S&P ratings for sharing this data with us.

decile over the total. Figure 2 shows the results of this exercise. In our sample, and in line with the aggregate evidence, defaults tend to happen more frequently to firms that are smaller, less profitable, more leveraged and with lower Altman Z-scores.

All in all, our proposed measure identifies firms in deep financial distress and it serves as a proxy for the more widely used concept of firm default.

2.2 Distance to Insolvency (DI) indicator

In the pioneer credit risk models of Merton (1974) and Leland (1994) a key state variable summarizing a firm's financial soundness is the Distance to Insolvency (DI), i.e. a measure of the firm's leverage adjusted by the volatility of the market value of its assets. DI is a key state variable since it summarizes the probability that the firm will become insolvent in the future. However, calculating a firm's DI in practice is a challenging task, as it requires one to measure separately the market value and the volatility of a firm's underlying assets, and the value of its liabilities. This requires both assumptions and the use of accounting data.

Atkeson et al. (2017) show that the DI of a firm can be efficiently approximated by the inverse of its equity volatility.[4] This provides a very simple measure of the DI, not subject to the inconsistencies of accounting data and independent of any ad-hoc assumptions.

We estimate the equity price volatility as the realized volatility computed from daily equity returns for each firm and each month from January 1999 to June 2020. As can be seen in Chart 3 panel a, there is a clear relationship between the DI measure and our proxy for firms' default. For the full sample period, firms whose DI is in the first quintile of the DI distribution are three times more likely to default than those in the second quintile. For the other quintiles the probability of default is less than half that of the second quintile.

As outlined before, our default proxy is based on the equity return. Therefore it could be argued that it trivially relates to information coming from the return itself, which is the sole ingredient of the price volatility, i.e. of our expected default indicator. In other words, it could be argued that the predictor and what we are predicting are somehow related entities. On this respect, however, it should be noted that the EDF measure also relates to the firm's volatility and therefore the indicator produced by Moody's is not immune to the same critique. Furthermore, as is also the case in Campbell et al. (2008), we look at default predictions over

[4]Atkeson et al. (2017) formally show that the inverse of equity volatility is an accurate measure of the DI if the DI is close to the Distance to Default. This happens when creditors are quick in forcing insolvent firms into default.

short (3 months) and long (1 year) horizons. The potential mechanical link between the DI measure and our default default proxy should become much weaker as the predictive horizon lengthens. Therefore the critique of using a trivial predictive factor at the 3-month horizon should be of a much lower importance when we look at how defaults evolved over the subsequent year.

For ease of interpretation, we also transform the DI into a probability of default following the transformation applied in the Merton model (i.e. applying a standard normal distribution as $z(t) = \phi(DI(t))$ where $\phi(.)$ is a normal cumulative density function). This is the same transformation that it is used in the calculation of the EDF, and thus, the transformed DI, i.e. the z(t), can be directly compared to the EDF measure that represents our benchmark.

2.3 Moody's Expected Default Frequencies (EDF) and Altman's Z-Score

EDFs are computed on a daily basis by Moody's for a large set of firms worldwide and for a number of predictive horizons. The computation of the EDF is based on the Merton (1974) model whereby a firm is classified as defaulting when the market value of its assets drops below its liabilities over a pre-specified interval of time. The key ingredients of this model are the current market value of the firm, the level of the firm's obligations and the assets' volatility. Using these three variables, it is possible to compute the distance to default − expressed in units of asset volatility − and further the EDF, i.e. the likelihood that the asset value falls below the value of outstanding debt over the chosen time interval. Note that while Moody's computes EDFs based on the model just described, it makes proprietary adjustments to some of the model's ingredients, such as allowing for various classes and maturities of debt, making use of its historical default database to estimate the empirical distribution of changes in distance to default or carrying out adjustments to the accounting information used to calculate the value of the liabilities. Figure 3, lower panel, evidences a positive and monotonic relationship between the EDF measure and subsequent firms' default.

Coming to the other indicator of firm's weakness, i.e. the Altman Z-score, it is computed following Altman (1968). In particular, for firm i, the indicator is defined as:

$$Z_i = 1.2 * X_{i,1} + 1.4 * X_{i,2} + 3.3 * X_{i,3} + 0.6 * X_{i,4} + 1.0 * X_{i,5} \quad (1)$$

Where for each firm i, $X_{i,1}$ = working capital / total assets, $X_{i,2}$= retained earnings / total assets, $X_{i,3}$= earnings before interest and taxes / total assets, $X_{i,4}$= market value of equity / book value of total liabilities and $X_{i,5}$= sales / total assets. All balance sheet variables come from the Compustat Global database and the market value of equity comes from Thomson Reuters Datastream.

2.4 Control variables

For the econometric analysis in Section 4 we make use of a number of covariates in the regressions. These include the 3-month Overnight Index Swap rate, the return on the Eurostoxx600 index, euro area investment grade corporate bond spreads, the VIX volatility index, total firm's assets, equity to assets ratio and market capitalization. All data is retrieved from Eikon.

3 Cumulative Accuracy Path

The first predictive ability test we employ is the so-called Cumulative Accuracy Path (CAP), which is based on the cumulative probability of default (using our proxy) of the entire population of firms, where the population is ordered from riskiest to safest according to the observed metric of interest (EDF or DI).[5] These cumulative probabilities of default are compared to those generated by a random forecast. The CAP is commonly used by banks and regulators to analyze the discriminatory ability of rating systems that evaluate credit risks. In particular, it is one of the key measures used by Moody's to benchmark their credit default forecasts (Sobehart et al. (2000)). Figure 4 shows CAP curves for the 3-month and 1-year predictive horizon, respectively. Both the EDF and the DI have forecasting power for strongly negative equity returns (our proxy for default) over a short horizon (3 months). As can be seen in Figure 4 both predictors forecast 3-month-ahead defaults significantly better than a random forecast.

However, EDFs appear less informative for longer predictive horizons while the DI metric maintains its forecasting properties to a large extent over the longer horizon. While both indicators lose forecasting power at the 1-year horizon, the DI maintains its predictive ability to a higher degree than the EDF (as can be seen by the EDF-based curve lying somewhat below

[5] To better explain the test, for a given fraction x of the total number of observations, the CAP curve is constructed by calculating the percentage y of the defaulters whose risk score is equal to or lower than the one for the fraction x. A good model concentrates the defaulters at the riskiest scores and therefore the percentage of defaulters identified, reported on the y-axis on the Chart showing the test, is expected to increase quickly as one moves along the x-axis. If the model assigns risk scores in a random way we would expect a 45-degree line outcome. So models whose CAP curve lies above the 45-degree line improve predictability over a random model.

the corresponding curve for the DI in Figure 4). Both predictors, however, still fare better than a random classification of defaults. Despite its widespread use for credit default measures assessment, CAPs present several shortcomings. First, they are an ordinal measure and thus do not allow for estimating risk based on a standalone number. Second, the time aggregation embedded in a CAP does neither allow to control for time varying factors nor to perform a multivariate analysis. Third, it is not possible to precisely quantify the economic significance of the results. For these reasons in the next section we employ a formal econometric analysis as our main tool to evaluating the DI as a measure for predicting future firms' defaults.

4 Hazard Models

We employ a Cox proportional hazard model to assess if and to what extent EDFs and DIs are statistically relevant in explaining our proxy of corporate default. In this context, we will also compare how the two predictors fare in relation to each other. Hazard models have been extensively used in the literature on corporate defaults and are considered one of the main reduced-form tools used to forecast defaults, as shown in Shumway (2001), Chava and Jarrow (2004) and Campbell et al. (2008).[6] In this class of models, the so-called hazard rate $\lambda(t)$, i.e. the probability of default at time t conditional on survival until time t, is

$$\lambda(t) = \theta(t)[exp(x(t)\beta)] \tag{2}$$

where the term $exp(x(t)\beta)$ allows the expected time to default to vary across firms according to covariates and $\theta(t)$ is the baseline hazard rate, which is common to all firms. As already detailed, our sample comprises all publicly listed firms in the euro area between January 1999 and July 2020. As is customary in the literature, we exclude financial firms from our sample[7]. While our initial dataset contains 7490 unique firms that have been listed at some point during our sample period, we do not have an EDF or DI observation for all our firm-months observations, thus leading to a reduction in the total amount of data points.[8] First, we estimate our model separately for EDFs and DIs. We run different specifications in which we add further controls

[6]Further, Bauer and Agarwal (2014) find that hazard model with time-varying covariates provide a superior performance compared to static accounting based models.

[7]The existing literature on corporate defaults excludes financial firms because default in this industry is usually treated differently from other industries

[8]In total, we have 571,069 month-firm EDF observations and 410,560 month-firm DI observations.

each time we estimate the model. As explained in Section 2, we employ a different set of market-based and accounting covariates, in order to check other possible factors that could jointly explain firm' defaults. We then also pool together the EDF and DI to check whether one variable dominates the other in a horse-race regression. In this specification, we also add the same controls used before.

In our analysis we test the predictive ability of EDFs and DIs at two different horizons, 3 months and 12 months ahead, in order to detect variations in the predictive content of these variables as the forecasting horizon changes. Therefore, all our results report regressions where the EDF and DI indicators are always lagged, by 3 or 12 months, compared to the observed default. One of the key assumptions of the Cox model is the proportional hazard function assumption. This assumption states that each covariate has a multiplicative effect in the hazard function that is constant over time. Our covariates are all time-varying, but we also test whether or not the proportionality assumption underlying the hazard models is respected. If not, this would mean that the impact of some covariates is not constant through our sample but varies with time. We test this assumption by looking at scaled Schoenfeld residuals. We reject the null hypothesis of proportionality for the EDF variable ($\chi^2 = 12.06$, p-value=0.0005), while we accept the null for the DI indicator ($\chi^2 = 0.54$, p-value=0.46). We also show the scaled residuals in Figure 5, where a non-random increasing pattern across our sample can be observed for the EDF. We address this issue with the standard procedure in the literature, by adding an interaction term between the EDF and time in our regressions.

4.1 Hazard model results

Table II shows the hazard ratios obtained when we study the explanatory effect of the EDF on our measure of corporate default. We run the same model on two different time horizons (3 and 12 months) to also test if the explanatory power of the EDF changes over different time frames. Columns 1 and 4 report univariate regressions at both predictive horizons. Further, the other columns report multivariate estimates, once we control for several market and accounting variables that might help forecast corporate bankruptcies. In the case of the EDF, the interpretation of the hazard ratios is not straightforward, as the effect of the EDF on corporate defaults changes over our sample due to the interaction term of this variable with time. More specifically, the impact of this variable increases with time. The value of the hazard ratio in

Column 1 (1.069) means that a unit increase in the EDF increases the probability of default by 6.9 percent in the first period of our sample. This effect then rises up to 12 percent at the end of the sample (i.e. as: $exp^{(log(1.069)+260*log(1.0002))}$). The coefficient of the EDF is significant in all our estimations at the 3 months horizon, even when the model is estimated with different sets of controls.

The coefficients associated with the EDF are more than halved relative to their 3-months value when we look at the 12-months horizon. Moreover, once we add all our controls to the regression estimates the EDF turns out to be not significant (Column 6 of Table II). Overall, this suggests that the explanatory power of the EDF decays at longer horizons, while it seems to be useful as a predictor at the shorter 3-month horizon. It is also important to note that most of our control variables are significant and with the expected sign. For example, increases in the 3-month yield and in the corporate bond spread increase the probability of a default, while an increase in leverage increases the probability of adverse outcomes at both horizons, even though not significantly. At the same time, higher market returns and bigger firm size are associated with lower default probabilities.

Table III reports estimates for the same Cox model as shown in Table II, but based on the DI indicator. In this case our estimates find that the DI measure is highly significant at both horizons, even after adding all the market and accounting based controls previously considered. Most importantly, the magnitude of the coefficient is twice as large for this variable relative to the comparable EDF coefficient[9] (1.14 vs 1.064) at the 3-months horizon. The result is even more striking once we look at a longer horizon, where the coefficient associated to the DI is very similar to the one presented for the 3-month ahead regression, while the comparable EDF coefficient is not significant and very close to one.

Finally, we compare the performance of the EDF with our own DI measure in horse-race regressions, to check whether or not one of the measures dominates the other as a predictor of corporate defaults. The results are shown in Table IV. Our simple DI measure dominates the EDF, both with and without controls. The EDF coefficient is very close to one and not significant in any of the regressions, thus implying a very small effect on corporate defaults, as the DI leads to a strong decline in the significance of the EDF coefficient in all the specifications where the two variables are present. If we focus on the regressions where we do not employ

[9]The two variables are directly comparable as both our EDF and DI measure track a probability of default over a particular horizon

any controls, an increase by 1 unit in the DI measure implies an increase in the probability of default by 15 and 14 percent at the 3- and 12-month horizon, respectively. At the same time, the EDF coefficient implies an increase in bankruptcy' probability of 0.6 percent 3-month ahead, and even a negative effect one year ahead. This finding is also confirmed once we add all the controls used before in the regression.

We also test whether or not another traditional indicator such as the Altman Z-score possesses any explanatory power for corporate defaults. We report the results of such regressions in Table V. While the Altman Z-score appears marginally significant at 10 percent when used alone in a regression, its magnitude is negligible compared to the DI and EDF variables. In fact, a rise of 1 unit in this variable would increase the probability of default by 0.5% 3 months ahead. Further, the variable becomes insignificant when we add the controls used in the previous regressions. In the last two columns we also add the EDF and DI as further controls, and we show that the DI keeps its magnitude and significance even in this specification.

We conduct a couple of robustness checks on our main result. First, we run the Cox model using a DI measure that is computed by looking at equity returns realized over a quarter of daily data rather than over a month, as is the case in our baseline. We report these results in Table VI. Similarly to our previous results, our DI measure is economically and statistically significant in all specifications. At the same time, when we run horse-race regression between the EDF and this version of the DI, the EDF is not significant at both horizons. However, the magnitude of the hazard ratios for the quarterly DI at the 12-months horizon are smaller compared to our preferred monthly DI measure (1.068 compared to 1.15 when we add all controls). This might signal that computing the DI using a longer time period, and thus more dated values of equity returns, might decrease its forecasting power at longer horizons.

Second, we exclude firms whose equity price does not move during 20% or more of the trading days in the sample. These can be reasonably identified as low-liquidity stocks with a significant fraction of stale prices. The conclusion of our analysis still holds for this smaller sample, as reported in Table VII.

These findings, combined together, allow us to draw the following conclusions. First, EDFs do have some predictive ability for corporate defaults, but mostly at short horizons. This fact seems to confirm the results obtained from the cumulative accuracy paths presented in the previous section. Second, our DI measure is significant as a predictor of bankruptcies at both short and longer horizons, and its magnitude is bigger than the estimated coefficients for the

EDF. This is a striking result, as the EDF is usually considered a benchmark when predicting future corporate distress and default. At least for the sample and the set of euro area firms we look at, this is clearly not the case, as our simple DI measure outperforms the EDF.

4.2 Out-of-sample forecasts

In this sub-section we evaluate the forecasting performance of the indicators in an out-of-sample exercise, following Bharath and Shumway (2008) in the particular type of exercise performed.

Columns 2 through 5 of Table VIII report the out-of-sample predictive ability of our two main indicators of interest. In order to perform this test, we proceed as follows. First, for each month, we sort firms in EDF and DI deciles. Then, we count the number of defaults that occur within each decile in the following 3 and 12 months, for each of the two indicators. For example, at the 3-months horizon 54% of defaulted firms were in the highest two deciles of the EDF distribution, while this number increases to 71.5% when we sort firms according to their DI. This percentage decreases to 49% and 64% at the 12-months horizon, respectively. Remarkably, the DI measure shows better results than the EDF at both horizons, which seems to confirm the in-sample results presented before and based on hazard models.

Further, we also test the out-of-sample properties of our Cox model estimates. We first estimate our Cox model[10] up to December 2007, and then sort our firms into deciles according to their predicted hazard ratio. Next, we compute how many defaults happen at the 3 and 12-months horizon (outside our estimation window) for each decile of our predicted hazard ratio. We then repeat this process by re-estimating the model adding one more period to the estimation sample and sorting again firms according to our estimated hazard rations. We proceed this way until we reach the end of our sample.

Columns 6 through 9 of Table VIII report the results of this exercise. They show that the DI has a better out-of-sample predictive ability compared to the EDF. In fact, the percentage of defaults observed in the last two deciles of the DI is 10 percentage points higher than the EDF at the 3-month horizon (77% compared to 67%) and 12 percentage points higher at the 12-months horizon, even if both numbers understandably decrease when we look at a longer horizon. It appears that the DI, once again, outperforms the EDF at both short and long horizons even when we look at the out-of-sample performance of these variables.

[10] We run model (1) and (4) of II for the EDF and model (1) and (4) of Table III for the DI

5 Aggregate data results

As pointed out in the previous sections, the DI indicator can be easily computed for listed firms from their return volatility. This feature is especially attractive as it avoids resorting to expensive or non-timely information, as is the case with the proprietary EDF data or with balance sheet indicators, the latter only available with a significant delay. The DI therefore provides a quick-to-compute and reliable assessment, as our findings so far have evidenced, about the fragility of a given firm. [11]

In this section we aim to transpose the good default forecasting performance of the DI - evidenced through our granular analysis - to aggregate data, thus aiming to check whether the information content of the DI still remains valid in this lower frequency setting. The aggregate setting is particularly relevant for the macro-finance literature as well as, for example, for applications evaluating the effect of monetary policy shocks on corporations and ultimately on key macro variables. Indeed, in this Section we also show how the DI could be employed to inform policy, by assessing the impact of the non-standard policy measures put in place by the Eurosystem since the burst of the COVID-19 pandemic on the fragility of listed firms.

Specifically, we include the median DI and EDF values for euro area firms into a monthly VAR together with the euro area industrial production index (IP), the VIX volatility index, the corporate (BBB rating) bond spread for euro area non-financial corporations (SP) and the default rate (DR) for euro area non-financial speculative grade corporations, as computed by Moody's. Our specification has six lags for the vector Y(t) = [DR(t), IP(t), SP(t), DI(t), EDF(t), VIX(t)]. We order the variables by the speed with which they react to the information flow, with the default rate being the slowest - as empirically it takes time for firms to go bankrupt after a given shock - and the VIX being the fastest. The main results of the VAR estimation are highlighted through the impulse response functions (IRF) of the corporate default rate, which are identified through a Choleski factorization of the covariance matrix based on ordering the six variables in Y(t) as described above. Focusing on the response of the euro area DR to the four financial shocks (i.e. a spread shock, a DI shock, an EDF shock and a VIX shock) Figure 6 shows that the corporate bond spread and DIs shock have similar effects on the default rate. The latter rises almost monotonically over time and the increase remains always significant in the case of the non-financial corporate bond spread and significant from around 6 to 12 months

[11] In addition, DIs can be computed at a daily frequency so even from this standpoint there is no loss of information relative to the EDFs.

after the shock in the case of the DI. Interestingly, the response of the default rate to a DI shock is significant despite the DI being ordered after the corporate spread, indicating that its explanatory power is not fully subsumed by the spread. By contrast, the IRF of the DR to a EDF and a VIX shock is rather flat or decreasing across time and remains significant only for around half a year after the shock. Overall these findings confirm the results based on firm-level data, i.e. that the information in the DI cannot be subsumed by other relevant financial indicators and that the best strategy from a forecasting standpoint is to consider such pieces of information jointly, as they convey different information across forecast horizons.

Further, we consider whether it remains true that the information content of the DI is comparable or better than the EDF at the aggregate level. To this end we employ again the VAR described above and perform the forecasting ability comparison test proposed by Diebold and Mariano (1995)). We estimate two versions of the VAR, the first one with the following five variables: the default rate, the industrial production index, the VIX, the corporate bond spread and the EDF. In our second specification the EDF is replaced by the DI. The two models are estimated from January 1999 on expanding samples, the first of which ends in January 2005. We look at forecast horizons between 1 and 12 months. Table IX shows the mean absolute error (MAE) for the two VAR models at four horizons together with the Diebold and Mariano test. This test is the t-stat of the intercept in a regression of the difference in the absolute values of the errors between the competing models, and a constant. Overall, with the exception of the 1-month horizon, the VAR which includes the DI shows a smaller error in predicting default rates relative to the VAR that instead includes the EDF, the difference being statistical significant as indicated by the test. Hence, the evidence from macro data seems to largely support our previous findings based on granular data, as the DI turn out to be preferred as predictor of aggregate default rates at all relevant horizons.

5.1 A policy application during the COVID-19 crisis

To illustrate how the information contained in the DIs can be used to characterise the effect of non-standard policy measures on the financial fragility of non-financial corporations, we use the VAR model described above to run a counterfactual exercise. We focus on the initial period of the COVID-19 pandemic, in which default rates remained largely subdued in partly thanks to the sizable monetary policy easing put in place by central banks across the globe. To put the exercise in context, it may be worth recalling that the unfolding of the COVID-19 pandemic since early 2020 had a significant impact on the euro area (as well as the global) economy and to counter its effects the European Central Bank (ECB) started the pandemic emergency purchase programme (PEPP) in March 2020. The PEPP is a temporary asset purchase programme of private and public sector securities. Eligible assets for purchasing include sovereign bonds, corporate bonds and asset-backed securities. Sovereign bonds represent the lion's share of the purchases. The programme was designed in order to counteract an unwarranted tightening of financial conditions and to support a smooth transmission of monetary policy. The PEPP was originally allocated 750 euro billion for asset purchases and later increased by 600 euro billion in June 2020 and by an additional 500 euro billion in December 2020 to a total of 1850 billion.

With this in mind, our policy application will be based on comparing the actual developments in DIs to three counterfactual paths that assume i) no policy support, i.e. no PEPP-related bond purchases at all, ii) purchases limited to what contained in the initial decision taken by the Eurosystem (March 18th 2020) and iii) support limited to what was initially decided plus the June 2020 Governing Council decision. In order to run this exercise we first translate the amount at disposal for purchases into a counterfactual 10-year interest rate and a counterfactual VIX value, and subsequently into a counterfactual DI value. The VIX is chosen as an instrument to this aim as it measures equity market volatility, which is basically the same type of information underlying the DI. More specifically, we employ the policy shocks identified in Altavilla et al. (2019) in a daily VAR to compute the response of 10-year OIS rates to such shocks. We cumulate these shocks over an horizon of one month. The impulse response functions of the VAR are also used to measure the cross-elasticity of the VIX with respect to the OIS. With these pieces of information we can compute the counterfactual development of the OIS 10-year rate, and therefore of the VIX, given the estimated cross-elasticity, relative to a situation where the policy shock (the amounts to be purchased) would have not been observed. Last, we transform the counterfactual values of the VIX into the DI counterfactual path by using the same percent deviations between the actual and counterfactual VIX values. [12] The VAR is estimated until March 2020 and from that date on we run three counterfactual exercises based on three different DI paths, each of them reflecting one of the three different hypotheses specified above for the amounts of bond purchases. The exercise is run up to July 2022 by using an unconditional DI forecast from the VAR (estimated up to July 2021) and then computing counterfactual DI paths between August 2021 and July 2022 in the same way as was done before April 2020 and July

[12]We thank Giulio Nicoletti for these computations.

2021.

Figure 7 shows the actual default rate values up to July 2021 and its unconditional forecast from the VAR, alongside with the three counterfactual default rate paths. Overall, if PEPP-related purchases would have not been implemented at all, default rates would have peaked at around 7 percent instead of the realised 5 percent. Further, the default rate path would have been persistently higher throughout the entire anaysed period. The other two counterfactual paths lie between the no-PEPP case and the actual default rate and overall show that all decisions taken by the Eurosystem to step up the PEPP did indeed contribute to alleviate the weight of the financial shock on the set of euro area non-financial firms.

6 Conclusion

We have analysed whether a simple measure of insolvency - called Distance to Insolvency (DI) and based on the inverse of the equity return's volatility - can anticipate corporate defaults as accurately as, or better, than the commonly used Moody's Expected Default Frequency (EDF) indicator for a large set of euro area firms since 1999. We explore both the firm-level dimension and aggregate data. Overall we find that, using Cox's hazard rate regressions, our simpler distress indicator performs better than the EDF, controlling for a number of covariates, especially at longer horizons. We show that the DI performs better than the EDF in forecasting corporate defaults also in an out of sample exercise. At the aggregate level, the DI shows once again superior forecasting power compared to the EDF, for horizons between 3 and 12 months. Lastly, we use the DI measure to simulate the evolution of corporate defaults during the COVID-19 crisis if the Eurosystem had not implemented the Public Emergency Purchase Program.

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7 Figures

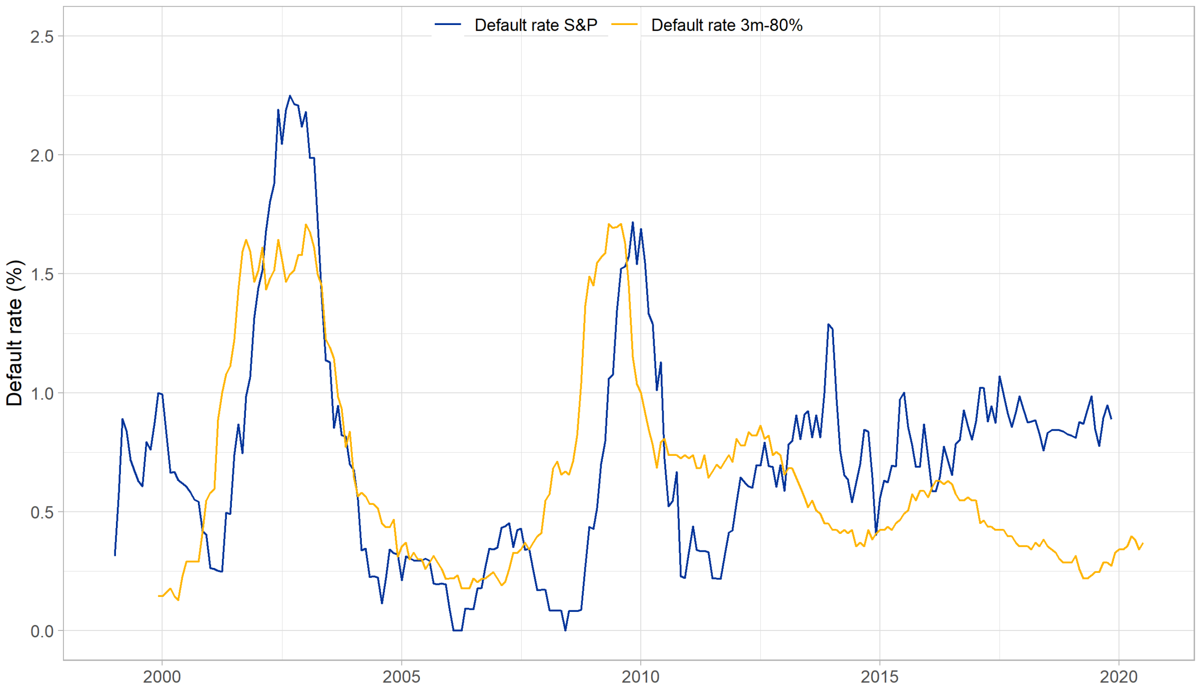

Figure 1: Cumulative 12-month trailing default rates
Default rates from S&P show the 12-month trailing default rate for European non-financial firms provided by S&P. Default 3m-80% shows the 12-month trailing default rate computed based on assigning default to firms which see an 80% or more decline in their stock price in a time interval of 3 months.

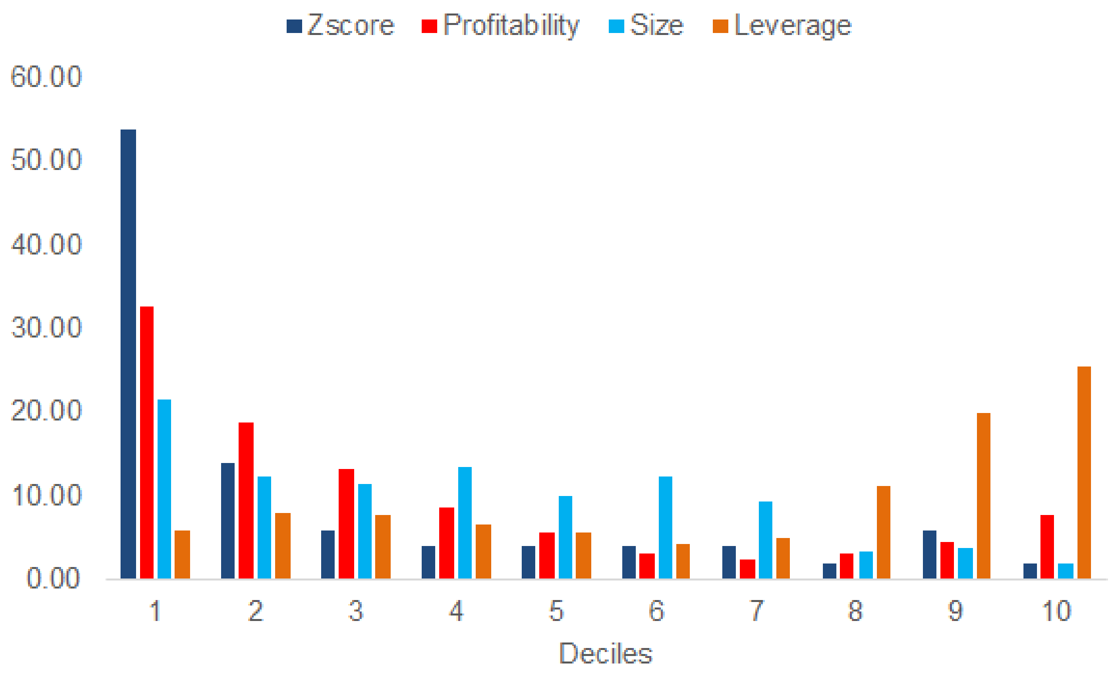

Figure 2: Number of observed defaults and firm characteristics
The chart shows the balance sheet characteristics of defaulted firms in our sample. Firms are splitted in deciles. We count the relative number of defaults in each decile of the variables over the total. Zscore is the Altman Z-score. Profitability is EBIT/total sales. Size is the logarithm of total assets. Leverage is calculated as (1 - book equity/total assets).

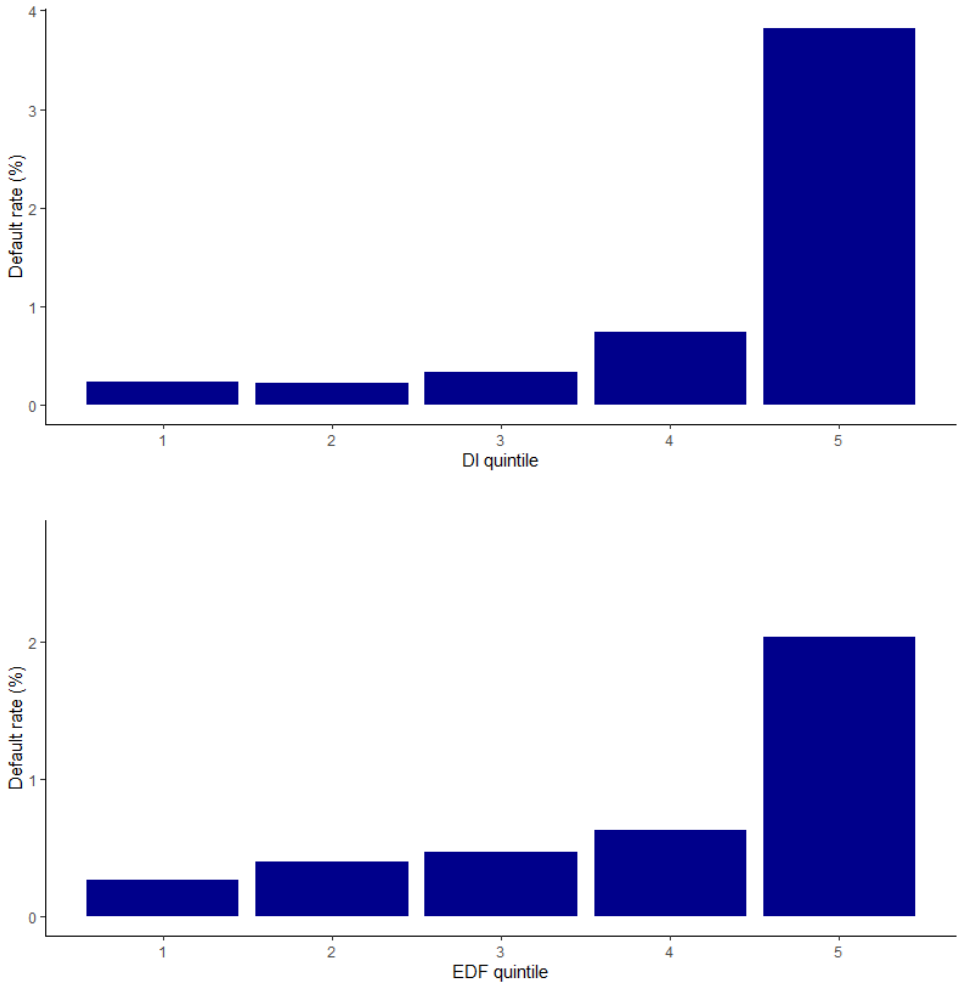

Figure 3: Default rates by DI and EDF quintiles
Bars show default rates (computed based on assigning default to firms which experience an 80% - or larger - decline in their stock price in a time interval of 3 months) for the group of firms classified in each EDF or DI quintile based on the full sample (1999-2020).

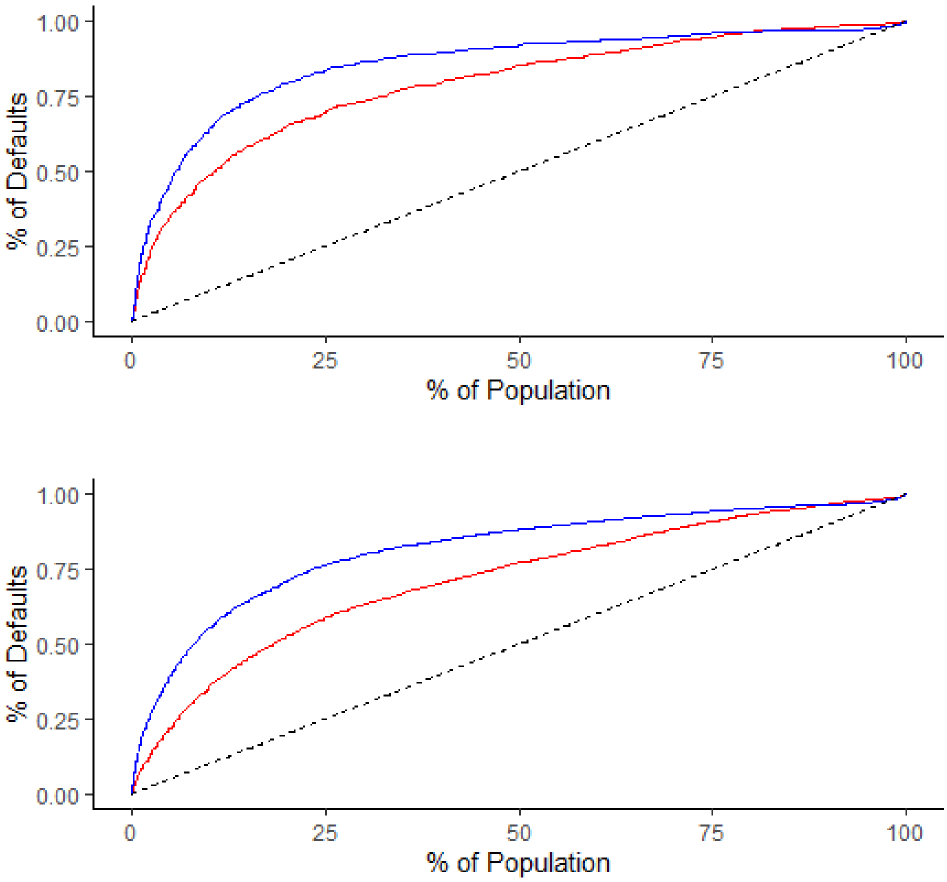

Figure 4: Cumulative Accuracy Paths (3- and 12-month ahead)
Based on default events (computed based on assigning default to firms which experience an 80% - or larger - decline in their stock price in a time interval of 3 months) in the full sample (1999-2020). The CAP curve shows the percentage of the defaulters whose risk score (EDF or DI) is equal to or lower than the one for the fraction x in the population, where the population is ordered from most to least risky based on the particular measure. The upper panel shows the CAP 3-month ahead, while the lower panel shows the 12-month ahead CAP.

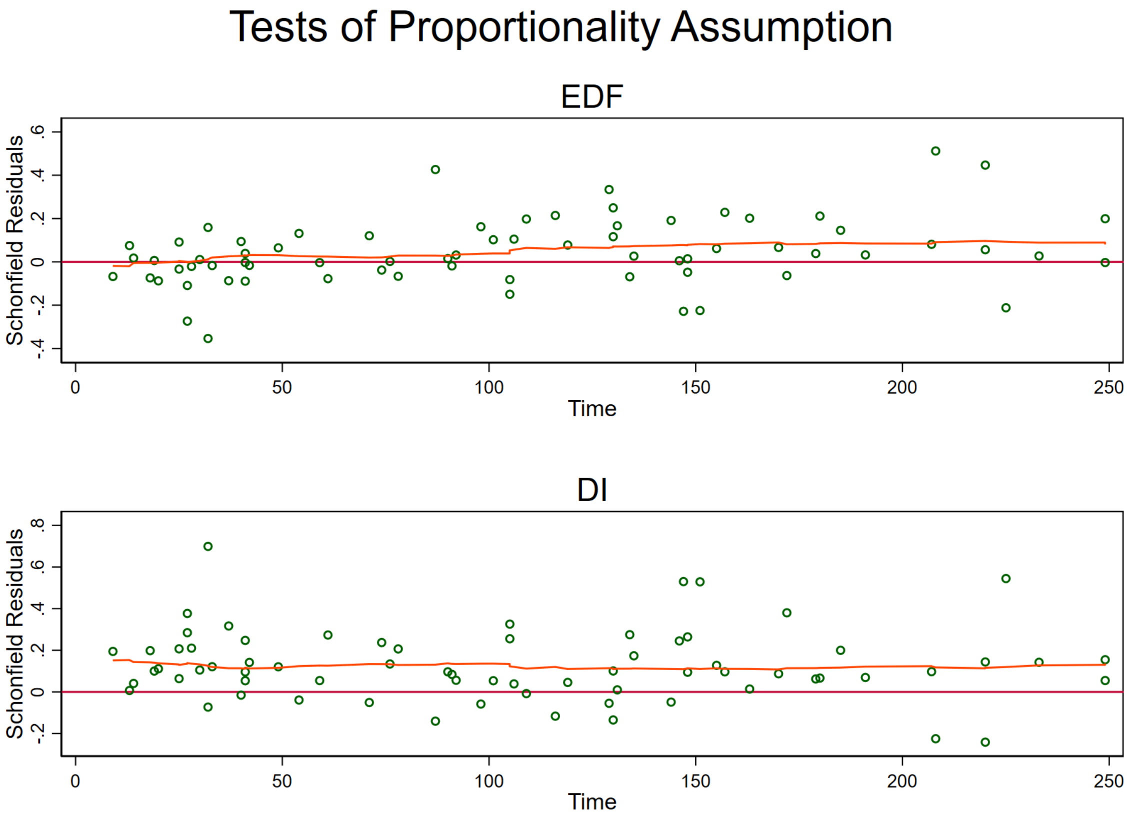

Figure 5: Proportionality Assumptions

The chart shows the results of the test on the proportionality assumption by using scaled Schoenfeld residuals on function of time in hazard models. A non-zero slope is an indication of a violation of the proportional hazard assumption.

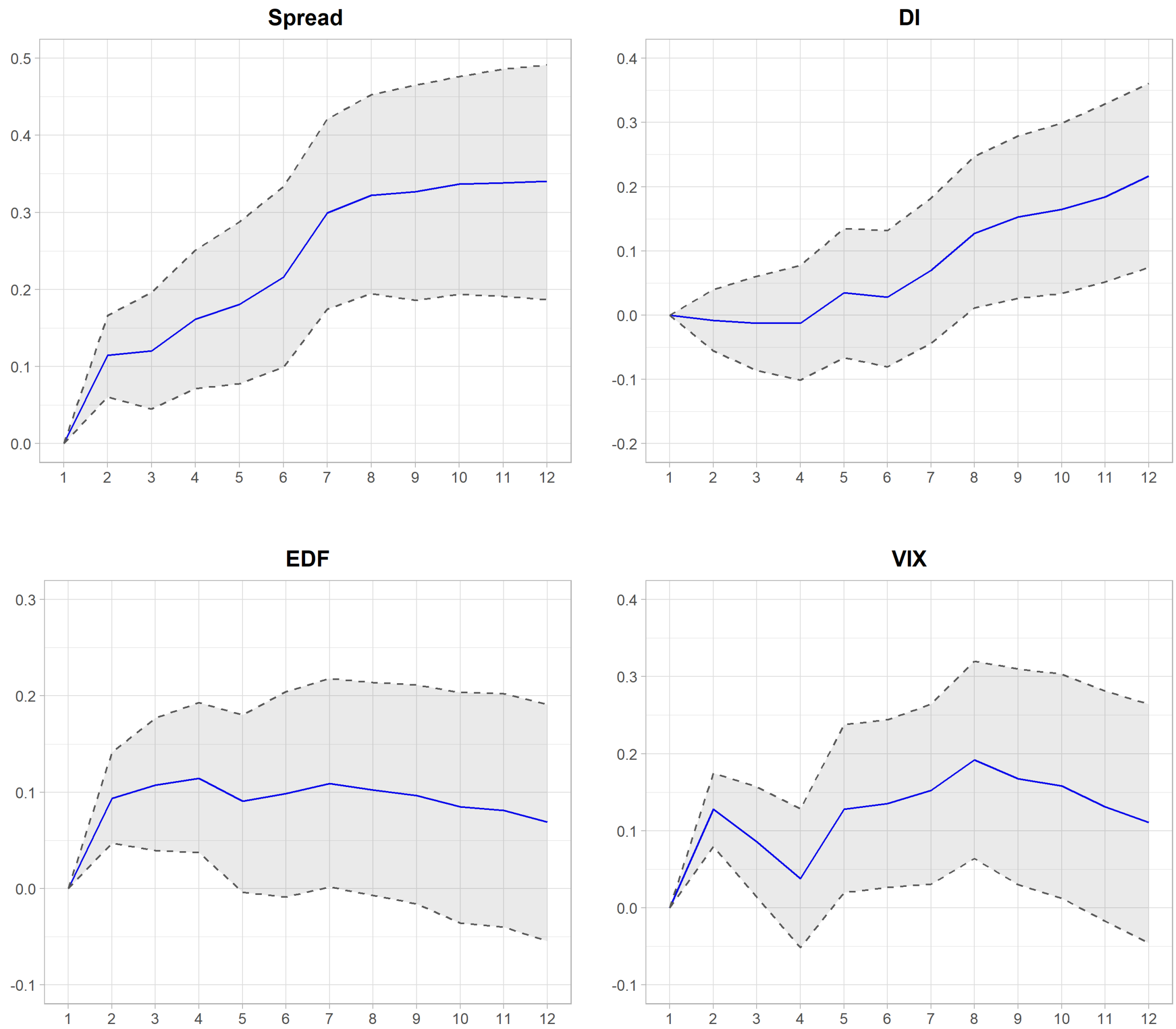

Figure 6: Impulse Response Functions
The chart shows the dynamic response of actual default rates of euro area non-financial speculative grade corporations to four shocks identified from a monthly VAR: a bond spread shock, a VIX shock, an EDF shock and a DI shock. Shocks are identified via a Choleski factorization of the VAR's covariance matrix. The x-axis denotes months after the shock.

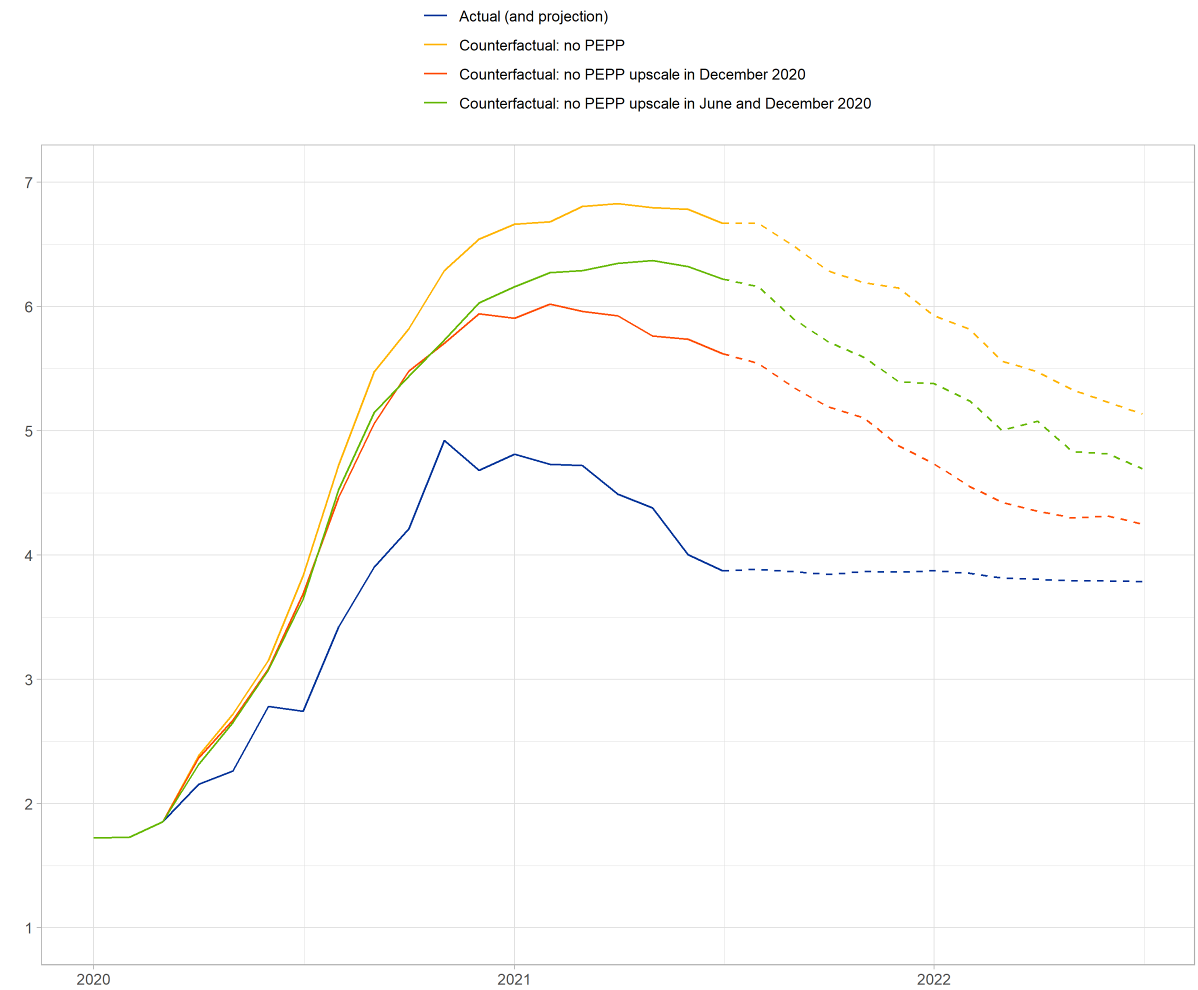

Figure 7: The effect of PEPP on mitigating corporate defaults
The chart shows actual and counterfactual default rates for euro area non-financial corporations. The counterfactuals are all based on simulations performed via a monthly VAR model and start in April 2020, each of them reflecting different assumptions about the amount of PEPP purchases carried out at selected points in time. Actual default rates are projected beyond July 2021 using the unconditional forecast from the VAR.

8 Tables

Table I: Summary Statistics
The table shows the summary statistics for the main variables in our study. 3-month returns are the firm-specific 3-month equity returns, DI is the modified distance to insolvency, EDF is the expected default frequency, Market Return is the 3-month return of the Eurostoxx 600, 3m OIS is the 3-month OIS rate, Corporate Spread is the overall spread between government bonds and investment grade corporate bonds (bps), VIX Index is the log of the VIX index, Size is the log of total assets (€bn), leverage is total liabilities/total assets, Market cap is the total market capitalisation (€mn) and Z-score is the Altman Z-score. The sample period is January 1999-July 2020.

	Mean	**Std. dev.**	**Min**	**0.25**	**Median**	**0.75**	**Max**
3-month return (%)	0.26	21.5	-62.50	-10.07	0.00	8.59	112.69
DI	1.91	4.74	0	0.0001	0.056	1.20	48.77
EDF	2.89	5.97	0.01	0.13	0.53	2.53	50.00
Market Return	0.004	0.08	-0.35	-0.03	0.01	0.05	0.31
3m OIS	1.59	1.71	-0.50	0.05	1.2	3.16	4.91
Corporate Spread	89.82	45.51	26.64	61.37	81.73	104.75	241.87
VIX Index	19.89	8.14	9.51	14.02	17.75	23.65	59.89
Size	5.45	2.63	-6.31	3.63	6.90	12.84	20.28
Leverage	0.57	0.23	0	0.41	0.59	0.75	1
Market cap	1381.87	5766.70	0	19.97	85.92	458.42	203511.8
Z-score	1.90	9.56	-4.72	0.54	1.16	2.12	981

Table II: Cox model estimates for Expected Default Frequency
The table shows the hazard ratio estimates obtained by the Cox proportional hazard model. The dependent variable is the time to default. T-stats are reported in square brackets. Standard errors are clustered at the firm level. Hazard ratios in bold are significant at the 5% level. EDF*Time is an interaction term in which the Expected Default Frequency is multiplied by Time. A hazard ratio above one implies an increase in the probability of an adverse outcome for an increase of one unit in the underlying explanatory variable. Likewise, a hazard ratio below one implies a reduction in the probability to observe a default.

	Expected Default Frequency					
	3M	**3M**	**3M**	**12M**	**12M**	**12M**
	(1)	(2)	(3)	(4)	(5)	(6)
EDF	**1.069**	**1.077**	**1.064**	**1.026**	**1.030**	1.011
	[13.8]	[11.34]	[5.02]	[3.32]	[2.76]	[0.52]
Mkt return		**0.065**	**0.024**		**0.050**	**0.030**
		[-4.33]	[-3.43]		[-3.52]	[-3.36]
3m yield		**1.654**	**1.608**		**1.689**	**1.762**
		[8.64]	[5.14]		[8.38]	[5.42]
Corporate Spread		**1.009**	**1.012**		**1.013**	**1.012**
		[4.92]	[2.73]		[5.47]	[3.14]
VIX index		**0.966**	0.982		**0.966**	0.975
		[-2.91]	[-1.10]		[-2.84]	[-1.44]
EDF*Time	**1.0002**	**1.0001**	**1.0005**	**1.0004**	**1.0004**	**1.0007**
	[3.25]	[1.87]	[4.13]	[7.24]	[5.85]	[7.56]
Size			**0.75**			**0.73**
			[-4.99]			[-5.15]
Leverage			1.98			3.01
			[1.20]			[1.84]
Market cap			0.99			1.00
			[-0.51]			[0.50]
Obs	621,710	409,267	134,275	572,595	388,864	127,857

Table III: Cox model estimates for the Distance to Insolvency

The table shows the hazard ratio estimates obtained by the Cox proportional hazard model. The dependent variable is the time to default. T-stats are reported in square brackets. Standard errors are clustered at the firm level. Hazard ratios in bold are significant at the 5% level. A hazard ratio above one implies an increase in the probability of an adverse outcome for an increase of one unit in the underlying explanatory variable. Likewise, a hazard ratio below one implies a reduction in the probability to observe a default.

	Distance to Insolvency					
	3M	**3M**	**3M**	**12M**	**12M**	**12M**
	(1)	(2)	(3)	(4)	(5)	(6)
DI	**1.15**	**1.16**	**1.14**	**1.16**	**1.15**	**1.14**
	[24.62]	[22.38]	[11.09]	[24.58]	[20.35]	[10.83]
Mkt return		**0.06**	**0.05**		**0.02**	**0.03**
		[-3.25]	[-2.39]		[-4.20]	[-2.76]
3m yield		**1.35**	**1.26**		**1.30**	**1.31**
		[5.09]	[2.46]		[3.95]	[2.82]
Corporate Spread		1.02	1.01		**1.01**	1.00
		[1.75]	[1.06]		[2.52]	[0.59]
VIX index		**0.96**	0.98		0.98	0.99
		[-2.67]	[-0.77]		[-1.32]	[-0.19]
Size			0.85			**0.83**
			[-1.79]			[-2.12]
Leverage			2.32			2.77
			[1.39]			[1.63]
Market Cap			1.00			1.00
			[-0.76]			[0.33]
Obs	393,623	245,317	109,522	364,168	235,513	106,601

Table IV: Cox model estimates for horse-race regressions between EDF and DI

The table shows the hazard ratio estimates obtained by the Cox proportional hazard model. The dependent variable is the time to default. T-stats are reported in square brackets. Standard errors are clustered at the firm level. Hazard ratios in bold are significant at the 5% level. EDF*Time is an interaction term in which the Expected Default Frequency is multiplied by Time. A hazard ratio above one implies an increase in the probability of an adverse outcome for an increase of one unit in the underlying explanatory variable. Likewise, a hazard ratio below one implies a reduction in the probability to observe a default.

Horse-Race Regressions				
	3M	**3M**	**12M**	**12M**
	(1)	(2)	(3)	(4)
DI	**1.150**	**1.136**	**1.141**	**1.108**
	[11.73]	[5.71]	[10.03]	[3.90]
EDF	1.006	0.972	0.990	1.000
	[0.55]	[-1.19]	[-0.42]	[0.13]
Mkt return		**0.062**		**0.042**
		[-2.00]		[-2.36]
3m yield		**1.33**		**1.35**
		[2.79]		[2.94]
Corporate Spread		1.006		1.005
		[1.10]		[1.00]
VIX index		0.98		0.99
		[-0.70]		[-0.22]
Size		0.87		**0.79**
		[-1.48]		[-2.87]
Leverage		1.83		2.20
		[0.88]		[1.38]
Marketcap		1.00		0.99
		[-0.57]		[-0.56]
EDF*Time	**1.0004**	**1.0006**	**1.0004**	**1.0007**
	[5.19]	[3.18]	[3.10]	[6.58]
Obs	390,804	86,783	363,662	83,541

Table V: Cox model hazard ratios for Altman's Z-score

The table shows the hazard ratio estimates obtained by the Cox proportional hazard model. The dependent variable is the time to default. T-stats are reported in square brackets. Standard errors are clustered at the firm level. Hazard ratios in bold are significant at the 5% level. A hazard ratio above one implies an increase in the probability of an adverse outcome for an increase of one unit in the underlying explanatory variable. Likewise, a hazard ratio below one implies a reduction in the probability to observe a default.

	Z-Score			
	3M	**3M**	**12M**	**12M**
	(1)	(2)	(4)	(5)
Z-score	**0.995**	0.999	0.995	0.999
	[-1.68]	[-0.22]	[-1.35]	[-0.35]
Mkt return		0.14	0.21	0.20
		[-1.52]	[-0.62]	[-0.68]
3m yield		**1.41**	1.41	1.39
		[2.82]	[1.39]	[1.31]
Corporate Spread		1.005	0.998	0.997
		[0.87]	[-0.16]	[-0.16]
VIX index		1.001	0.956	0.958
		[0.03]	[-0.76]	[-0.73]
Size		1.05		1.11
		[0.70]		[0.95]
Leverage		2.41		1.90
		[1.25]		[1.90]
Market cap		1.00		1.00
		[-1.02]		[-0.57]
DI			**1.14**	**1.15**
			[3.88]	[4.54]
EDF			1.03	1.03
			[0.74]	[0.95]
Obs	40,005	33,835	18,672	18,008

Table VI: Cox model hazard ratios for modified DI variable

The table shows the hazard ratio estimates obtained by the Cox proportional hazard model. The dependent variable is the time to default. T-stats are reported in square brackets. Standard errors are clustered at the firm level. Hazard ratios in bold are significant at the 5% level. A hazard ratio above one implies an increase in the probability of an adverse outcome for an increase of one unit in the underlying explanatory variable. Likewise, a hazard ratio below one implies a reduction in the probability to observe a default. This modified version of the DI is estimated with quarterly equity returns.

	Quarterly DI measure					
	3M	3M	3M	12M	12M	12M
	(1)	(2)	(3)	(4)	(5)	6)
DI	**1.14**	**1.118**	**1.101**	**1.130**	**1.068**	1.047
	[18.63]	[6.15]	[2.94]	[16.22]	[3.02]	[1.65]
Edf			1.040			1.015
			[1.390]			[0.580]
Mkt return		**0.081**	0.088		**0.065**	**0.057**
		[-1.76]	[-1.61]		[-1.96]	[-1.92]
3m yield		1.138	1.16		1.17	1.248
		[1.02]	[1.07]		[1.23]	[1.59]
Corporate Spread		0.996	0.995		0.998	1.001
		[-0.53]	[-0.71]		[-0.22]	[0.12]
VIX index		1.022	1.027		1.022	1.017
		[0.84]	[0.98]		[0.9]	[0.63]
Size		**0.804**	**0.820**		**0.745**	**0.739**
		[-2.58]	[-1.96]		[-4.08]	[-3.75]
Leverage		1.843	0.682		3.505	2.535
		[0.77]	[-0.41]		[1.44]	[0.88]
Market cap		0.999	0.999		0.999	1.000
		[-0.31]	[-0.24]		[-0.27]	[-0.15]
Obs	155,186	94,157	94,157	160,096	95,460	91,802

Table VII: Cox model hazard ratios for DI variable of more liquid firms

The table shows the hazard ratio estimates obtained by the Cox proportional hazard model. The dependent variable is the time to default. T-stats are reported in square brackets. Standard errors are clustered at the firm level. Hazard ratios in bold are significant at the 5% level. A hazard ratio above one implies an increase in the probability of an adverse outcome for an increase of one unit in the underlying explanatory variable. Likewise, a hazard ratio below one implies a reduction in the probability to observe a default. The sample includes only more liquid stocks in which equity prices move at least during 80 percent of trading days.

DI measure excl. less liquid firms				
	3M	3M	12M	12M
	(1)	(2)	(3)	(4)
DI	**1.13**	**1.12**	**1.13**	**1.06**
	[9.99]	[4.79]	[9.73]	[2.90]
EDF	1.00	0.98	0.99	1.02
	[-0.34]	[-0.88]	[-0.75]	[1.01]
Mkt return		**0.04**		**0.05**
		[-2.36]		[-2.27]
3m yield		**1.35**		**1.36**
		[2.89]		[3.03]
Corporate Spread		1.00		1.00
		[0.27]		[0.22]
Vix Index		1.00		1.00
		[-0.20]		[0.12]
Size		0.89		**0.83**
		[-1.27]		[-2.08]
Leverage		2.01		1.67
		[0.96]		[0.73]
Marketcap		1.00		1.00
		[-0.74]		[-0.65]
Observations	342,210	211,247	320,506	205,102

Table VIII: Defaults by EDF and DI decile and out-of-sample forecasts
The table reports the fraction of defaults that correspond with each decile of the forecast variable. The last row sums up the last two deciles for each variable. Columns 2-5 report the share of defaults corresponding each EDF and DI deciles 3 and 12-months before the default took place. Columns 6-10 report out-of-sample forecasts for the models in Columns 2 and 5 of Tables 2 and 3, respectively. In particular, the columns show the share of defaults corresponding to each decile of the predicted hazard ratio, estimating the models first up to December 2007 and then repeating the process adding one more month at a time to the estimation until the end of the sample

	3m		12m		3m		12m	
Decile	EDF	DI	EDF	DI	EDF model	DI model	EDF model	DI model
1	3.8	4.2	4.7	4.2	3.6	2.4	6.1	3.1
2	4.3	1.7	5.3	2.7	3.6	2.2	6.0	2.0
3	4.3	1.7	5.6	1.2	2.7	1.6	4.9	1.7
4	4.0	1.4	4.5	1.2	4.1	1.1	3.2	3.4
5	3.8	2.0	5.6	3.0	1.8	1.6	3.9	3.4
6	5.4	3.1	7.0	7.8	2.3	1.1	8.3	6.4
7	7.5	6.8	7.9	6.9	6.8	6.6	8.2	6.8
8	12.1	7.6	10.1	9.6	9.0	6.4	8.4	10.2
09-10	54.7	71.5	49.0	64.0	67.0	77.0	51.0	63.0

Table IX: Diebold Mariano tests
The table shows the results of the Diebold Mariano test to check the predictive ability of the EDFs and the DIs for the defult rate (DR) of euro area non-finacial corporations. The test is based on DR projections obtained from two non-nested VAR models estimated on expanding samples. The DM test is performed as the t-stat of the intercept in a regression of the difference in mean absolute errors (MAE) between the two competing VAR model and a constant.

	MAE EDF	**MAE DI**	**DM-test (t-stat)**
1-month horizon	1.38	1.27	-0.79
3-month horizon	6.10	5.03	-1.92
6-month horizon	20.16	15.50	-2.67
12-month horizon	99.96	74.78	-2.09