What Drives Aggregate Credit Risk?

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A deep understanding of the drivers of credit risk is valuable for financial institutions as well as for regulators from multiple viewpoints. The systemic component of credit risk drives losses across portfolios and thus poses a threat to financial stability. Traditional approaches consider macroeconomic variables as drivers of aggregate credit risk (ACR). However, recent literature suggests the existence of a latent risk factor influencing ACR, which is regularly interpreted as the latent credit cycle. We explicitly model this latent factor by adding an unobserved component to our models, which already include macroeconomic variables. In this paper we make use of insolvency rates of Austrian corporate industry sectors to model realized probabilities of default. The contribution of this paper to the literature on ACR risk is threefold. First, in order to cope with the lack of theory behind ACR drivers, we implement state-of-the-art variable selection algorithms to draw from a rich set of macroeconomic variables. Second, we add an unobserved risk factor to a state space model, which we estimate via a Kalman filter in an expectation maximization algorithm. Third, we analyze whether the consideration of an unobserved component indeed improves the fit of the estimated models.

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1 Introduction and Motivation

The enormous rise in the number of publications on credit risk over the last decades bears testimony to an increasing interest in this topic. From a systemic perspective, the level of aggregate credit risk (ACR) is of major interest as – in contrast to idiosyncratic (borrower-specific) credit risk – it cannot be diversified away and is therefore a potential source of financial instability. Although the nature of ACR suggests that it is primarily of concern to regulators, central banks and supervisory authorities, more and more commercial banks and other financial institutions seek a deeper understanding of ACR as this is essential to managing risk, maintaining a sound capital planning process and applying meaningful stress testing programs as well as a consistent approach to designing an adequate rating model philosophy[2]. The value of structured products, or of any portfolio with non-zero credit risk, is largely determined by their inherent systemic component – an important point that should be clear after the 2008/2009 financial crisis.

In addition, the growing relevance of forecasting ACR is evident from the numerous stress tests carried out by central banks around the world, as ACR forecasts constitute a precondition for stress-testing. To be able to perform efficient system-wide stress testing, central banks or any other supervisory authorities need a structured approach to forecasting ACR.

Hence, a profound understanding of ACR drivers is of high relevance for banks and supervisors alike. Numerous papers have addressed this topic in recent years; inter alia Nickell et al. (2000), Koopman and Lucas (2005) and Couderc and Renault (2005). However, any approach to finding significant drivers of ACR faces two major challenges:

– Given the lack of a clear-cut theoretical framework explaining the causes and driving factors of ACR in a financial system, a long list of macroeconomic variables is a priori available for explaining ACR. Select-

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[2] *See the distinction between point-in-time and through-the-cycle models, e.g. in Heitfield (2005).*

ing among them becomes even more challenging when taking the possible dynamic lag structure of these macroeconomic variables into account.

– At the same time, there is mounting evidence of latent factors driving (aggregate) credit risk, as emphasized recently by Lown and Morgan (2004), Jimenez and Mencia (2009), Koopman et al. (2009) and Bruche and Gonzalez-Aguado (2010). With no directly measurable metric at hand, the question is how to incorporate this evidence into an econometric model.

In this paper we present an approach that deals with both of the above issues in a state-of-the-art fashion. In order to manage the high number of possible explanatory variables for ACR, we make use of advanced variable selection techniques (Hastie et al., 2009). We cope with the second issue by following the approach of Jimenez and Mencia (2009) and Koopman et al. (2009), treating the credit cycle as a latent factor.

Since Kalman (1960) described a recursive solution to the discrete data linear filtering problem (Kalman filter), the idea of incorporating an unobserved state variable into a state space model has led to an extensive amount of literature in various fields of science. In economics, state space models are used as a very flexible tool in time series analysis.[3] Harvey and Koopman (2009) give a short introduction into the various applications of state space models in economics and finance. The most prominent applications are macroeconomic models used to identify the natural rate of unemployment, permanent consumption, the output gap or the expected rate of inflation, and time series models such as trend-cycle decomposition and seasonal component models (Burmeister et al., 1986).

Only recently, state space models have drawn attention in credit risk-related research. The respective papers aim at exploring the so-called "hidden," "unobserved" or "latent" credit risk factors.[4] In general, these different terms all point to models that try to incorporate unobserved factors (defined as state variables) in credit risk analysis. The evolution of these (unobserved) states is usually driven by transition probabilities.

Crowder et al. (2005), Bruche and Gonzalez-Aguado (2010), Koopman et al. (2008) and Banachewicz et al. (2008) assume that the state variable (latent risk factor) is discrete and the number of states is at least two (a "good" and a "bad" state). The resulting models are commonly referred to as hidden Markov models.[5] By contrast, Koopman and Lucas (2005), Jimenez and Mencia (2009) and McNeil and Wendin (2007) choose a more general approach in terms of state space by modeling it as a continuous state variable.[6] This setup-up leads to the classical state space model described by Kalman (1960).

Nevertheless, there is no common theoretical view on the source and/or definition of latent factors. They could be related to (a mixture of) general

[3] *For example, to estimate their parameters, autoregressive moving average models, dynamic stochastic general equilibrium models and time-varying coefficient models can be put into a state space form.*

[4] *In this paper, we use the expression latent risk factor to refer to the general idea of including additional unobserved predictors in various models. In our models, latent risk factors are added as unobserved components.*

[5] *See Rabiner (1989) for details on recursions and filter techniques used to extract the not directly observed sequence of hidden states from the system being modeled in which only the state-dependent output variables are observed.*

[6] *A continuous state variable leads to more restrictions on other model assumptions, in particular on the transition equation. See Minka (1999) for more details.*

credit market conditions such as the leverage and/or solvency ratios of creditors, collateral and other asset values or it could, via the lending channel, supply adjunct criteria such as banks' capital buffers and lending criteria, etc. In any case, the latent factor should be a variable that is unobserved (at least in our dataset), but still has a significant and persistent impact on credit risk.

In view of the recent financial crisis, one promising idea would be to relate the credit cycle to the leverage cycle, as explicitly defined by Geanakoplos (2010) and Fostel and Geanakoplos (2008). In their papers, they argue that a small initial drop in the value of assets and collateral causes a big drop in the wealth of leveraged "optimists," which is then amplified by forced sales and uncertainty.

A second credit cycle theory assumes the following relation between credit standards, banking competition and the phase of the business cycle. In a nutshell, empirical studies report that (too) lenient credit standards during an economic upturn result in the build-up of high credit risk, which materializes in the ensuing economic downturn.[7] As analyzed by Ruckes (2004), such behavior can be supported by banks' profit-maximizing strategies in a simple game theoretic setting. In line with his model, credit standards vary anti-cyclically and therefore might enhance the influence of the macroeconomy on ACR.

Third, the credit cycle could be explained by the theory of cyclical default correlation (Giesecke, 2004), which can be understood as a partly systemic risk factor founded in the existence of direct ties (e.g. financial, legal or client-supplier links) between firms.[8]

Our paper tests whether there is evidence for a latent effect on ACR. It builds on previous work by Boss (2002) and Boss et al. (2009) describing the current OeNB macro-to-probability of default models. We extend these OeNB models in two ways. First, we add a new dimension to the discussion about the link between the macroeconomy and credit risk measures by enlarging the set of possible macroeconomic predictors.[9] We apply advanced variable selection algorithms to find the best macroeconomic predictors for a given model size. Second, we integrate an unobserved factor into the models via a state space formulation, thus enriching them by explicitly modeling the hypothesized credit cycle.

In a next step, we interpret the sector-specific results. Finally, we evaluate the results by comparing the state space model output with the output obtained from the traditional models that are based on macroeconomic factors only.

2 Model Specifications

In this section we outline the econometric theory and estimation procedures behind the models used to explain ACR. In terms of data, we use – in line with previous work by Boss (2002) and Boss et al. (2009) – quarterly default frequency rates from 1985 to the first quarter of 2011 as provided by *Kreditschutzverband von 1870* to approximate sectoral corporate probabilities of default in Austria. These default frequency rates are calculated by dividing the number of quarterly defaults by

[7] *See e.g. Lang and Nakamwa (1995) and Bonfim (2009).*

[8] *Such direct ties could lead to contagion effects that describe the default dependence between interconnected corporates. See e.g. Eisenberg and Noe (2001).*

[9] *In a classical multivariate framework, this boils down to re-examining the trade-off between the bias and variance of estimated results.*

Table 1

Possible Explanatory Macroeocnomic Variables[1]

Abbreviation	Meaning	Transformation
ATX	Austrian Traded Index	YoY-Log-Difference
CPNReal	Real private credit, amount outstanding	YoY-Log-Difference
DDR	Real domestic demand	YoY-Log-Difference
GONReal	Real gross operating surplus	YoY-Log-Difference
HIC	Harmonised Index of Consumer Prices	YoY-Rel-Difference
IER	Real equipment investment	YoY-Log-Difference
IOR	Real other investment	YoY-Log-Difference
LTIReal	Real long-term interest rate	No
MTR	Real imports	YoY-Log-Difference
PCR	Real private consumption	YoY-Log-Difference
POIL	Oil price in domestic currency	YoY-Log-Difference
PRO	Average labor productivity	YoY-Log-Difference
PSNReal	Real private sector savings	YoY-Log-Difference
PYR	Real private sector disposable income	YoY-Log-Difference
STIReal	Real short-term interest rate	No
URX	Unemployment rate	YoY-Rel-Difference
WURYD	Real compensation per employee	YoY-Log-Difference
XTR	Real exports	YoY-Log-Difference
YER	Real GDP	YoY-Log-Difference

Source: The OeNB's macroeconomic database, Bloomberg.

[1] For each variable, up to six quarterly lags are considered.

the total number of firms. The corporate sectors in question are construction, production, trade, transport, tourism and services.[10] The macroeconomic variables used to construct our design matrix are taken from the OeNB's macroeconomic database. The set of explanatory variables $\{x_j\}_{j=1}^{k}$ might contain lagged dependent variables, which multiplies the pool of candidate predictors. Specifically, we extend the original dataset by one to six lags of each time series.

As a starting point for modeling ACR, we look at the linear observable macroeconomic factor model:

$$y_{i,t} = \beta_{0,i} + \sum_{j=1}^{k} x_{j,t}\,\beta_{j,i} + \epsilon_{i,t}, \qquad (1)$$

where y_i is the logit-transformed sectoral default frequency rates[11] $(i \in \{0,1,2,..,7\})$, k is the number of macroeconomic predictors and $t \in \{1,2,..,T\}$ constitutes the time index. x_j is the j^{th} transformed macroeconomic predictor.[12]

How to Select Explanatory Variables?

In this section, we address the first issue raised in the introduction: As, in our opinion, general equilibrium literature on credit markets does not provide the sufficient theoretical background for deriving explanatory variables, the list of candidate predictors is extensive and, as a consequence, candidate predictors might even outnumber observations. In previous work on the topic, regressors have been selected by mere qualitative reasoning (see e.g. Jimenez and Mencia, 2009 and Koopman et al., 2008). Boss et al. (2009) group the variables into thematic sets and allow only one variable from each set to be selected. In order to deal with the high variance-versus-low bias trade-off in a nonheuristic way, we depart from these qualitative approaches and consider a data-driven subset selection mechanism.

One of the available subset selection algorithms is the so-called *Best Subset Selection*[13], which selects for each $k \in \{0,1,2,..,p\}$ the subset of size k that gives the smallest residual sum of squares. The variance-versus-bias trade-off is directly linked to the choice of k and is therefore a discrete mechanism.

[10] Corporate sectors are classified according to NACE Rev. 2, the classification of economic activities applied throughout the European Union (European Commission, 2008). See Zeller et al. (2008) for more details.

[11] The logit transformation ensures that the default frequency rates used remain within the interval (0;1). A probit transformation would serve the same purpose. Other popular approaches to modeling dependent ratios without transforming them include the fractional logistic regression by Papke and Wooldridge (1996) and beta regression models (Ferrari and Cribari-Neto, 2004). A discussion of the advantages and disadvantages of the different approaches to modeling dependent ratios would be beyond the scope of this paper.

[12] See table 1 for details.

[13] See Hastie et al. (2009) for details.

With respect to model interpretation, Best Subset Selection offers the choice of k input variables from the set of p variables. However, a severe drawback is the computational cost of this method. The fact that the number of possible models increases exponentially with p puts a relatively low bound on feasible values of p ($p < 50$) even with a fast algorithm such as the leaps and bounds procedure at hand.[14] Consequently, the application of Best Subset Selection would require a preselection of the variables considered above, especially when one wants to account for a dynamic lag structure.

Alternatives to this approach are *Forward and Backward Stepwise Selection*[15]. Forward Stepwise Selection starts with an intercept and sequentially adds the regressors which contribute most to an improvement of the fit (as measured e.g. by the *Bayesian information criterion* – BIC) until k variables are selected (Hastie et al., 2009). Backward Stepwise Selection starts with the full model and sequentially drops the least important variables in terms of model fit until k variables are reached. While not as computationally demanding as Best Subset Selection, these algorithms might not select the "optimal" set from the perspective of the minimal residual sum of squares. A comparison between Best Subset Selection and Forward Stepwise Selection applied to different subsamples of our dataset shows that the two mechanisms produce relatively similar results. As Backward Stepwise Selection requires the number of candidate predictors to be smaller than the number of observations, $p < T$, a preselection of variables – as in the case of Best Subset Selection – would still be necessary to make the selection procedure applicable.

As a third alternative selection procedure, *shrinkage methods*[16] appear to be promising. In contrast to subset selection, shrinkage methods do not retain or discard a variable but "shrink" the regression coefficients by imposing a penalty on their size. For example, the *elastic net* procedure proposed by Zou and Hastie (2005) is a shrinkage method which uses a convex combination of the L1 (lasso) and the L2 (ridge regression) norm as the penalty restriction in the standard minimization of the sum of residual squares (with respect to the vector β) to estimate equation (1). While promising at first sight, the combination of shrinkage methods with the estimation of latent factors (see below) requires a largely revised estimation procedure and is beyond the scope of this paper.

By way of summary, we find that Best Subset Selection and Backward Stepwise Selection both require a preselection of variables, while shrinkage methods do not, in general, allow for including latent factors within the state space framework.[17] Therefore, we will use Forward Stepwise Selection, which does not require any form of variable preselection and shows a promising performance in simulation exercises (Hastie et al. 2009).

[14] *See Furnival and Wilson (1974) for details.*

[15] *See Hastie et al. (2009) for details.*

[16] *See Hastie et al. (2009) for details.*

[17] *The question of how to combine the elastic net algorithm with an unobserved component in a Bayesian framework is currently being examined in an ongoing research project.*

How to Incorporate the Latent Credit Cycle?

In a next step we extend our macroeconomic factor model by "latent risk factors." Motivated by the discussion presented in section 1, we add an unobserved risk factor to the framework of equation (1) and will refer to this new equation as the measurement equation (2). We explicitly model the latent credit cycle as an autoregressive state process that evolves through time and refer to this specification as the state equation (3).

$$y_{i,t} = X_{i,t}\,\Gamma_i + z_{i,t}\,\lambda_i + v_{i.} \qquad v_{i,t} \sim \mathcal{N}(0, r_i) \tag{2}$$

$$z_{i,t} = z_{i,t-1}\,\phi_i + w_{i,t} \qquad w_{i,t} \sim \mathcal{N}(0, q_i) \tag{3}$$

In addition to the previous notation, $\lambda_i, \Gamma_i, \Phi_i, q_i$ and r_i are parameters to be estimated, $z_{i,t}$ is the unobserved factor, and $v_{i,t}$ and $w_{i,t}$ are error terms. Capital letters denote matrices (or vectors) and small letters scalars. Moreover, we assume that $Cov(v_{i,t}, w_{i,t}) = 0$ and that there are no cross-correlations in the state and measurement equation between the sectors i, $Cov(w_{j,t}, w_{i,t}) = 0$ and $Cov(v_{i,t}, v_{i,t}) = 0$ for any $i \neq j$.

We estimate the equation systems (2) and (3) via an expectation maximization algorithm (EM algorithm)[18]. Based on an initial set of parameters ($\lambda_i, \Gamma_i, \phi_i, q_i$ and r_i), the unobserved component is extracted via the Kalman filter in the expectation step. Given the unobserved component z_i, the likelihood of equation (2) is maximized with respect to the parameter set. These steps are repeated until convergence.[19]

However, the state space representation of a given dynamic system might not be uniquely defined by a given parameter set $\lambda_i, \Gamma_i, \phi_i, q_i, r_i$ without restricting some of these parameters. This can be seen from the fact that the likelihood function of the equation system would remain unchanged as multiplying equation (3) with any non-zero factor or nonsingular matrix would measure the unobserved factor on a different scale.[20]

Consequently, we fix the metric of the unobserved variable by restricting $q_i = 1$ without loss of generality.

3 Results

In this section we present evidence of the relevance of the latent factor in our dataset as well as an analysis of the most frequently selected variables. For this purpose we estimate models for each of the corporate sectors under review with a varying number of explanatory variables. The explanatory variables are chosen by applying the Forward Stepwise Selection method described in section 2. For each number of explanatory variables ranging from 1 to 15, we estimate the top five models according to their explained sum of squares, which results in 75 models per sector.[21] Additionally, to gain insight into the importance of latent factors for explaining ACR, we estimate these models with and without an unobserved component. To compare the respective results, we follow Koopman

[18] *See McLachlan and Thriyambakam (1996) for details.*

[19] *See Shumway and Stoffer (2006) and Holmes (2010) for details.*

[20] *For more details, see Hamilton (1994) and Carro et al. (2010).*

[21] *Thus, models of different sizes do not compete with each other, and applying any selection criteria such as the Akaike information criterion (AIC) or the Bayesian information criterion (BIC) would result in the same selection of variables.*

et al. (2009) and conduct a likelihood ratio (LR) test defined by

$$2(l_u - l_r) \overset{a}{\sim} \chi^2_m, \qquad (4)$$

where l_u represents the likelihood of the unrestricted model with the latent factor, l_r the restricted models without this factor and m the number of restrictions implemented. The only imposed restriction is $\lambda_i = 0$.

Is a Latent Factor Present in Aggregate Credit Risk?

To judge whether latent factors are statistically significant, chart 1 plots the likelihood ratio statistics for all models per sector, with the x axis representing the number of included predictors per model. Note that for each given number of explanatory variables, five models are estimated. The horizontal line in each plot represents the 99% critical value of the x^2 distribution.[22] Thus, values above the line indicate a statistically significant contribution of the latent factor to the model fit and can thus be interpreted as evidence for the existence of an unobserved component. The results shown in chart 1 are quite surprising: While there is evidence for a latent factor in smaller models, i.e. models with about 1 to 7 explanatory variables, this evidence clearly vanishes when considering models of larger size.[23]

This behavior is similar in all sectors with the exception of construction. Especially in the production sector, any significant contribution of the estimated unobserved component series is lost early (in terms of model size). As the model fit obtained by the variables selected by the algorithm alone is already rather high, it cannot be significantly improved by the unobserved component A similar pattern is visible for the service, trade, transportation and tourism sectors.

The construction sector constitutes an exception in this context since here, including a latent factor results in a more persistent significant improvement of the model fit. However, for model sizes beyond a certain threshold the improvement of the model fit is insignificant in this case as well. We relate this finding to the fact that the construction sector mainly consists of corporates working in *structural* and *civil* engineering. While the main customers in structural engineering are households, a large portion of orders in civil engineering is publicly assigned and could thus cause the behavior of this sector to differ from that of other sectors.

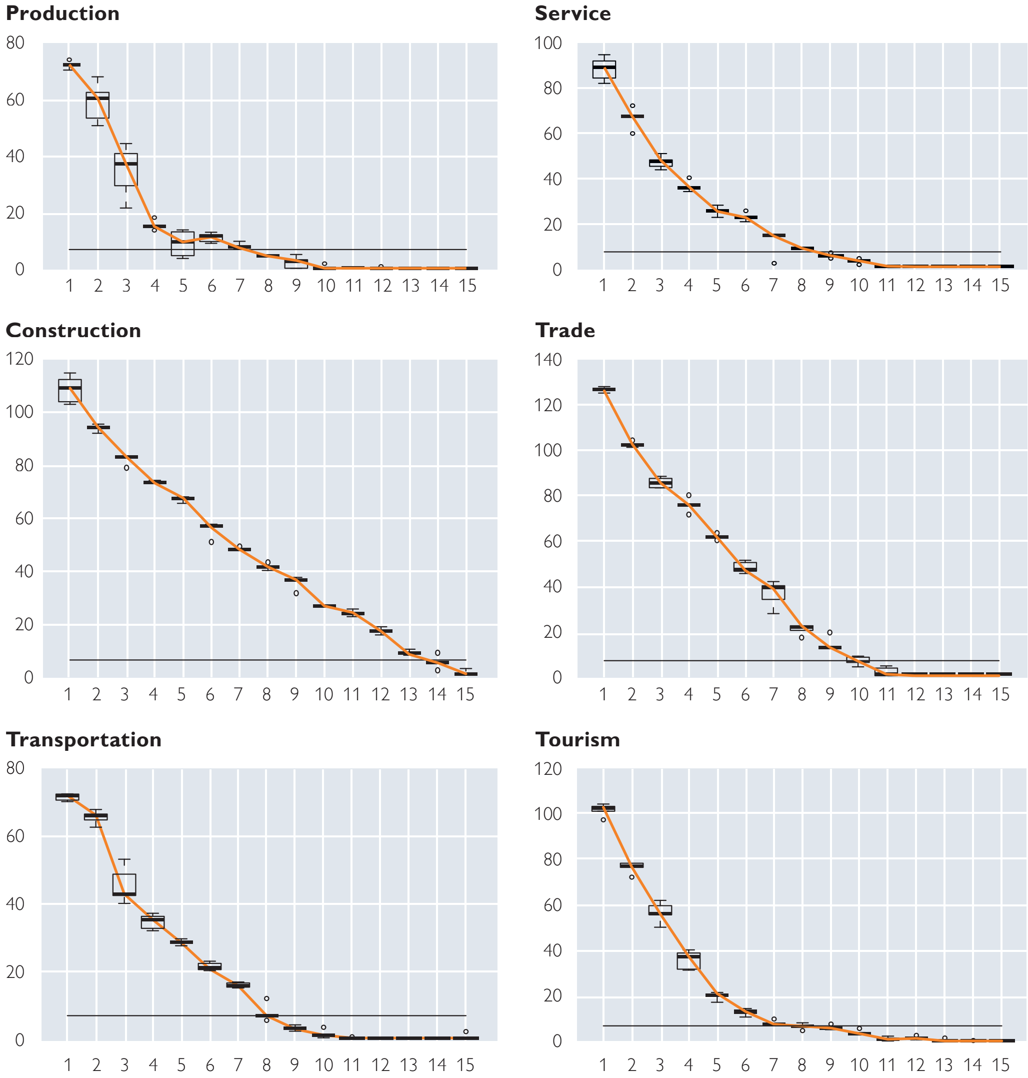
All in all, the results described above are somewhat surprising. On the one hand, it is obvious that the inclusion of more variables reduces the space that a time series estimated by the Kalman filter technique can fill. On the other hand, the model sizes discussed here are far from "large" and there is ample literature underlining the importance of the inclusion of a latent factor in the model (e.g. Lown and Morgan, 2004; Jimenez and Mencia, 2009; Koopman et al., 2009; and Bruche and Gonzalez-Aguado, 2010). One important distinction between our approach and e.g. the approach followed by Jimenez and Mencia

[22] *From a strictly statistical point of view the results, especially the critical values resulting from the LR test, have to be taken with caution. First, they are only asymptotically valid. Second, we treat the likelihoods of the restricted models without explicitly conditioning them on the model selection criterion.*

[23] *To a very large extent, our LR test results can be confirmed by applying the BIC, which explicitly takes the length of the time series into account.*

Chart 1

Likelihood Ratio Statistics (y axis) versus Number of Included Explanatory Variables (x axis) for all Corporate Sectors (varying y scale)[1]



Source: Authors' calculations.

[1] The black horizontal line represents the 99% critical value of the x^2 distribution.

(2009) and Koopman et al. (2009) is that they selected variables by mere qualitative reasoning. The set of macroeconomic candidate predictors considered in previous work is generally smaller than in our models. Jimenez and Mencia (2009), for instance, only consider real GDP growth, interest rates and, in an enlarged set-up, also bond spreads and a sector-specific additional variable, while Bruche and Gonzalez-Aguado (2010) only consider real GDP growth.

In a closer examination of the difference between previous findings in the literature and our findings, we set up a downsized macroeconomic environment in which we only include real GDP growth, short- and long-term interest rates and inflation – all up to six lags. With this much smaller macroeconomic variable set, we conduct Best

Subset Selection[24] for model sizes from 1 to 15 for each sector. Chart 2 presents the results, which are easily summarized: In all sectors there is substantial evidence of a significant improvement when considering the Kalman series *irrespective of the size of the model*. Clearly, our results show that an enriched dataset combined with a modern selection technique like Forward Stepwise Selection is able to capture dynamics that are otherwise deemed *unobserved*.

Which Fundamentals Drive Aggregated Defaults?

An additional question is which macroeconomic variables are selected by the forward selection algorithm. For this purpose, we point to chart 3 and table 2. Chart 3 presents the frequency with which estimated models contain a certain explanatory variable or its lagged cousin, thus indicating its importance in explaining aggregated defaults in the individual sectors. The respective red bar represents the fraction in which this variable has a positive coefficient.[25] Hence, in the construction sector, for instance, the variable HIC[26] (inflation) – or any of its lags – was selected in about 90% of all models and nearly always had a positive sign.

A closer look at chart 3 reveals interesting results. In all sectors but construction, funding costs such as the real short-term interest rate (STIReal), the real long-term interest rate (LTIReal) but also inflation (HIC) and real private credit growth (CPNReal) play an important role.

First, the explanatory variable LTIReal appears very frequently in models explaining defaults in the production, trade and tourism sectors. The sign of its coefficient is positive in the majority of cases, indicating rising defaults when LTIReal is high. Clearly, a higher interest rate raises the cost of funding in these sectors. In contrast, the service and transportation sectors seem to be affected by STIReal. An intuitive explanation for this finding is that these sectors rather tend to be financed by short-term lending and are thus more vulnerable to STIReal. While this interpretation seems plausible for the service sector, the negative signs of coefficients for the transportation sector suggest a different background: STIReal might be a timely indicator of economic activity. Hence, a reduction of STIReal, which is highly correlated with the central bank's target rate, might be a first indicator of an economic downturn, which would increase the default rate in the transportation sector.

Furthermore, in the same five sectors (all but construction) HIC has a positive influence on aggregate defaults in the majority of cases. As stated by Qu (2008), the role of inflation in firm defaults can be examined from two perspectives: first, the perspective of prices that companies charge for their goods and services and second, the perspective of factor prices. Higher prices of goods and services ceteris paribus increase earnings and thereby improve a company's creditworthiness. Higher factor prices lead to increased produc-

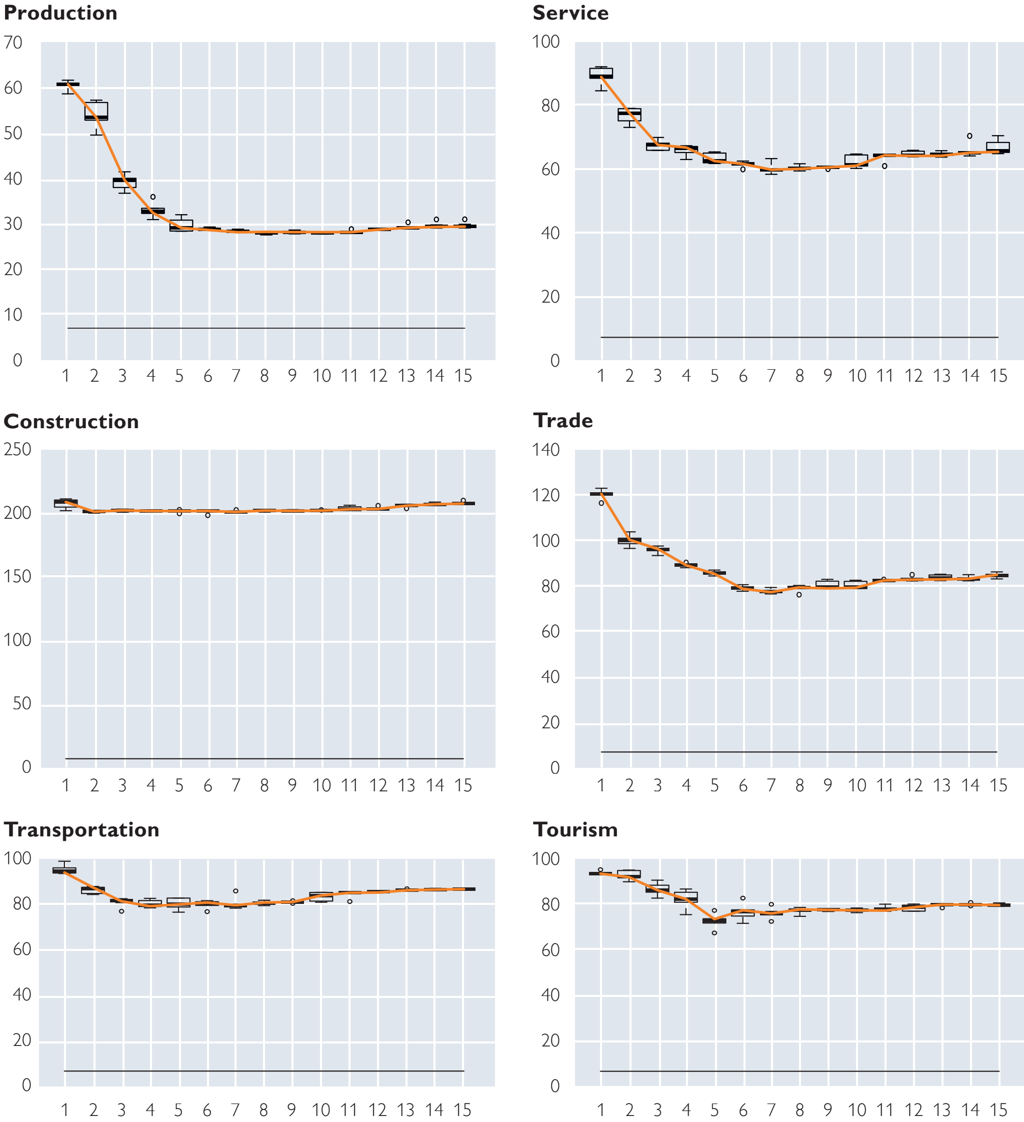
[24] *We chose Best Subset Selection as it is computationally feasible for this smaller set of explanatory variables and superior to Forward Stepwise Selection since Best Subset Selection finds the optimal model among all possible models.*

[25] *In cases in which the algorithm chose a dynamic lag structure, i.e. the variable appeared more than once in one equation due to the lag specification, the red bar shows the number of models for which the sum of the respective coefficients is positive.*

[26] *Abbreviations as quoted in table 1 denote the variables transformed as indicated in the right-hand column of the table.*

Chart 2

Likelihood Ratio Statistics (y axis) versus Number of Included Explanatory Variables (x axis) for All Corporate Sectors (varying y scale)[1]



Source: Authors' calculations.

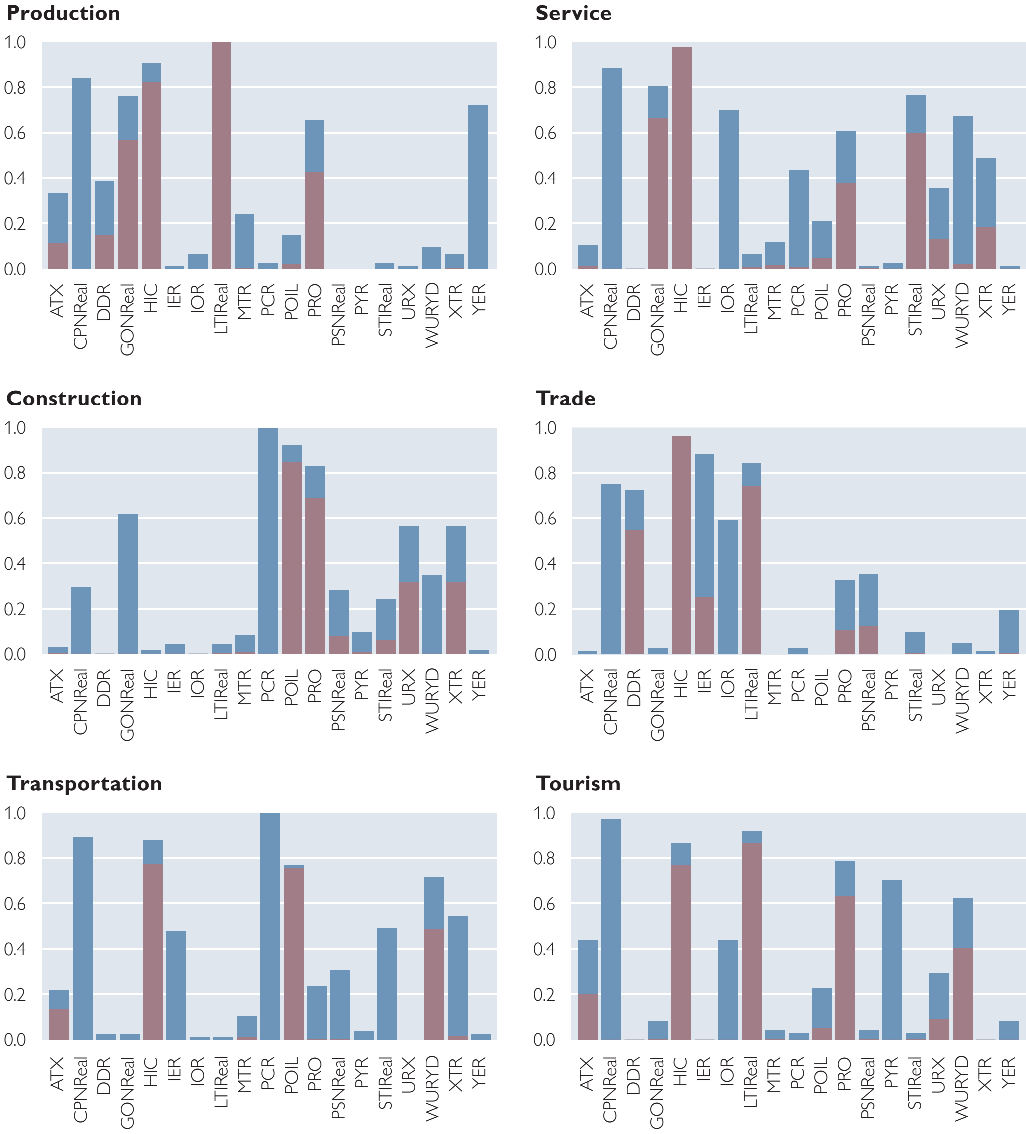
[1] *The black horizontal line represents the 99% critical value of the* χ^2 *distribution. It is important to note that here we only include four possible candidate predictors (STIReal, LTIReal, HIC and YER).*

tion costs and tend to weaken creditworthiness – a fact which implies an increase in credit risk. Additionally, higher inflation is also a proxy of economic uncertainty. In our dataset, the second effect obviously dominates the first, leading to positive coefficients in the majority of models. In all six sectors, CPNReal has a solely negative coefficient. Even in the construction sector, the model inclusion probability is above 30%.

Although this result is in line with Bonfim (2009), many studies on credit risk especially in developing economies search for a positive coefficient of credit growth. The theoretical assumption is that rapid credit growth in boom phases

Chart 3

Frequency of Selected Variables[1]



Source: Authors' calculations.

[1] *Red bars show the fractions assigned to positive coefficients for the particular macroeconomic variable.*

might lead to higher defaults in immediately following downturns.[27] With regard to the Austrian corporate credit market, we clearly cannot support this hypothesis. However, we do not include dummies for rapid credit growth and/or consider lags up to several years as other studies do.[28] The negative sign in our results can be interpreted as follows: In good times, productive investment projects arise and companies might at least meet their short-term payment obligations – a circumstance

[27] *See Jimenez and Saurina (2006) and Bank for International Settlements (2010).*

[28] *See Foos et al. (2010) and Berger and Udell (2004) among many others.*

which, ceteris paribus, reduces the number of insolvencies.

Aside from the above, the variable YER (real GDP growth), is frequently selected with a negative sign in the production sector.[29] Moreover, the variable GONReal (real gross operating surplus growth), surprisingly, enters more than 70% of the production models with a positive sign. In the construction sector, the selection algorithm selected the variable PCR (real private consumption) with the expected negative sign in about 90% of all models. This highlights the influence of housing construction, a segment of construction whose main customers are households. Second, the variable POIL (oil price) enters over 90% of the models with a positive sign.

A particularly interesting finding is that the oil price also constitutes an important driver of defaults in the transportation sector as it defines the price of the main input good. In line with findings for other sectors, PCR is selected with the expected negative sign in more than 90% of the models. In addition, a further transportation-specific variable emerges: XTR (real export growth) proves to be important in the transportation sector. Clearly, more exports lead to more business activity and thus reduce the level of risk.

The aggregate insolvency rates in the service sector are influenced by a couple of variables, which reflects the fact that services consist of 38 different NACE sectors.[30] Aside from the general variables (STIReal, LTIReal, HIC and CPNReal), the most prominent additional variables are the real growth of compensation per employee (WURYD) as well as real other investment growth (IOR). The negative sign for WURYD indicates that households' income growth is a good proxy for more corporate revenues that lead to lower credit risk.

Additional variables in the trade sector are real equipment investment (IER) growth, real other investment (IOR) growth and real domestic demand (DDR) growth. As chart 3 shows, investment growth (IER, IOR) appears to be more important in the trade sector than in other sectors. In most models, the expected negative sign can be observed.

Finally, tourism is the only sector in which real private disposable income growth (PYR) is selected with a negative coefficient in more than 70% of the models. This clearly shows that households spend their higher disposable income on holiday activities, which causes revenues in the tourism sector to go up and insolvency rates to go down.

Summing up, we find a number of variables which drive ACR across multiple sectors and are thus particularly crucial for understanding ACR. These variables include inflation, interest rates and (negative) credit growth. Furthermore, we identify sector-specific variables, such as exports in the transportation sector or investment in equipment in the trade sector, which highlight the importance of taking sectoral differences into account when analyzing ACR in corporate sectors.

4 Conclusions

This paper focuses on the determinants of aggregate credit risk (ACR). On the

[29] *Interestingly, YER seems to be of importance only in the production sector. However, in many other sectors direct subcomponents of YER, such as XTR (real export growth) or PCR, are selected and indicate that the additional information contained in YER does not significantly contribute to explaining aggregate credit risk.*

[30] *See Zeller et al. (2008) for more details*

Table 2

Frequency of Selected Variables and Respective Fraction of Positive Coefficients

	Production		Service		Construction		Trade		Transportation		Tourism	
	relative	+	relative	+	relative	+	relative	+	relative	+	relative	+
ATX	0.33	0.33	0.11	0.09	0.03	0.03	0.01	0.00	0.22	0.61	0.44	0.45
CPNReal	0.84	0.00	0.89	0.00	0.29	0.00	0.76	0.00	0.89	0.00	0.97	0.00
DDR	0.39	0.39	0.00	0.00	0.00	0.00	0.73	0.75	0.03	0.03	0.00	0.00
GONReal	0.76	0.75	0.81	0.82	0.61	0.00	0.03	0.03	0.03	0.00	0.08	0.04
HIC	0.91	0.91	0.99	1.00	0.01	0.00	0.97	1.00	0.88	0.88	0.87	0.89
IER	0.01	0.00	0.00	0.00	0.04	0.00	0.89	0.29	0.48	0.00	0.00	0.00
IOR	0.07	0.00	0.71	0.00	0.00	0.00	0.60	0.00	0.01	0.00	0.44	0.00
LTIReal	1.00	1.00	0.07	0.07	0.04	0.04	0.85	0.88	0.01	0.01	0.92	0.95
MTR	0.24	0.01	0.12	0.12	0.08	0.08	0.00	0.00	0.11	0.11	0.04	0.04
PCR	0.03	0.01	0.44	0.01	1.00	0.00	0.03	0.01	1.00	0.00	0.03	0.00
POIL	0.15	0.15	0.21	0.22	0.92	0.92	0.00	0.00	0.77	0.99	0.23	0.23
PRO	0.65	0.65	0.61	0.62	0.83	0.83	0.33	0.34	0.24	0.03	0.79	0.81
PSNReal	0.00	0.00	0.01	0.01	0.28	0.28	0.36	0.37	0.31	0.01	0.04	0.01
PYR	0.00	0.00	0.03	0.00	0.09	0.08	0.00	0.00	0.04	0.00	0.71	0.00
STIReal	0.03	0.00	0.77	0.78	0.24	0.24	0.11	0.05	0.49	0.00	0.03	0.03
URX	0.01	0.01	0.36	0.36	0.56	0.56	0.00	0.00	0.00	0.00	0.29	0.30
WURYD	0.09	0.00	0.68	0.03	0.35	0.00	0.05	0.03	0.72	0.68	0.63	0.64
XTR	0.07	0.03	0.49	0.38	0.56	0.56	0.01	0.00	0.55	0.03	0.00	0.00
YER	0.72	0.00	0.01	0.00	0.01	0.00	0.20	0.01	0.03	0.00	0.08	0.00

Source: Authors' calculations.

one hand, we explicitly measure the importance of latent risk factors via a state space system for different corporate sectors and model sizes. On the other hand, we evaluate the influence of observable macroeconomic variables in different corporate sectors by analyzing the choices of the Forward Stepwise Selection procedure.

We find that enhancing a macro-to-probability of default model by incorporating a latent risk factor only improves the model considerably if the model is allowed to select from a small number of possible predictors. We show that this finding is not explained by the selection procedure applied but is attributable to a limited set of variables. The limited number of included variables also explains why some of the relevant literature finds strong support for including unobserved risk factors in macro-to-probability of default models.

As pointed out in the introduction, the literature has not yet agreed upon a meaningful economic interpretation of the credit cycle as an unobserved credit risk factor. Mainly on the basis of the likelihood ratio tests performed, we conclude that the significance of the explanatory value of the unobserved factor depends on the number and quality of the macroeconomic variables that are selected as predictors. Since the results for the construction sector show that influential observable predictors might not always be available, there is (state) space open to different credit cycle theories. At the same time, the inclusion of an unobserved component into an ACR model comes at little methodological costs. When forecasting aggregate levels of credit risk, it therefore seems to be prudent to work with a state space model.

Coming back to the *credit cycle* theories mentioned in the introduction, we think that the second theory, which assumes that (too) lenient credit standards during an economic upturn result in the build-up of high credit risk which then materializes in the ensuing economic downturn, does not apply to the highly competitive Austrian banking sector.[31] This view is supported by the negative coefficient of credit growth (CPNReal) in all corporate sectors observed. Since this paper analyzes the Austrian corporate sector, we are not in the position to judge whether the credit cycle can be interpreted as the leverage cycle, which would require the modeling of ACR for mortgage loans in the retail sector. Finally, among the above-mentioned credit cycle theories the cyclical default correlation hypothesis seems to be the most promising option in support of our findings. The persistent importance of the unobserved factor in the construction sector for different models sizes underpins this argument as direct ties between firms in the construction sector are often observed.

Moreover we find several variables which drive ACR simultaneously in a number of sectors and are thus particularly crucial for modeling ACR. These variables include interest rates, inflation and (negative) credit growth. However, there are also considerable sectoral differences between the selected variables. Among the sector-specific variables we find e.g. the oil price and exports in the transportation sector, investment in equipment in the trade sector and short-term interest rates in the service sector. Most of the selected variables show the expected sign in the regressions performed and can be explained by general economic theory and/or by specific sectoral economic conditions. Overall, our analysis suggests that only an enlarged set of macroeconomic variables can explain ACR in a comprehensive way – and a comprehensive explanation of ACR is without doubt crucial for the development of macroeconomic scenarios for stress-testing exercises.

Our findings also clearly indicate that taking model uncertainty into account is of high importance in a field where, a priori, many regressors constitute candidate predictors for explaining ACR. We accounted for model uncertainty by estimating 75 models for each corporate sector. However, there are more sophisticated statistical methods to perform model averaging. In particular the concept of Bayesian model averaging could be a promising advancement for future research projects.

[31] *High competition in the lending market generally results in low net interest margins. These, in turn, require strict lending standards which generally rule out subprime lending.*

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