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Assessing Sovereign Default Risk: A Bottom-Up Approach

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Abstract

This study assesses sovereign default risk of individual U.S. states utilising information about default risk at the company level. We link integrated risk factors of the private sector to the overall sovereign risk of state governments in conjunction with additional financial variables. Using data on Moody's KMV expected default frequencies (EDFs) on corporate default risk, we derive credit risk indicators for different industries. Building on these measures, we then develop state level credit risk indicators encompassing industry compositions to explain the behaviour of credit default swap (CDS) spreads for individual states. We find that market-based measures of private sector credit risk are strongly associated with subsequent shifts in sovereign credit risk premiums measured by CDS spreads. The developed credit risk indicators are highly significant in forecasting sovereign CDS spreads at weekly and monthly sampling frequencies. Overall, our findings suggest a strong predictive link between market expectations of private sector credit quality and expectations of sovereign credit quality - a connection that is not directly discernible from scoring models.

Key words: Sovereign Credit Risk, Default Risk, CDS Spreads, Moody's KMV EDFs

JEL: G32, G12, G17

1 Introduction

In recent years there has been an increased interest in sovereign credit risk, see, e.g., Pan and Singleton (2008); Caceres et al. (2010); Ang and Longstaff (2013); Longstaff et al. (2011); Aizenman et al. (2013); Janus et al. (2013). Sovereign risk is typically measured by credit spreads associated with the probability of default (PD) on sovereign debt securities, as there is uncertainty about receiving scheduled payments on time. Since the onset of the global financial crisis (GFC), Europe in particular has been the focus of much of this concern. While research on sovereign risk and advanced risk management tools had also accumulated before the European debt crisis, the crisis was still considered as a relatively unforeseen event by many market participants. Despite being preceded by the GFC, in early 2009 neither observed CDS spreads nor ratings for European sovereign entities provided an indication of the magnitude of the soon-to-occur sovereign debt crisis. This may indicate a need to assess and predict sovereign credit risk using more responsive measures based on additional risk sources. Further, despite much effort from governments and global financial institutions, sovereign debt sustainability remains a major concern, which motivates us to develop a new framework for predicting sovereign default risk.

This study provides a new bottom-up approach to assess sovereign default risk at the state-level for 18 state governments in the U.S. As argued by Ang and Longstaff (2013), each U.S. state government retains the authority to establish its independent legal system and the ability to issue state bonds. As a result, state bonds are similar to federal bonds and the economic behaviour of a state government can be considered as being similar to a sovereign entity. Given the recent financial distress of large municipalities such as Detroit or the U.S. territory of Puerto Rico, we also believe that a deeper analysis of sovereign debt at the state level is an important exercise for the financial industry. We start with Moody's KMV expected default frequencies (EDFs) to assess credit risk at the corporate level for industries of economic importance. We then aggregate information of EDFs at the company level to develop industry credit risk indicators (ICRIs). In a second step, the constructed ICRIs are then used to derive state credit risk indicators (SCRI), based on the industry composition of each state. Thus, using our framework we calculate real-time bottom-up credit risk indicators at the state-level. Clearly, our motivation for constructing the SCRIs is to better understand whether variation in default risk in the private sector can improve prediction for market views on a sovereign's ability to service its debt obligations. Our study follows the motivation of Altman and Rijken (2011) in investigating the influence of the private sector on a sovereign entity's default risk. We assume that publicly listed companies contribute to a sovereign entity's wealth and, thus, also to its risk of default. The derived SCRIs are then investigated with regards to their predictive power for changes in credit default swap (CDS) spreads for the individual states. We find that the derived market-based measures of private sector credit risk are strongly associated with subsequent shifts in sovereign credit risk premiums measured by CDS spreads. Overall, the developed SCRIs are highly significant in forecasting sovereign CDS spreads at weekly and monthly sampling frequencies.

Traditionally, the assessment of sovereign risk has heavily relied on macroeconomic variables containing information on economic conditions and aggregated national accounts. Different econometric frameworks using macroeconomic variables have been applied to explain the behavior of sovereign risk over time. Grinols (1976) applies both discriminant and discrete analyzes to a sample of 64 nations to identify five significant national account variables in his assessment of debt service capability. Morgan (1986) studies debt rescheduling based on new short-term debt data and variables representing economic shocks, using logit and discriminant models. A more recent example is Haugh et al. (2009), in which a range of macroeconomic explanatory variables are incorporated in a panel model to study the sovereign spread differentials among European countries. Others studies such as Fuertes and Kalotychou (2004) and Hilscher and Nosbusch (2004) also examine the predictive power of similar variables.

A common approach across all these studies is the reliance on macroeconomic data, such as annual GDP growth rates, the balance of trade, tax receipts or debt servicing ratios, etc. Although there is a significant body of research supporting the explanatory power of macroeconomic variables, the forecasting ability of these variables for crises or changes in credit quality of sovereigns has been questioned. In a comprehensive overview paper, Babbel (1996) argues that macroeconomic approaches generally fail to perform satisfactorily and that the claimed predictive power of macroeconomic models is only illusory and. The author argues that upon closer inspection the studies are mostly unsuccessful. Bertozzi (1995) also questions the ability of macroeconomic models to provide a signal for early warning. One possible reason for the inadequate response times of macroeconomic models are the infrequent updates of input data, which are subject to delayed release by government statistical offices. If models are used to make timely projections of future movements in sovereign risk, it is beneficial rather to look for early warning signals in order to harness the limited time that policy makers and financial managers typically have to change strategies (Neziri, 2009; Bertozzi, 1995). Thus, models that only use one set of observations per year will undoubtedly have difficulties in capturing changes in sovereign risk in a timely manner (Oshiro and Saruwatari, 2005). Aizenman et al. (2013) also argues that while macroeconomic factors are statistically and economically important determinants of sovereign risk, the pricing of this risk for Eurozone Periphery countries is not predicted accurately either in-sample or out-of-sample with these factors.

Therefore, over the last decade sovereign risk has typically been measured by more timely and frequently available data from financial variables such as sovereign bond prices or credit default swap spreads, see, for example, Pan and Singleton (2008); Beber et al. (2009); Hui and Chung (2011); Fender et al. (2012); Aizenman et al. (2013); Ang and Longstaff (2013); Arce et al. (2013); Calice et al. (2013); Groba et al. (2013); Janus et al. (2013); Dewachter et al. (2015); Chen et al. (2016). Hereby, studies have focussed particularly on CDS spreads, since they provide a more direct measure of sovereign risk. Pan and Singleton (2008) analyze default risk and recovery rates implicit in the term structure of sovereign CDS spreads. Ang and Longstaff (2013) adopt CDS spreads for the U.S. Treasury, individual U.S. states, and major Eurozone countries, to study the nature of systemic sovereign credit risk. Aizenman et al. (2013) examine CDS as a measure of sovereign default risk and argue that CDS spreads provide a good proxy for market-based pricing of default risk. The authors also provide a market-based real-time indicator of sovereign credit quality and default risk. Beber et al. (2009); Arce et al. (2013); Calice et al. (2013) focus on price discovery, liquidity spill-over and flight-to-quality effects in the sovereign CDS market. Groba et al. (2013) focus on financially distressed economies inside the European Union and their impact on the CDS market.

One limitation of these studies in assessing sovereign risk is that so far little attention is given to the private sector, which can give a more direct measure of economic activities in a sovereign entity. The tax receipts and national wealth of a sovereign government are closely related to the productivity and economic output of companies, which are sensitive to financial crises and a slowdown of the economy. By incorporating company level information into the risk assessment process, we therefore use important forward-looking information that can also help to predict financial distress at the state or government level. Due to the importance of measuring default risk at the firm level in financial markets, credit rating agencies such as Standard & Poor's, Fitch or Moody's KMV provide timely information on default risks at the company level.

To take advantage of the abundant company level data for assessing sovereign risk, Altman and Rijken (2011) were among the first to propose a bottom-up approach to incorporate private sector information in the assessment process, considering this information as a crucial determinant of sovereign risk. They test the predictive power of factors generated from listed companies in one country, assuming that the national financial health relies on the economic performance of the private sector. Altman and Rijken (2011) focus on major European countries during the debt crisis and assess the probability of sovereign default based on credit risk from the private sector. Their prediction model demonstrates greater effectiveness in providing advance warnings compared to those of credit rating agencies. Incorporating listed company information also enlarges the available data points and gives greater opportunity for investigating sovereign default risk.

One disadvantage of the approach developed by Altman and Rijken (2011) is that in order to assess corporate credit scores, they use financial statement variables related to company leverage, profitability, and liquidity that are updated infrequently only. Thus, these measures rather provide a picture of retrospective performance of a company. In addition, macroeconomic variables such as GDP growth and inflation that are available at a low frequency only are also included into the model (Altman and Rijken, 2011).

Instead, this study assesses sovereign risk at the state level, using market variables encompassing industries of economic importance to each state. State government defaults are different from corporate defaults because of different legal enforcements. Unlike the bankruptcy procedure following the default of a company, a state government's assets cannot be credibly liquidated or transferred to the debtor (Ang and Longstaff, 2013). Therefore, we argue that state governments can be considered as independent sovereign entities. Our motivation is to better understand whether variation in default risk in the private sector can improve prediction for a sovereign's ability to service its debt obligations. Our study follows the motivation of Altman and Rijken (2011) by investigating the influence of the private sector on a sovereign entity's credit risk. We assume that publicly listed companies contribute to a sovereign entity's wealth and also its risk of default, and use Moody's KMV EDFs for individual companies to create industry-level and state-level credit risk indicators. EDFs are forward-looking measures of default risk, based on the structural model developed by Merton (1974) combined with information on historical defaults. The accuracy of EDFs for predicting defaults has been documented in a number of studies, see, e.g. Kealhofer (2003); Bharath and Shumway (2008); Dwyer and Korablev (2007). Next to the developed EDF-based industry- and state-level credit risk indicators, our model also incorporates additional financial variables that have been suggested to have predictive power for default risk. In contrast to previous studies, we use a bottom-up approach for sovereign risk, while our model aims to predict CDS spreads that may be particularly useful for capturing and forecasting short-term changes in sovereign risk. The developed model may also provide early warning indicators to investors and policy-makers who are concerned about sovereign credit risk at the country or state level.

We examine the default risk of 18 state governments in the United States covering the time period from June 2006 to April 2013. In our analysis we treat each of the states as an independent sovereign entity. CDS spreads on state government debt are used to measure the default risk for each of these states. We first develop industry credit risk indicators that are then used to calculate the SCRIs based on the industry composition of each state. Each industry has its own default index that is built on the credit risk of listed companies in the sector.

Our results indicate that the developed SCRIs, using information from the private sector, are highly significant in predicting CDS spreads for the vast majority of the states considered in this study. Applied regression analysis strongly supports the benefits of incorporating company level information on default risk next to macro-financial variables for the assessment of sovereign credit risk. Our findings are also confirmed by robustness checks using different frequencies as well as alternative state credit risk indicators based on the major industries in each state only. We also apply quantile regression to estimate the coefficients for the independent variables at different quantiles of the distribution. Additionally, we test the predictive relationship using both through-the-cycle and point in time measures of company credit risk. The conducted robustness checks confirm our findings on the usefulness of the developed credit risk indicators.

Overall, our results emphasize the importance of information from the private sector for predicting sovereign default risk. Our findings complement those of Altman and Rijken (2011), using a distinctively different and more timely assessment method. Firstly, instead of using company scores, our study adopts Moody's KMV EDFs to assess corporate level credit risk. Secondly, our analysis focuses on a significantly longer time horizon, examining sovereign risk of state governments in the U.S. over seven years, also covering the pre- and post-financial crisis period. Moreover, constructing and incorporating ICRIs addresses the influence of industry compositions on overall sovereign risk, which was not examined by Altman and Rijken (2011). Further, financial companies are not excluded in this study, addressing one of the caveats of Altman and Rijken (2011). Finally, in contrast to previous studies that have applied bottom-up approaches to sovereign default risk, our model examines CDS spreads that may be particularly useful for capturing and forecasting short-term changes in sovereign risk. The developed approach can also be used to derive early-warning indicators for investors and policy-makers who are concerned about sovereign credit risk at the country or state level.

The remainder of this paper is organized as follows. Section 2 provides a brief review of the EDF measure and then describes our approach to derive bottom-up industry and state credit risk indicators. Section 3 describes the data and the applied models, while Section 4 provides results for the conducted empirical analysis as well as various robustness checks. Section 5 concludes and provides suggestions for future work.

2 Bottom-Up Credit Risk Indicators

2.1 Industry Credit Risk Indicators

In the following, we aim to derive industry and state specific credit risk indicators that will reflect information on default risk available at the company level. Hereby, for each industry a sector-specific indicator of default risk is developed that can then be used to derive state-specific indicators of default risk.

We use Moody's KMV one-year EDFs to measure corporate credit risk in the private sector as a predictive measure of credit risk at the firm level. We include all U.S. companies available in the Moody's KMV EDF universe and use one-year EDF estimates as measures for a company's credit risk. The timely availability of EDFs allows for almost immediate incorporation of new information and we believe that this metric may also provide information for explaining dynamic changes in the measurement of sovereign credit risk. One-year EDFs provide an estimate of the probability of default for a particular company within a time horizon of twelve months. Unlike credit ratings that typically involve a relative rank-order scale, EDFS are measured at a quantitative scale (Moody's, 2012). Note that a number of previous empirical studies has also confirmed the usefulness of EDFs or the Merton distance to default for predicting bankruptcies at the corporate level. Kealhofer (2003) shows that EDFs contain additional information for default prediction that is not entirely incorporated in ratings. Results by Bharath and Shumway (2008) suggest that almost two thirds of defaulting firms had probabilities in the higher decile based on the Merton distance to default during the quarter they defaulted. Dwyer and Korablev (2007) also emphasize the usefulness of EDFs for predicting defaults when computing accuracy ratios for North America, Europe and Asia.

The EDF model belongs to a class of structural credit risk models pioneered by Merton (1974), incorporating more realistic assumptions and enriching the originally suggested model with empirical data on defaults to reflect real-world measures of credit risk (Moody's, 2012). Starting from Merton's framework, the model assumes that a firm's value follows a stochastic process with an expected growth rate and volatility. The model assesses the probability of asset values falling below its liabilities payable, the so-called default point. The distance to default (DD) is then calculated as the difference between the expected outcome for the firm's value based on the underlying stochastic process and the default point, measured by the number of standard deviations of the annual percentage change in the market value of the firm's assets. To derive real-world PDs, Moody's KMV then conduct a mapping process to generate PDs from DDs. The relationship between DD and PD is developed based on empirical observations to account for the actual number of default for different DDs. A mapping procedure is then applied to create EDFs for companies based on their DDs. Moody's frequently updates their EDF estimates and ratings to reflect the company's credit risk based on new information, such as e.g. changes in market volatility. The real-world probability of default at time t (EDF_t) can then be denoted by Equation 1 (De Servigny et al., 2004):

$$EDF_t = F(-\frac{(log(V_t) - log(X) + (\mu - \sigma_V^2/2)(T-t)}{\sigma_V\sqrt{T-t}}) \quad (1)$$

where F is the function mapping the distance to default calculated by a Merton-type model to the actual EDF. Hereby, V_t denotes the value of the firm at time t, X is the default threshold, μ is the expected return on assets, and σ_V is the asset volatility of the firm. $T - t$ is set equal to 1 in the calculation, according to the calibration of EDFs to a one-year horizon.

We use Moody's one-year EDFs from June 2006 to April 2013 for all U.S. listed companies at weekly and monthly frequency. For the considered time horizon, EDFs range from 1 basis point to a maximal PD of 35%. Over time, some companies have been delisted and newly listed companies have been added. A total of 8105 companies are included into our study over the sample period. Note that one-year EDFs are actually updated on a daily basis, while the average number of observations on a typical trading day is around 4300. We use weekly observations on EDFs that are recorded on the last trading day for that week. When the Friday of a week coincides with a public holiday and no observation is available, the observed EDF on the Thursday of the same week is used. During the whole study period, we only observe 12 public holidays falling on a Friday.

In order to assign companies to industries, a set of industry classifications is constructed. The definition of each industry is based on Moody's EDF industry definitions as well as industry categories defined by the U.S. Department of Commerce, Bureau of Economic Analysis (BEA). Note that Moody's KMV assigns companies to a total of 61 detailed industries, including one unassigned category that contains companies without a clearly matching industry. The BEA on the other hand adopts 20 industry categories only. We define industry classifications by combining the two schemes, such that ICRIs can be constructed using Moody's EDF, and the indices can later be combined according to BEA's statistics on GDP compositions for each state. The new classification is shown in Table 1 alongside the corresponding industries defined by Moody's KMV and the BEA.

According to the BEA industry classification, U.S. listed companies that were originally assigned to 61 industries by Moody's KMV, are then regrouped into 15

New category	BEA	Moody's
1.Agriculture, forestry, fishing and hunting	1.Agriculture, forestry, fishing and hunting	N02 Agriculture N33 Lumber & Forestry
2.Mining	2.Mining	N38 Mining N39 Oil Refining
3.Utilities	3.Utilities	N58 Utilities Nec N59 Utilities, Electric N60 Utilities, Gas
4.Construction	4.Construction	N13 Construction N14 Construction Materials
5.Durable goods	5.Durable goods	N05 Automotive N11 Computer Hardware N15 Consumer Durables N20 Electrical Equipment N21 Electronic Equipment N27 Furniture & Appliances N34 Machinery & Equipment N35 Measure & Test Equipment N36 Medical Equipment N49 Semiconductors N50 Steel & Metal Products N54 Transportation Equipment
6.Nondurable goods	6.Nondurable goods	N04 Apparel & Shoes N10 Chemicals N17 Consumer Products N40 Oil, Gas & Coal Expl/Prod N41 Paper N42 Pharmaceuticals N43 Plastic & Rubber N44 Printing N52 Textiles N53 Tobacco
7.Retail/Wholesale trade	7.Wholesale trade 8.Retail trade	N08 Business Products Whsl N16 Consumer Durable Retl/Whsl N18 Consumer Products Retl/Whsl N26 Food & Beverage Retl/Whsl
8.Transportation and warehousing	9.Transportation and warehousing	N03 Air Transportation N55 Transportation N56 Trucking
9.Information	10.Information	N07 Broadcast Media N12 Computer Software N45 Publishing N51 Telephone N61 Cable TV
10.Finance and insurance	11.Finance and insurance	N06 Banks and S&Ls N23 Finance Companies N24 Finance Nec N29 Insurance - Life N30 Insurance - Prop/Cas/Health N31 Investment Management N47 Real Estate Investment Trusts N48 Security Brokers & Dealers
11.Real estate, rental and leasing	12.Real estate and rental and leasing	N32 Lessors N46 Real Estate
12.Professional, scientific and technical services	13.Professional, scientific and technical services	N09 Business Services N19 Consumer Services N37 Medical Services
13.Arts, entertainment and recreation	18.Arts, entertainment and recreation	N22 Entertainment & Leisure
14.Accommodation and food services	19.Accommodation and food services	N25 Food & Beverage N28 Hotels & Restaurants
15.Other	14.Management of companies and enterprises 15.Administrative and waste management services 16.Educational services 17.Health care and social assistance 20.Other services, except government	N01 Aerospace & Defense N57 Unassigned

Table 1. Assigned industry classifications based on allocated industry definitions from BEA and Moody's KMV. The first column provides the classification of industries applied in this study, column 2 and 3 present corresponding industries from BEA and Moody's KMV that were assigned to each category. The classification typically follows BEA..

industries. Note that the Moody's KMV industry classification of a company may change multiple throughout the study period, such that every time a change occurs the company will be assigned accordingly to a new industry category. At each point in time, EDF values for all companies in the same industry are collected, and the ICRI is defined as the median of the observed EDFs for this industry.

Figure 1 presents the derived ICRIs for six of the 15 industries. We find that the considered industry credit risk indicators behave quite differently during the study period as a result of different sensitivities to movement in economic conditions. We also observe that all ICRIs increase significantly during the GFC period between 2008 and 2009, and typically move back to their pre-crisis level afterwards. ICRIs for *real estate, rental and leasing* as well as for *arts, entertainment and recreation* are the two most volatile amongst the 15 indices and are presented in the upper panel of Figure 1. Median default probabilities for these categories reach as high as 12% during the GFC and exhibit a declining trend afterwards. It is no surprise that the real estate sector was affected greatly by the subprime credit crunch, while the economic crisis could possibly have led to a decrease in demand of entertainment activities from the general public.

The middle panel of Figure 1 illustrates that the industry categories *mining* and *retail/wholesale trade* are less volatile in comparison to the two industry categories described above. Their ICRIs peak at approximately 5% in the middle of 2009 which is less than half of the median EDF for the real estate categor. Finally, in the lower panel of Figure 1 we present the derived ICRIs for *agriculture, forestry, fishing and hunting* and *utilities*. As illustrated, these industries were clearly least affected by the GFC, indicated by the small change in the overall level of default probabilities. Throughout the entire sample period the median EDF does not exceed a value of 1% for these two industries.

2.2 State Credit Risk Indicators

In a next step we then combine the 15 ICRIs to generate a predictive credit risk indicators at the state level. Hereby, for each state we define a SCRIs as the weighted average of the ICRIs. The weight of each industry as a contributor to the SCRIs is based on an industry's GDP percentage contribution to the entire state GDP, following the decomposition for the last 10 years provided by BEA. The BEA annually releases the total GDP for each state and for each industry in the regional economy. The contribution of each industry to the state's total GDP can be calculated as a percentage over the last ten years. For each state, the 10-year average contributions of an industry sector are taken as weights, since the compositions have been relatively stable over the last decade. A summary of the compositions for industries across states can be found in Table 2, where the average composition, the maximum and minimum percentage, and difference between the two are shown for each industry. As expected, the GDP contribution for each industry varies significantly across the 18 states. Thus, although the same set of industry indices is used to generate the SCRIs, different weight combinations of the ICRIs will generate specific risk profiles for each of the considered states throughout the sample period.

Based on the 15 ICRIs and corresponding contributions for each state, the SCRIs

Table 2. Summary statistics of the composition of industry in each state based on U.S. Department of Commerce, Bureau of Economic Analysis (BEA)..

	Average	Max	Min	Max-Min
Agriculture, forestry, fishing and hunting	0.70%	2.15%	0.18%	1.97%
Mining	0.91%	9.37%	0.01%	9.36%
Utilities	1.91%	2.57%	1.22%	1.35%
Construction	5.06%	8.75%	3.51%	5.24%
Durable goods	6.92%	15.39%	2.47%	12.92%
Nondurable goods	5.53%	14.82%	1.28%	13.54%
Retail/Wholesale trade	13.31%	16.26%	8.60%	7.65%
Transportation and warehousing	2.81%	3.96%	1.40%	2.56%
Information	4.85%	9.62%	2.16%	7.46%
Finance and insurance	11.85%	39.33%	6.09%	33.25%
Real estate, rental and leasing	15.01%	19.48%	10.33%	9.15%
Professional, scientific and technical services	8.72%	14.30%	5.50%	8.80%
Arts, entertainment and recreation	1.09%	2.60%	0.67%	1.94%
Accommodation and food services	3.74%	16.41%	2.06%	14.35%
Other	17.60%	21.98%	13.15%	8.83%

are created as the weighted average of the 15 indices in each of the 18 states, calculated according to Equation (2):

$$\begin{bmatrix} ICRI_{1,1} & \cdots & ICRI_{1,15} \\ \vdots & \ddots & \vdots \\ ICRI_{1,360} & \cdots & ICRI_{15,360} \end{bmatrix} \times \begin{bmatrix} w_{1,1} & \cdots & w_{1,18} \\ \vdots & \ddots & \vdots \\ w_{15,1} & \cdots & w_{15,18} \end{bmatrix} = \begin{bmatrix} SCRI_{1,1} & \cdots & SCRI_{1,18} \\ \vdots & \ddots & \vdots \\ SCRI_{360,1} & \cdots & SCRI_{360,18} \end{bmatrix} \tag{2}$$

Recall that we have 360 weekly observations for the EDFs and ICRI. $ICRI_{t,j}$ then denotes the ICRI value at time t for industry j, with $t = 1, ..., 360$ and $j = 1, ..., 15$, while $w_{j,k}$ represents the weight for industry j in state k with $k = 1, ..., 18$. The product of the two matrices then yields 18 time series of SCRIs, one for each of the states considered in this study. Thus, $SCRI_{t,k}$ denotes the state risk indicator at time t for state k. We present the time series for the derived SCRI for California in Figure 2. Based on the different industry contributions for each state, we also observe a quite different behaviour in the developed state credit risk indicators throughout the sample period. Overall, we believe that the derived SCRIs will provide an appropriate measure of private sector credit risk for the considered states.

3 Data and Models

We use market data on CDS spreads of 18 US state governments for the time period June 2, 2006 to April 26, 2013 in order to examine the relationship between the constructed bottom-up SCRIs and sovereign default risk at the state level. Using weekly observations, we analyze CDS spreads for the following states: California, New York, Texas, Florida, Illinois, Pennsylvania, Ohio, New Jersey, Michigan, Massachusetts, North Carolina, Virginia, Wisconsin, Maryland, Connecticut, Delaware, Nevada and Rhode Island. CDS spreads for all state governments are obtained from Datastream and Bloomberg and are quoted in basis points. We decided to use five-year CDS spreads, because they have the greatest liquidity. Note that due to limited availability of CDS spreads for some of the states during the sample period, not all time series are of equal length. Table 3 provides summary statistics of the CDS spreads for the 18 state governments, including the number of observations, the mean, maximum and minimum spread and the standard deviation of the observed spreads. Table 3 also presents the initial point in time when information on CDS spreads was available for a particular state.[2]

Next to the developed SCRIs, we relate changes in CDS spreads for the considered states to five additional financial variables that are expected to capture changes in general financial and economic conditions. Note that due to the forward-looking nature of this study and the use of data at a relatively high (weekly) frequency we decided not to include any macroeconomic explanatory variables into our analysis. We argue that despite the impact of macroeconomic conditions on the ability of state's government to service its debt, variables that are updated only infrequently throughout the year and often on a delayed basis are not appropriate for the purpose of this study.

We use the Chicago Board Options Exchange Market Volatility Index (VIX) as a forward-looking measure of volatility in the equity market and uncertainty faced by investors. We also include the term spread, i.e. the difference between short-term government bills (1 month) and long-term government bonds (20 years). Changes in the term spread are often used as an indicator of economic conditions and credit risk, since the spread is expected to contain information on future economic growth and has been successfully applied to forecasting the probability of a recession, see, e.g., Stock and Watson (1989), Dotsey (1998). Both the VIX and term spread are expected to be positively related to state CDS spreads, as both variables can be considered as indicators for increasing risks in equity and debt markets. These variables have also been widely suggested as determinants of sovereign risk in previous studies, see,

[2]Note that four states have missing values after the first available observation, namely North Carolina (from 24/09/2010 to 29/10/2010), Virginia (from 25/03/2011 to 29/06/2012), Delaware (from 09/12/2011 to 24/02/2012), Rhode Island (from 24/09/2010 to 22/10/2010).

e.g., Hilscher and Nosbusch (2004), Giesecke and Kim (2011), Longstaff et al. (2011), Dieckmann and Plank (2012), just to name a few. Welch and Goyal (2008) also identify a link between equity premiums required by investors and the market volatility and term spread. We also include returns of the S&P 500 index as a measure of stock market performance as well as 5-year U.S. treasury CDS spreads. Finally, we consider returns of the S&P US issued investment grade corporate bond index (the CDX IG index). While the coefficients of the treasury CDS spreads are expected to be positive for all states, market returns and the returns of CDX IG index are expected to be negatively correlated with state sovereign CDS spreads.

We believe that these additional variables will complement information contained in the derived bottom-up SCRIs. Note that a similar set of explanatory variables has also been applied Ang and Longstaff (2013), when assessing systemic sovereign credit risk for several European countries and states in the US. We collect weekly observations for all variables for the sample period June 2006 to April 2013. Data for the VIX is available from Bloomberg, while yields on federal securities are available from the U.S. Treasury database. Data on the S&P 500 index is sourced from CRSP, while U.S. treasury CDS spreads and the CDX IG index are available through Datastream.

We then examine the following model to measure the impact of the considered explanatory variables on CDS spreads in the 18 states:

$$\begin{aligned} CDS_{i,t} =& \beta_{0,i} + \beta_{1,i} * SCRI_{i,t-1} + \beta_{2,i} * VIX_{t-1} + \beta_{3,i} * TS_{t-1} + \beta_{4,i} * SP500_{t-1} \\ &+ \beta_{5,i} * TCDS_{t-1} + \beta_{6,i} * CDX_{t-1} + \epsilon_i \end{aligned} \tag{3}$$

In the above equation, $CDS_{i,t}$ denotes the observed CDS spread for state i in period t, while $SCRI_{t-1}$ denotes the constructed state credit risk indicator at $t-1$. VIX denotes the Chicago Board Options Exchange Market Volatility Index, TS the term spread, $SP500$ the return on the S&P500 index, TCDS the treasury CDS spread, and CDX refers to the return on the CDX IG index. Since we are particularly interested in the predictive power of these factors, all explanatory variables are measured in period $t-1$. In contrast to some previous studies that are linked to infrequent default events, such as Oshiro and Saruwatari (2005) and Giesecke and Kim (2011), we focus on CDS spreads as observable dependent variables that are assumed to capture market perceptions for the default risk for these states. Note that while the observed CDS spreads could also be transformed into PD estimates when additional assumptions on recovery rates for the states are applied, we decided to focus on the prediction of CDS spreads only in this study.

Figure 3 provides a plot of the CDS spreads for the states of California, New York, Texas, Florida, Illinois and Ohio from December 2007 to April 2013. For all states

Table 3. Summary statistics for weekly 5-year CDS spreads for the 18 states considered..

	Obs	Mean	Max	Min	σ	Available from
California	281	198.3	455.0	46.0	83.9	Dec 2007
New York	360	121.1	356.8	29.0	69.4	Jun 2006
Texas	284	74.5	205.0	20.0	35.4	Nov 2007
Florida	360	104.4	273.0	35.0	46.8	Jun 2006
Illinois	284	184.0	360.0	24.3	81.6	Nov 2007
Pennsylvania	360	72.9	157.0	45.0	37.4	Jun 2006
Ohio	257	121.0	280.0	34.5	42.0	May 2008
New Jersey	360	125.8	370.0	29.0	75.0	Jun 2006
Michigan	272	162.7	404.8	39.0	79.4	Feb 2008
Massachusetts	280	107.1	246.0	20.6	49.1	Dec 2007
North Carolina	246	93.0	179.4	20.7	39.0	Jul 2008
Virginia	296	69.0	146.5	36.0	24.9	Jun 2006
Wisconsin	173	97.4	145.6	29.0	23.7	Jan 2010
Maryland	360	70.2	175.2	12.5	38.9	Jun 2006
Connecticut	206	118.8	166.0	63.4	24.4	May 2009
Delaware	192	58.2	105.0	27.7	14.3	Jun 2009
Nevada	271	145.3	373.2	40.0	63.6	Feb 2008
Rhode Island	142	123.6	168.7	60.0	26.0	Jul 2010

Descriptive statistics are based on CDS spreads denoted in basis points. We report mean, maximum, minimum, standard deviation as well as the beginning of the sample period for each state. For all states, the last observation of the sample period is April 2013..

we find that CDS spreads were at a low level at the beginning of 2007 and increase significantly during the GFC. The highest spreads could be observed in 2008, typically followed by several smaller peaks and troughs, with the CDS spreads exhibiting a declining trend in later periods of the sample.

4 Empirical Analysis

4.1 Baseline Model

In a first step, we estimate the coefficients for model (3), where all six explanatory variables are included to assess sovereign default risk. The model is estimated for each state separately, using the derived SCRI as well as the five additional explanatory variables.

Table 4 presents the results for the estimated regression model for each state. We find that the average explanatory power of the estimated models, measured by R^2, across all states is around 0.64. The coefficient of determination ranges from 0.28 for Connecticut up to 0.83 for New Jersey, while we find that for 15 out of the considered 18 states, R^2 is higher than 0.5.

We are particularly interested in the predictive power of the developed SCRIs, which is presented in the first column of Table 4. The coefficient of the variable is positive and significant at the 1% level for 15 out of 18 states in the study. The estimated coefficients in 16 states show the expected sign, suggesting that an increase in a state's credit risk at the firm level at time t will typically lead to an increase in sovereign risk for the state at time $t+1$. The obtained results are consistent with our hypothesis formulated in the previous section and confirm the importance of information from the firm level in assessing overall sovereign risk.

	R^2	Obs	SCRI	VIX	TS	S&P500	T-CDS	CDX IG
California	0.66	281	40.27∗∗∗	−0.91∗∗∗	17.80∗∗∗	1.13	2.37∗∗∗	6.59∗∗
			(5.55)	(0.35)	(4.52)	(1.01)	(0.22)	(2.98)
New York	0.74	360	58.72∗∗∗	−0.70∗∗∗	−6.19∗∗∗	1.52∗∗	1.47∗∗∗	1.97
			(3.74)	(0.24)	(1.81)	(0.70)	(0.14)	(2.10)
Texas	0.81	284	24.68∗∗∗	0.22∗∗	−4.29∗∗∗	1.02∗∗∗	1.01∗∗∗	2.15∗∗
			(2.03)	(0.11)	(1.37)	(0.32)	(0.07)	(0.94)
Florida	0.77	360	32.88∗∗∗	0.23	−4.18∗∗∗	1.35∗∗∗	1.03∗∗∗	1.83
			(2.21)	(0.15)	(1.11)	(0.44)	(0.09)	(1.31)
Illinois	0.56	284	−26.31∗∗∗	−0.24	17.16∗∗∗	1.27	4.06∗∗∗	4.52
			(6.62)	(0.38)	(4.79)	(1.11)	(0.24)	(3.29)
Pennsylvania	0.55	360	−35.10∗∗∗	−0.26	2.56∗∗	0.25	1.81∗∗∗	1.43
			(2.80)	(0.17)	(1.26)	(0.49)	(0.10)	(1.48)
Ohio	0.70	257	18.74∗∗∗	0.33∗∗	−12.59∗∗∗	1.78∗∗∗	1.73∗∗∗	3.14∗∗
			(3.05)	(0.17)	(2.39)	(0.49)	(0.12)	(1.42)
New Jersey	0.83	360	28.69∗∗∗	0.10	3.82∗∗	1.64∗∗∗	2.36∗∗∗	4.05∗∗
			(3.11)	(0.21)	(1.57)	(0.62)	(0.13)	(1.84)
Michigan	0.76	272	61.26∗∗∗	−0.14	4.29	2.12∗∗∗	1.84∗∗∗	6.47∗∗∗
			(5.09)	(0.28)	(3.90)	(0.81)	(0.19)	(2.39)
Massachusetts	0.75	280	25.83∗∗∗	−0.10	−3.18	1.31∗∗∗	1.76∗∗∗	2.59∗
			(3.08)	(0.18)	(2.34)	(0.51)	(0.11)	(1.51)
North Carolina	0.62	246	38.04∗∗∗	−1.23∗∗∗	8.94∗∗∗	0.46	0.26∗	3.97∗∗∗
			(3.17)	(0.17)	(2.57)	(0.52)	(0.14)	(1.51)
Virginia	0.77	295	32.58∗∗∗	−0.82∗∗∗	2.88∗∗∗	−0.47∗	−0.35∗∗∗	−0.46
			(1.43)	(0.09)	(0.62)	(0.26)	(0.06)	(0.73)
Wisconsin	0.40	173	29.01∗∗∗	0.75∗∗	−1.71	0.99	0.58∗∗	−0.41
			(6.78)	(0.32)	(2.96)	(0.69)	(0.25)	(1.56)
Maryland	0.60	360	26.39∗∗∗	−1.06∗∗∗	−0.82	0.41	0.90∗∗∗	2.95∗∗
			(2.47)	(0.17)	(1.24)	(0.49)	(0.10)	(1.46)
Connecticut	0.28	207	4.63	0.54	−5.19∗	1.02	1.46∗∗∗	0.89
			(5.18)	(0.33)	(3.06)	(0.68)	(0.21)	(1.65)
Delaware	0.41	192	11.65∗∗∗	0.65∗∗∗	−2.97	1.07∗∗∗	0.47∗∗∗	1.30
			(3.06)	(0.19)	(1.88)	(0.39)	(0.11)	(0.89)
Nevada	0.77	271	39.65∗∗∗	−0.13	5.23	1.41	1.92∗∗∗	4.79∗∗∗
			(3.79)	(0.22)	(3.13)	(0.63)	(0.15)	(1.86)
Rhodes Island	0.53	142	57.90∗∗∗	−0.16	−4.01	0.85	0.74∗∗∗	−0.22
			(8.39)	(0.40)	(3.25)	(0.76)	(0.29)	(1.57)

Table 4. Results for regressing state CDS spreads on SCRI, VIX, TS, SP500, Treasury CDS, and CDX IG using weekly observations. For each state, the coefficient of determination (R^2) is provided in the first column, followed by the number of observations in the second column. Estimated coefficients are reported in the subsequent columns, with heteroskedasticity and autocovariance consistent (HAC) standard errors (Newey and West, 1987) in brackets. *,**,*** indicate significance of the coefficients at the 10%, 5% and 1%, respectively..

We further observe that while the coefficients for the SCRIs are mostly positive and significant for the 18 states, estimated coefficients for the other explanatory variables, except for the Treasury CDS spreads, are generally less significant and sometimes provide coefficients with different signs. We argue that this is not necessarily a contradiction for the expected relationship between these variables and default risk at the state level, since changes in less significant variables may possibly be captured by other variables, in particular the developed bottom-up SCRIs. For example, the estimation of EDFs for a company will take into account the volatility of the individual stock that will also be related to the overall volatility in the equity market. Therefore, it is likely that information similar to that provided by the VIX will also be incorporated in the derived SCRIs. Changes in the VIX will most likely be accompanied by changes in EDFs, and consequently in SCRIs. Therefore, estimated coefficients for the VIX may have unexpected signs since the linkage between the VIX and observed state CDS spreads is already partially explained by the estimated coefficient for the SCRI. Similar arguments can be made regarding the other explanatory variables.

In order to further investigate the predictive performance of the constructed SCRIs, the regression results are compared to the results for a restricted models without SCRI as explanatory variable. [3] We carry out model comparison tests for each state to examine the superior fit of the full model in comparison to the nested models and present the results in Table 5. The first two columns provide the R^2s for the models, with the column indicating the goodness-of-fit for the nested model, and the second column referring to the full model (3) that also includes the SCRI as predictive variable. The third and fourth column then present the F-statistics and the corresponding p-values for significance of a superior fit of the full model.

Our findings suggest that the coefficient of determination is typically much higher for the full model that includes the SCRIs. The average R^2 also increases from 0.52 for the restricted model in comparison to 0.64 for the full model, while the R^2 even doubles for the state of Virginia. Conducted model comparison tests also significantly support the full model as being superior for 17 out of 18 states. These results clearly support the hypothesis that the inclusion of the developed bottom-up state credit risk indicators significantly improves the models' ability to predict sovereign risk measured by CDS spreads for the individual states.

Overall, our results strongly support the predictive power of information from the private sector in assessing sovereign default risk at the state level. Information on default risk at the company level is an important determinant of the market's view on the ability of a state government to service its debt securities. The estimated positive coefficients for the derived bottom-up credit risk indicators imply that changes in

[3]Model estimates and coefficients for the restricted models are not reported here but are available upon request to the authors.

	Restricted Model	Full Model	F-stat	p-value
California	0.59	0.66	52.70	0.00
New York	0.55	0.74	246.60	0.00
Texas	0.71	0.81	147.86	0.00
Florida	0.63	0.77	220.51	0.00
Illinois	0.53	0.56	15.82	0.00
Pennsylvania	0.35	0.55	157.17	0.00
Ohio	0.66	0.70	37.78	0.00
New Jersey	0.78	0.83	85.16	0.00
Michigan	0.63	0.76	144.82	0.00
Massachusetts	0.68	0.75	70.35	0.00
North Carolina	0.39	0.62	144.16	0.00
Virginia	0.36	0.77	518.67	0.00
Wisconsin	0.33	0.40	18.32	0.00
Maryland	0.47	0.60	114.32	0.00
Connecticut	0.27	0.28	0.80	0.37
Delaware	0.36	0.41	14.54	0.00
Nevada	0.68	0.77	109.41	0.00
Rhodes Island	0.36	0.53	47.66	0.00

Table 5. Results for conducted model comparison tests to examine the superior fit of the full model in comparison to a restricted model that excludes the SCRIs. The first column provides the coefficient of determination for the nested model, the second column the coefficient of determination for the full model. The third and fourth column present the F-statistic and the corresponding p-values for significance of a superior fit of the full model..

the average credit risk in the private sector for a state at time t can help to predict upcoming changes in sovereign risk at $t+1$. In the following sections we will conduct a number of tests to examine the robustness of the obtained results.

4.2 Robustness Checks

4.2.1 Results for Monthly Frequency

We first test the predictive power of the created SCRIs for state CDS spreads by also looking at monthly observations. Overall, financial variables such as CDS spreads are expected to react rather quickly to changes in market perceptions on credit risk conditions at the company or state level. However, information contained in the constructed SCRIs may also influence perceived risks for the credit quality of a state over a longer time horizon. Therefore, the SCRIs are expected to still have significant predictive power for state CDS spreads when the relationship is examined using monthly instead of weekly frequencies. We re-estimate model (3) using monthly observations, applying a one-month lag to the explanatory variables. If the suggested relationship between the derived bottom-up risk indicators and state CDS spreads is robust, the estimated models should yield similar results for the explanatory power of the models as well as with regards to the significance and sign of the estimated coefficients.

	R^2	Obs	SCRI	VIX	TS	S&P500	T-CDS	CDX IG
California	0.68	65	39.57***	−1.02	17.19*	−0.49	2.09***	13.54**
			(11.94)	(0.87)	(9.74)	(2.26)	(0.45)	(5.61)
New York	0.78	83	57.76***	−0.50	−5.58	0.29	1.32***	8.17**
			(7.52)	(0.55)	(3.59)	(1.47)	(0.28)	(3.87)
Texas	0.84	66	23.64***	0.14	−4.93*	1.25*	0.98***	3.46**
			(4.09)	(0.27)	(2.69)	(0.67)	(0.13)	(1.67)
Florida	0.83	83	31.45***	0.15	−5.04**	0.69	1.08***	7.72***
			(4.20)	(0.33)	(2.08)	(0.86)	(0.17)	(2.27)
Illinois	0.55	66	−31.90**	−0.13	18.65*	1.96	4.00***	10.14
			(15.05)	(1.02)	(10.59)	(2.63)	(0.52)	(6.59)
Pennsylvania	0.57	83	−39.98***	0.11	2.46	−0.01	1.86***	7.01**
			(5.97)	(0.42)	(2.65)	(1.09)	(0.21)	(2.88)
Ohio	0.76	60	18.96***	0.36	−14.98***	1.07	1.62***	5.55**
			(6.18)	(0.40)	(4.72)	(1.02)	(0.24)	(2.52)
New Jersey	0.84	83	28.71***	0.02	4.48***	1.68	2.22***	8.34**
			(6.46)	(0.51)	(3.22)	(1.33)	(0.26)	(3.50)
Michigan	0.80	63	64.46***	−0.31	−0.94	2.07	1.61***	7.13**
			(10.52)	(0.68)	(7.86)	(1.74)	(0.37)	(4.31)
Massachusetts	0.77	65	25.58***	−0.24	−5.43	1.89*	1.70***	5.99**
			(6.56)	(0.43)	(4.94)	(1.13)	(0.23)	(2.81)
North Carolina	0.68	57	39.17***	−1.23***	6.76	−0.71	0.07*	5.28**
			(6.44)	(0.43)	(5.06)	(1.10)	(0.28)	(2.68)
Virginia	0.81	68	33.29***	−0.85***	2.27*	−0.70	−0.37***	1.26
			(3.06)	(0.22)	(1.28)	(0.56)	(0.12)	(1.39)
Wisconsin	0.57	40	27.72*	1.11	−0.58	1.21	0.54	5.56**
			(14.42)	(0.69)	(6.54)	(1.57)	(0.49)	(2.62)
Maryland	0.62	83	26.95***	−1.35***	−0.66*	−0.86	0.87***	5.32**
			(5.22)	(0.41)	(2.59)	(1.07)	(0.21)	(2.82)
Connecticut	0.45	48	−2.44	0.98	−3.49	3.36**	1.21***	7.26***
			(10.03)	(0.65)	(6.14)	(1.48)	(0.37)	(2.61)
Delaware	0.59	45	13.72**	0.58*	−5.28	2.37***	0.44**	3.90***
			(5.84)	(0.35)	(3.72)	(0.79)	(0.20)	(1.36)
Nevada	0.82	63	43.94***	−0.44	−0.10	1.41	1.71***	6.49**
			(7.63)	(0.51)	(6.10)	(1.31)	(0.28)	(3.26)
Rhodes Island	0.64	33	60.25***	−0.38	−9.00	1.74	1.04*	4.47*
			(17.35)	(0.81)	(7.25)	(1.68)	(0.55)	(2.60)

Table 6. Results for regressing state CDS spreads on SCRI, VIX, TS, SP500, Treasury CDS, and CDX IG using monthly observations. For each state, the coefficient of determination (R^2) is provided in the first column, followed by the number of observations in the second column. Estimated coefficients are reported in the subsequent columns, with heteroskedasticity and autocovariance consistent (HAC) standard errors (Newey and West, 1987) in brackets. *,**,*** indicate significance of the coefficients at the 10%, 5% and 1%, respectively..

Regression results for monthly observations are shown in Table 6. Our findings illustrate that also for monthly frequencies, 15 out of 18 states yield positive and significant coefficients for the constructed SCRIs. Also treasury CDS spreads and the CDX IG index remain highly significant in most of the estimated models. The average R^2 across all states is 0.70, and for most states is slightly higher similar in comparison to the results for weekly data. [4] Thus, while the number of observations in each state

[4]Note, however, that as pointed out by Boudoukh et al. (2008) higher levels of predictability with

is much smaller because of the change from weekly to monthly frequency, our main results on the predictive power of the constructed SCRI for sovereign default risk at the state level are confirmed.

4.2.2 Using ICRIs based on the mean of corporate risk measures

We also test the predictive relationship between the SCRIs and state CDS spreads, using a slightly different approach for the construction of the SCRIs. Hereby, instead of using the median of the observed EDFs for all companies in a specific industry, we use the mean of the EDFs to construct the ICRI. The mean is expected to be more sensitive to changes in EDFs of companies with a higher default risk. A SCRI based on such ICRIs will probably also exhibit more volatility through time. Results for this alternative specification of the SCRIs are reported in Table 7.

Our findings suggest that the results are also quite robust with regards to the construction of the ICRIs and SCRIs. Again we find that for 15 out of 18 states the model yields positive and significant coefficients for the constructed SCRIs. The average R^2 for the estimated models is 0.64 and thus very similar to the baseline specification of the model. Also with regards to the significance of the coefficients and the explanatory power of the estimated models for the individual states the results are qualitatively the same. However, we observe that in comparison to the baseline model, the estimated SCRI coefficients are much smaller in magnitude. This is a result of the skewed distribution of company EDFs for each industry that leads to the mean typically being significantly higher than the median. At the same time, neither the sign nor the magnitude of the estimated coefficients for the other explanatory variables does change significantly. Overall, these findings strongly support the robustness of the results reported earlier.

4.2.3 A bottom-up Credit Risk Indicator using Top Industries only

So far the derived SCRIs were based on all industries contributing to a state's GDP output. However, one could argue that it is typically the major industries with a large contribution to a state's GDP that will have a larger influence on market perceptions of sovereign risk. Therefore, as an additional robustness check, we examine the sensitivity of our results with regards to the construction of the bottom-up indicators. To do this, we use an alternative approach and only include the five largest industries in a state

widening horizons are to be expected in longer term horizon regressions. As the sampling error that is almost surely present in small samples shows up in each regression, both the estimator and R^2 are proportional to the forecast horizon. Therefore, better results for long horizons in the form of higher increasing R^2s generally provide little if any evidence for a better forecasting performance over and above the weekly results. From this perspective, the increasing explanatory power of the applied models for monthly horizons should be interpreted with care.

	R^2	Obs	SCRI	VIX	TS	S&P500	T-CDS	CDX IG
California	0.70	281	25.57***	−1.28***	13.46***	0.41	2.11***	4.78*
			(2.62)	(0.33)	(4.26)	(0.95)	(0.22)	(2.98)
New York	0.72	360	27.47***	−0.56**	−11.08***	1.27*	1.31***	1.14
			(1.91)	(0.24)	(2.01)	(0.73)	(0.15)	(2.19)
Texas	0.83	284	12.59***	0.16	−5.98***	0.79***	0.97***	1.42
			(0.89)	(0.11)	(1.32)	(0.30)	(0.06)	(0.89)
Florida	0.77	360	16.26***	0.27*	−7.54***	1.14***	0.94***	1.20
			(1.11)	(0.15)	(1.20)	(0.44)	(0.09)	(1.32)
Illinois	0.54	284	−6.63**	−0.63	13.13***	1.04	3.87***	3.81
			(3.52)	(0.39)	(5.00)	(1.14)	(0.24)	(3.38)
Pennsylvania	0.48	360	−12.97***	−0.52***	4.04***	0.19	1.76***	1.43
			(1.36)	(0.18)	(1.43)	(0.53)	(0.11)	(1.59)
Ohio	0.73	257	10.78***	0.14	−14.27***	1.44***	1.73***	2.35*
			(1.30)	(0.16)	(2.24)	(0.47)	(0.11)	(1.36)
New Jersey	0.83	360	15.35***	0.08	0.12	1.37**	2.21***	3.25*
			(1.54)	(0.20)	(1.66)	(0.61)	(0.13)	(1.82)
Michigan	0.76	272	28.36***	−0.23	4.26	1.60**	1.93***	5.24**
			(2.27)	(0.28)	(3.82)	(0.81)	(0.18)	(2.37)
Massachusetts	0.76	280	13.32***	−0.18	−4.62**	1.03**	1.71***	1.87
			(1.41)	(0.17)	(2.31)	(0.50)	(0.11)	(1.48)
North Carolina	0.65	246	18.71***	−1.40***	9.31***	0.12	0.42***	3.22**
			(1.47)	(0.17)	(2.42)	(0.50)	(0.13)	(1.47)
Virginia	0.68	295	14.19***	−0.66***	−0.29	−0.46	−0.33***	−0.67
			(0.85)	(0.10)	(0.81)	(0.31)	(0.07)	(0.88)
Wisconsin	0.42	173	10.60***	0.96***	2.41	0.97	0.65***	−0.33
			(2.18)	(0.28)	(2.19)	(0.68)	(0.25)	(1.53)
Maryland	0.63	360	15.02***	−1.14***	−4.52***	0.10	0.74***	2.03
			(1.18)	(0.16)	(1.27)	(0.47)	(0.10)	(1.40)
Connecticut	0.28	207	2.58	0.51*	−5.38**	0.95	1.50***	0.82
			(1.97)	(0.30)	(2.62)	(0.68)	(0.21)	(1.64)
Delaware	0.42	192	4.97***	0.69***	−2.40	1.04***	0.50***	1.36
			(1.21)	(0.17)	(1.67)	(0.38)	(0.12)	(0.89)
Nevada	0.77	271	18.50***	−0.16	5.99*	1.14*	1.92***	3.97**
			(1.78)	(0.22)	(3.11)	(0.64)	(0.15)	(1.88)
Rhodes Island	0.62	142	21.06***	0.16	2.75	0.59	0.94***	−0.23
			(2.17)	(0.31)	(2.29)	(0.68)	(0.26)	(1.40)

Table 7. Results for regressing weekly state CDS spreads on the newly developed SCRI based on mean of the EDFs for each industry to construct the ICRIs. Additional explanatory variables are the same as in the baseline model, i.e., VIX, TS, SP500, Treasury CDS, and CDX IG. For each state, the coefficient of determination (R^2) is provided in the first column, followed by the number of observations in the second column. Estimated coefficients are reported in the subsequent columns, with heteroskedasticity and autocovariance consistent (HAC) standard errors (Newey and West, 1987) in brackets. *,**,*** indicate significance of the coefficients at the 10%, 5% and 1%, respectively..

(with regards to their contribution to GDP) when constructing the SCRIs. Typically the five major industries constitute more than half of the total GDP of a state and, thus, are expected to be highly influential for the state's economy.

In a first step we identify the five major industries for each state. We observe that certain industries such as retail/wholesale trade and the real estate sector typically play a dominant role in most states, while other the contribution of other industries varies significantly across the states. For example, the mining industry is the fourth largest industry in Texas, which only constitutes a small proportion to the GDP in most of the other states. We also find that companies in the information sector (media, computer software, publishing and telephone,) make a large contribution to state GDPs in California and Wisconsin, but not elsewhere.

The SCRIs are then computed as the weighted average of the corresponding ICRIs for the five major industries. We then test the predictive power using the revised SCRIs with concentrated industry compositions together with the additional explanatory variables. SCRIs based on the most important industries for a state only are still expected to provide important information for the assessment of sovereign default risk. Thus, the quality of results should not be significantly affected by this revised construction of the indices.

Table 8 shows regression results for the revised SCRIs. The average R^2 is 0.65 and 15 states have positive, significant coefficients also for the revised SCRIs. The higher overall R^2 indicates even a slightly better fit of the models when only major industries are used for construction of the SCRIs. Overall, the results confirm the predictive power of the developed bottom-up credit risk indicators.

4.2.4 Through-the-Cycle Credit Risk Measures

In a next step, we examine the predictive relationship when the effect of the credit cycle on company level default risk is excluded to a high degree. Therefore, instead of using point-in-time EDFs at the company level to derive the ICRIs and SCRIs, we use Moody's KMV's through-the-cycle EDFs (TTCEDFs)to develop these indicators. The conducted robustness tests will then help us to confirm whether credit risk information at the company level is significant in assessing sovereign risk at all stages of the credit cycle.

Like standard EDFs, also TTCEDF provide a measure of credit quality for a firm over a one-year time horizon. However, standard EDFs are so-called point-in-time (PIT) measures and thus incorporate not only information about a companys individual credit risk profile, but also geographic, sectoral as well as cyclical macro-credit factors. Hence, Moody's KMV argues that standard PIT EDF measures as we have used them so far in this analysis typically provide early warning signals of rapid changes in default risk. On the other hand, TTCEDF measures isolate a company's underlying credit trend from the macro-credit cyclical effect. TTCEDF are primarily driven by changes in a company's long-run credit quality, which tends to be more stable over time and exhibit less variation. Thus, while we expect EDFs and TTCEDFs to share a similar (long-run) trend since they are both developed using a company's own credit risk profile, the values of the two measures may differ significantly during, e.g., a major credit crisis since TTCEDFs will minimize the impact of the macro-credit cycle.

To derive the revised risk indicators, we implement the same approach as outlined

	R^2	Obs	SCRI	VIX	TS	S&P500	T-CDS	CDX IG
California	0.64	281	30.17***	−0.70*	21.99***	1.27	2.50***	7.24**
			(4.94)	(0.36)	(4.48)	(1.03)	(0.22)	(3.05)
New York	0.73	360	55.91***	−0.53**	−5.99***	1.57**	1.48***	2.17
			(3.67)	(0.23)	(1.83)	(0.71)	(0.15)	(2.13)
Texas	0.81	284	21.58***	0.20*	−3.07**	1.00***	1.01***	2.24**
			(1.76)	(0.11)	(1.32)	(0.32)	(0.07)	(0.94)
Florida	0.79	360	29.99***	0.32**	−3.59***	1.37***	1.04***	1.99
			(2.09)	(0.15)	(1.12)	(0.44)	(0.09)	(1.32)
Illinois	0.58	284	−26.35***	−0.25	17.56***	1.31	4.08***	4.58
			(6.14)	(0.37)	(4.73)	(1.10)	(0.23)	(3.27)
Pennsylvania	0.57	360	−33.39***	−0.35**	2.41*	0.23	1.80***	1.34
			(2.66)	(0.17)	(1.26)	(0.49)	(0.10)	(1.48)
Ohio	0.72	257	16.96***	0.38**	−12.00***	1.82***	1.74***	3.25**
			(2.90)	(0.16)	(2.38)	(0.49)	(0.13)	(1.43)
New Jersey	0.84	360	25.63***	0.20	4.23***	1.69***	2.38***	4.23**
			(2.97)	(0.21)	(1.58)	(0.62)	(0.13)	(1.86)
Michigan	0.77	272	55.34***	−0.08	9.04**	2.18**	1.91***	6.97***
			(4.98)	(0.29)	(3.85)	(0.83)	(0.19)	(2.45)
Massachusetts	0.77	280	24.46***	−0.03	−2.97	1.32***	1.77***	2.65*
			(2.91)	(0.17)	(2.33)	(0.51)	(0.11)	(1.51)
North Carolina	0.63	246	33.61***	−1.12***	9.59***	0.49	0.28*	4.11***
			(2.89)	(0.17)	(2.59)	(0.52)	(0.14)	(1.53)
Virginia	0.79	295	28.45***	−0.76***	2.92***	−0.47*	−0.33***	−0.41
			(1.24)	(0.08)	(0.62)	(0.26)	(0.06)	(0.73)
Wisconsin	0.40	173	23.84***	0.97***	0.53	1.14	0.55**	−0.26
			(6.96)	(0.32)	(2.91)	(0.70)	(0.25)	(1.58)
Maryland	0.62	360	24.93***	−1.02***	−0.57	0.41**	0.90***	3.00**
			(2.31)	(0.16)	(1.23)	(0.49)	(0.10)	(1.45)
Connecticut	0.28	207	5.13	0.51	−5.57*	1.00	1.47***	0.84
			(4.82)	(0.33)	(3.04)	(0.68)	(0.21)	(1.64)
Delaware	0.40	192	10.77***	0.68***	−2.79	1.09***	0.45***	1.33
			(3.03)	(0.19)	(1.94)	(0.39)	(0.11)	(0.90)
Nevada	0.76	271	36.57***	0.07	7.00**	1.50**	1.96***	5.14***
			(3.76)	(0.21)	(3.15)	(0.65)	(0.15)	(1.89)
Rhodes Island	0.52	142	56.95***	−0.12	−4.22	0.86	0.70**	−0.22
			(8.41)	(0.40)	(3.31)	(0.77)	(0.29)	(1.57)

Table 8. Results for regressing state CDS spreads on SCRI, VIX, TS, SP500, Treasury CDS, and CDX IG, using weekly observations and constructing the SCRIs based on the state's top five industries only. For each state, the coefficient of determination (R^2) is provided in the first column, followed by the number of observations in the second column. Estimated coefficients are reported in the subsequent columns, with heteroskedasticity and autocovariance consistent (HAC) standard errors (Newey and West, 1987) in brackets. *,**,*** indicate significance of the coefficients at the 10%, 5% and 1%, respectively..

earlier for the construction of the original SCRIs. Weekly TTCEDFs for all listed companies are collected as the observed TTCEDF values on the last trading day of a week. Using the same industry categories as described in Table 1, companies are then grouped into 15 industries and the median TTCEDF of all companies in the same industry is taken as the industry's TTCEDF. This results in 15 through-the-cycle industry credit risk indicators (TTCICRIs).

Figure 4 demonstrates the significant differences between the original ICRI and the new TTCICRI. As expected, the industry of real estate, rental and leasing was greatly affected during the subprime credit crisis, leading to a peak of default risk implied by the ICRI in late 2008 and during 2009. However, as shown in the upper panel, TTCICRI based PD estimates for the industry are significantly less affected by the GFC period. Similar observations can be made for the industry of retail/wholesale trade and utilities in the middle and bottom panel of Figure 4. The effect of the GFC is diminished for the derived TTCICRIs resulting in a more stable measure of credit risk at the company and industry level. Still we find that also for the constructed TTC industry measures that average values as well as the dynamics of the risk indicators differ significantly for the 15 industries.

Based on an industry's percentage contribution to total GDP in each state, the TTCICRIs are then used to derive through-the-cycle state credit risk indicators (TTC-SCRIs). The same set of industry weights that has been used for the construction of the SCRIs is adopted here, such that the TTCSCRI for each state is essentially a weighted average of the 15 TTCICRIs. We plot the original SCRI as well as the TTC-SCRI for California in Figure 5. As expected, the two time series differ significantly, in particular during the time from late 2008 to early 2010, when the TTCSCRI is significantly less affected by market conditions prevalent during the crisis period. Similar observations can be made for the other states in our sample.

We then apply model 3, replacing the SCRIs with the calculated TTCSCRIs, to examine the predictive power of the explanatory variables for sovereign default risks. We consider observations at weekly frequencies and present the results for the regression in Table 9. We find that the average explanatory power (measured by R^2) is 0.65, and therefore, quite similar to the results obtained for the original SCRIs. Again we find that for 15 of the 18 states the estimated coefficients for the TTCSCRI are both positive and significant, which is consistent with previous findings in this study. Thus, our results on the predictive power of the constructed SCRIs also holds for measures being based on through-the-cycle EDFs. Overall, these results strongly confirm the usefulness of adopting information from the private sector in assessing sovereign risk in all stages of a credit cycle.

4.2.5 Quantile Regression Models

In a last step, we conduct additional robustness tests for the applied regression model using quantile regression. Quantile regression has been used widely in the fields of economics and finance and provides a powerful tool to generate robust inferences while not explicitly resting on the assumption of stationarity for the considered of variables (Angrist and Pischke, 2008; Zhou and Wu, 2009). The method allows to compute several different regression curves corresponding to various quantiles of the dependent variable and thus provides a more complete picture of the relationship between the

	R^2	Obs	TTCSCRI	VIX	TS	S&P500	T-CDS	CDX IG
California	0.72	281	461.97***	−1.75***	−5.08	−0.17	2.65***	3.86
			(41.96)	(0.33)	(5.03)	(0.93)	(0.18)	(2.73)
New York	0.76	360	437.08***	−0.76***	−12.35***	0.81	2.08***	1.20
			(24.93)	(0.22)	(1.84)	(0.68)	(0.13)	(2.01)
Texas	0.8	284	183.82***	0.15	−9.94***	0.69	1.22***	1.67*
			(16.41)	(0.12)	(1.74)	(0.33)	(0.06)	(0.98)
Florida	0.79	360	239.24***	0.29**	−8.70***	0.98**	1.39***	1.31
			(15.00)	(0.14)	(1.18)	(0.43)	(0.08)	(1.27)
Illinois	0.54	284	−66.67	−0.77*	12.83**	0.91	3.70***	3.33
			(55.67)	(0.41)	(6.01)	(1.16)	(0.22)	(3.41)
Pennsylvania	0.47	360	−176.98***	−0.60	4.26***	0.25**	1.45***	1.13
			(19.82)	(0.18)	(1.47)	(0.54)	(0.10)	(1.61)
Ohio	0.74	257	213.84***	0.01	−23.60	1.15*	1.77***	1.84*
			(23.32)	(0.16)	(2.78)	(0.46)	(0.11)	(1.33)
New Jersey	0.84	360	245.83***	−0.01**	−1.48***	1.11	2.64***	3.16*
			(21.20)	(0.20)	(1.62)	(0.59)	(0.11)	(1.75)
Michigan	0.79	272	553.22***	−0.65	−19.49***	0.83*	2.16***	4.00
			(38.1)	(0.27)	(4.52)	(0.77)	(0.16)	(2.24)
Massachusetts	0.75	280	214.57***	−0.25	−10.61***	0.93*	1.98***	1.87
			(24.61)	(0.18)	(2.83)	(0.51)	(0.10)	(1.51)
North Carolina	0.74	246	395.75***	−1.75***	−8.89***	−0.58	0.42***	1.89
			(22.48)	(0.15)	(2.67)	(0.44)	(0.11)	(1.28)
Virginia	0.66	295	174.91***	−0.59***	0.28	−0.54*	0.13**	−0.25
			(10.92)	(0.10)	(0.82)	(0.32)	(0.06)	(0.89)
Wisconsin	0.45	173	191.18***	0.36	−8.89***	0.35	0.54**	−0.90
			(31.63)	(0.32)	(3.33)	(0.68)	(0.24)	(1.49)
Maryland	0.54	360	139.57***	−0.79***	−2.60*	0.44	1.22***	3.21**
			(18.43)	(0.17)	(1.43)	(0.53)	(0.10)	(1.56)
Connecticut	0.28	207	53.33	0.38	−7.76**	0.83	1.47***	0.73
			(37.5)	(0.35)	(3.82)	(0.70)	(0.20)	(1.64)
Delaware	0.40	192	81.53***	0.67***	−3.55	0.97**	0.42***	1.36
			(25.34)	(0.20)	(2.29)	(0.40)	(0.11)	(0.90)
Nevada	0.8	271	378.34***	−0.45**	−11.11***	0.60	2.15***	3.30*
			(30.57)	(0.21)	(3.72)	(0.61)	(0.13)	(1.78)
Rhodes Island	0.62	142	338.28***	−0.45	−12.22***	0.03	0.56**	−0.81
			(35.93)	(0.35)	(3.29)	(0.70)	(0.26)	(1.42)

Table 9. Results for regressing state CDS spreads on TTCSCRI, VIX, TS, SP500, Treasury CDS, and CDX IG, using weekly observations. For each state, the coefficient of determination (R^2) is provided in the first column, followed by the number of observations in the second column. Estimated coefficients are reported in the subsequent columns, with heteroskedasticity and autocovariance consistent (HAC) standard errors (Newey and West, 1987) in brackets. *,**,*** indicate significance of the coefficients at the 10%, 5% and 1%, respectively..

variables (Mosteller and Tukey, 1977). Thus, results from quantile regression will provide additional information beyond the focus of least squares estimates only. As suggested by Cade and Noon (2003); Koenker and Hallock (2001) quantile regression has the potential to reveal the relationship between explanatory variables and the dependent variable that have been overlooked by standard regression models. Further, a conditional median regression is more robust than the conditional mean regression in terms of outliers in the observations (Yu and Moyeed, 2001).

In the following, we test the predictive relationship between the considered explanatory variables state CDS spreads at different quantiles. Naturally, we are specifically interested in the results for the SCRIs for various states. Results from conducted quantile regression will demonstrate possible changes in the predictive relationship for different ranges of the distribution for CDS spreads. Thus, they allow us to draw conclusions on this relationship for different levels of sovereign risk, for example during crisis periods or periods where market participants had a rather low perception of sovereign risk. Naturally, in particular results for upper quantiles of the dependent variable are of interest, since higher values for market CDS spreads are indicative of a higher sovereign risk at the state level, which could be of particular concern for policy-makers and investors.

Figure 6 provides an overview of the results for the state of California and for the six explanatory variables, namely the state-specific SCRI, the VIX, the term spread (TS), S&P500 returns, treasury CDS spreads, and CDX IG. Estimated values of the coefficient for each quantile are represented by the black dotted line. The horizontal solid line represents the OLS estimate, while the two dashed lines represent the 90% confidence intervals for the least squares estimate from the previous regression model (3). The shaded grey area depicts a 90% confidence band for the quantile regression estimates.

As illustrated by the figure, the value of the estimated coefficient for SCRI in California is very steady around 50 at all quantiles, as indicated by the dotted line. The estimated coefficients for the conducted quantile regressions also are very close to the 90% confidence interval of the mean estimation of the coefficients, as marked by the two dashed lines. Thus, for California, our result suggest that the estimated coefficient for the SCRI is not only positive and significant at its mean value, but also at various quantiles of the distribution. Therefore, these results further confirm our previous conclusions about the strong and significant predictive relationship between the derived SCRI and state CDS spreads.

However, quantile regression results for the other five explanatory variables show different variation patterns. For example, results for TS and TCDS show a clear upward trend from the lower quantiles to the higher quantiles, indicating a higher influence on the sovereign CDS spreads in more distressed situations, while such a behavior could not be observed for the estimated coefficients for the derived SCRI. This could imply that the extremely high level of sovereign risk is more likely to be driven by market conditions, and the influence from the private sector is stable across different quantiles of the distribution. This is a possibility, considering that the performance in the private sector aids in predicting the state government's intrinsic ability to service its debt payments, while the CDS spread is a market-based variable that is more likely to be influenced by overall market conditions.

As indicated by the quantile regression results for California, the predictive relationship defined in the OLS regression model is largely consistent at different quantiles of the distribution.

Quantile regression results for the estimated coefficients for SCRI of six exemplary states are presented in Figure 7. Clearly, the behaviour of estimated coefficients for SCRI at different varies from state to state.

Typically the quantile regression estimates for the SCRI coefficients are consistent with OLS estimates, in particular for quantiles ranging from 0.4 to 0.6. Thus, while OLS and quantile regression coefficients are not identical, the difference between the estimates is often not significant for many of the considered quantiles, even when the confidence interval for the OLS coefficient is relatively narrow. For a small number of states, including, e.g. New York and Pennsylvania, estimated coefficients based on quantile regression significantly deviate from the OLS estimate for the coefficient.

The significant deviation away from the mean estimate in the coefficients of SCRIs for higher quantiles indicates a possible change in the predictive relationship between SCRI and state CDS spreads. The coefficients are still significant in forecasting sovereign risk, however the expected change in a state's CDS spread caused by one unit variation in corresponding SCRI varies across states. The size and the direction of the change differ when the CDS spread is very high, such as during a credit crisis. The predictive relationship, particularly for states such as Pennsylvania when the quantile regression estimate is outside the confidence band of OLS estimate, should be reassessed when facing a major economic crisis. In these cases, the influence of market-based variables such as VIX and CDX IG should be given special attention.

Overall, our results suggest that the coefficients for the SCRIs based on quantile regression are typically consistent with values from the OLS regression for most states, at least in the mid-range of the quantiles. On the other hand, quantile regression estimates can deviate significantly for some states, in particular at very high or low quantiles of the distribution. However, the coefficient for the SCRI is typically still positive and significant also for these quantiles. However, the results may suggest further investigation of the predictive relationship between the derived SCRIs and state CDS spreads under extreme economic scenarios such as economic crises, using also non-linear models. We leave this task to future research.

5 Conclusion

In this paper we develop a bottom-up approach for assessing sovereign risk at the state level, using new bottom-up credit risk indicators based on information about default risk at the company level. Our study is motivated by the simple rationale that the ability of state governments to service debt is affected by tax revenues from the private sector, the latter being dependent on the attendant economic activity and the performance of major industries in a state. The recent default of a large municipality such as Detroit and the U.S. territory of Puerto Rico also encourages us to examine more thoroughly the dynamics and prediction of sovereign debt at the state level.

Using Moody's KMV EDF data to measure corporate default risk, we construct industry credit risk measures that are then used to derive state-specific indicators for default risk based on the industry composition for each state. In combination with additional explanatory variables, namely the VIX, the spread between short-term government bills and long-term government bonds, returns from the S&P500, U.S. treasury CDS spreads, and investment grade corporate bond index returns, the derived credit risk indicators are then examined with respect to their forecasting ability for U.S. state CDS spreads.

Our study complements and extends earlier work by Altman and Rijken (2011) in several dimensions. First, in contrast to the reliance on scoring models in Altman and Rijken (2011), our approach uses EDFs that are based on a structural model for quantifying credit risk at the company level. Unlike balance sheet information that is typically used for scoring models, market-based EDF measures are available at a daily frequency for a large universe of private companies. More importantly, our approach overcomes many of the shortcomings of scoring models primarily reliant on accounting information. Second, this study examines a sample of sovereign U.S. state governments that are selected without reference to their financial health, thus mitigating the potential selection bias inherent in Altman and Rijken (2011)), which focuses on European sovereign entities that are known to be distressed.

Our results show that market-based measures of private sector credit risk are strongly associated with subsequent shifts in sovereign credit risk premiums measured by CDS spreads. Our findings also suggest that the developed credit risk indicators are more suitable than the considered financial variables for forecasting sovereign CDS spreads at weekly and monthly sampling frequencies. These findings suggest a strong predictive link between market expectations of private sector credit quality and those of sovereign credit quality - a connection that is not directly discernible from scoring models. Moreover, we find that the link between private and public sector credit risk generalizes beyond the sample of distressed European sovereign entities studied by Altman and Rijken (2011).

Overall, our results suggest that in order to model and manage sovereign risk exposure, governments should consider the effect of new policies on the private sector. Policies that are beneficial to companies, such as subsidies and tax credits, may not only stimulate the economy and help companies achieve higher profit targets, but also generate a positive effect on the long-run sovereign risk of a state government. The implication for investors who have risk exposure to foreign sovereign risk is to include an analysis of the overall performance of the country's private sector into their models. At the very least, private sector based metrics complement market-based measures of macroeconomic expectations in forecasting sovereign risk. A closer look at company level information is also helpful for investors in making informed decisions. As our study suggests, fluctuations in credit quality of resident corporations appear to be strongly linked to subsequent variation in sovereign credit quality. Therefore, based on our findings we strongly recommend additional research on the relationship between credit risk at the corporate level and sovereign default risk.

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Figure 1. Time series of ICRIs for *real estate, rental and leasing* and *arts, entertainment and recreation (upper panel)*, *mining* and *retail/wholesale trade (middle panel)*, and *agriculture, forestry, fishing and hunting* and *utilities (lower panel)* for the sample period June 2006 to April 2013..

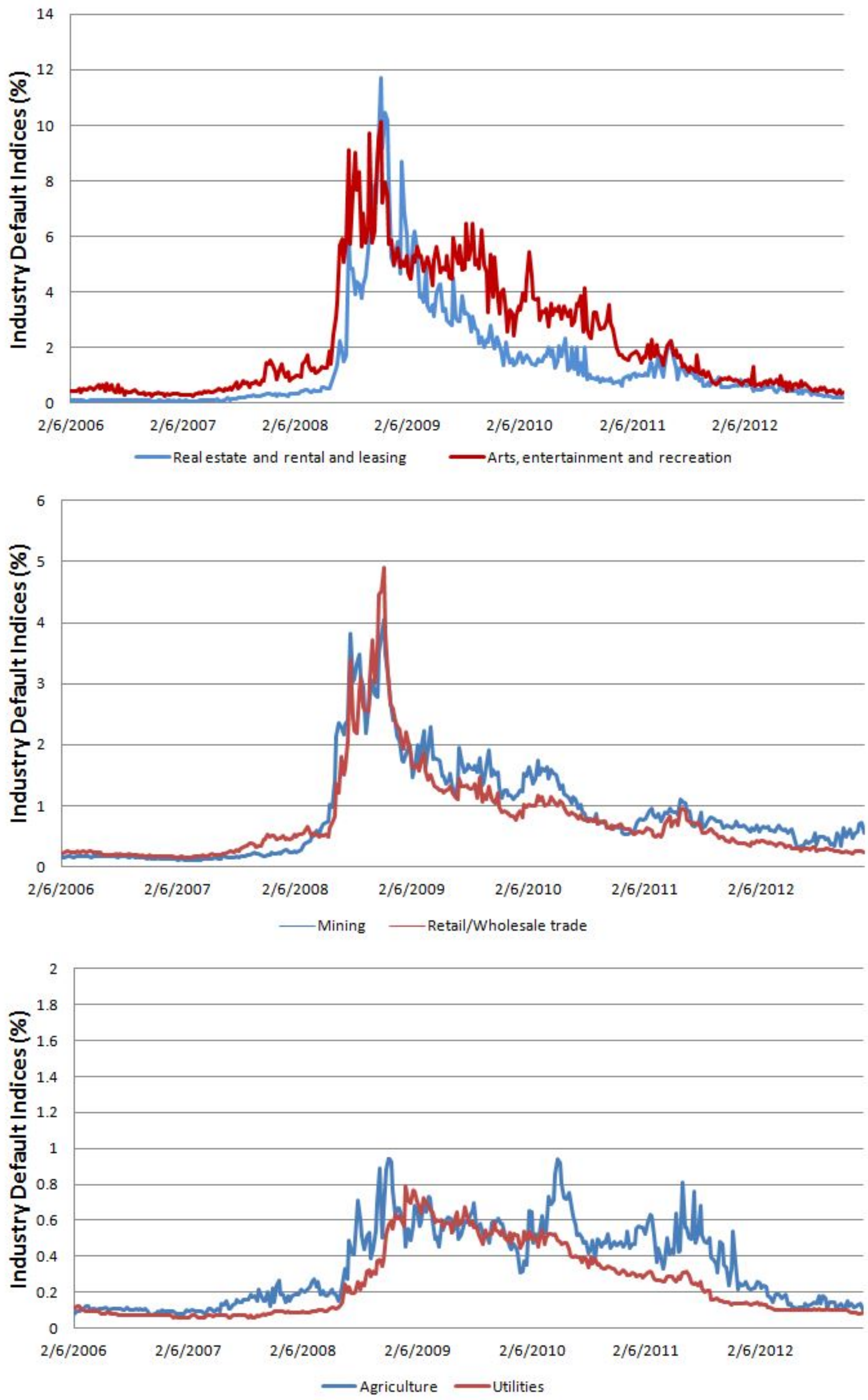

Figure 2. Time series of California's constructed SCRI for the sample period June 2, 2006 to April 26, 2013..

Figure 3. Time series of weekly observations for CDS spreads for the states of California *(upper left panel)*, New York *(upper right panel)*, Texas *(middle left panel)*, Florida *(middle right panel)*, Illinois *(lower left panel)* and Ohio *(lower right panel)* from December 2007 to April 2013..

Figure 4. Time series of constructed TTCICRI and ICRIs for selected industries: *real estate, rental and leasing (upper panel)*, *retail/wholesale trade (middle panel)*, and *(utilities) lower panel* for the sample period June 2006 to April 2013..

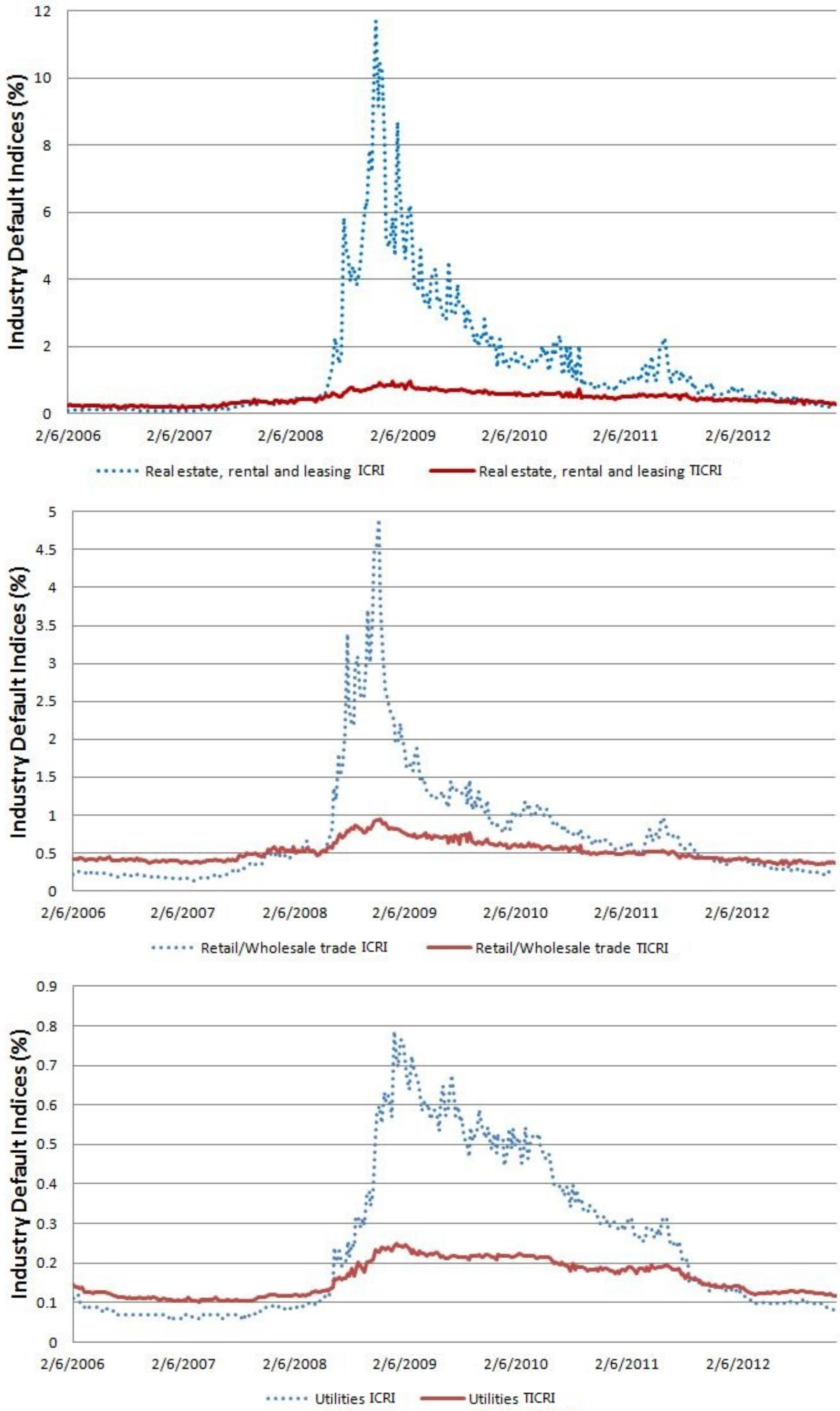

Figure 5. Time series of constructed TTCSCRI and SCRI for the state of California during the sample period June 2006 to April 2013..

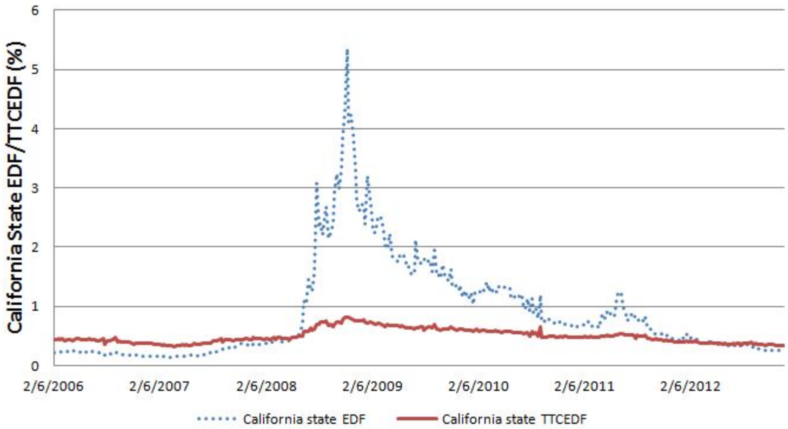

Figure 6. Results for conducted quantile regression for California. Estiated coefficients for different quantiles are represented by the black dotted line. Each plot provides results for quantiles ranging from 0 to 1, while the vertical axis indicates the value of the estimated coefficient. The solid line in each graph shows the ordinary least squares estimate and the two dashed lines represent the 90% confidence intervals for the estimated coefficient using OLS regression. The shaded grey area depicts a 90% confidence band for the quantile regression estimates..

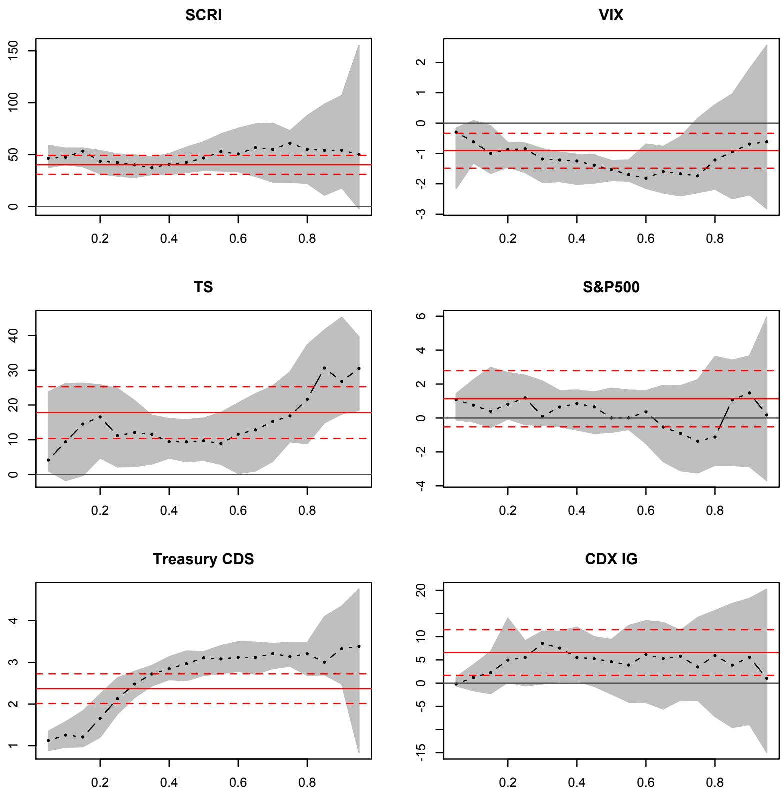

Figure 7. Quantile regression results for California *(upper left panel)*, New York *(upper right panel)*, Texas *(middle left panel)*, Florida *(middle right panel)*, Illinois *(lower left panel)* and Pennsylvania *(lower right panel)*. We present quantile regression estimates (the black dotted line) for quantiles ranging from 0 to 1, while the vertical axis indicates the value of the estimated SCRI coefficient at different quantiles. The solid line in each graph shows the ordinary least squares estimate and the two dashed lines represent 90% confidence intervals of the OLS estimate. The shaded grey area depicts a 90% confidence band for the quantile regression estimates..