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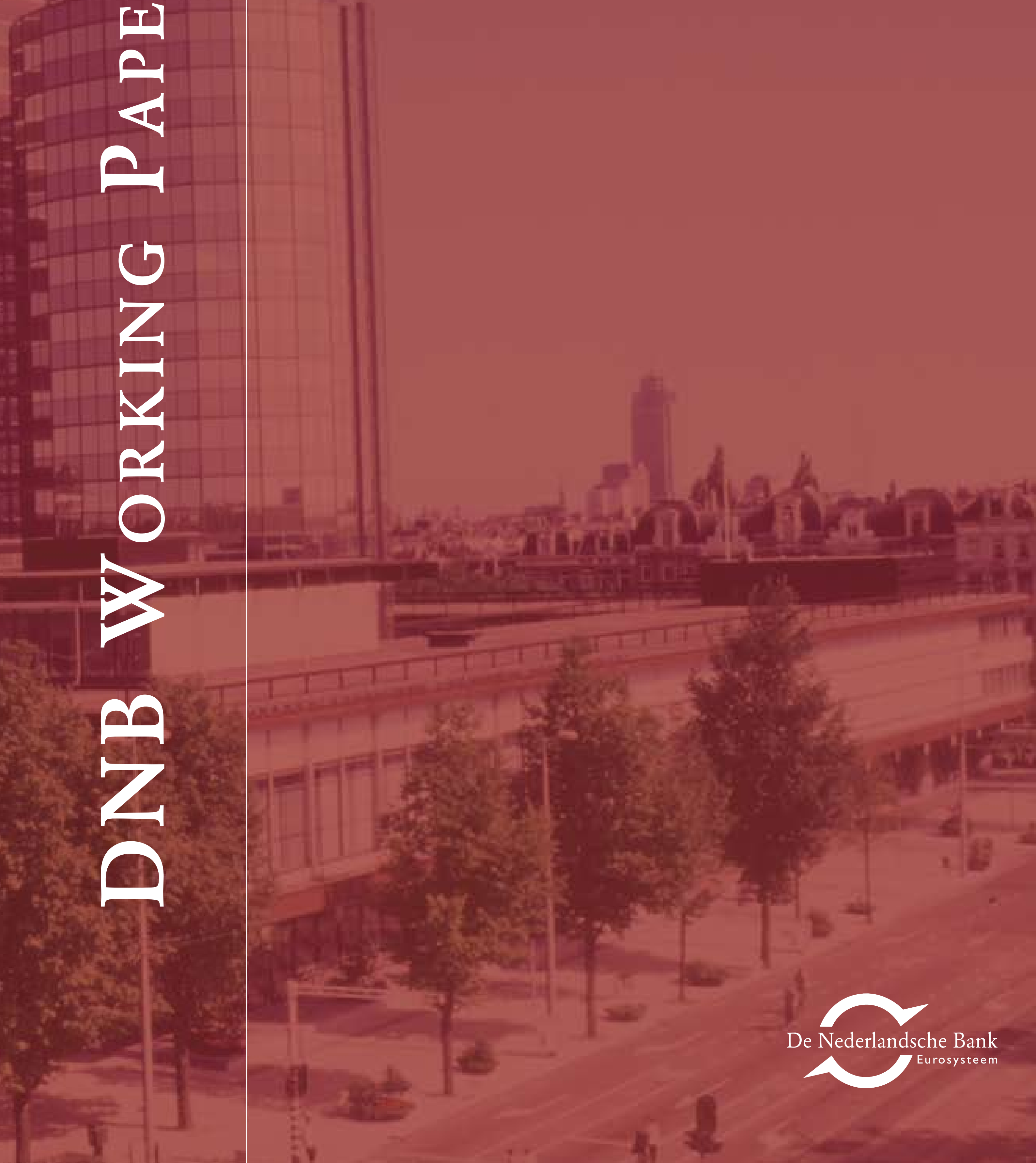

De Nederlandsche Bank
Eurosysteem

Modelling Industry-level Corporate Credit Risk for the Netherlands

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* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

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Abstract

This paper examines corporate credit risks in the Netherlands at the industry-level, addressing two key questions. First, to what extent are corporate credit risks driven by idiosyncratic financial factors or systematic macroeconomic factors? Second, did debt financing in the late 1990s indeed push a large number of firms into bankruptcy in the subsequent years? To this end, bankruptcy rates are regressed on a number of industry-specific financial ratio's and macroeconomic variables in a panel-regression framework covering six industries from 1992 to 2005. I find that an industry's bankruptcy rate rises with an increase in leverage and a decrease in profitability and liquidity. Adding macroeconomic variables shows that lower GDP growth, higher interest rates, and an appreciating currency raise credit risks. Applying a model with parameter heterogeneity illustrates that systematic factors primarily account for the overall rise in bankruptcy rates between 2000 and 2003, but that idiosyncratic factors dominate in the worst-affected industries. This includes the IT industry where the build-up of debt was most pronounced and compounded losses.

* Ruud Vermeulen (rvermeulen@imf.org) drafted this paper while he was employed at De Nederlandsche Bank in the Financial Stability Division. The views expressed in this paper are those of the author, and do not necessarily reflect those of De Nederlandsche Bank. All remaining errors are mine. The author would like to thank the participants of DNB's Research Group on Financial Stability for their valuable comments on an earlier version. In particular, the author would like to thank Jan-Willem van den End and Ronald Bosman for sharing their views in many stages of this project and Mostafa Tabbae for his research assistence.

1 Introduction

The recent credit crisis demonstrates the relevance to financial stability of credit risk in general and of its proper assessment by creditors and investors. While its origin lies in the failure to accurately appreciate mortgage credit risk, neglected corporate credit risk has equally been at the root of a number of financial crises and may well have been underestimated as well in the preceding years of cheap money. Corporate credit risk may rise or fall with changes in profitability, liquidity, and solvency of firms that satisfy their financing needs on money and capital markets. It will materialize if firms fail to meet their obligations and default on their debt. If unanticipated and systemic, a rising number of corporate defaults may threaten financial stability.[1] Modelling corporate credit risks should therefore be a key ingredient of financial stability analyses.

Aside from the credit crisis, corporate credit risk models have gained interest for two reasons. First, concerns have risen with respect to corporate re-leveraging. Cautiously raising external finance as the economic upturn gained momentum in 2005, firms continued to re-leverage even though economic prospects have deteriorated and credit standards have tightened. This may predict defaults to rise in the medium term. Second, modelling credit risks gained relevance as banks move to weighting assets by risk under Basel-II. Banks' internal rating-based models are (to be) validated and scrutinised by supervisory authorities, requiring them to be, at the minimum, familiar with credit risk models.

By estimating how financial ratios at the industry level and macroeconomic variables at the country level (idiosyncratic and systematic factors, respectively) contribute to corporate bankruptcy rates, this paper addresses two issues relevant to financial stability. First, can corporate credit risks effectively be mitigated by diversifying credit portfolios across industries? That depends on the default correlation between industries, which in turn depends on the degree to which industries are vulnerable to systematic factors. Second, to what extent does an increase in leverage raise corporate credit risk? Identified as the main culprit of rising corporate defaults after the IT bubble burst in the early 2000s, the relative contribution of leverage to the surge in bankruptcy rates in the Netherlands has not been tested empirically. Moreover, doing so allows us to substantiate recent concerns on corporate re-leveraging. Finally, while not addressed in this paper, modelling corporate credit risk to determine how changing financial and macroeconomic conditions affect bankruptcy rates may facilitate estimating the potential second-round effects of the recent credit crisis.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 specifies our model, presents the regression results, and tests the robustness of the preferred credit risk model. Section 4 applies that model to the latest default cycle, identifying the most relevant factors behind the run-up in default rates. Finally, the main findings are summed up in Section 5.

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[1] Basel-II dictates unexpected losses to be covered by regulatory capital and expected losses to be covered by loan loss provisioning. A bank's resilience to shocks is determined by its solvency, which may be impaired if *un*expected losses affects its capital adequacy or expected losses that are not adequately provisioned for do materialize (i.e. underprovisioning). Such losses entail a systemic risk if they accumulate for a (large) number of (large) banks.

2 Literature review of corporate credit risk models

This section presents a brief overview of the existing approaches to and empirical literature on modelling corporate credit risk. The aim is not to provide an extensive literature review rather than to position our model relative to existing empirical models.

2.1 Approaches to modelling credit risk

Corporate credit risk models can broadly be classified into two classes: *market-based* and *fundamentals-based* models (Chan-Lau, 2006). Market-based models typically build on Merton's option pricing theory (1974) to estimate the probability that a firm's creditors execute their claim against the firm's assets. In these models, the probability of a firm's net worth (market value of assets minus book value of liabilities) becoming negative for a given stock price and volatility determines its probability of default (PD). The high frequency of market data, allowing up-to-date estimates of PDs, and the forward-looking nature embedded in market data that capture market participants expectations explain the wide-spread interest in these models. Moody's KMV model (2001) and IMF's contingent claims approach (Gapen *et al.*, 2004) are both examples of market-based models that are applied by a growing number of policymakers in financial stability analyses.[2] Hillegeist *et al*. (2004) and Tudela and Young (2003) show that market-based models outperform fundamentals-based models in terms of accuracy. A major drawback of the market-based approach, however, is that it can only be applied to listed firms, which typically have different characteristics (e.g. access to bank credit, market discipline and scrutiny, regulation) and therefore tend to behave differently from non-listed firms. Moreover, while listed firms typically represent a significant share of total employment, they often cover a minor share of the total number of firms.[3] Therefore, many practitioners view market-based models as complementary to rather than a substitute for fundamentals-based models.

Fundamentals-based models derive corporate default probabilities from macroeconomic conditions, firms' financial statements, or credit rating information. Within this class, Chan-Lau (2006) distinguishes four approaches to model PDs: the *macroeconomic-based*, *accounting-based*, *ratings-based*, and *hybrid* models. Macroeconomic-based models explain PDs out of macroeconomic conditions, typically including both cyclical and financial market indicators (e.g. GDP growth, output gap, interest rates and security prices and volatility, respectively). Some macroeconomic-based models explicitly allow for spill-over effects between financial and real variables and feedback effects between these variables and PDs. For instance, following agency cost theory, an increase in interest rates raises a firm's cost of capital by more than the increase due to the negative effect on that firm's net worth, which raises its external finance premium (Bernanke and Gertler, 1989, 1996). Similarly, a

[2] Within DNB, Van den End and Tabbae (2006) developed an indicator for financial stability following Moody's KMV approach (see DNB working paper No. 30: *Measuring financial stability: applying the MfRisk model to the Netherlands*).

[3] For instance, in the Netherlands in 2006 stock market data are available for some 150 firms (± 90 of which non-financial) that only represent about 0.02% of all registered firms that are economically active in the Netherlands (±750,000).

low PD signals to creditors that a firm is in good shape, allowing it to borrow at favourable conditions. Accounting-based models use firms' financial ratios to explain changes in PDs. These ratios usually include profitability, liquidity, leverage, and debt service indicators. Ratings-based models include credit rating information of credit registries or agencies. By observing downgrades for a given credit rating and period of time, the implicit PD can be derived as the share of downgrades in the total number of corporate bonds outstanding. Finally, hybrid models blend the explanatory variables included in the models discussed. For a more detailed overview of these four kinds of fundamentals-based models and their characteristics, see Chan-Lau (2006).

2.2 Empirical applications

An overview of some recent empirical applications of fundamentals-based models is presented in Table 1. While this overview is largely confined to models developed by central banks, numerous models have been developed before by market participants. Large banks, for instance, often use their own vendor models for internal credit risk modelling. Renowned examples of such models include CreditportfolioView/McKinsey, CreditMetrics/JP Morgan, and the Altman Z-score (macroeconomic-based, ratings-based and accounting-based models, respectively). However, for reason of conciseness, this section only discusses models developed by central banks.

An example of a macroeconomic-based model is the one developed by Vlieghe (2001). He finds that an increase in leverage, real interest rates, and real unit wages raises the economy-wide PD, while an increase in real GDP reduces it. The model developed by Virolainen (2004) includes an industry-specific debt ratio, but is set up as a macroeconomic-based model. He estimates PDs at the industry-level by regressing an industry-specific macroeconomic index (a logit-transformed inverse default rate) on a number of variables. He shows that an industry's PD rises with an increase in that industry's indebtedness and a widening output gap. Finally, both studies include a dummy variable to control for bankruptcy law.

Clearly, these macroeconomic models, using aggregated data only, are not well-suited for including firms' financial ratios as determinants of credit risk. Firms' behaviour is largely treated as an exogenous factor, with failures primarily resulting from changing macroeconomic conditions. By contrast, models that use disaggregated, firm-level data incorporate firms' behaviour by including financial ratios that approximate e.g. firms' investment and financing decisions. Examples of such models are the accounting-based models of Lennox (1999) and Bunn and Redwood (2003). They use financial ratios of UK firms to assess the variation in PDs in a qualitative dependent variable regression framework (i.e. probit and logit). Both studies confirm that an increase in profitability and liquidity lowers a firm's PD, while an increase in leverage raises it. Also, both studies include a dummy variable for firm size and find that large firms have lower PDs than small firms. Due to the limited number of macroeconomic variables included in the empirical analyses, these studies can be classified as accounting-based, rather than hybrid models.

Table 1 Applications of fundamentals-based PD-models

		macroeconomic-based models				*accounting-based models*				*hybrid model*
		Vlieghe (BoE, 2001)		Virolainen (BoF, 2004)		Lennox (1999)		Bunn (BoE, 2003)		Jacobson *et al* (Riksbank, 2005)
Estimation method		least squares		logit		probit/logit		probit		logit
Dependent variable		change in PD		index$_j$ inversely related to PD$_j$		default status of firm i [2]		PD		default status of firm i [2]
Explanatory variables	sign	variable	sign	variable	sign	variable	sign	variable	sign	variable
Financial ratios			-	debt$_j$ to value added$_j$	-	sales to receivables	-	gross profit to interest payments	-	EBITDA to total assets
			+	dummy$_{9303}$*(debt$_j$ to value added$_j$)	-	quick ratio	+	debt to assets (DTA)	+	total liabilities to total assets
					-	gross cash flows [3]	-	current ratio	-	liquid assets to total liabilities
					+	capital gearing [4]	+	dummy$_{PROFM_NEG}$ [7]	+	inventories to total sales
					-	return on capital [5]	+	dummy$_{PROFM_S}$ [8]	+	total liabilities to total sales
							+	dummy$_{PROFM_M}$ [9]	+	interest payments to EBITDA
							+	dummy$_{LLF}$ [10]	-	dummy$_{PAYDIV}$ [14]
							-	dummy$_{SUBS}$ [11]		
							-	dummy$_{LS}$ [12]		
Other idiosyncratic variables					+/-	dummy$_j$ [6]	+/-	dummy$_j$ [6]	+	dummy$_{PR}$ [15]
					-	number of employees	-	number of employees	+	dummy$_{TA}$ [16]
Macro variables	+	PD	+	output gap	-	number of bankruptcies	-	GDP growth rate	-	output gap
	-	net debt to GDP	-/+	nominal interest rate	-	change in business confidence			-	inflation
	-	output gap	-	dummy$_{9303}$ [13]					+	nominal interest rate
		real input prices	+	dummy$_{9303}$*output gap					-	real exchange rate
	+	real unit wages	-	dummy$_{9303}$*real interest rate						
	+	real interest rate								
		nominal interest rate								
		birth-rate of new firms								
		non-res. real estate prices								
	-	dummy$_{86}$ [1]								
Sample characteristics										
time dimension		1975Q1-1999Q1		1986Q1-2003Q2		1987-1994		1991-2001		1990Q1-1999Q2
cross section dimension				industries j = 1 .. 6		listed firms i = 1..949		firms i = 1 .. 105,687		firms i = 1 .. 250,000
country		UK		Finland		UK		UK		Sweden

[1] dummy for 1986 Insolvency Act from 1986 onwards
[2] non-bankrupt (0); bankrupt (1)
[3] EBITDA to (capital employed + current liabilities - intangibles)
[4] debt to (capital employed + s.t. borrowing - intangibles)
[5] EBIT to (capital employed + s.t. borrowing - intangibles)
[6] dummy for industry j
[7] dummy for gross profit margin < 0
[8] dummy for 0 < gross profit margin < 0.03
[9] dummy for 0.03 < gross profit margin < 0.06
[10] dummy for loss-making leveraged firms ($D_{PROFM\_NEG} = 1$ and DTA > 0.35)
[11] dummy for subsidiaries
[12] dummy for loss-making subsidiaries ($D_{PROFM\_NEG} = 1$ and $D_{SUBS} = 1$)
[13] dummy for change in bankruptcy law from 1993Q1 onwards
[14] dummy for paying out dividends
[15] dummy for payment remark
[16] dummy for tax arrears

NB: For notational convenience, sub-marks i and t, as well lags have been excluded.

An example of a hybrid model is that of the Sveriges Riksbank (Jacobson *et al.*, 2005), in which both financial ratios and macroeconomic variables are used to estimate firms' PDs. Jacobson *et al*. (2005) confirm previous findings on the relationship between a firm's PD and its profitability, liquidity, leverage, and debt service costs, as well as the output gap and interest rate. Inflation and real exchange rates are also included as explanatory variables, but only the latter proved to be significant. While the model that only includes financial ratios performs rather poorly relative to the one including both financial ratios and macroeconomic variables, Jacobson *et al*. (2005) show that omitting financial ratios from the latter model lowers the explanatory power of their default model by some 30%. Hence, the hybrid structure succeeds to raise the accuracy of the PD-model.

3 An industry-level credit risk model for the Netherlands

In this section, an industry-level credit risk model for the Netherlands is introduced, using both financial ratios and macroeconomic variables. The rationale for applying a hybrid model is twofold. First, like Jacobson *et al.* (2005), it is expected to raise the model's accuracy. Corporate credit risks do not simply arise from changing macroeconomic conditions, nor are isolated from these, while any stress firms encounter will inevitably be displayed in their financial ratios. Second, it allows us to gauge the extent to which credit risks are driven by common or idiosyncratic factors. The risks to financial stability are likely to be larger if credit risks are primarily driven by the former (Pain and Vesala, 2004; Jacobson *et al.*, 2005). To see why, note that default correlations among firms across industries will be larger the more vulnerable they are to common shocks. The larger default correlations are, the more limited banks' opportunity to diversify credit risks across industries. In our model, systematic risks arise from worsening macroeconomic conditions, while idiosyncratic risks arise from worsening industry-specific financial ratios. In interpreting the results, however, two important caveats should be born in mind. First, systematic and idiosyncratic risks can not completely be isolated due to multicollinearity.[4] Second, the idiosyncratic financial ratios are based on industry-level aggregates that do not allow for an identification of the distinctive characteristics of bankrupt firms relative to non-bankrupt firms. As a result, the significance of the financial ratios is likely to be lower in this model relative to a model based on (truly idiosyncratic) firm-level data.

3.1 Model specification

Following Virolainen (2004), credit risk is modelled by taking the logit-transformed industry-specific default rate as the dependent variable which is assumed to be determined by a number of exogenous

[4] The distinction between systematic and idiosyncratic is somewhat discretionary (and therefore arbitrary). To isolate genuine idiosyncratic risks, a firm-level credit risk model would be more appropriate.

macroeconomic variables capturing the state of the economy. To capture the financial state of each industry, some exogenous, industry-specific financial ratios are added to the model. As such, this approach allows industries to differ not only in terms of their sensitivity to changing macroeconomic conditions, but also in terms of their average balance sheet strength. A logit functional form is preferred here for three reasons. First, it constrains the distribution of estimated PDs between 0 and 1. Second, as the empirical literature has shown, non-linearities are likely to exist between PD and e.g. profitability and leverage ratios.[5] Third, as the logistic distribution has fatter tails than the normal distribution and PDs are known to have a skewed distribution, it seems an appropriate functional form. Using this form, the PD for industry *j* is given by:

$$PD_{j,t}(X_{j,t-L}, Z_{t-L}) = \frac{1}{1+e^{-(\beta' X_{j,t-L} + \gamma' Z_{t-L})}} \quad , \tag{1}$$

in which $\beta' X_{j,t-L}$ and $\gamma' Z_{,t-L}$ capture the financial soundness of industry *j* and overall macroeconomic conditions at time *t-L*, respectively, with *L* acting as the lag operator. The parameters $X_{j,t-L}$ and Z_{t-L} represent vectors of industry-specific financial ratios and macroeconomic variables, respectively (with β' and γ' being vectors of their coefficients). Rewriting equation *(1)* by logit transformation yields:

$$\ln\left(\frac{PD_{j,t}}{1-PD_{j,t}}\right) = \beta' X_{j,t-L} + \gamma' Z_{t-L} \tag{2}$$

To arrive at an estimable regression equation, $X_{j,t-L}$ and $Z_{,t-L}$ need to be substituted for their constituting financial and macroeconomic variables. As discussed in Section 2, the literature shows that profitability, liquidity, and leverage affect firms' PD, for which I choose to include the following ratios: return on assets ($ROA_{j,t-L}$), the current ratio ($CR_{j,t-L}$), and the debt-to-assets ratio ($DTA_{j,t-L}$), respectively. These ratios surfaced in a selection procedure that comprised of assessing candidate variables' co-movement with PDs, both visually and statistically (i.e. correlation coefficients), and the significance of their coefficients in simple univariate and multivariate regression analyses. The presentation and discussion of the selection procedure is beyond the scope of this paper and is therefore omitted here. Table A1 in the Appendix nonetheless shows all variables that have been considered. An additional idiosyncratic variable that we include is the share of large firms active within an industry ($N_{j,t-L}$). Allowing for differences in firm size is consistent with the notion that small firms are more credit-constrained (see Gertler and Gilchrist, 1993, 1994; Freixas and Rochet, 1997).

As a relatively small number of variables qualify for measuring macroeconomic conditions, the macroeconomic variables included in the model have not been subjected to a selection procedure. The growth rate of GDP ($GDPGR_{t-L}$) is our preferred measure of cyclical conditions as output gap definitions are usually based on deviations from some measure of trend or potential GDP, the choice

[5] A nice complementary property, as Lennox (1999) shows, is that it eliminates heteroscedasticity in these models. For a discussion of the choice of the functional form in the presence of non-linearities, see Lennox (1999).

of which is arbitrary in our relatively short sample period. Short-term and long-term interest rates (I_ST_t and I_LT_{t-L}) are included to capture firms' external financing costs, with the latter also capturing expectations for future inflation and GDP growth. Since interest rates show a downward trend as inflation rates have come down, we include these in first differences. The change in equity prices ($\Delta EQPR_{j,t-L}$) is included to capture both business confidence or prospects and equity financing costs. Finally, as the Netherlands is a small open economy, the change in the EUR/USD exchange rate (ΔXR_{t-L}) is included to take firms' competitiveness into account. Rewriting equation (2) yields:

$$\ln\left(\frac{PD_{j,t}}{1-PD_{j,t}}\right)=\beta_0+\beta_1 ROA_{j,t-1}+\beta_2 CR_{j,t-1}+\beta_3 DTA_{j,t-1}+\beta_4 N_{j,t-L}$$
$$+\gamma_1 GDPGR_{t-1}+\gamma_2\Delta I\_LT_{t-1}+\gamma_3\Delta I\_ST_t+\gamma_4\Delta EQPR_{j,t-1}+\gamma_5\Delta XR_{t-1}+\mu_{j,t} \quad (3)$$

where Δ acts as a first-difference operator and $\mu_{j,t}$ denotes a random error term (assumed independent and identically normally distributed). All explanatory variables except the short-term interest rate are lagged by one year for a number of reasons. First, as firms' operational performance typically deteriorates way ahead of a default, let alone court-declared bankruptcy, a lag of one year for the financial ratios seems justified. Second, Dutch Chamber of Commerce data show that firms issue their annual reports with an average delay of 1 to 1.5 years relative to the book year. Using contemporaneous accounting data to assess PDs therefore only includes a small share of the corporate sector at the last observation and is not likely to give representative results. The finding that the financial ratios perform best at a lag of one year in the variable selection procedure supports both points. Third, macroeconomic variables that embody expectations (i.e. I_LT_{t-L}, $EQPR_{j,t-L}$) or only affect PDs after some time (i.e. XR_{t-L} due to the maturity of contracts) should be lagged. The short-term interest rate should not be lagged, as the pass-through to firms' capital cost is nearly instant (see DNB, 2006). Finally, to assess whether our model has any predictive power, and hence can be applied for forecasting, lagging the explanatory variables is inevitable.

3.2 Data

The dataset includes annual data on six industries from 1992 to 2005. The industries are defined in Table A1 in the Appendix. To assess the explanatory and predictive power of cyclical conditions for industry-specific PDs, it is required that the sample includes at least one full business cycle. The sample meets that requirement, as it contains the aftermath of the recession in the early 1990s and a full cycle in the early 2000s. The dependent variable ($PD_{j,t}$) is constructed by dividing the number of firms that went into bankruptcy within an industry by the number of active firms in that industry at time t. The bankruptcy rate is a frequently used proxy for the corporate default rate, which in turn represents the *ex post* corporate default probability. For definitions and sources of the explanatory variables and for the descriptive statistics of the dependent variable and the financial ratios, see Tables A1 and A2 in the Appendix. The financial ratios are derived from aggregated balance sheet and income statement items per industry.[6] Accounting variables are included in ratios rather than levels to avoid econometric problems due to non-stationarity of the variables.[7] Only one of the macroeconomic variables proved non-stationary, which is dropped from the final model presented below. Finally, note that, except for $EQPR_{j,t-L}$, the macroeconomic variables only vary across time.

3.3 Regression results

Noting that substantial cross-industry differences exist in both levels and changes of financial ratios, equation (3) is estimated in a panel least squares regression model with cross-section fixed effects. To arrive at the preferred model, I choose for a "simple to general" model selection procedure, adding explanatory variables one by one, which I deem most transparent. In doing so, I follow a three-step approach. First, a model is estimated that only includes selected financial ratios, which serves as the base model. Second, an idiosyncratic firm-size variable is added to see how this alters the base model results. Finally, macroeconomic variables are added at different lags.

Table 2 Regression output

Dependent variable: $LN(PD_{j,t}/(1-PD_{j,t}))$ Method: Panel Least Squares with cross section fixed effects

Model	1	2	3	4	5	6	7	8	9	10	11
Idiosyncratic Variables											
Constant	-4.10 ***	-5.17 ***	-4.79 ***	-4.16 ***	-4.04 ***	-4.97 ***	-4.48 ***	-4.18 ***	-3.91 ***	-4.20 ***	-3.97 ***
	-5.42	*-5.69*	*-9.25*	*-6.48*	*-10.59*	*-8.89*	*-13.71*	*-13.88*	*-13.09*	*-14.71*	*-14.18*
$ROA_{j,t-1}$	-4.94 ***	-4.04 ***	-4.20 ***	-1.38	-1.54 *	-1.86 **	-2.34 ***	-1.50 **	-1.96 ***	-1.75 ***	-2.16 ***
	-4.23	*-3.27*	*-4.18*	*-1.51*	*-1.95*	*-2.36*	*-3.54*	*-2.40*	*-3.21*	*-3.36*	*-3.76*
$CR_{j,t-1}$	-0.87 ***	-0.70 **	-0.58 **	-0.65 ***	-0.61 ***	-0.40 **	-0.30 *	-0.40 **	-0.55 ***	-0.56 ***	-0.58 ***
	-3.23	*-2.43*	*-2.19*	*-3.24*	*-3.21*	*-2.23*	*-1.80*	*-2.59*	*-3.53*	*-4.43*	*-3.98*
$DTA_{j,t-1}$	1.36	1.34		0.48		1.38 *					
	1.09	*1.05*		*0.54*		*1.76*					
$N\_LET_{j,t-1}$		50.35 **		22.62		22.09 *					
		2.43		*1.53*		*1.69*					
$N\_LET_{j,t-1} * DTA_{j,t-1}$			119.87 ***		52.72 **		62.69 ***	44.36 **	45.40 **	72.50 ***	57.76 ***
			3.55		*2.06*		*2.85*	*2.20*	*2.33*	*4.33*	*3.10*
Systematic Variables											
$GDPGR_{t-1}$				-12.96 ***	-12.46 ***			-6.42 ***	-8.07 ***	-9.76 ***	-7.76 ***
				-8.22	*-7.84*			*-4.06*	*-4.74*	*-6.79*	*-4.87*
$GDPGR_{t-2}$						-12.71 ***	-12.17 ***	-8.70 ***	-8.20 ***	-3.60 ***	-8.03 ***
						-10.13	*-9.86*	*-6.24*	*-5.77*	*-2.72*	*-6.04*
ΔI_LT_{t-1}									0.02 *	0.01	0.02 **
									1.92	*1.19*	*2.10*
ΔI_ST_{t}									0.04 **	0.02 *	0.05 ***
									2.11	*1.96*	*2.91*
$\Delta EQPR_{t-1}$										0.00	
										-0.31	
ΔXR_{t-1}										0.00	0.00 ***
										0.61	*3.07*
R^2	0.65	0.66	0.69	0.84	0.84	0.87	0.88	0.90	0.92	0.95	0.93
R^2 adjusted	0.61	0.61	0.65	0.81	0.82	0.85	0.86	0.89	0.90	0.94	0.91
# OBS	78	72	72	72	72	72	72	72	72	55	72
DW statistic	0.66	0.58	0.59	1.29	1.27	1.37	1.34	1.38	1.53	1.37	1.50
Akaike info criterion	0.01	0.00	-0.11	-0.71	-0.77	-0.95	-1.02	-1.23	-1.33	-2.04	-1.45
F-statistic	16.16	13.36	17.29	31.68	36.95	42.01	49.64	57.47	54.70	60.97	58.41

Note: t-statistics are in italic, * denotes significance at a 10% level, ** denotes significance at a 5% level, *** denotes significance at a 1% level

[6] For instance: $DTA_{j,t-L} = \left[\frac{\sum_{i=1}^{n} debt_i}{\sum_{i=1}^{n} assets_i} \right]_{j,t-L}$, where *n* represents the number of firms *i* in industry *j* at time *t-L*.

[7] Unit root tests (see Table A2 in the Appendix) reject non-stationarity for all but one of the included explanatory variables. The leverage ratio is non-stationary. Its explosive behaviour can be explained by the limited number of time-series observations against the background of an exceptional build-up of debt in the late 1990s.

The regression results are presented in Table 2. For a detailed description of the regression output, we refer to the Appendix. Model 11 is the preferred one. All variables enter highly significantly with the expected signs, thereby outperforming the other models. The model explains over 90% of the variation in PDs. Having included a number of macroeconomic variables also reduced serial correlation. Note that the Durbin-Watson statistic indicates that the initial models suffer from serial correlation, obscuring the interpretation of the coefficients somewhat. This is not a major concern, as the dependent variable does not show a trend, mitigating the underestimation of error terms. The decline in serial correlation once macroeconomic variables are added, indicates that the error term initially captures the explanatory power of omitted variables such as those related to cyclical conditions. With a Durbin-Watson statistic of 1.5, model 11 is no longer subject to serial correlation.

To summarize the results, I find that an industry's average default rate rises with an increase in corporate indebtedness conditional on the relative firm size in that industry and a decrease in profitability and liquidity. While these idiosyncratic financial ratios capture an industry's financial soundness and hence creditworthiness rather well, some 30% of the variation in PDs across industries and time is left unexplained. This drops to less than 10% once common macroeconomic variables are added. The results show that cyclical conditions have a relatively large effect on PDs. Not surprisingly, if GDP growth accelerates fewer firms will encounter stress. At the same time, as the output gap closes and the economy approaches its capacity limits as witnessed by rising inflation and inflation expectations and hence interest rates, the improvement in firms' creditworthiness will start levelling off. Finally, a depreciating EUR/USD exchange rate improves an industry's competitiveness, and as such lowers its PD. The results compare favourably to those of other studies discussed in Section 2. The signs and, to a lesser extent, the relative magnitudes of the coefficients of the included variables are consistent with earlier findings. Like other studies have shown, profitability and output growth are key determinants of firms' default rate. Contrary to other studies, however, leverage only affects firms' default rate if conditioned on firm size. This may be explained by the relatively high level of consolidation and internationalization of the Dutch corporate sector, making Dutch firms relatively less dependent on bank financing. The explanatory power of our hybrid model exceeds that of Virolainen (2004), suggesting that adding industry-specific financial ratios to a credit risk model that only includes macroeconomic variables indeed raises its accuracy. As such, modelling credit risk at the country and industry level in a single model may also enrich macro stress-testing frameworks, which I leave for future work.

3.4 Robustness and model refinement

To verify the robustness of model 11 and to refine it, this section analyses four alternative models that specifically allow for cross-industry disparities in both the constant terms and the coefficients of the explanatory variables (i.e. parameter heterogeneity). Once the fixed effect structure is dropped, model 11 loses more than a third of its explanatory power, while all explanatory variables but profitability and two-year lagged GDP growth turn insignificant. Hence, the industry-specific constant term captures a large share of the cross-industry variation in PDs. Model 12 modifies model 11 by adding industry dummy variables for the debt ratio and GDP growth rate. Next, a similar model is estimated, but without the fixed effects structure (model 13). Finally, I estimate a model without and one with fixed effects that include industry dummies for all explanatory variables except relative firm size (model 14 and 15). For these four alternative models, I choose to include variables only if they enter below a significance level of 5%.

The regression output is reported in Table A3 in the Appendix. The results suggest that model 11 is fairly robust, even though the industry-specific constant terms account for a large share of the model's explanatory power. Nearly all variables retained some explanatory power after allowing for heterogeneity in coefficients as well as foregoing the fixed effect structure. Moreover, the size and sign of the coefficients did not change dramatically. Only in two instances did the sign conflict with expectations. The profitability and liquidity ratios consistently affect PDs for all industries in three out of four models. The significance of the debt ratio varied per industry and specification, but suggested it to be of particular relevance to the transport and catering industries. Lagged GDP growth affects all industries' PDs in all models, albeit with different magnitudes. The other macroeconomic variables, particularly the short-term interest rate and exchange rate, proved somewhat less robust as these did not affect all industries in all models. Indeed, the results demonstrate that credit risk determinants differ significantly between industries. Consistent with earlier findings, industries differ in their vulnerability to rising debt levels and economic downturns. In this regard, particularly the transport and catering industries are outliers. Finally, the results show that allowing for a more tailored specification further raises the explanatory power of our model. The explanatory variables included in model 15 succeed to explain about 95% of the variation in PDs. Moreover, they apparently eliminated any residual serial correlation.

The model that allows for parameter heterogeneity better captures bankruptcy rate dynamics at the industry level. This can also be demonstrated by plotting estimated PDs against actual PDs, which is done for model 11 and model 15 in figure A1 in the Appendix. It clearly shows that the fitted PD values derived from model 15 deviate less, in terms of level and direction, from the actual PDs than those derived from model 11. Given that it outperforms model 11, model 15 is subsequently selected as our preferred model. Moreover, as Pesaran *et al.* (2004) demonstrate, allowing for parameter heterogeneity better captures tail behaviour in credit loss distributions, which nicely suits our needs.

4 Application to the latest default cycle in the Netherlands

A decomposition of industry-specific PDs into its determinants facilitates assessing the relative contribution of these to the latest run-up in PDs. Due to the logit-transformed specification only the *change* in PDs can be decomposed into its determinants. Using model 15, the contribution of macroeconomic variables and financial ratios to the change in PDs will be analyzed. Subsequently, the effect a change in PDs has on banks' balance sheets is assessed by calculating expected loan losses and decomposing the change in these into their determinants. In doing so, this section aims to address two questions. First, did the deterioration in common macroeconomic or industry-specific financial conditions primarily cause the surge in corporate defaults rates in 2000-2003? This question is relevant in determining the relative risks to banks' balance sheets and financial stability. Second, did debt financing in the late 1990s indeed have a major effect on the collapse of a large number of firms in the subsequent years, as has often been argued? This question is particularly relevant for the transport industry, as that includes the IT industry that was at the core of the latest default cycle.[8]

4.1 The blame game: macroeconomic vs. financial conditions

The first question can be addressed by decomposing the percent change in PDs into their two classes of determinants, i.e. financial ratios and macroeconomic variables. Figure A2 in the Appendix shows that credit risk in the manufacturing, construction, trade, and catering industries is primarily driven by overall macroeconomic conditions, whereas credit risk in the transport and services industries is primarily driven by industry-specific financial ratios. Focussing on the 2000-2003 downturn, the cumulative contribution of worsening macroeconomic conditions to the increase in estimated PDs in equals about 95-100% for the manufacturing, construction, trade, and catering industries. For the transport and services industries, this share equals roughly 50% and 40%, respectively. Hence, the deterioration in macroeconomic conditions primarily caused the surge in PDs in 2000-2003.

Falling GDP growth accounts for the bulk of this surge. The downturn that started in 2001 and saw GDP growth plunge from about 4% at the turn of the century to virtually 0% in 2002-2003, in 2003 accounts for a 25% increase in the PD of the trade industry up to a nearly 60% increase in that of the catering industry. Cyclical conditions thus weigh heavily on firm performance. Notwithstanding some heterogeneity in industries' cyclical sensitivity, this does not explain why deteriorating macroeconomic conditions push far more firms into bankruptcy in one industry than the other. Even though macroeconomic factors may primarily drive PDs, idiosyncratic financial factors may still account for actual default. For instance, Lopez (2004) finds that firms' default correlation negatively relates to their PDs, implying that idiosyncratic factors become more important the closer a firm moves to default. Similarly, Bakshi *et al.* (2004), using bond spreads to capture credit risk, find that idiosyncratic factors are relatively more important for low-grade bonds.

To assess how worsening common macroeconomic and idiosyncratic financial conditions affect banks' balance sheets, the expected losses (EL) during 2000-2003 can roughly be estimated

[8] Statistics Netherlands groups firms active in transport, storage, and communication together in a single industry, in accordance with SBI classification (see Table A1 in the Appendix). The variables used in the model are only reported at this level of aggregation.

using model 15. Unfortunately, data on how bank loans are distributed over Dutch industries are not available. Moreover, banks only report loan loss provisions (LLP) made for EL on their entire credit portfolio, making it difficult to disentangle their corporate credit loss expectations. Nonetheless, given that changes in corporate credit quality predominantly determine banks' LLP, changes in EL derived from our model can be compared with the reported changes in banks' LLP. Expected loan losses are derived by taking:

$$EL = PD * LGD * EAD \tag{4}$$

Assuming a constant loss given default (LGD) of 50%[9], EL can be calculated by multiplying the estimated PDs by half of total debt outstanding (i.e. exposure at default, EAD).[10] This gives an EL of about EUR 2.8 billion at the peak of the default cycle, in 2003.[11] In 1999, when the bankruptcy rate stood at its lowest in the sample period, EL is estimated at only EUR 1.1 billion. These figures incorporate firms' total debt and therefore represent the expected loss to all creditors. The share of bank loans to the corporate sector (DNB data) in total corporate debt (Statistics Netherlands data) averages 44% in our sample period.[12] However, as banks also invest in corporate bonds, their EAD exceeds the total amount of corporate loans. Also given the uncertainty with respect to recovery rates, the estimated EL can be interpreted as an upper bound to banks' corporate loan losses. Assuming that expected losses on corporate loans account for 80% of total loss provisions, actual corporate LLP equals EUR 1.3 billion in 1999 and EUR 2.8 billion in 2003. These figures come close to the loss estimates, suggesting that the credit risk model succeeds to mimic, in aggregate, banks' credit risk assessments. Similarly, the change in estimated EL between 1999 and 2003 (EUR 1.7bn) roughly corresponds to the estimated change in bank's corporate LLP (EUR 1.5bn).

In Figure A3 in the Appendix, the change in EL during 2000-2003 is decomposed into its determinants per industry. Worsening macroeconomic conditions account for more than 75% of the increase in EL. That does not seem to have taken banks by surprise, given that their provisioning pattern shown in Figure A4 in the Appendix coincides with the EL pattern of the manufacturing and trade industries (accounting for some 65% of total EAD), whose PDs are primarily driven by macroeconomic factors. The correlation coefficient between banks' reported LLP and the change in EL for these two industries averages 95%. This coefficient equals only 41% for the services industry and is even negative for the transport industry (-55%), which can not simply be explained by the smaller EAD for those industries (together account for 25-30% of total EAD). Exactly those two industries faced a sharp increase in EL due to worsening financial ratios. This suggests that despite the fact that banks tend to model credit risk bottom-up using borrower-specific data, the deterioration in

[9] Here, we follow Virolainen (2004), implying that we are somewhat more conservative than required by the standard approach under Basel II (which sets the recovery rate at 55%, or the LGD at 45%).
[10] Some simplifying assumptions need to be made here. For instance, we assume that debt is evenly distributed across all firms included in our sample and that default is evenly distributed across firms of all sizes.
[11] The total outstanding debt of the 188,568 firms included in our sample in 2003 amount to EUR 422 billion. Aggregating the products of industry-specific debt, industry-specific PDs and a constant LGD of 0.5 yields EUR 2.8 billion.
[12] As the denominator on average includes 150,000 firms, while the nominator includes all firms holding a bank loan, the actual share of bank loans in corporate finance is likely to be a bit smaller.

idiosyncratic financial factors was not as much accounted for as the deterioration in systematic macroeconomic factors. However, recall that due to multicollinearity, systematic factors can not perfectly be isolated from idiosyncratic factors.

To summarize, on average worsening common macroeconomic conditions primarily caused the run-up in PDs as well as EL in 2000-2003, while worsening industry-specific financial ratios magnified these in some industries. The estimated EL compares reasonably to a rough approximation of banks' corporate LLP[13], implying that the model captures banks' corporate credit risk assessment fairly well. Moreover, the development of the estimated EL and banks' LLP allows me to draw two conclusions, albeit with a considerable degree of caution. First, banks *on average* seem to have weathered the 2000-2003 downturn without corporate credit losses severely biting into their capital. Second, the results imply that particularly deteriorating financial ratios in the transport and services industries might have surprised some banks, leading to unexpected or even stress losses.

4.2 The blame game continued: the role of debt financing

Turning to our second question, decomposing the increase in PDs into all its determinants shows that the build-up of debt did not have a dramatic effect on PDs (see Figure A4 in the Appendix). It did, however, raise the transport industry's PD up to 11% in 2001. The surge in capital gearing in the late 1990s is also most pronounced in that industry. Between 1997 and 2000 total debt outstanding rose some 170%, while the average debt load jumped by 80% in 2000 alone. Yet, the decomposition of PDs shows that it was not the build-up of debt that caused PDs to surge in the transport industry, but rather falling profitability and liquidity ratios. Indeed, the single largest contribution of worsening financial conditions to the increase in total EL stems from the fall in profits in the transport industry in 2001, followed by the fall in liquidity in that industry in the subsequent years. While the industry's return on assets already decreased markedly in 2000, creditors still poured in a record amount of loans in that year.[14] This suggests that they either did not condition loans on profitability or did not see the fall in profitability coming. Put differently, the "new economy" either led to imprudent, lax credit policies or to unrealistic assumptions in banks' credit risk models. As the transport industry's PD rose by more than 90% between 1999 and 2003, a large number of loans turned sour. The transport industry also witnessed the largest reduction in debt between 2000 and 2003. Unfortunately, data constraints do not allow for an analysis of how this exactly affected banks' balance sheets, but it inevitably had a large impact on those banks that were exposed to this industry. In short, the build-up of debt in the late 1990s did not substantially raise PDs in the early 2000s on its own. However, the rise in PD and EL in the transport (particularly IT) industry can partially be attributed to the rise in

[13] At a lag, however, since we have used bankruptcy rather than default rates in our credit risk model. For instance, a firm may have failed to service or even defaulted on its debt quite some time before it has been declared bankrupt. To be able to assess actual rather than expected losses, we should make some assumptions w.r.t. the distribution of loan losses across time. Yet, this is beyond the scope of this paper.

[14] With nearly EUR 36bn, the single largest absolute increase in debt for all observations. The 8%-points increase in DTA also represents the single largest relative increase in debt for all observations.

leverage that was not accompanied by a proportional rise in profitability. Creditors apparently did not anticipate or ignored falling profitability and liquidity ratios in this industry, exposing them to relatively large losses.

5 Concluding remarks

This paper presents an industry-level credit risk model for the Netherlands, incorporating both idiosyncratic financial ratios and common macroeconomic variables. This hybrid structure raises the model's accuracy significantly. The model manages to explain about 95% of the variation in bankruptcy rates across time and industries. Second, the hybrid structure allows for an analysis of the extent to which corporate credit risk is driven by idiosyncratic or systematic factors. These factors are interdependent and therefore difficult to isolate in an econometric framework, which calls for some caution in interpreting the results. The results show that on average corporate credit risk in the Netherlands is primarily driven by systematic factors (i.e. cyclical conditions), while idiosyncratic factors (i.e. profitability, liquidity and debt ratios) tend to magnify it. Interestingly, idiosyncratic factors dominate in the IT industry that was at the core of the boom-bust cycle in the early 2000s. Without formal testing of co-movements between rising PDs across industries, this supports the finding of Lopez (2004) that idiosyncratic factors gain weight closer to default. Finally, a decomposition of the change in default rates reveals that the build-up of debt in the late 1990s did not substantially raise default rates in the early 2000s on its own. Yet, the rise in default rates and expected losses in the transport industry (IT industry in particular) can partially be attributed to the rise in leverage that was not accompanied by a proportional rise in profitability.

The model can be applied for macro stress testing, but is less suitable for stress testing individual corporate loan portfolios as idiosyncratic risks are still rather broadly defined. To this end, a firm-level credit risk model would be more appropriate. These extensions are left for future work.

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Appendix

Table A1 Explanatory variables and dimension of the dataset

	notation	*interpretation*	*ratio*	*source*
X_1	$PROFM_{j,\ t\text{-}L}$	profit margin	pre-tax profits / net sales	Statistics Netherlands
	$ROA_{j,\ t\text{-}L}$	return on assets	pre-tax profits / total assets	Statistics Netherlands
X_2	$CR_{j,\ t\text{-}L}$	current ratio	current assets / short-term debt	Statistics Netherlands
	$QR_{j,\ t\text{-}L}$	quick ratio	(current assets - inventories) / short-term debt	Statistics Netherlands
	$WCTA_{j,\ t\text{-}L}$	working capital to assets	working capital / total assets	Statistics Netherlands
X_3	$DTA_{j,\ t\text{-}L}$	debt to assets	total debt / total assets	Statistics Netherlands
	$DTE_{j,\ t\text{-}L}$	debt to equity	total debt / equity	Statistics Netherlands
X_4	$STDR_{j,\ t\text{-}L}$	short-term debt ratio	short-term debt / total debt	Statistics Netherlands
	$INTCOV\_BROAD_{j,\ t\text{-}L}$	interest coverage (broad)	pre-tax profits / net interest payments	Statistics Netherlands
	$INTCOV\_SMALL_{j,\ t\text{-}L}$	interest coverage (small)	net profits / net interest payments	Statistics Netherlands
N	$N\_LET_{j,\ t\text{-}L}$	share of large firms in total	number of large firms / total number of firms	Statistics Netherlands
Z_1	$GDPGR_{t\text{-}L}$	GDP growth rate		DNB
Z_2	$\Delta I\_ST_{t\text{-}L}$	short-term interest rate		DNB
Z_3	$\Delta I\_LT_{t\text{-}L}$	long-term interest rate		DNB
Z_4	$\Delta EQPR_{j,\ t\text{-}L}$	equity prices		DNB
Z_5	$\Delta XR_{t\text{-}L}$	EUR/USD exchange rate		DNB

j	*notation*	*interpretation*	*industry*	*SBI codes*
1	MAN	manufacturing	mining and quarrying; manufacturing	10 - 37
2	CON	construction	construction	45
3	TRD	trade	repair and maintenance of consumer goods; wholesale, commission and retail trade	50 - 52
4	CAT	catering	hotels and restaurants	55
5	TRS	transport	transport, storage, and communication	60 - 64
6	SER	services	letting of property and commercial services	70 - 74
t	1992 - 2005			

NB: Only those industries (i) for which the PD could be calculated and (ii) that are relevant for monitoring credit risks are included. Therefore, agriculture (SBI code: 01-05), public services (SBI code: 40-41), central and local government, social security, education, health care, environment, and other services (SBI code: 75-93) have been excluded. The financial industry (SBI code: 65-67) has also been excluded, since its characteristics differ too much from the other industries, and our aim is to assess banks' credit risks on their *non-financial* corporate sector exposure.

Table A2 Descriptive statistics and unit root tests

	Included					Excluded			
Idiosyncratic Variables									
	PD [1]	ROA	CR	DTA	N_LET*DTA	PROFM	QR	WCTA	DTE
Statistics									
Mean	0.9%	6.2%	1.3	57.0%		5.9%	108.4%	10.6%	136.4%
Median	0.9%	6.0%	1.3	58.8%		5.8%	106.5%	12.1%	142.5%
Maximum	1.7%	16.2%	1.7	66.4%		18.1%	161.1%	26.1%	197.6%
Minimum	0.3%	-9.5%	0.9	43.6%		-16.8%	81.7%	-2.4%	77.5%
Std. Dev.	0.3%	3.6%	0.2	5.7%		4.7%	16.7%	7.0%	29.4%
Skewness	0.5	-1.5	-0.4	-0.8		-2.0	0.6	-0.1	-0.3
Kurtosis	2.8	10.1	2.9	2.7		12.5	3.0	2.0	2.5
# OBS	78	78	78	78	72	78	78	78	78
Unit Root Test [2]									
Statistic	-3.23	-1.85	-1.75	-0.37	-2.98	-2.38	-1.06	-1.18	-0.58
Probability	0.00 ***	0.03 **	0.04 **	0.35	0.00 ***	0.01 ***	0.14	0.12	0.28
Sytematic Variables									
	GDPGR	Δ I_LT	Δ I_ST	Δ XR		Δ EQPR			
Statistics									
Mean	2.3%	-0.4	-0.6	1.5		6.0			
Median	2.4%	-0.6	-0.4	0.8		16.6			
Maximum	4.3%	2.3	1.6	17.3		118.9			
Minimum	0.1%	-1.8	-2.9	-13.6		-294.7			
Std. Dev.	1.4%	1.2	1.1	8.4		76.4			
Skewness	-0.1	1.0	-0.3	0.1		-1.5			
Kurtosis	1.7	3.2	3.0	2.3		6.3			
# OBS	84	78	78	78		55			
Unit Root Test [2]									
Statistic	-1.84	-10.37	-6.24	-7.70		-0.87			
Probability	0.03 **	0.00 ***	0.00 ***	0.00 ***		0.19			

1) The unit root test is on logit(PD) or ln(PD/(1-PD))
2) Levin, Lin and Chu t-Test (assumes asymptotic normality) with H_0 assuming a common unit root process
* denotes significance at a 10% level, ** denotes significance at a 5% level, *** denotes significance at a 1% level

Table A3 Correlation matrix panel data

	$PD_{j,t}$	$ROA_{j,t-1}$	$CR_{j,t-1}$	$DTA_{j,t-1}$	$GDPGR_{t-1}$	$GDPGR_{t-2}$	Δ I_ST_t	Δ I_LT_{t-1}	Δ $EQPR_{t-1}$	Δ XR_{t-1}
$PD_{j,t}$	1.00									
$ROA_{j,t-1}$	-0.22	1.00								
$CR_{j,t-1}$	0.10	0.07	1.00							
$DTA_{j,t-1}$	-0.32	-0.51	0.06	1.00						
$GDPGR_{t-1}$	-0.58	0.42	-0.07	-0.18	1.00					
$GDPGR_{t-2}$	-0.60	0.26	0.04	-0.07	0.68	1.00				
Δ I_ST_t	0.05	-0.04	-0.21	0.03	-0.02	0.17	1.00			
Δ I_LT_{t-1}	0.09	-0.06	-0.26	0.01	-0.07	0.12	0.75	1.00		
Δ $EQPR_{t-1}$	-0.53	0.29	0.20	-0.09	0.41	0.58	-0.31	-0.48	1.00	
Δ XR_{t-1}	0.22	0.02	0.07	0.01	-0.20	-0.22	-0.35	-0.40	0.10	1.00

Table A4 Regression output by industry

Dependent variable: $LN(PD_{j,t}/(1-PD_{j,t}))$ Method: Panel Least Squares with industry dummy variables

Model	Industry	Constant	ROA_{t-1}	CR_{t-1}	DTA_{t-1}	N_LET_{t-1}	$GDPGR_{t-1}$	$GDPGR_{t-2}$	ΔI_LT_{t-1}	ΔI_ST_t	ΔXR_{t-1}	Regression diagnostics	
12	TOTAL	-4.41 ***	-1.72 ***	-0.45 ***		28.51 ***	-9.65 ***	-5.89 ***	0.02 **	0.05 ***	0.00 ***	R^2	0.94
fixed effects		*-13.83*	*-3.17*	*-3.30*		*2.95*	*-6.17*	*-4.51*	*2.34*	*3.07*	*3.39*	R^2 adjusted	0.93
	CAT	-4.26					-1.08 ***	-18.30 ***				# OBS	72
							2.81	*-4.15*				DW statistic	1.60
	SER	-5.94			3.21 **							Akaike info criterion	-1.62
					2.09							F-statistic	58.67
13	TOTAL	-4.04 ***	-1.30 **	-0.68 ***		28.57 ***	-12.64 ***	-4.82 ***	0.02 **	0.04 ***	0.00 ***	R^2	0.94
no fixed effects		*-25.92*	*-2.32*	*-5.33*		*10.39*	*-7.23*	*-3.35*	*2.34*	*3.02*	*3.22*	R^2 adjusted	0.93
	TRD				0.63 ***		-4.95 **	-11.77 **				# OBS	72
					3.95		*2.49*	*-2.27*				DW statistic	1.71
	CAT						-1.74 ***	-17.54 ***				Akaike info criterion	-1.61
							3.45	*-4.22*				F-statistic	58.17
	TRS				1.14 ***		-8.12 **						
					7.14		*2.10*						
	SER				0.43 ***								
					3.94								
14	TOTAL	-3.55 ***	-1.76 ***	-0.72 ***		14.73 ***	-8.19 ***	-7.28 ***	0.03 ***			R^2	0.94
no fixed effects		*-19.46*	*-3.32*	*11.94*		*11.94*	*-6.35*	*-5.99*	*2.73*			R^2 adjusted	0.93
	CAT				-0.39 ***			-14.35 ***		0.13 ***	0.01 ***	# OBS	72
					-3.00			*-3.18*		*4.55*	*3.60*	DW statistic	1.52
	TRS				0.52 ***							Akaike info criterion	-1.62
					5.57							F-statistic	80.92
15	TOTAL	-4.39 ***		-1.05 ***	1.60 ***		-11.54 ***	-7.16 ***				R^2	0.96
fixed effects		*-10.95*		*-6.19*	*2.81*		*-8.22*	*-6.55*				R^2 adjusted	0.95
	TRD	-7.16		1.14 ***			-5.01 ***					# OBS	72
				3.93			*3.01*					DW statistic	1.99
	CAT	-4.44						-11.41 **		0.18 ***	0.01 ***	Akaike info criterion	-1.92
								-2.07		*6.76*	*4.83*	F-statistic	69.86
	TRS	-3.88	-3.23 ***				-1.33 ***				0.01 **		
			-3.26				*3.83*				*2.21*		
	SER	-3.78	-4.57 **				-3.95 **						
			-2.29				*2.02*						

Note: t-statistics are in italic: ** denotes significance at a 5% level, *** denotes significance at a 1% level
Guidance in reading the table: TOTAL represents the regression equation that holds for all industries. Coefficients for individual industries are only reported when they differ significantly from those in TOTAL. These coefficients are included as the sum of the coefficient for that industry's dummy variable and that for TOTAL. Where the coefficients for the explanatory variables did not significantly differ from those in TOTAL, industry-specific coefficients for the constant term have been omitted.

Text A1 Detailed description of estimation results (Models 1-11)

Models 1-3 estimate industry-specific PDs out of one-year lagged financial ratios only. The coefficients of the profitability and liquidity ratios enter highly significantly and with the expected sign, while the leverage ratio (DTA) fails to enter significantly, but shows the expected sign (model 2). The weak significance of DTA may be explained by the fact that we do not condition it on relative firm size. By aggregating debt at industry-level and dividing it by total assets, the ratio does not take differences in financing between small and large firms into account. A large body of literature investigating these differences exists (for an overview see Altman and Sabato, 2007), with some authors finding evidence of credit constraints for small firms. Similarly, the debt overhang of small firms tends to be lower than that of large firms. This justifies incorporating the share of large firms per industry in our regression model, which is expected to improve the explanatory power of DTA. Model 2 shows that adding a relative firm size variable (N_LET) separately does not improve the explanatory power of DTA. Not surprisingly, the coefficient of N_LET is positive and significant, implying that the larger the share of large firms in an industry, the higher is that industry's PD. This finding is consistent with a decomposition of PDs by firm size. Although the number of small firms entering bankruptcy easily exceeds that of large firms, the default rate of small firms is on average more than 25% lower than that of large firms. One of the most discussed and obvious distinguishing characteristic of large firms relative to small firms is their financial structure, which is captured by DTA. Specifically conditioning DTA on relative firm size indeed does raise the significance of DTA substantially, and thereby the overall fit of the model (R^2 and F-statistic of model 3). While the interaction term blurs the individual contribution of corporate indebtedness to industry-specific PDs, it better captures the effect of leverage on default.

In models 4-8 lagged GDP growth is added, which raises the fit of the model dramatically while reducing serial correlation somewhat. Not surprisingly, adding one-year lagged GDP growth reduces the size and significance of the coefficients of the financial ratios, ROA and DTA in particular (model 4). This model, however, suffers from multicollinearity as cyclical conditions are closely related to corporate leverage. Cyclical conditions not only affect PDs through the balance sheet (e.g. agency cost) channel, but also through the bank lending channel. For instance, Jiménez and Saurina (2005) find evidence of pro-cyclical bank lending practices, with credit standards being significantly loosened during upswings, weakening the credit quality of bank loan portfolios, and tightened during downswings. Indeed, we find that debt growth and GDP growth are positively correlated, particularly when the latter leads the former by one year.[15] Multicollinearity is not that much of a concern, as our estimators are still best linear unbiased as well as maximum likelihood estimators. Nonetheless, it does raise the standard errors and hence reduce the significance of the coefficients somewhat. While the individual coefficients of DTA and N_LET are both insignificant in model 13, their joint coefficient is significant in model 14, confirming our earlier finding that conditioning the industry-specific debt ratio on relative firm size better captures the leverage effect on default and is hence appropriate. In doing so, the performance of the other financial ratios that are not necessarily related to firm size improves. Using two-year rather than one-year lagged GDP growth raises the fit of the model as all financial ratios now enter significantly, both in the model which includes relative firm size separately (model 6) and that which includes relative firm size jointly with DTA (model 7). Hence, the short-term dynamics of industry-specific PDs seem to be well-captured by these financial ratios. Holding both short-term and medium-term cyclical conditions constant by including GDP growth at a one-year and two-year lag somewhat reduces the performance of the financial ratios (model 8). However, some 90% of the variation in PDs across industries and time is now explained by industry-specific financial conditions and overall cyclical conditions.

Models 9-11 extent the preceding models by adding changes in prices (i.e. interest rates, exchange rates, equity prices) as explanatory variables. The one-year lagged change in long-term interest rates and contemporary change in short-term interest rates is included in model 9. Both enter significantly with a positive sign. The interpretation of the short-term interest rate is straightforward: an increase in this rate raises firms' borrowing costs and as such industry-specific PDs. The lagged change in long-term interest rates has been included to assess how changing growth and inflation expectations affect PDs. Whether inflation will have real effects on the corporate sector is dependent on whether firms are in fact credit constrained (see Vlieghe, 2001, and references therein). If so, an increase in (expected) inflation will lead to an increase in PDs. Our results support that hypothesis. Adding the lagged change in industry-specific equity prices and the EUR/USD exchange rate raises the fit of the model (model 10), but at the cost of reducing the number of observations. Moreover, both variables fail to enter significantly. Omitting industry-specific equity prices yields our final model (model 11).

[15] The average correlation coefficient between $GDPGR_{t-1}$ and $TDGR_t$ equals 0.70, and ranges between 0.60 and 0.87 for the catering and services industry, respectively.

Figure A1 Actual and fitted values for PD

PD in percentages

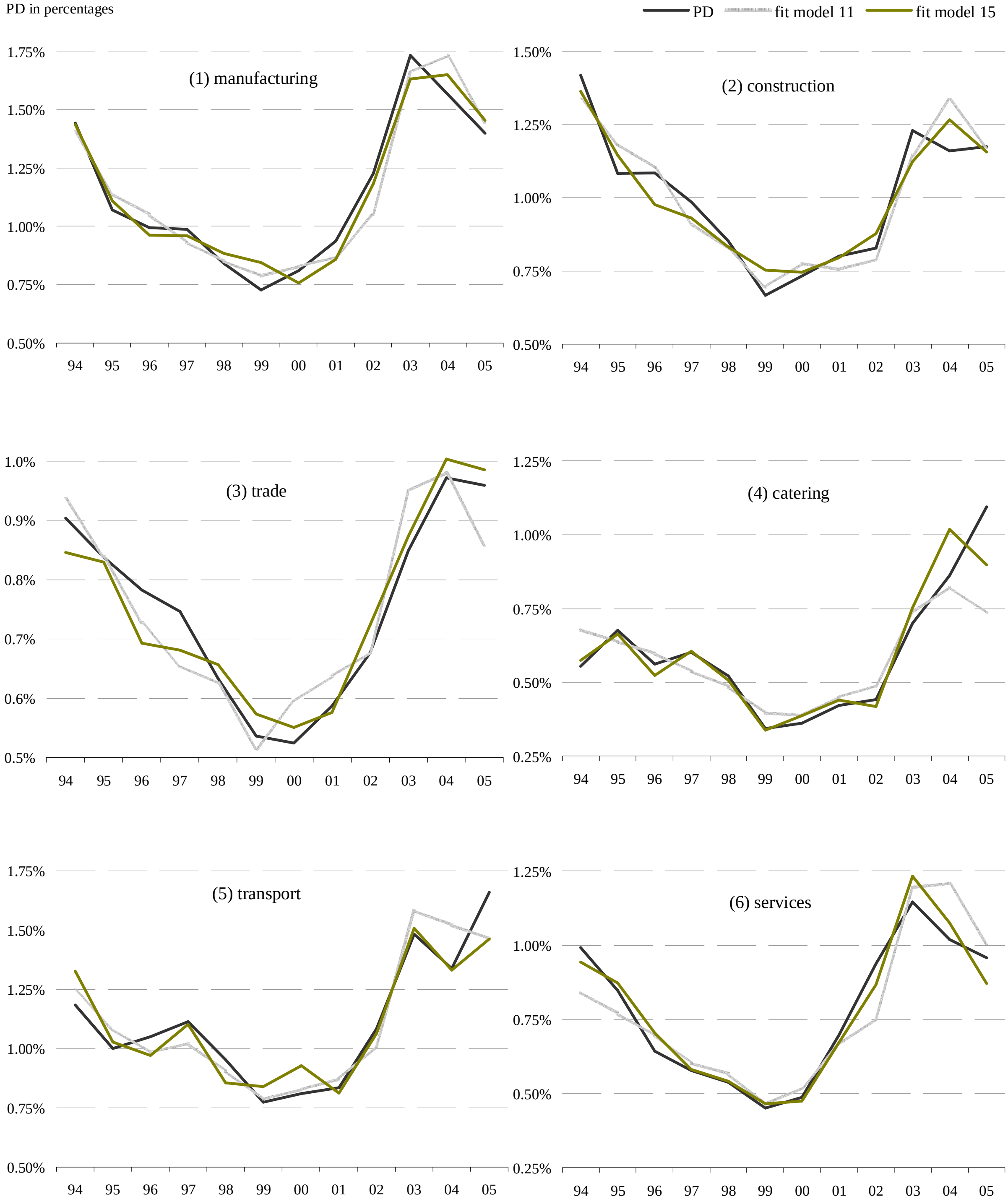


Figure A2 Decomposition of the percent change in PD
Calculated contributions of explanatory variables in percentage points

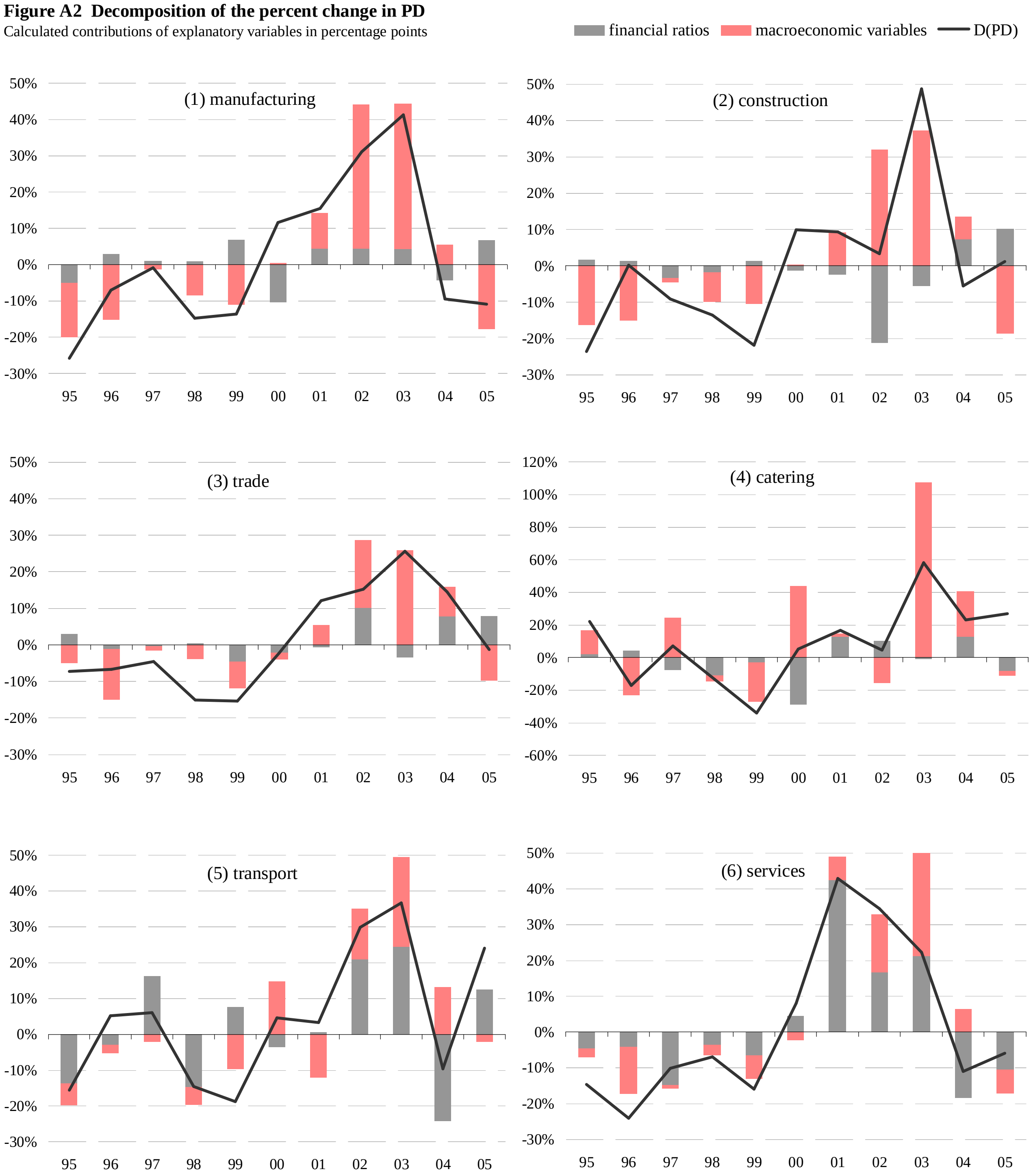


Figure A3 Decomposition of the absolute change in EL

Contributions of change in determinants of PD and change in EAD in EUR millions

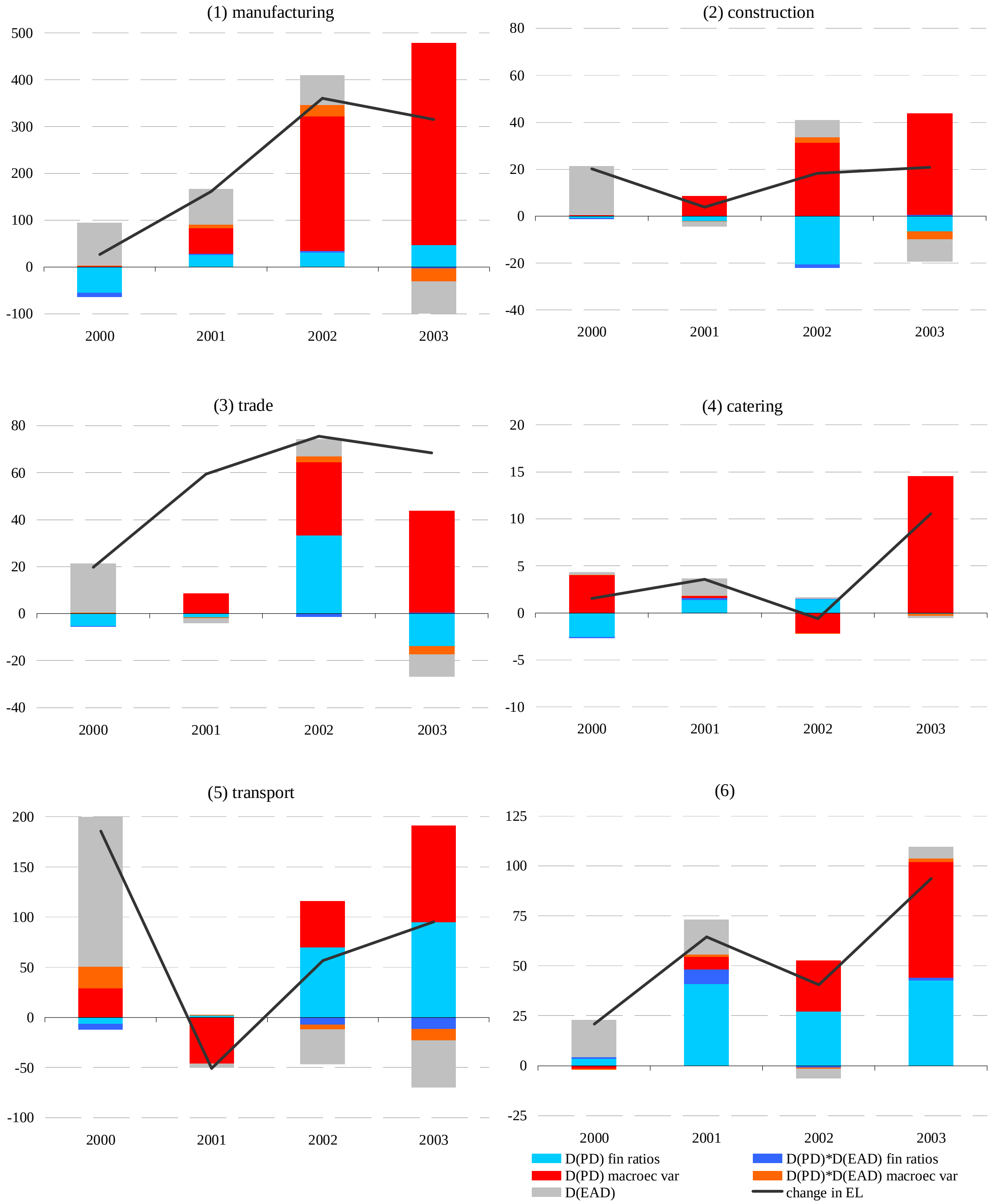
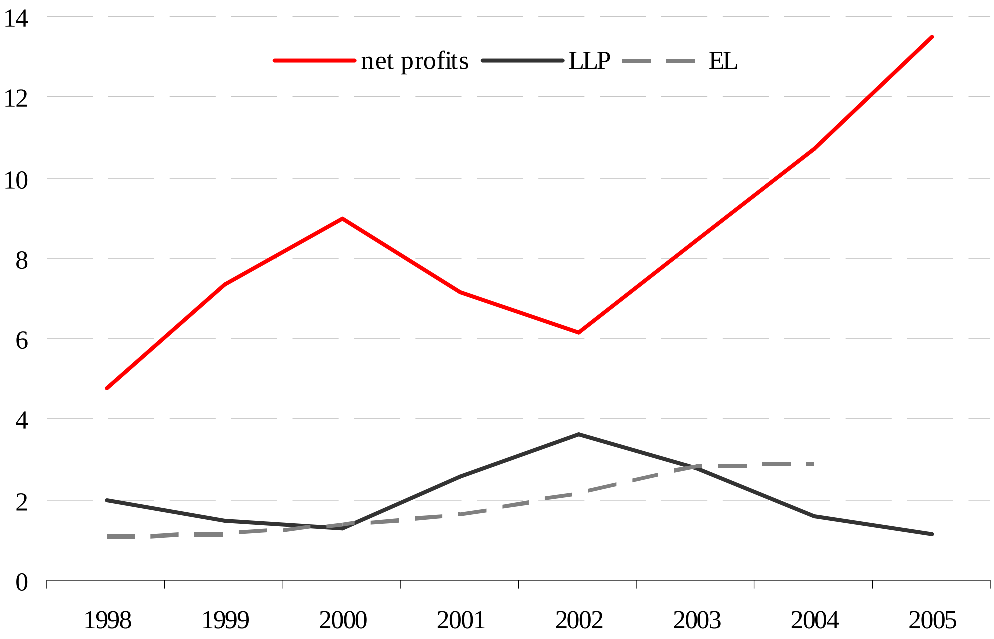


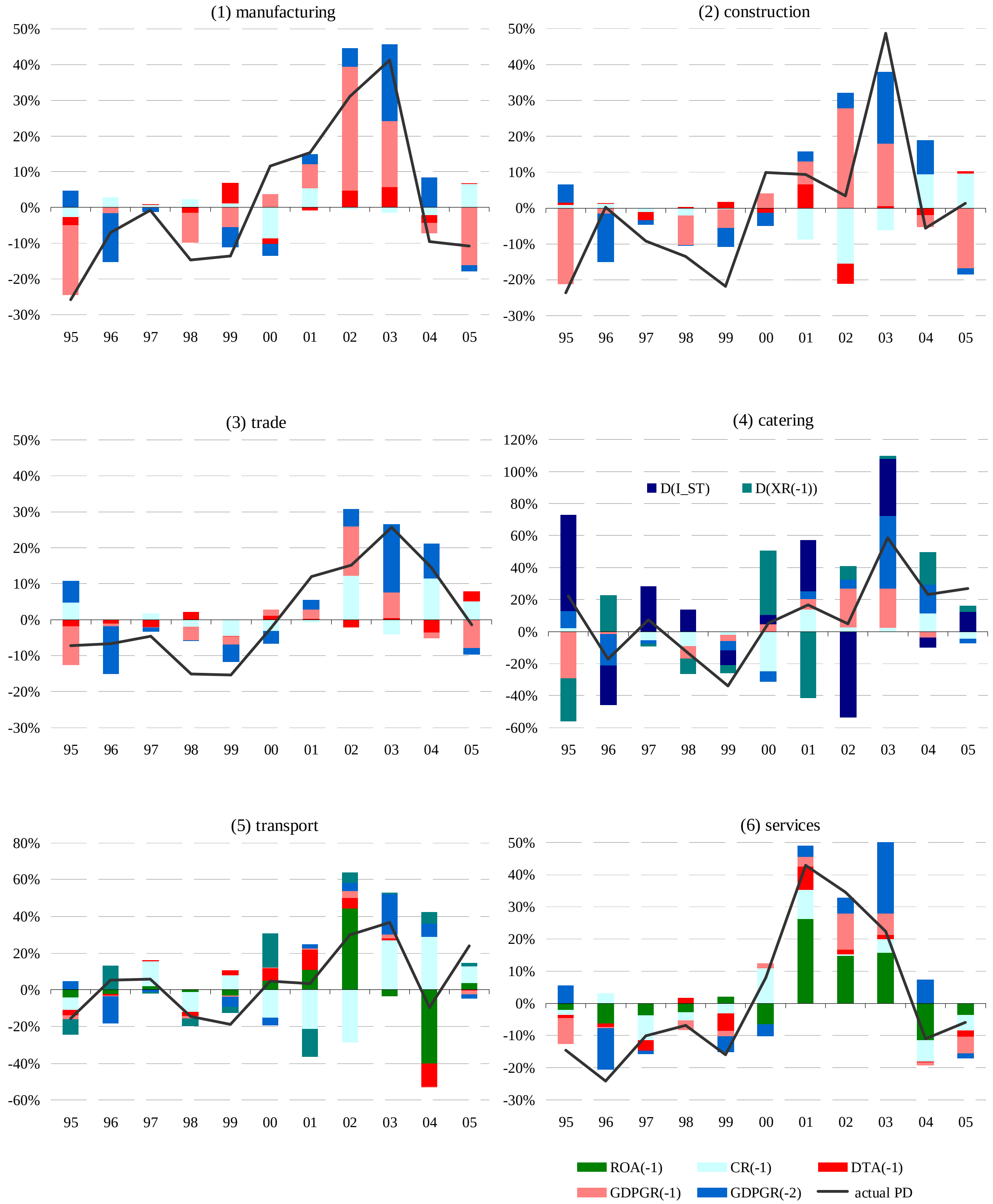
Figure A4 Banks' net profits and LLP vs model estimate of EL
In EUR billions



Source: DNB and model outcome (EL)

Figure A5 Decomposition of the percent change in PD

Calculated contribution of explanatory variables in percentage points



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