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Explaining Corporate Credit Default Rates with Sector Level Detail*

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Abstract

We model corporate loan default rates in four main economic sectors using quasi-panel methods and find that economic sectors respond differently to changing economic and financial conditions in terms of time, intensity or dynamics. We propose using techniques that allow both long run and short run components, while maintaining a flexible unified framework to capture heterogeneity across economic sectors (error correction panels). We also undertake a stress testing exercise, which justifies more granular level modelling due to heterogeneity across sectors. We conclude that such unified framework provides more robust results. From practical point of view, evidence from Slovak corporate sector confirms that construction sector is far more vulnerable to shocks than manufacturing, business services or trade.

1. Introduction

Stress testing has become in recent years a standard tool to assess robustness of the banking sector. Overall stability, or rather vulnerability, to exceptional but plausible events of individual banks is being tested in regular intervals by European Banking Association and by many other authorities. Their aim is to identify structural vulnerabilities and overall risk exposure in the financial system that could lead to instability of the financial systems.

Stress testing on the aggregate level can be performed using different approaches. The simplest assessment tool could be using macro-prudential indicators, which measure degree of health of individual institutions, or of the financial system or interlinkages present in the system. The assessment can be however also more complex - based on studying the links between the aggregate macroeconomic and financial variables and risks to the financial institutions balance sheets.

Recent updates in bank regulation (Basel III) and accounting standards (namely IFRS9 Financial Instruments effective as of 2018) have made banks across

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the board to implement valuation models that do account for economic cycle (Buesa et al., 2019). This is necessary, since assessment of the loan loss provisioning is directly related to profit and loss account and to the level of own funds and therefore also to capital requirement (Krüger et al., 2018). Banks therefore routinely report expected credit losses along the entire life of all financial instruments exposed to credit risk. As a result, provisions and expected loss is directly dependent not only on credit quality of financial instruments, but also on the stage of economic cycle.

Banks do naturally assess their own risk exposures and therefore their models focus on probabilities of default in their specific loan portfolios. We however take the economy wide perspective. We employ sector level probabilities of default, use a nouvelle modelling framework to link them to macro-economic and financial variables and perform economy wide stress tests of default probabilities in individual sectors. In other words, we are assessing vulnerabilities originating from the macroeconomic and financial environment and weighing on the corporate sector loan default probabilities. Although statistically, corporate sector directly relates only to 25% of banking sector portfolio in the euro area (2018), this link between corporate and banking sector has been more intensive in Slovakia (33%). Undoubtedly, corporate sector is closely linked also to other sectors of the economy and therefore also to other items of the bank's portfolio and overall financial stability of the system.

In order to assess vulnerabilities originating from macroeconomic environment, we develop a framework that has a capacity to capture how macroeconomic and financial variables feed into the corporate sector credit. The measures of credit risk used in this context include probability of default (PD), the loss given default (LGD), the exposure at default (EAD) or even very simplistic measure of non-performing loans (NPL). Given that PD is the most straightforward interpretation of credit risk in terms of corporate sector wellbeing[1] and due to data availability for Slovakia, we adhere to this measure in our study.

In this study, we set up a quasi-panel data model and assess effects of economic and financial conditions on corporate default rates. Understanding heterogeneity of corporate sector, we work with sectoral break down of as many variables as possible, including sector specific default rates. We use data for Slovakia over the past 19 years of history (2001 to 2019). With this dataset, for the first time, we employ the sample that included almost two full economic cycles. Current modelling practice in banks is either to use ECM models to address both long term and short-term component of an individual sector or SUR models to address sectoral heterogeneity in a unified framework. Alongside of these approaches, we also propose PMG estimator, which incorporates both error correction and cross-sector heterogeneity in a unified framework and retains enough flexibility at the same time.

We fit the relevant models in a comparable fashion. Our results (both the overall robustness and partial test statistics) suggest superiority of the PMG

[1] Certainly, probability of default is also far from perfect as a measure of credit risk, as it may be subject to distortion in terms of productivity or size of the company. For instance, Anderson et al. (2019) claim that distressed banks may tend to protect highly leveraged low productivity businesses from failure and therefore underestimated PD ratios in bad times. Similarly, Sivak et al. (2013) provide the evidence that smaller and younger firms in central and eastern Europe, which are naturally more vulnerable to shocks, tend to avoid applying for credit if they anticipate being rejected.

estimator. Context wise, we find that sector specific corporate loans default rates relate to different macroeconomic determinants. Construction sector for instance is closer related to risk premium and debt level, while manufacturing tends to be more sensitive to short term interest rate and services to private debt. In a stress testing exercise, we also confirm that manufacturing and especially construction sector is more vulnerable to changes in macroeconomic and financial environment than other sectors.

The rest of the paper proceeds as follows. In the section 2, we provide the economic rationale and past research findings in the area of propagation of macro-economic and financial shocks into the credit risk measures. In the section 3 we introduce data and plot some illustrative charts. In the section 4 we describe the models and technical details. We navigate through the main results and discuss them in the section 5. Apart from this, it introduces predictions from the proposed models as well as stress test exercise. Section 6 concludes.

2. Economic Rationale and Related Literature

Linking bank risk portfolio indicators with macro environment and generating plausible stress scenarios can help banks better to understand its risk profile as well as to identify possible threats in their portfolios. The outputs of forecasting and stress testing can be then used in decision making to prepare bank portfolios for potential negative consequences of economic downturn[2].

A prominent risk to the bank portfolio arises from its loan quality. For this reason, proper assessment and outlook for the health and sustainability of corporate loans is necessary. Loan default rates, loan default probabilities and factors, which may alter them are at the centre of the focus.[3]

Several studies have analysed the relationship between macroeconomic environment and loan default rates in the past. Virolainen (2004) estimated a macroeconomic credit risk model for the Finnish corporate sector. He used industry-specific corporate sector default rates between 1986 and 2003. This period also includes a severe recession with significantly higher-than-average default rates in the early 1990s. The estimated model provides and insight into corporate credit risk conditional on current macroeconomic conditions. Furthermore, the paper presents some applications of the model for macro stress testing, i.e. analysing the effects of various adverse macroeconomic events on the banks' credit risk in corporate sector. His results suggest a significant relationship between corporate sector default rates and key macroeconomic factors including GDP, interest rates and corporate indebtedness. However, from the stress tests he concludes that Finnish corporate sector credit risk was fairly limited in the macroeconomic environment of that time. The idea to set up a model that allows for sector level characteristics is central and serves as a motivation to our paper. Interestingly, just a handful of sector level stress

[2] Kohn and Liang (2019) among others look at the qualitative consequences of stress tests, among which they assess i) countering potential procyclicality of bank capital, ii) improvement of risk management and capital planning, and iii) cost and availability of credit.

[3] Some studies look also on the other leg of dependency, namely they find that credit supply is reduced and interest rate on small business loans raised predominantly in banks that are affected by stress tests (Cortes et al., 2018).

test applications have been done in the region, e.g. Valentiny-Endresz and Vasary (2008) for Hungary or Fisher et al. (2017) for Germany.[4]

Misina et al. (2006) looked at Canadian entities in banking sector and investigated losses in the loans portfolio as a function of changing conditions in different industries. The authors assessed a relationship between macroeconomic environment and sector-based default rate, on the premise that systemic vulnerabilities can result from common exposures - whether from exposures to similar classes of assets or, ultimately to similar risk factors. Consequently, a series of stress tests under different scenarios have also been undertaken.

Jakubík (2006) studies corporate default rates and models them using two approaches, first by empirical model and second by latent factor model based on the Merton's idea[5]. Both of these models are derived from individual default probability models using the Finish 1988-2003 economy dataset of Virolainen (2004). First, linear vector autoregressive models were used to examine the extent to which do macroeconomic indicators affect corporate default. Then, micro founded factor model was used to exploit more disaggregate industrial data to predict loan default rates and set up a stress test.

Simons and Rolwes (2009) examined the relationship between macroeconomic and financial variables and default rates in Dutch companies. They used a simple logistic regression (logit) model in order to consider correlations of default rates across sectors. The authors found that there is a certain dependency between macroeconomic variables and firms' default behaviour and thus examined the default behaviour in 2007 based on (though to be) adverse macroeconomic scenarios of zero GDP growth for two consecutive quarters. The result of the analysis proved an obvious relationship between the default rate and GDP, oil price, interest rates and exchange rates. They found moderate (and different across sectors) effect on corporate default rates, however their finding has not been confirmed as universal across countries.

3. Data

Our analysis is based on quarterly data spanning over the period between 2000Q1 and 2019Q1 (i.e. 77 observations). Macro variables used in the main part of the analysis are all publicly available, sectoral and aggregate default rates (default probabilities) are compiled by the National Bank of Slovakia.

Although there are loan default probabilities available for the two-digit NACE sectors (18), we aggregate them into the main 6 sectors: Agriculture (AGRO), Manufacturing (MANU), Construction (CONS), Trade (TRAD), Business Services (BUSS) and Public Services (PUBS). Since the data for AGRO are very sparce and noisy and the data for PUBS are unreliable for conceptual reasons[6], we will further work only with the main four sectors of the economy (i.e. 308 observations).

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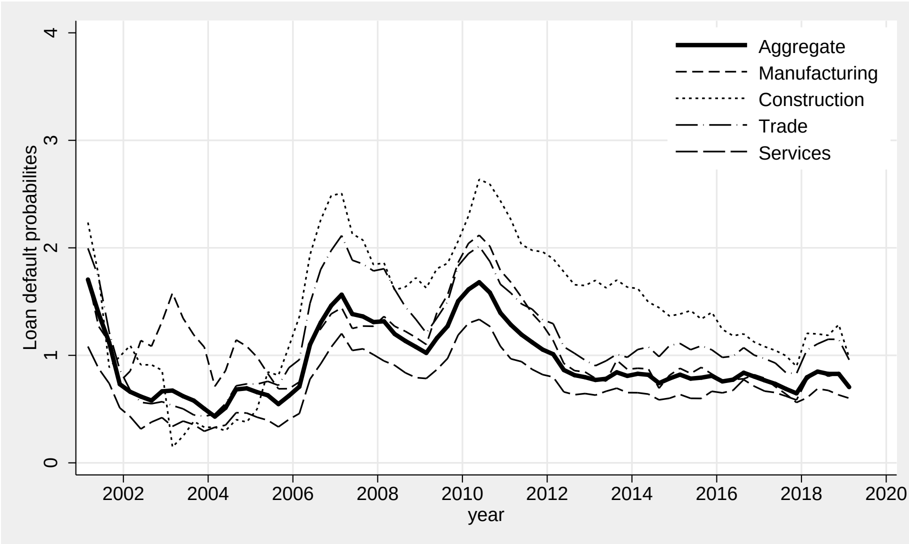
[4] The two macro stress testing studies performed on Slovak data up to date had used aggregate default rates (Zeman and Jurča, 2008) or bundled loans to sectors according to their *ex-ante* assessed sensitivity (Klacso, 2014).

[5] Merton (1974)

[6] Motivation for default of public loans are different to those in the corporate sector and therefore reflected in the series, which is volatile and erratic.

Figure 1 Aggregate and Sectoral Default Probability



Notes: Confidence in Industry serves as a proxy for output in Manufacturing, Confidence in Construction for Construction, Confidence in Retail Trade for Trade and Confidence in Service for Services. Default probabilities are annual rolling averages.

Source: Own calculations using the dataset of default probabilities from the National Bank of Slovakia

The Figure 1 pictures development of the computed empirical default rates for the aggregate economy and for the four individual sectors. In line with expectations, we witness rapid increase in defaulted loans after the global financial crisis in 2009 and 2010; however similarly steep increase can be observed in early 2006. This can be attributed to a one-off effect when bulk of loans mainly in construction and trade had been written off due to the change in legislation (new bankruptcy law)[7] entering into force in 2006. This legislation effect has been accounted in the model for by a separate dummy variable attributed to the first two quarters of 2006.

Within the macro variables, the most explanatory power is naturally attributed to the series measuring economic performance. Most of the authors have considered GDP, or variables derived from the GDP (e.g. output gap) or other conceptually similar variables (e.g. value added). We use the latter three, but we also alternate GDP series with the DG ECFIN economic sentiment indicator.[8] We do this for three reasons. First, both the output series and the output gap are suffering from too little cyclical variation except for dramatic reversal in 2008. On the contrary, confidence indicator seems to be more cyclically responsive to the economic environment. Second, indicator of sentiment is a zero-sum measure similarly to the output gap,

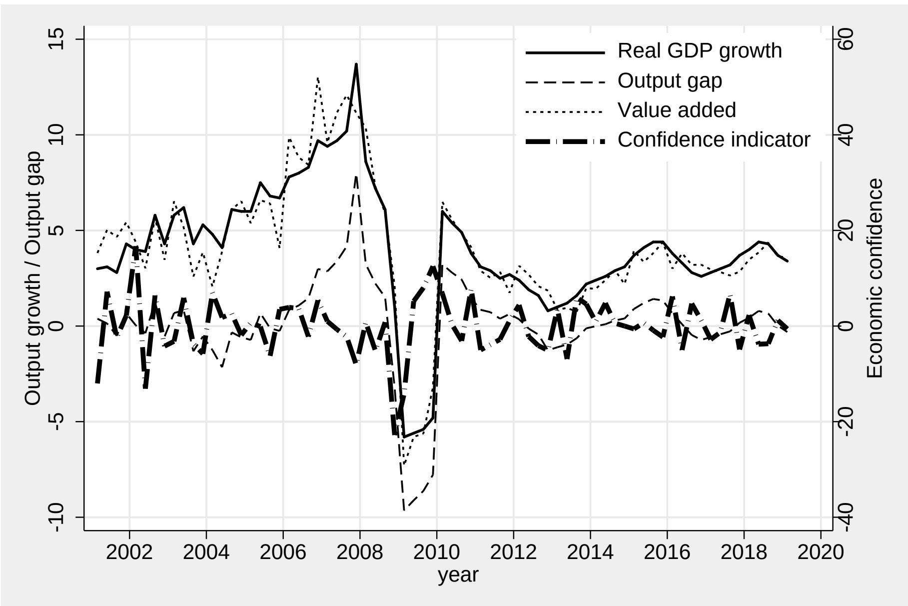
[7] The new legislation (paragraph 69 and 70 of the act 7/2005) extended the subject of the bankruptcy also for the assets used as collateral in the loan agreement, therefore when this legislation entered into force; banks were motivated to reclassify the entire stock of un-serviced loans to the correct category. Before, banks were penalized for doing so by higher provisions with no eventual return from a defaulted loan.

[8] Used as a first difference of annual change to DG ECFIN Economic Sentiment Indicator (seasonally adjusted balance).

however it does not suffer from large positive spike just before the crisis, followed by large negative freefall in the first year of crisis as it is in the case of output gap. Third, survey of economic sentiments is a good predictor of the output and often used also as a nowcasting variable for future output (Castle et al., 2013). Survey based measure of sentiment also may fair better in reflecting sector specific or aggregate situation in the corporate sector than the statistical concept of GDP. Since defaulting on a loan has some delay, we test for the optimal lag length and use four quarters lag in the OLS specification.

Other explanatory variables are quite standard. We use 6-months Euribor for short term interest rate, to which most of the corporate loans are indexed to. We use annual difference of the interest rate, because we want to capture a change in the level of interest rates rather than tightness of the policy in general. Similarly, to the output measure, we find the optimum lag length for the OLS specification, which turns out to be 4 quarters.

Figure 2 Output Variables



Notes: Output gap is computed as a deviation from HP filtered trend of real GDP growth with λ=1600. Real GDP growth and value added are year on year changes. Confidence indicator is computed as an annual difference and is plotted on the left axis.

Source: Eurostat

In order to capture the outlook and risk faced by the economic agents we also include a risk premium among the explanatory variables. Risk premium is calculated as a spread between the long-term interest rate (10-year benchmark government bond) of Slovakia and Germany. The measure combines the information of extra risk incurred and priced by the market for operating in Slovakia. For corporate sector indebtedness, we use the ratio of gross corporate debt over its value added. For the value added itself, we use gross value added of the GDP production method. The legislation change dummy described above completes the list of explanatory variables used in the model. Full description of the dataset is outlined in the *Appendix*, part 1.

4. The Model

We use loans transition probability matrix to compute sector *j* specific default rates.

Often, a default is modelled as a binary variable in a logit model. We however use data describing historical evidence of defaults and therefore empirical default rates as a continuous variable falling into the range of [0,1]. The two concepts may be connected via the following logistic functional form

$$L(p_t) = ln\left(\frac{1 - p_t}{p_t}\right) = y_t \tag{1}$$

Industry specific default rate is then expressed as a set of loans from which a subset has defaulted, and the rest have not. Such probabilities are then transformed into an index y_t that reflects macroeconomic conditions, which can be explained by exogenous macroeconomic factors. Modelling default rates indirectly using an index y_t allows better interpretation since such index of corporate health reflects the state of economy while being an inverse to corporate default rate. We expect the economic performance to be positively related with the industry-specific indices, and the interest rate and the corporate indebtedness to be related negatively.

We start with a simple OLS estimator. We estimate an aggregate and sector specific equations and set the ground for methodological improvements by using more complex modelling frameworks to follow.

Since we have sector specific dependent variables that could be interrelated, we can easily expect residuals to be cross correlated in this set up. Therefore, we estimate the model as a seemingly unrelated regression model (SUR).

We therefore estimate:

$$\begin{gathered} y_{1t} = \beta_1 x_{1t} + \varepsilon_{1t} \\ \vdots \\ y_{Nt} = \beta_N x_{Nt} + \varepsilon_{Nt} \end{gathered} \tag{2}$$

for period $t = 1,\dots,T$ and sector $i = 1,\dots,N$.

where y_{it} is a vector of computed default rates for the four sectors, x_{it} is a sector-specific explanatory variable (short-term interest rate, risk premium, output variable and debt ratio), appearing in the *i-th* sectoral equation. If ε_{it} were not correlated (see Table A7 in the *Appendix*), OLS and SUR coefficients would be very similar.

However, SUR model assumes stationarity of the series, which does not necessarily apply in this case, especially when macro variables (usually integrated at the first order) are involved. This assumption can be relaxed with the autoregressive lag family of models, which allow inclusion of stationary, non-stationary or cointegrated time series.[9] In Autoregressive Distributed Lag (ARDL) model however, each cross-section (sector, in our case) would have to be regressed separately. However, it is more convenient to use re-parametrisation of ARDL model into a pooled mean group (PMG) estimator proposed by Pesaran, Shin and Smith (1999).

There are number of benefits using the PMG framework. It allows us to comfortably distinguish between long-run and short-run components, while we can fix the long-run relationship between an individual sector dependent variable and aggregate variables (interest rate and risk premium). At the same time it allows keeping these and other first-differenced exogenous variables as a short-run shocks pulling the sector specific development towards or away from the long-run equilibria. It also considers dynamics by allowing lead-lag relationship.

In fact, we are departing from the ARDL(1,p,q) model

$$y_t = c_0 + c_1 t + \sum_{j=1}^{p} \varphi_j \, y_{t-j} + \sum_{j=0}^{q} \beta'_j \, x_{t-j} + u_t \tag{3}$$

where $c_0 + c_1 t$ depicts constant and trend, $\sum_{j=1}^{p} \varphi_j \, y_{t-j}$ set of endogenous variables in a lagged structure and $\sum_{j=0}^{q} \beta'_j \, x_{t-j}$ set of exogenous variables and applying the Pesaran et al. (1999) re-parametrisation into the pooled mean group estimator (PMG). Alternative PMG estimators for this specification that we will estimate is

$$\begin{aligned} \Delta y_{it} = \theta_{0i} + \tau_i(y_{it-1} - \theta_1 F_t - \theta_2 P_{it}) + \\ + \sum_{j=0}^{p} \varphi_{ij} \, \Delta F_{it-j} + \sum_{j=0}^{p} \varphi_{ij} \, \Delta P_{it-j} + u_{it} \end{aligned} \tag{4}$$

where y_{it} is a sector-specific index of corporate health, which we explain by financial variables (the aggregate short term interest rate, yield curve slope and interest rate risk premium) F_t , performance indicators (as output, and alternatively by gross value added or economic sentiment) and corporate indebtedness P_{it}, and by a common error correction term, however maintaining sector-specific slopes in the long-run relationship. Vector of explanatory variables including the differenced series of those present in the long-run in the p-periods lag structure reflect the short-term movement around the sector-level equilibria. PMG estimator is a maximum likelihood panel estimator allowing short-run coefficients and error variances to differ across cross-sectional units. We assume series connected through the long-run are all I(1) processes and cointegrated (see tests in the *Appendix,* part 2), making the residual term u_t a stationary series.

5. Results

We first estimate the baseline OLS model with aggregate national data, where dependent variable is the index of corporate health, based on the transformed aggregate default rates from the equation (1). Results are reasonably robust

[9] Full set of assumptions are dealt with in more detail in Pesaran, Shin and Smith (2001).

(see Table 1) and economically sound. First, corporate sector seems to benefit from flatter slope of a yield curve (measured as a spread between long and short rate). This relates to bank lending conditions, which tend to improve, when longer rates are compressed. This is especially so in the environment, where vast amount of corporate financing originates in the banking sector. Second, higher level of debt weighs on the corporations and negatively affects economic conditions. Third, lagged economic performance has a correct sign across all four indicators, although not always significant.

For the two best performing model specifications, we have added additional explanatory variables (short term rates and sovereign risk premium) and tested, whether they help better to inform the index of corporate health, ergo corporate default rates. At the same time these also serve as controls to confirm that explanatory variables (which also allow for sectoral breakdown and can therefore use them in further analysis) remain significant.

Table 1 OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Lag dependent	0.393***	0.493***	0.518***	0.383***	0.344***	0.319***
	(0.101)	(0.102)	(0.096)	(0.106)	(0.105)	(0.110)
Short-term interest rate					-0.0404**	-0.0457*
					(0.020)	(0.026)
Yield curve slope	-0.0939***	-0.0438*	-0.0372	-0.0871***	-0.157***	-0.165***
	(0.030)	(0.025)	(0.023)	(0.030)	(0.052)	(0.053)
Interest rate spread					0.115	0.135**
					(0.071)	(0.066)
Corporate debt	-1.021***	-0.708***	-0.693***	-0.985***	-0.844***	-0.815***
	(0.236)	(0.216)	(0.216)	(0.238)	(0.259)	(0.249)
Performance indicator	**GDP**	**Output gap**	**Sentiment**	**Value added**	**GDP**	**Value added**
	0.0360***	1,105	0.000711	0.0309**	0.0256*	0.0230*
	(0.013)	(1.662)	(0.005)	(0.013)	(0.014)	(0.013)
Constant	3.190***	2.497***	2.367***	3.206***	3.422***	3.532***
	(0.533)	(0.503)	(0.469)	(0.563)	(0.561)	(0.587)
R2	0.583	0.539	0.536	0.574	0.599	0.599
RMSE	0,259	0,272	0,273	0,263	0,257	0,261
DW	2.222	2.236	2.261	2.167	2.208	2.166
Observations	72	72	72	72	72	72

Notes: Standard errors in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01. We document t statistics in parentheses. Confidence levels (* p < 0.05, ** p < 0.01, *** p < 0.001) are denoted by p-values. Sample length: 2001Q1-2018Q4

As a result, we confirm that accommodative monetary policy (lower interest rate level) improves corporate health and compresses loan default rates. The only seemingly counterintuitive, but still robust result is that the higher is the sovereign risk premium, the healthier are the corporates, i.e the lower corporate default probabilities are to be expected. This is closely relates to the concept of economic convergence. Although small open economy of the Central and Eastern Europe had surely been priced differently by the markets for inherent risk, this risk has been rewarded by higher returns and solid economic performance especially in the first decade of the century. Rewarding for the inherent risk that is rationalising the significant coefficients in some of the specifications has led to the present situation, when Slovakia, becoming a part of the euro area, is already priced reasonably close to the core euro area economies, and achieving similar output growth rates.

In the remaining part of the paper we exploit richer data by sectors and check whether additional information from diverse development in individual sectors can still improve modelling of the corporate default rates.

Dependent variables in individual sectors naturally co-move (also observable in the Figure 1), which would result in substantially correlated residuals. To take this into account we estimate the system using the GLS estimator of SUR model. We depart from the specification number (4) of the OLS estimate with value added as a proxy for economic performance. This specification features favourable fit (Table 1) and allows for sectoral breakdown (of value added and corporate debt). In order to provide fully transparent comparison of the transition from the OLS to SUR estimator, OLS estimates by sector are also included in the *Appendix*, part 3, Table A5.

As it is obvious from the Table 2, the breakdown of value added does not help the fit at all. The rest of the coefficients paste a similar picture as in the OLS. However, three additional benefits arise from the SUR estimator. First, the model is estimated together. Second, disturbances can be contemporaneously correlated. And third, it is the simplest model that allows differentiated perspective on default rates estimates by sector.

The results suggest some variation in how corporate default rates can be explained in different sectors. Clearly, looking at the yield curve slope coefficient, construction sector is the most vulnerable to the expectations of economic outlook. According to the estimate, one percentage point increase in the slope of the yield curve makes probability of default in construction to increase by 10 basis points[10] while for the manufacturing sector this is only 6.5 basis points. Higher long-term rates *vis-a-vis* economic partners seem also improving economic environment (and therefore compress default rates) more in construction than for instance in manufacturing or service sector. This could be for instance due to higher returns from real estate sector as an alternative to the bond market. The results also convey that indebtedness of corporate sector is a serious constrain for manufacturing and to some extent for construction but does not seem to bite in the trade sector. Interestingly, along other explanatory variables, value added, although in sectoral level, performs poorly.

Different responsiveness to general level of short rates in individual sectors is not particularly clear. Irresponsiveness of default rates in construction sector could perhaps be rationalised by longer term prospects for real estate market, both on the demand and supply side, which are indeed observable on the other coefficients wherein longer rates are embedded. The main message from the SUR estimate is that index of corporate health (log transformed from sectoral default rates) can be well

[10] Backward transformation of index of corporate health to default probability is performed after multiplying the coefficient by relevant slope of a yield curve.

explained by aggregate and sector specific macro variables. The model is considerably well specified and well fitted.[11]

Table 2 SUR Estimates

	MANU	CONS	TRAD	SERV
Short-term interest rate	-0.196***	0.0811	-0.120***	-0.0307
	(0.030)	(0.097)	(0.030)	(0.039)
Yield curve slope	-0.270***	-0.448**	-0.370***	-0.282***
	(0.059)	(0.197)	(0.054)	(0.061)
Interest rate premium	0.296***	0.552**	0.495***	0.341***
	(0.080)	(0.277)	(0.078)	(0.087)
Corporate debt for individual sectors	-0.345***	-0.725**	-0.0211	-0.292*
	(0.120)	(0.359)	(0.137)	(0.152)
Value added for individual sectors	0.0962	-0.211	0.239	-0.0599
	(0.394)	(1.018)	(0.345)	(0.411)
Constant	5.109***	4.457***	4.776***	5.194***
	(0.109)	(0.278)	(0.093)	(0.111)
R2	0.479	0.548	0.507	0.376
RMSE	0.334	0.855	0.310	0.369
Chi2	60.54	79.60	72.82	44.07
p-value	0.000	0.000	0.000	0.000

Notes: Standard errors in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01. We document standard errors in parentheses. Dependent variable is sector specific index of corporate health. Three common financial variables are complemented with other two sector specific variables: corporate debt and value added.

While in SUR, we only account for the cross-correlations of residuals, alternative pooled mean group (PMG) framework represents a panel approach where both stable relationship and short-term movements co-exist, side by side in a unified framework. PMG framework also allows us to model sector-based index of corporate health in individual sectors (transformed from loan default rates), with both long term and short-term component on the side of explanatory variables. The estimator yields the results documented in the Table 3.

The results confirm similar message than the one received from the SUR model. Coefficients do slightly differ, but in general are in the same ballpark as medians across the sectors from the previous estimates. Error correction term turns out to be relatively strong, taking less than 6 months to return to equilibrium. Use of 4 quarters lags in short run component is determined by the smallest RMSE and the highest adjusted R2 (see test in the table A8 in the *Appendix*, part 5).

[11] Two sets of tests have been performed for the SUR estimate. Pairwise tests for coefficients between equations and test for spatial autocorrelation. Overall fit is somewhat lower than it is the case for equation-by-equation OLS, but this is due to presence of correlation in error terms, which is accounted for by the SUR estimator and withholds some of the power from explanatory variables. We report this correlation matrix of errors in the *Appendix*, part *5*.

Table 3 PMG Estimates (Aggregate)

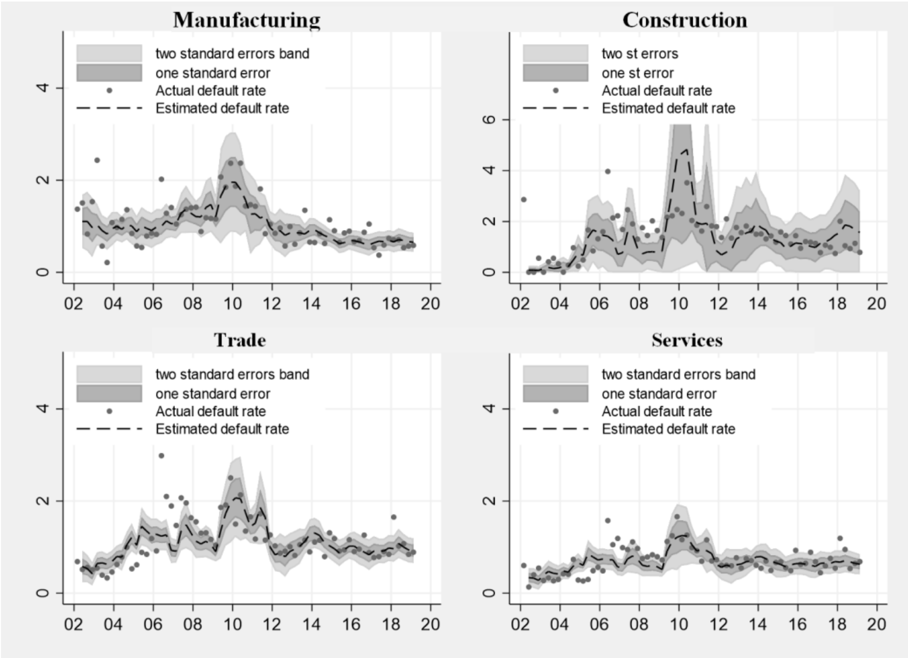
		coef	st.err		
Long-run	Interest rate	-0.1294***	(0.0280)	Overall	
	Yield curve slope	-0.4143***	(0.0489)	Obs.	268
	Interest rate premium	0.5267***	(0.0751)	R2	0.6202
	Corporate debt	-0,4424	(0.2841)	RMSE	0.4549
	Value added	-1.0707	(0.8377)	LL	-100.16
		MANU	**CONS**	**TRAD**	**SERV**
	Error correction term	-0.4623***	-0.5816***	-0.6826***	-0.6418***
	_cons	2.2771***	2.7749***	3.2490***	3.4210***
	R2	0.5081	0.6450	0.5522	0.5528
	RMSE	0.3184	0.7652	0.2082	0.2725

Notes: Standard errors in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01. Confidence levels (* p<0.05, ** p<0.01, *** p<0.001) are denoted by p-values. Dependent variable is sector specific index of corporate health. First three variables are common national level financial variables, while corporate debt and value added are also broken down to sectors of manufacturing, construction, trade and business services. Full estimate including all short-run coefficients is available in the *Appendix,* part 4.

In order to manifest the prediction ability of the models, we cross-check the two approaches (SUR and PMG) by fitting the predicted values of loan default rates calculated from the estimated sector specific indices of corporate health and backward calculating the log-transformation from the equation (1).

The fitted values of sector specific loan default rates have relatively narrow confidence band. This is suggesting that sector cross-correlations in SUR may be wiping out the variability of estimated sector specific default rate. On the other hand, applying a panel approach of the pooled mean group (PMG), the relationship of individual sectors is only bound together by common coefficient on long-term variables, allowing for differentiated error-correction terms and slopes in individual sectors. Sectors are thus subject to relaxed individual sector adjustment, while still modelled in unison. As previously, we can also transform index of corporate health back to default rates and compute fitted values for individual sectors.

Figure 3 Predicted Default Rates in the Four Sectors According to the SUR Model

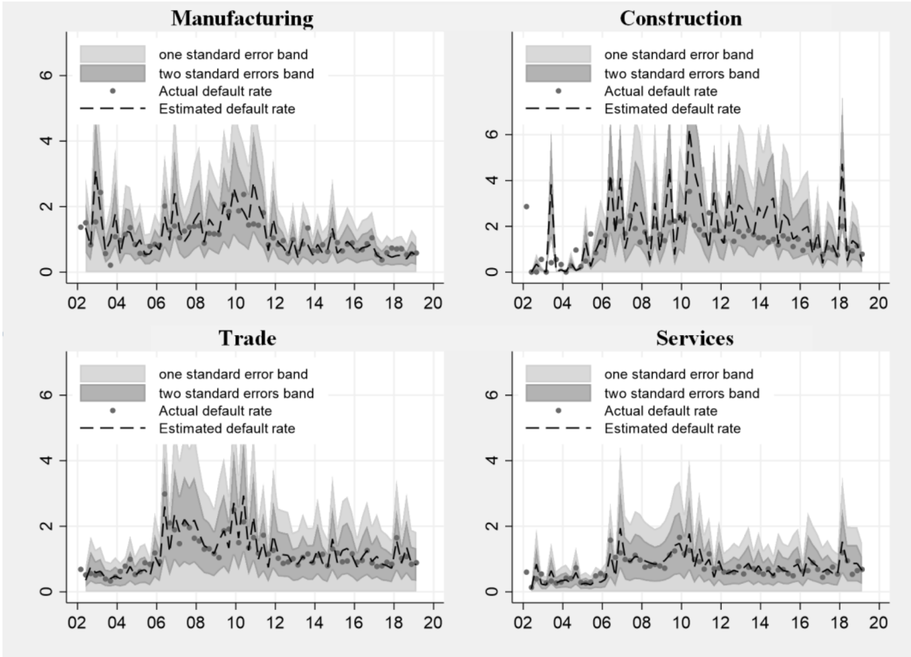


Notes: The dashed line represents point estimate of sector specific loan default rate fitted from the SUR model, grey areas are a one and two standard errors and dots represent actual observed default rates.

Comparing the two sets of fitted models implies that pooled mean group model allows for more volatility of the estimated values while their performance in terms of uncertainty around the fitted values is in terms of tightness somewhat superior. PMG estimator provides more cross-sector freedom, although lack of available data by sector (heavier dependence of loan default rates on financial data) makes it more difficult to exploit all the benefits of this panel specification. It is obvious from both approaches that if loan default rates are excessively volatile, goodness of fit is far from perfect (construction sector). More persistent pick-ups or free-falls could however be fitted considerably well (as it is documented on the historical paths in practically all other sectors).

In general, we can conclude that diverse development in individual sectors could be captured if sufficiently flexible panel data specification was used. The aim of the analysis to model loan default rates in sectoral break down is therefore well justified.

Figure 4 Predicted Default Rates in the Four Sectors According to the PMG Model



Notes: The dashed line represents point estimate of sector specific loan default rate fitted from the PMG model. Grey area are one and two standard errors and are calculated as a sum of the fitted errors for each sector separately. The dots represent actual observed default rates.

5.1 Stress Testing Exercise

Considerably robust framework that we have developed earlier, allows us to engage in testing different scenarios. We present one such exercise in this study. Our stress scenario is a financial crisis followed by a downfall of output of a similar scale as we witnessed between the 2008Q4 and 2009Q3 and is being currently[12] predicted at the onset of the coronavirus crisis. In this scenario, we assume short term interest rate remaining fixed at the current zero lower bound (we expect that eventual short-term interest rate cut in the negative territory could be only negligible). Since zero lower bound constrains central authorities to apply standard monetary easing, they are likely to activate new round of unconventional monetary policy measures.

Consequently, yield curve would remain flat and long run yields compressed. Countries with less fiscal space however would possess higher risk premium, but growth expectations for risk premium in longer maturities are limited. For this reason, our central stress scenario for expected sovereign risk premium accounts only for a half of what it has been in the early days of the Global Financial Crisis and expects risk premium to increase by 150 basis points. The debt ratio scenario follows the same flow of arguments as the output and is set to follow the same pace as between 2008Q4 and 2009Q3.

[12] The cut-off in this paper is dated to the end of March 2020.

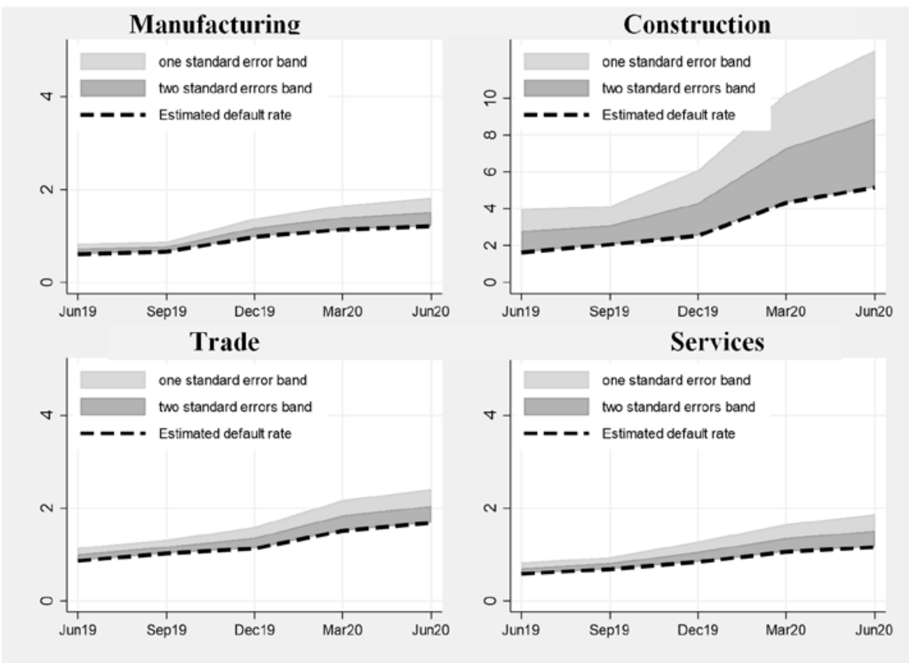
Table 4 Stress Scenario

Variable	Scenario	0	1	2	3	4
Short term interest rate	fixed at zero lower bound	0.000	0.000	0.000	0.000	0.000
Yield curve slope	as between 08Q4 - 09Q3	0.000	0.644	2.684	3.686	3.981
Interest rate spread	+ 150 bps	0.000	1.500	1.500	1.500	1.500
Corporate Debt	as between 08Q4 - 09Q3	0.000	-0.027	0.455	0.249	0.152
Output (Value Added)	as between 08Q4 - 09Q3	0.000	-0.037	-0.133	-0.117	-0.115

Notes: All stressed variables are expressed as centred at the "quarter zero". Financial variables (first three) are uniform for all sectors. Corporate debt is expressed as annual log difference growth of debt to GDP ratio. Output is expressed as a growth difference relative to the "quarter zero" level. "Quarter zero" relates to 2008Q3.

We apply this scenario for both approaches and use one year out-of-sample horizon. We assume the shock hitting in the third quarter of 2019. The results suggest that the stress test scenario has the most adverse effect in the construction sector. It must also be noted (as also seen in results), that uncertainty around such mid-point estimate is sizable. On the other hand, the effects on manufacturing, trade and services remain moderate, but not negligible. Under the modelled stress scenario, loan default rates in construction would almost triple and reach 5% within four quarters, while the simulation also suggests that other sectors default rates would about double in size.

Figure 5 Stress Scenario Default Rates Using SUR in the Four Sectors



These findings very much follow a common economic understanding of risks in the corporate sector exposed to a financial crisis, i.e. construction companies operating with high leverage making the sector the most vulnerable and very much driven by expectations of economic outlook and investment climate.

Stress test responses are indeed subject to a sizable uncertainty around the estimates (especially when using the PMG estimator), which is a consequence of the model structure.[13] General message is however clear and has been referred to earlier, i.e. framework featuring sector level modelling embedded in one system, while accounting for long run relationships and short run fluctuations requires rich volatility across sectors and time, which it has capacity to exploit.

6. Conclusion

We have exploited two alternative model frameworks that could serve as a basis for stress test simulations of macroeconomic scenarios. The main theoretical contribution is putting together a modelling framework that allows systematic modelling of several sectors in the economy, while preserving its specifics and accounting for cross-correlations between the sectors. The two empirical contributions are i) the use of multiple comparable panel approaches in a sector driven analysis of corporate loan default and ii) that this is the first time (according to our knowledge) the sector-based analysis of corporate loan default is performed in such detail on a dataset of an emerging economy.

We find that pooled mean group estimator provides well suited framework for stress testing exercise of sector specific default rates. Empirical exercise of this kind also confirms that individual sectors are subject to different vulnerabilities and their response to stress scenario could differ both in timing and scale. In our exercise, construction sector (and to lesser extent manufacturing) proves to be more sensitive to changes in macroeconomic conditions. Setting the shock at the comparable level to the Global Financial Crisis of 2008, we observe loan default rates in construction sector to triple in size with considerably higher uncertainty than it is the case in manufacturing, trade and services.

Despite acceptable criticism of autonomous setting of shocks in the stress testing exercise, the message stands out rather clear, i.e. that while reaping the benefits of estimating default probabilities in one system, it is possible and of utmost importance to monitor individual sector loans separately given response to macroeconomic shocks among them may largely differentiate.

[13] To make the structure clearer, as a robustness test, we have also produced SUR and PMG estimates with explanatory variables smoothed as four quarters moving averages (*Appendix*, parts 6 and 7). While results from SUR suggest only little difference to baseline, where responses are more sluggish, results from PMG estimates suggest a different story. This could be however expected, since smoothing wipes out short run responses, while in SUR it affects mainly cross-correlations and linear relationships remain largely unaffected.

APPENDIX

1. Dataset

Table A1 Dataset

Variable name	Label	Construction of the series	Type	Source
Index of corporate health	y_t	logistic transformation of corporate default rates	sector	National Bank of Slovakia
Short term interest rate	r_t	6-months EURIBOR	aggregate	Eurostat
Yield curve slope	yc_t	spread between 10-year benchmark SVK souvereign bond yield and 3-month EURIBOR	aggregate	Eurostat
Interest rate premium	b_t	spread between SVK and DEU 10-year benchmark souvereign bond yields	aggregate	Eurostat
Corporate debt	d_t	share of accumulated stock of credit to private sector on value added	sector	Eurostat
Value added	VA_t	Gross value added in the reference sector, GDP production method	sector	Eurostat
Economic sentiment	S_t	Year on year difference of economic sentiment in the reference sector	sector	Eurostat
GDP	Y_t	annualised GDP growth in %	aggregate	Eurostat
Output Gap	OG_t	HP filtered cycle of GDP	aggregate	Eurostat

2. Unit Root and Cointegration Tests

As the first step, we have used a panel unit root test to see, whether series, which we break down to sectors, are stationary. To allow for heterogeneity in the autoregressive coefficients, which are assumed to change freely among the sectors, we applied the IPS test (Im, Pesaran and Shin, 2003), which is a generalisation of time series unit root tests to panel data.

Table A2 IPS panel Unit Root Test Results

AR parameter: Panel-specific	*H0: Unit root (assumes individual unit root processes)*			
Panel means: Included	*H1: Some panels are stationary*			
Time trend: Not included				
	level		1st difference	
	t-bar	p-value	t-bar	p-value
Log of value added	-1.4871	0.5187	-5.0332	0.0000
Log of debt to GDP	-1.4912	0.5193	-3.6748	0.0000

For other variables that do not differentiate across sectors we test for unit root by standard ADF test.

Table A3 ADF Test for Unit Root Results

	H0: Unit root (assumes individual unit root processes) *H1: Some panels are stationary*			
	level		1st difference	
	Z(t)	p-value	Z(t)	p-value
Short term interest rate	-2.591	0.0950	-6.178	0.0000
Yield curve	-0.744	0.8350	-6.025	0.0000
Interest rate premium	-2.659	0.0815	-7.898	0.0000

All of the variables may be considered as non-stationary and integrated of order one, I(1), at a significance level of 5%. We therefore proceed assuming the series are non-stationary. In the next step, we test for panel cointegration to ensure that there is a long run relationship between the variables entering the model, i.e. to ensure that PMG estimator is consistent.

We use Pedroni (1999) test, which assumes a single cointegrating vector, and at the same time allows the coefficients of each cointegration relation to differ among sectors.

Table A4 Pedroni Panel Cointegration Test Results

Panel specific cointegration vector Panel specific AR parameters Panel means are included	*H0: No cointegration* *H1: All panels are cointegrated*	
	t-statistics	p-value
Modified Phillips-Perron t	-6.4514	0.0000
Phillips-Perron t	-10.2594	0.0000
Augmented Dickey-Fuller t	-10.8889	0.0000

The cointegration tests broadly reject the null hypothesis of no cointegration to the conclusion that the series share a common long run trend and thus allowing the estimation of our empirical model with the PMG estimator.

3. Estimates

Table A5 OLS Estimate by Sector, with Identical Explanatory Variables as in the SUR Estimate

	MANU	CONS	TRAD	SERV
Short-term interest rate	-0.191***	0.163	-0.0924***	0.0351
	(0.031)	(0.106)	(0.033)	(0.049)
Yield curve	-0.241***	0.283	-0.339***	-0.285***
	(0.063)	(0.208)	(0.062)	(0.066)
Interest rate spread	0.277***	0.293	0.433***	0.343***
	(0.081)	(0.293)	(0.093)	(0.095)
Value added	0.00255	0.0105	-0.0132**	0.00162
	(0.004)	(0.010)	(0.005)	(0.007)
Corporate debt	-0.528***	-1.124***	0.260	0.271
	(0.145)	(0.419)	(0.233)	(0.256)
Constant	5.105***	4.382***	4.786***	5.193***
	(0.117)	(0.296)	(0.093)	(0.118)
r2	0.488	0.570	0.567	0.375
N	68	68	68	68

Notes: We document t statistics in parentheses. Confidence levels (* p < 0.05, ** p < 0.01, *** p < 0.001) are denoted by p-values. Sample length: 2001Q2-2019Q1

4. PMG Estimates, Full Transcript

Table A6 Full Results from the PMG Estimator, Including Sectoral Level Coefficients

		coef	***st.err***		
Long-run	Interest rate	-0.1294***	(0.0280)	*Overall*	
	Yield curve slope	-0.4143***	(0.0489)	*Obs.*	*268*
	Interest rate premium	0.5267***	(0.0751)	*R2*	*0.6202*
	Corporate debt	-0.4424	(0.2841)	*RMSE*	*0.4549*
	Value added	-1.0707	(0.8377)	*LL*	*-100.16*
	Error correction term	-0.4623***	-0.5816***	-0.6826***	-0.6418***
Short-run	Interest rate	MANU	CONS	TRAD	SERV
	diff lag 1	0.0170	-0.7886*	-0.1184	-0.1462
	diff lag 2	-0.2398	0.0346	-0.0180	0.1218
	diff lag 3	-0.1404	0.0751	-0.1895	-0.2527
	diff lag 4	-0.0758	-0.0576	-0.2491*	0.0119
	Yield curve slope				
	diff lag 1	-0.0431	-0.8483*	0.2289*	0.1116
	diff lag 2	-0.2136	0.5367	-0.0403	0.0858
	diff lag 3	0.0563	-0.1481	-0.1294	-0.1768
	diff lag 4	0.0200	-0.0066	-0.1105	0.1397
	Interest rate premium				
	diff lag 1	0.3145*	0.6378	-0.0986	0.0345
	diff lag 2	0.4310**	-1.116**	0.0623	-0.2721*
	diff lag 3	-0.2811	0.2205	-0.1378	-0.0427
	diff lag 4	0.0096	0.0026	0.0949	-0.0915
	Corporate debt				
	diff lag 1	0.7500**	-1.9614**	-0.1184	0.1470
	diff lag 2	0.9068**	-0.0586	-0.0827	0.9804***
	diff lag 3	0.3646	2.9360***	0.0170	-0.3054
	diff lag 4	0.0637	-1.1805	-0.1286	-0.1192
	Value added				
	diff lag 1	0.6329	0.6031	1.2690**	-0.6726
	diff lag 2	2.0933***	4.015***	0.6060	0.1617
	diff lag 3	1.9097**	0.7862	1.3289**	0.0393
	diff lag 4	0.5728	-1.0458	0.2972	-0.2723
	_cons	2.2771***	2.7749***	3.2490***	3.4210***
	R2	*0.5081*	*0.6450*	*0.5522*	*0.5528*
	RMSE	*0.3184*	*0.7652*	*0.2082*	*0.2725*

Notes: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Test of Lag Structure

Table A7 Correlation Matrix of Error Terms from the SUR Estimator

	MANU	CONS	TRAD	SERV
MANU	1			
CONS	-0.0512	1		
TRAD	0.4922	0.2302	1	
SERV	0.3647	0.3412	0.7933	1

Table A8 Selection of the Lag Structure in the PMG Estimator

k			MANU	CONS	TRAD	SERV	TOTAL	AIC / Obs.	R2-adj
5	Lag 0	R2	0.3291	0.4387	0.3823	0.3906	0.4234	-175.20	
10		RMSE	0.3971	1.1023	0.2507	0.3560	0.6250	288	0.4025
5	Lag 1	R2	0.3663	0.6016	0.3586	0.5554	0.5694	-147.24	
15		RMSE	0.3782	0.9307	0.2545	0.3044	0.5401	284	0.5453
5	Lag 2	R2	0.5148	0.6304	0.5286	0.5565	0.6106	-111.258	
20		RMSE	0.3213	0.8479	0.2167	0.2846	0.4874	280	0.5806
5	Lag 3	R2	0.5081	0.6450	0.5522	0.5528	0.6202	-100.158	
25		RMSE	0.3184	0.7652	0.2082	0.2725	0.4485	276	0.5822

6. Alternative Estimates with Smoothed Default Rates (SUR)

Table A9 Estimates with Smoothed Default Rates from SUR Model (Sectors)

	MANU	CONS	TRAD	SERV
Short-term interest rate	-0.165***	-0.0266	-0.0860***	-0.0294
	(0.015)	(0.041)	(0.026)	(0.028)
Yield curve slope	-0.193***	-0.321***	-0.306***	-0.255***
	(0.029)	(0.081)	(0.048)	(0.046)
Interest rate premium	0.163***	0.195*	0.367***	0.285***
	(0.039)	(0.114)	(0.069)	(0.065)
Corporate debt *for individual sectors*	-0.467***	-0.259**	-0.193**	-0.216**
	(0.063)	(0.129)	(0.089)	(0.091)
Value added *for individual sectors*	-0.850***	-0.476	-0.0602	-0.370
	(0.208)	(0.356)	(0.219)	(0.246)
Constant	5.091***	4.684***	4.752***	5.176***
	(0.054)	(0.124)	(0.086)	(0.084)
R2	0.768	0.541	0.507	0.456
RMSE	0.161	0.420	0.285	0.282
Chi2	225.5	84.35	73.41	62.88
p-value	0.000	0.000	0.000	0.000

Notes: Standard errors in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01.

Figure A1 Predicted Default Rates Using SUR Model (Sectors)

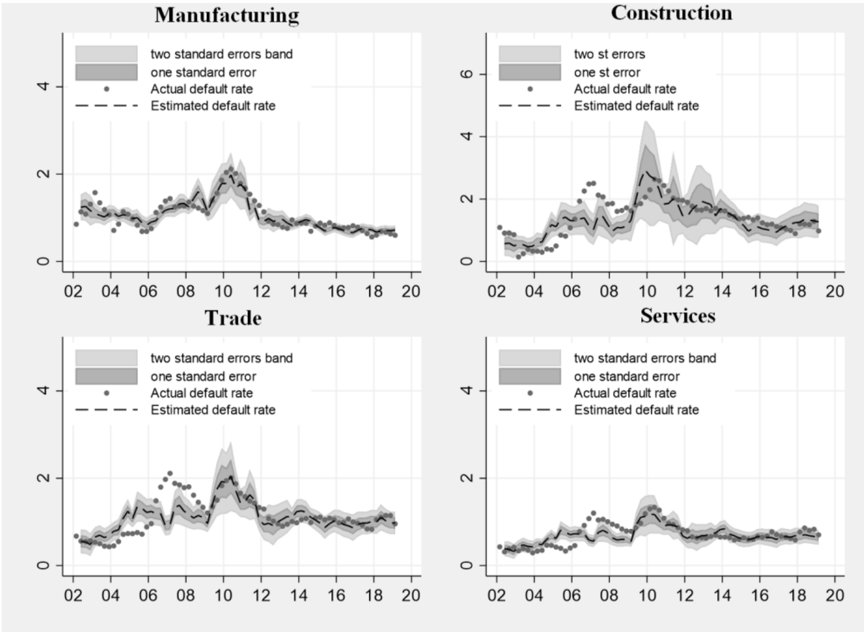
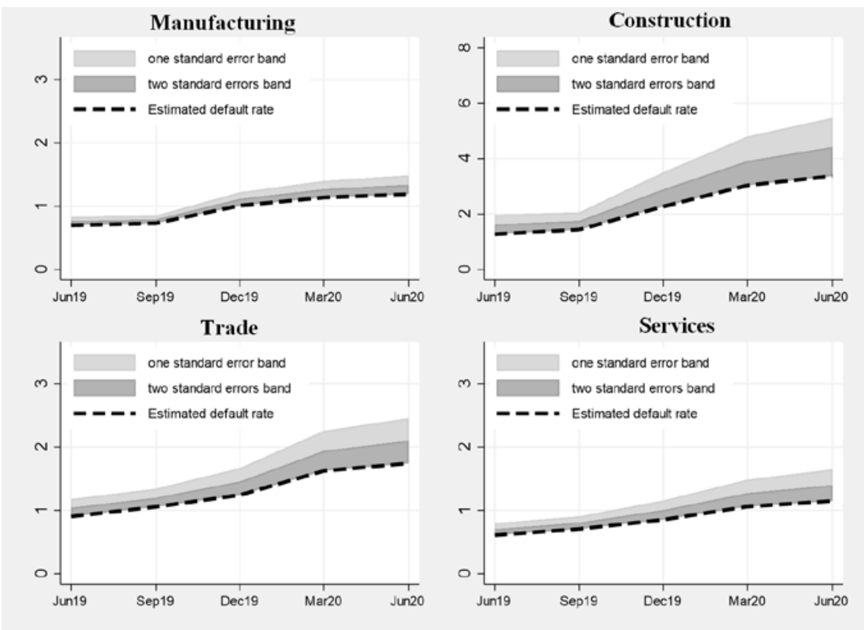


Figure A2 Stress Scenario Default Rates Using SUR Model (sectors)



7. Alternative Estimates with Smoothed Default Rates (PMG)

Table A10 Estimates with Smoothed Default Rates from PMG Model (Sectors)

		coef	**st.err**		
Long-run	Interest rate	-0.083***	(0.0377)	*Overall*	
	Yield curve slope	-0.4301***	(0.0648)	*Obs.*	*268*
	Interest rate premium	0.5115***	(0.1022)	*R2*	*0.5717*
	Corporate debt	-1.5394	(0.4375)	*RMSE*	*0.1135*
	Value added	-0.1893	(1.1385)	*LL*	*234.12*
	Error correction term	-0.0118	-0.2113***	-0.174***	-0.1896***
Short-run	Interest rate	MANU	CONS	TRAD	SERV
	diff lag 1	-0.0728	-0.2437**	-0.0490	-0.0756
	diff lag 2	-0.1227*	0.0350	-0.0615	0.0225
	diff lag 3	-0.0053	-0.0329	-0.0610	-0.1108*
	diff lag 4	-0.1407**	0.2141**	-0.0876*	-0.0131
	Yield curve slope				
	diff lag 1	-0.0959*	-0.1665*	0.0216	-0.0009
	diff lag 2	-0.0699	0.201**	-0.0222	0.0256
	diff lag 3	-0.0453	-0.0050	-0.0589	-0.0882*
	diff lag 4	-0.1057**	0.1454	-0.0614	0.0300
	Interest rate premium				
	diff lag 1	0.1213**	0.0274	-0.0206	0.0067
	diff lag 2	0.2244***	-0.3098***	0.0510	-0.0703
	diff lag 3	-0.0354	0.0983	-0.0098	0.0198
	diff lag 4	0.1302**	-0.1381	0.0889*	0.0090
	Corporate debt				
	diff lag 1	0.0919	0.0395	0.0113	0.3868***
	diff lag 2	0.1844	-0.0421	-0.0502	0.5069***
	diff lag 3	0.1331	0.6978***	0.0906	0.1172
	diff lag 4	0.0462	-0.4965***	0.0620	0.0190
	Value added				
	diff lag 1	-0.2209	-0.2158	0.0218	-0.3333
	diff lag 2	0.2068	0.0072	-0.0188	-0.0462
	diff lag 3	0.5108**	-0.3954	0.3396**	-0.3323
	diff lag 4	0.6412**	-0.5412**	0.2214	-0.3660*
	_cons	0.0409	0.9723***	0.8092***	1.0151***
	R2	0.4468	0.6354	0.5269	0.4888
	RMSE	0.1025	0.1599	0.0789	0.0962

Notes: Standard errors in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01.

Figure A3 Predicted default rates using PMG model (sectors)

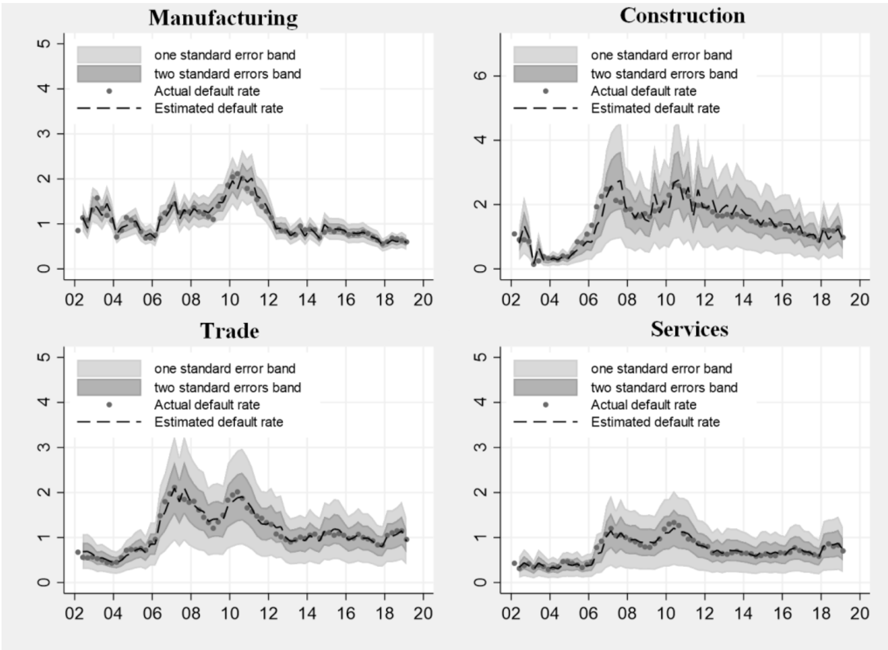
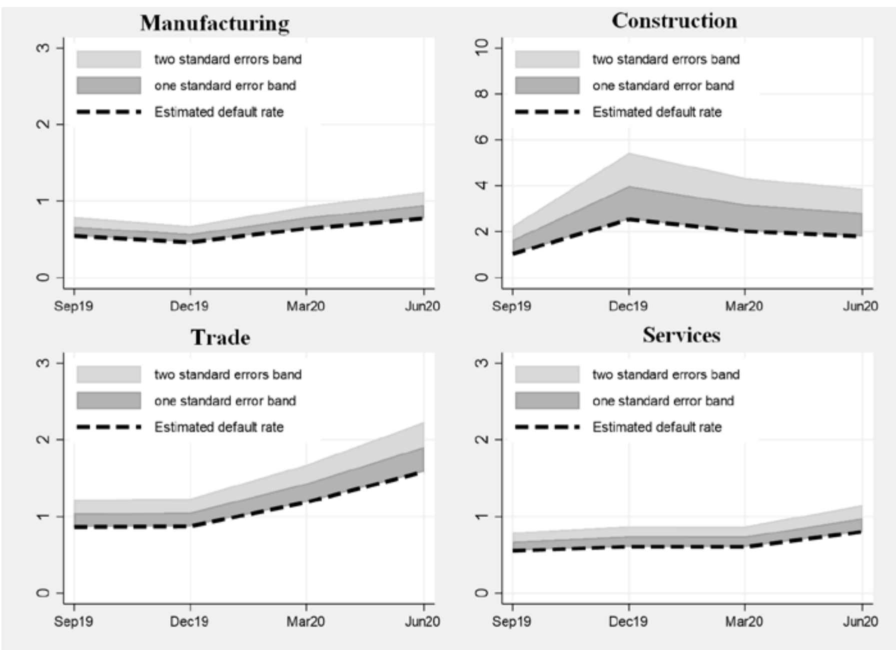


Figure A4 Stress scenario default rates using PMG model (sectors)



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