NUS Credit Research Initiative Technical Report

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Credit Research Initiative†
National University of Singapore

A Special Preface

After dedicating 14 years to the Credit Research Initiative (CRI), Professor Jin-Chuan Duan, the founder, is due to retire from the National University of Singapore on June 30, 2023. The launch of the CRI in July 2009 marked a pioneering step in offering, as a public good, daily-updated corporate credit risk assessments on a global scale. The CRI platform has also set the new scientific and operational standards for credit risk analysis. The CRI team thanks Professor Duan for his inspirational leadership and many contributions in this remarkable journey.

This updated document describes the implementation of the system which the Credit Research Initiative (CRI) at the National University of Singapore (NUS) uses to produce probabilities of default (PD) and actuarial spread (AS) among other CRI products. As of the time of preparing this version of the technical report, the CRI covers close to 92,000 exchange-listed firms (including delisted ones) in 136 economies around the world (see Table A.1). Of them, close to 43,000 firms have sufficient data to release daily updated PD and AS. The PD and AS for all firms are freely available to users who can provide evidence of their professional qualifications to ensure that they will not misuse the data. General users who do not request global access are restricted to a list of 5,000 firms. The individual company PD/AS data, along with aggregate PD/AS at the economy and sector level, can be accessed at `http://nuscri.org`.

The primary goal of this initiative is to drive research and development in the critical area of credit risk analytics and to contribute to credit rating reform. As such, a transparent methodology is essential to this initiative. Having the details of the methodology available to the public means that there is a base from which suggestions and improvements can be made. The objective of this technical report is to provide a full exposition of the CRI system. Readers of this document who have access to the necessary data and who have a sufficient level of technical expertise will be able to implement a similar system on their own. For a full exposition of the conceptual framework of the CRI system, see Duan and Van Laere [2012].

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The system used by the CRI will evolve as new innovations and enhancements are applied. The main changes reflected in this 2023 version of technical report are model developments amongst other operational implementations. As of 1st June 2023, operations have adopted the NUS-CRI 2020 industry classification, an update from its 2007 version, which is based on the 2020 Bloomberg Industry Classification Standard (BICS) to be in line with a newer market standard. The technical report has also detailed the implementation of an additional smoothing parameter to the DTD δ estimation that mitigates sporadic jumps in δ for those sector-calibration groups that fall close to the 10-company threshold. This 2023 version of the technical report further describes the operational implementation of default correlations in the computation of default rate (and default number) distributions to better estimate the impact of a common shock to a credit portfolio's expected joint-defaults and credit loss. Details regarding the new DC methodology can be found in Chapter 3

As of this reference date, the operational CRI system has been implemented with the model parameters calibrated on May 2023 by using available data up to April 30th 2023 (henceforth, April calibration). Therefore, all subsequent empirical results (e.g., Tables and Figures in Appendix) are estimated based on April calibration. Further updates to the technical report will be available via new addenda on the web portal to document any changes to the system since the publication of this 2023 version.

In the remainder of this technical report, the PD model and its computational details will be explained in details. As an application of the model, the computation of AS and CVI will be discussed in a much concise manner. Wherever no confusion is caused, "the model" refers to the PD model. The sections are organized as follows. Section 1 describes the forward-intensity framework for the PD model which was pioneered in Duan et al. [2012]. The description includes monthly calibration procedures, which are performed on a monthly basis, and individual firm's PD computations, which are performed on a daily basis.

Section 2 describes the input variables of the model as well as the data used to produce these inputs. This model uses both input variables that are common to all firms in an economy and input variables that are firm-specific. Another critical component to the estimation process is the default data, and this is also described in this section.

While Section 1 sketches the framework of the model, Section 3 fills in the implementation details that are necessary for application, given real world issues such as bad or missing data. The technical details needed to develop an operational system are also provided, including details on the monthly calibration, daily computation of individual firm's PDs, and aggregation of PDs. Firms' distance-to-default (DTD) in a Merton-type model is one of the firm-specific variables. The DTD formulation adopted by the CRI system modifies the standard one to allow a meaningful calculation of DTD for financial firms. Under the new NUS-CRI 2020 industry classification, real estate firms are also treated as financial firms as the sample of firms in this sector mainly contain REITs, which are similar in capital structure to financial firms. While most academic studies on default prediction exclude financial firms from consideration, it is important to include them due to the fact that the financial sector is vital to every economy. The calculation for DTD is detailed in this section.

Section 4 shows empirical analyses for economies currently under the CRI coverage. Initially, all the economies adopted the same set of extant variables used in Duan et al. [2012]. In 2018, we took one step forward by designing new variables to improve default prediction and started applying variable selection specific to certain economies (e.g., China). For details, refer to Subsection 2.1. Sections 5 and 6 explain how the CVI and AS are formulated. A detailed theoretical background can be found in Duan [2014]. Section 7 introduces a new CRI product "CriSIFI" that aims at identifying the systemic risks of all banks and insurers under the CRI coverage. The methodology that maps the PDs to the Probability of Default implied Rating (PDiR) is explained in Section 8. Section 9 discusses future developments.

1 Model Description

The quantitative model that is currently being used by the CRI is a forward-intensity model introduced in Duan et al. [2012]. Certain aspects of the estimation technique are taken from Duan and Fulop [2013]. This model allows PD forecasts to be made at a range of horizons. In the current CRI implementation, PDs are forecast from a horizon of one month up to a horizon of five years. At the CRI website, for every firm, the probabilities of that firm defaulting within one month, three months, six months, one year, two years, three years, and five years are given. The ability to assess credit quality for different horizons presents a useful tool for risk management, credit portfolio management, policy setting, and regulatory purposes, since short- and long-term credit risk profiles can differ greatly depending on a firm's liquidity, debt structure, and other factors.

The forward-intensity model is a reduced form model in which the PD is computed as a function of different input variables. These can be firm-specific or common to all firms within an economy. The other category of the default prediction model is the structural model, whereby the corporate structure of a firm is modeled in order to assess the firm's PD.

A similar reduced form model by Duffie et al. [2007] relies on modeling the time series dynamics of the input variables in order to make PD forecasts for different horizons. However, there is little consensus on assumptions for the dynamics of variables such as accounting ratios, and the model output will be highly dependent on these assumptions. In addition, the time series dynamics will be of very high dimension, making their estimation unrealistic. For example, applying the two common variables and two firm-specific variables as in Duffie et al. [2007] to a sample of 10,000 firms would give rise to 20,002 state variables.

Given the complexity in modeling the dynamics of state variables, the Duffie et al. [2007] approach will be difficult to implement if different forecast horizons are of interest. The key innovation of the forward-intensity approach is that that model can be consistently and efficiently calibrated, and the PDs for different horizons can be easily computed using only the value of the input variables at the time of default prediction. Thus, the model's specification and implementation become far more tractable.

Fully specifying a reduced form model includes the specification of the function that computes a PD from the input variables. This function is parameterized, and finding appropriate parameter values is referred to as model calibration. The forward-intensity model can be calibrated by maximizing a pseudo-likelihood function. The calibration is carried out by groups of economies and all firms within a group of economies will share the same parameter values along with each firm's variables in order to compute the firm's PD.

Subsection 1.1 will describe the modeling framework, including the way PDs are computed based on a set of parameter values for the economy and a set of input variables for a firm. Subsection 1.2 explains how the model can be calibrated. Subsection 1.3 details the way parameters are estimated based on the Sequential Monte Carlo (SMC) technique.

1.1 Modeling Framework

While the forward-intensity corporate default prediction model of Duan et al. [2012] was originally formulated in continuous time, an operational implementation requires discretization in time. Since the model is more easily understood in discrete time, the following exposition of the model will begin in a discrete-time framework.

Variables for default prediction can have vastly different update frequencies. Financial statement data is updated only once a quarter or even once a year, while market data like stock prices are typically available at frequencies of fractions of a second. A sensible compromise between these two extremes is to have a fundamental time period Δt of one month in the modeling framework. As will be seen later, this does not preclude updating the PD forecasts on a daily basis. This is important since, for example, large daily changes in a firm's stock price can signal changes in credit quality even when there is no change in financial statements.

Thus, for the purpose of calibration and subsequently for computing time series of PDs, the input variables at the end of each month will be kept for each firm. The input variables associated with the i^{th} firm at the end of the n^{th} month (at time $t = n\Delta t$) is denoted by $X_i(n)$. This is a vector consisting of two parts: $X_i(n) = (W(n), U_i(n))$. Here, $W(n)$ is a vector of variables at the end of month n that is common to all firms in the economy and $U_i(n)$ is a vector of variables specific to firm i.

In the forward-intensity model, a firm's default is signaled by a jump in a Poisson process. The probability of a jump in the Poisson process is determined by the intensity of the Poisson process. The forward-intensity model draws an explicit dependence of intensities at time periods in the future (i.e., forward intensities) to the values of input variables at the time of prediction. With forward intensities, the PD for any forecast horizon can be computed knowing only the values of the input variables at the time of prediction, without needing to simulate future values of the input variables.

There is a direct analogy to interest rate modeling. In spot-rate models where dynamics on a short-term spot rate are specified, bond pricing requires expectations on realizations of the short rate. Alternatively, bond prices can be computed directly if the forward-rate curve is known.

One issue in default prediction is that firms can exit public exchanges for reasons other than default, such as mergers and acquisitions (M&A) or switch from being traded on an exchange to OTC. In order to take these other exits into account, defaults and other exits are modeled as two independent Poisson processes, each with their own intensity. While defaults and non-default exits are mutually exclusive by definition, the assumption of independent Poisson processes does not pose a conceptual problem since the probability of a simultaneous jump in the two Poisson processes theoretically equals zero. In the discrete time framework, the probability of simultaneous jumps in the same time interval is non-zero. As an implementation assumption, a simultaneous jump in the same time interval by both the default Poisson process and the non-default type exit Poisson process is grouped into default. In this way, there are three mutually exclusive possibilities during each time interval: survival, default and non-default exit. As with defaults, the forward intensity of the Poisson process for other exits is a function of the input variables. The parameters of this function can also be calibrated.

To further illustrate the discrete framework, the three possibilities for a firm at each time point are diagrammed. Either the firm survives for the next time period Δt, or it defaults within Δt, or it has a non-default exit within Δt. This setup is pictured in Fig. 1. Information about firm i is known up until time $t = m\Delta t$ and the figure illustrates possibilities in the future between $t = (n-1)\Delta t$ and $(n+1)\Delta t$. Here, m and n are integers with $m < n$.

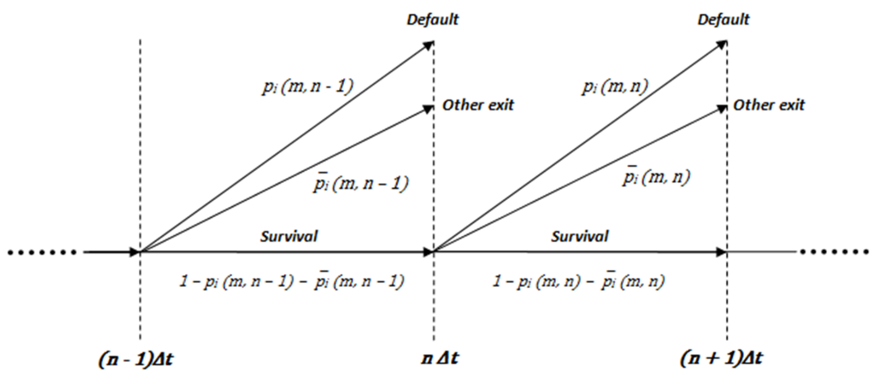

Figure 1: Default-other exit-survival tree for firm i, viewed from time $t = m\Delta t$.

The probabilities of each branch are, for example: $p_i(m,n)$ the conditional probability viewed from $t = m\Delta t$ that firm i will default before $(n+1)\Delta t$, conditioned on firm i surviving up until $n\Delta t$. Likewise, $\bar{p}_i(m,n)$ is the conditional probability viewed from $t = m\Delta t$ that firm i will have a non-default exit before $(n+1)\Delta t$, conditioned on firm i surviving up until $n\Delta t$. It is the modeler's objective to determine $p_i(m,n)$ and $\bar{p}_i(m,n)$, but for now it is assumed that these quantities are known. With the conditional default and other exit probabilities known, the corresponding conditional survival probability of firm i is $1 - p_i(m,n) - \bar{p}_i(m,n)$.

With this diagram in mind, the probability that a particular path will be followed is the product of the conditional probabilities along the path. For example, the probability at time $t = m\Delta t$ of firm i surviving until $(n-1)\Delta t$ and then defaulting between $(n-1)\Delta t$ and $n\Delta t$ is:

$$\mathrm{Prob}_{t=m\Delta t}[\tau_i = n, \tau_i < \bar{\tau}_i] = p_i(m, n-1) \prod_{j=m}^{n-2} [1 - p_i(m,j) - \bar{p}_i(m,j)] . \tag{1}$$

Here, τ_i is the default time for firm i measured in units of months, $\bar{\tau}_i$ is the other exit time measured in units of months, and the product is equal to 1 if there is no term in the product. The condition $\tau_i < \bar{\tau}_i$ is the requirement that the firm defaults before it has a non-default type of exit. Note that by measuring exits in units of months, if, for example, a default occurs at any time in the interval $[(n-1)\Delta t, n\Delta t]$, then $\tau_i = n$.

Using Eq. (1), cumulative default probabilities can be computed. At $m\Delta t$ the probability of firm i defaulting at or before $n\Delta t$ and not having an other exit before $t = n\Delta t$ is obtained by taking the sum of all of the paths that lead to default at or before $n\Delta t$:

$$\mathrm{Prob}_{\,t=m\Delta t}[m < \tau_i \le n, \tau_i < \bar{\tau}_i] = \sum_{k=m}^{n-1} \left\{ p_i(m,k) \prod_{j=m}^{k-1} [1 - p_i(m,j) - \bar{p}_i(m,j)] \right\} . \tag{2}$$

While it is convenient to derive the probabilities given in Eqs. (1) and (2) in terms of the conditional probabilities, expressions for these in terms of the forward intensities need to be found, since the forward intensities will be functions of the input variable $X_i(m)$. The forward-intensity for the default of firm i that is observed at time $t = m\Delta t$ for the forward time interval from $t = n\Delta t$ to $(n+1)\Delta t$, is denoted by $h_i(m,n)$, where $m \le n$. The corresponding forward intensity for a non-default exit is denoted by $\bar{h}_i(m,n)$. Because default is signaled by a jump in a Poisson process, its conditional probability is a simple function of its forward-intensity:

$$p_i(m,n) = 1 - \exp[-\Delta t\; h_i(m,n)]. \tag{3}$$

Since joint jumps in the same time interval are assigned as defaults, the conditional other exit probability needs to take this into account:

$$\bar{p}_i(m,n) = \exp[-\Delta t\; h_i(m,n)] \times \{1 - \exp[-\Delta t\; \bar{h}_i(m,n)]\}. \tag{4}$$

The conditional survival probabilities in Eqs. (1) and (2) are computed as the conditional probability that the firm does not default in the period and the firm does not have a non-default exit either:

$$\mathrm{Prob}_{\,t=m\Delta t}[\tau_i, \bar{\tau}_i > n+1 |\; \tau_i, \bar{\tau}_i > n] = \exp\{-\Delta t[h_i(m,n) + \bar{h}_i(m,n)]\}. \tag{5}$$

It remains to be specified the dependence of the forward intensities on the input variable $X_i(m)$. The forward intensities need to be positive so that the conditional probabilities are non-negative. A standard way to impose this constraint is to specify the forward intensities as the exponential of different linear composites of the input variables:

$$\begin{aligned} h_i(m,n) &= \exp[\beta(n-m)\cdot Y_i(m)], \\ \bar{h}_i(m,n) &= \exp[\bar{\beta}(n-m)\cdot Y_i(m)]. \end{aligned} \tag{6}$$

Here, β and $\bar{\beta}$ are coefficient vectors that are functions of the number of months between the observation date and the beginning of the forward period $(n-m)$, and $Y_i(m)$ is simply the vector $X_i(m)$ augmented by a preceding unit element: $Y_i(m) = (1, X_i(m))$. The unit element allows the linear combination in the argument of the exponentials in Eq. (6) to have a non-zero intercept.

In the current implementation of the forward-intensity model in the CRI, the maximum forecast horizon is 60 months (5 years) and there are 16 input variables plus the intercept in general, so there are 60 sets of β and $\bar{\beta}$. While this is a large set of parameters, as will be seen in Subsections 1.2 and 1.3, the calibration is tractable because the default parameters can be calibrated separately from the other exit parameters, and the total number of parameters are greatly reduced after constraining the term-structure of the parameter estimates to be Nelson-Siegel functions.

Before expressing the probabilities in Eqs. (1) and (2) in terms of the forward intensities, a notation H is introduced for the forward intensities so that it becomes clear which parameters the forward-intensity depends on:

$$H(\beta(n-m), X_i(m)) = \exp[\beta(n-m)\cdot Y_i(m)]. \tag{7}$$

This is the forward default intensity. The corresponding notation for other exit forward intensities is then just $H(\bar{\beta}(n-m), X_i(m))$. So, the probability in Eq. (1) is expressed in terms of the forward intensities, using Eq. (3) as the conditional default probability and Eq. (5) as the conditional survival probability:

$$\begin{aligned} &\text{Prob}_{\,t=m\Delta t}[\tau_i = n, \tau_i < \bar{\tau}_i] \\ &= \{1-\exp[-\Delta t\ H(\beta(n-1-m), X_i(m))]\} \\ &\quad \times \prod_{j=m}^{n-2} \exp\left\{-\Delta t\ [H(\beta(j-m), X_i(m)) + H(\bar{\beta}(j-m), X_i(m))]\right\} \\ &= \{1-\exp[-\Delta t\ H(\beta(n-m-1), X_i(m))]\} \\ &\quad \times \exp\left\{-\Delta t \sum_{j=m}^{n-2}\left[H(\beta(j-m), X_i(m)) + H(\bar{\beta}(j-m), X_i(m))\right]\right\}. \end{aligned} \tag{8}$$

This probability will be relevant in the next part during the calibration. The cumulative default probability given in Eq. (2) in terms of the forward intensities is then:

$$\begin{aligned} &\text{Prob}_{\,t=m\Delta t}[m < \tau_i \le n, \tau_i < \bar{\tau}_i] \\ &= \sum_{k=m}^{n-1}\Bigg\{\{1-\exp[-\Delta t\ H(\beta(k-m), X_i(m))]\} \\ &\quad \times \exp\left\{-\Delta t \sum_{j=m}^{k-1}[H(\beta(j-m), X_i(m)) + H(\bar{\beta}(j-m), X_i(m))]\right\}\Bigg\}. \end{aligned} \tag{9}$$

This formula is used to compute the main output of the CRI: an individual firm's PD over various time horizons. The β and $\bar{\beta}$ parameters are obtained when the firm's economy is calibrated, and using those together with the firm's input variables yields the firm's PD.

1.2 Pseudo-Likelihood Function

The data set used for calibration can be described as follows. For the economy as a whole, there are N end of month observations, indexed as $n = 1, \ldots, N$. Of course, not all firms will have observations for each of the N months as they may start later than the start of the economy's data set or they may exit before the end of the economy's data set. There are a total of I firms in the economy, and they are indexed as $i = 1, \ldots, I$. As before, the input variables for the i^{th} firm in the n^{th} month is $X_i(n)$. The set of all observations for all firms is denoted by X.

In addition, the default times τ_i and non-default exit times $\bar{\tau}_i$ for the i^{th} firm are known if the default or other exit occurs after time $t = \Delta t$ and at or before $t = N\Delta t$. The possible values for τ_i and $\bar{\tau}_i$ are integers between 2 and N, inclusive. If a firm exits before the month end, then the exit time is recorded as the first month end after the exit. If the firm does not exit before $t = N\Delta t$, then the convention can be used that both of these values are infinite. If the firm has a default type of exit within the data set, then $\bar{\tau}_i$ can be considered as infinite. If instead the firm has a non-default type of exit within the data set, then τ_i can be considered as infinite. The set of all default times and non-default exit times for all firms is denoted by τ and $\bar{\tau}$, respectively. The first month in which firm i has an observation is denoted by t_{0i}. Except for cases of missing data, these observations continue until the end of the data set if the firm never exits. If the firm does exit, the last needed input variable $X_i(n)$ is for $n = \min(\tau_i, \bar{\tau}_i) - 1$.

The calibration of the β and $\bar{\beta}$ parameters is done by maximizing a pseudo-likelihood function. The function to be maximized violates the standard assumptions of likelihood functions, but Appendix A in Duan et al. [2012] derives the large sample properties of the pseudo-likelihood function.

1.2.1 Pseudo likelihood function for the parameters' estimation

In formulating the pseudo-likelihood function, the assumption is made that the firms are conditionally independent of each other. In other words, correlations arise naturally from shared common factors $W(n)$ and any correlations between different firms' firm-specific variables. With this assumption, the pseudo-likelihood function for the horizon of ℓ months, a set of parameters β and $\bar{\beta}$ and the data set $(\tau, \bar{\tau}, X)$ is:

$$\mathcal{L}_\ell(\beta, \bar{\beta}; \tau, \bar{\tau}, X) = \prod_{m=1}^{N-1} \prod_{i=1}^{I} P_{\min(N-m,\ell)}(\beta, \bar{\beta}; \tau_i, \bar{\tau}_i, X_i(m)). \tag{10}$$

Here, $P_{\min(N-m,\ell)}(\beta, \bar{\beta}; \tau_i, \bar{\tau}_i, X_i(m))$ is a probability for the i^{th} firm, with the nature of the probability depending on what happens to the firm during the period from month m to month

$m + \min(N - m, \ell)$. This is defined as:

$$\begin{aligned}
&P_\ell(\beta, \bar{\beta}; \tau_i, \bar{\tau}_i, X_i(m)) \\
&\quad = 1_{\{t_{0i} \le m, \min(\tau_i, \bar{\tau}_i) > m+\ell\}} \\
&\qquad \times \exp\left\{ -\Delta t \sum_{j=0}^{\ell-1} [H(\beta(j), X_i(m)) + H(\bar{\beta}(j), X_i(m))] \right\} \\
&\quad + 1_{\{t_{0i} \le m, \tau_i \le \bar{\tau}_i, \tau_i \le m+\ell\}} \times \{1 - \exp[-\Delta t \, H(\beta(\tau_i - m - 1), X_i(m))]\} \\
&\qquad \times \exp\left\{ -\Delta t \sum_{j=0}^{\tau_i - m - 2} [H(\beta(j), X_i(m)) + H(\bar{\beta}(j), X_i(m))] \right\} \\
&\quad + 1_{\{t_{0i} \le m, \bar{\tau}_i \le \tau_i, \bar{\tau}_i \le m+\ell\}} \times \{1 - \exp[-\Delta t \, H(\bar{\beta}(\bar{\tau}_i - m - 1), X_i(m))]\} \\
&\qquad \times \exp[-\Delta t H(\beta(\tau_i - m - 1), X_i(m))] \\
&\qquad \times \exp\left\{ -\Delta t \sum_{j=0}^{\bar{\tau}_i - m - 2} [H(\beta(j), X_i(m)) + H(\bar{\beta}(j), X_i(m))] \right\} \\
&\quad + 1_{\{t_{0i} > m\}} + \ 1_{\{\min(\tau_i, \bar{\tau}_i) \le m\}}.
\end{aligned} \tag{11}$$

In other words, if the i^{th} firm survives from the observation time at month m for the full horizon ℓ until at least $m + \ell$, then the probability is the model-based survival probability for this period. This is the first term in Eq. (11). The second term handles the cases where the firm has a default within the horizon, in which case the probability is the model-based probability of the firm defaulting at the month that it ends up defaulting, as given in Eq. (8). The third term handles the cases where the firm has a non-default exit within the horizon, in which case the probability is the model-based probability of the firm having a non-default type exit at the month that the exit actually does occur. The expression for this probability uses the conditional non-default type exit probability given in Eq. (4). The final two terms handle the cases where the firm is not in the data set at month m - either the first observation for the firm is after m or the firm has already exited. A constant value is assigned in this case so that this firm will not affect the maximization at this time point.

The pseudo-likelihood function given in Eq. (10) can be numerically maximized to give estimates for the coefficients β and $\bar{\beta}$. Notice though that the sample observations for the pseudo-likelihood function are overlapping if the horizon is longer than one month. For example, when $\ell = 2$, default over the next two periods from month m is correlated to default over the next two periods from month $m + 1$ due to the common month in the two sample observations. However, in Appendix A of Duan et al. [2012], the maximum pseudo-likelihood estimator is shown to be consistent, in the sense that the estimators converge to the "true" parameter value in the large sample limit.

Notice though that each of the terms in Eq. (11) can be written as a product of terms containing only β and terms containing only $\bar{\beta}$. This will allow separate maximizations with respect to β and with respect to $\bar{\beta}$, that is, the defaults and other exits.

The β and $\bar{\beta}$ specific versions of Eq. (11) are:

$$
\begin{aligned}
&P_\ell^{\beta}(\beta; \tau_i, \bar{\tau}_i, X_i(m)) \\
&\quad = 1_{\{t_{0i} \le m, \min(\tau_i, \bar{\tau}_i) > m+\ell\}} \exp\left\{ - \Delta t \sum_{j=0}^{\ell-1} H(\beta(j), X_i(m)) \right\} \\
&\qquad + 1_{\{t_{0i} \le m, \tau_i \le \bar{\tau}_i, \tau_i \le m+\ell\}} \exp\left\{ - \Delta t \sum_{j=0}^{\tau_i - m - 2} H(\beta(j), X_i(m)) \right\} \\
&\qquad\quad \times \{1 - \exp[-\Delta t\, H(\beta(\tau_i - m - 1), X_i(m))]\} \\
&\qquad + 1_{\{t_{0i} \le m, \bar{\tau}_i \le \tau_i, \bar{\tau}_i \le m+\ell\}} \exp\left\{ - \Delta t \sum_{j=0}^{\bar{\tau}_i - m - 2} H(\beta(j), X_i(m)) \right\} \\
&\qquad\quad \times \exp[-\Delta t\, H(\beta(\tau_i - m - 1), X_i(m))] \\
&\qquad + 1_{\{t_{0i} > m\}} + 1_{\{\min(\tau_i, \bar{\tau}_i) \le m\}},
\end{aligned} \tag{12}
$$

$$
\begin{aligned}
&P_\ell^{\bar{\beta}}(\bar{\beta}; \tau_i, \bar{\tau}_i, X_i(m)) \\
&\quad = 1_{\{t_{0i} \le m, \min(\tau_i, \bar{\tau}_i) > m+\ell\}} \exp\left\{ - \Delta t \sum_{j=0}^{\ell-1} H(\bar{\beta}(j), X_i(m)) \right\} \\
&\qquad + 1_{\{t_{0i} \le m, \tau_i \le \bar{\tau}_i, \tau_i \le m+\ell\}} \exp\left\{ - \Delta t \sum_{j=0}^{\tau_i - m - 2} H(\bar{\beta}(j), X_i(m)) \right\} \\
&\qquad + 1_{\{t_{0i} \le m, \bar{\tau}_i \le \tau_i, \bar{\tau}_i \le m+\ell\}} \exp\left\{ - \Delta t \sum_{j=0}^{\bar{\tau}_i - m - 2} H(\bar{\beta}(j), X_i(m)) \right\} \\
&\qquad\quad \times \{1 - \exp[-\Delta t\, H(\bar{\beta}(\bar{\tau}_i - m - 1), X_i(m))]\} \\
&\quad + 1_{\{t_{0i} > m\}} + 1_{\{\min(\tau_i, \bar{\tau}_i) \le m\}}.
\end{aligned} \tag{13}
$$

Then, the β and $\bar{\beta}$ specific versions of the pseudo-likelihood function are given by:

$$\mathcal{L}_\ell^{\beta}(\beta; \tau, \bar{\tau}, X) = \prod_{m=1}^{N-1} \prod_{i=1}^{I} P_\ell^{\beta}(\beta; \tau_i, \bar{\tau}_i, X_i(m)) \tag{14}$$

$$\mathcal{L}_\ell^{\bar{\beta}}(\bar{\beta}; \tau, \bar{\tau}, X) = \prod_{m=1}^{N-1} \prod_{i=1}^{I} P_\ell^{\bar{\beta}}(\bar{\beta}; \tau_i, \bar{\tau}_i, X_i(m)). \tag{15}$$

With the definitions given in Eqs. (13) and (15), it can be seen that:

$$\mathcal{L}_\ell(\beta, \bar{\beta}; \tau, \bar{\tau}, X) = \mathcal{L}_\ell^{\beta}(\beta; \tau, \bar{\tau}, X)\mathcal{L}_\ell^{\bar{\beta}}(\bar{\beta}; \tau, \bar{\tau}, X). \tag{16}$$

Thus, $\mathcal{L}_\ell^{\beta}$ and $\mathcal{L}_\ell^{\bar{\beta}}$ can be separately maximized to find their respective parameters. Section 1.3 will further explain how the optimum parameters can be estimated.

1.2.2 Modified pseudo likelihood function for India's default data

TransUnion Credit Information Bureau India Limited (CIBIL)[1] has been publicly releasing the list of Indian defaulted firms in each quarter from Q1/2001 onwards. This additional

[1]https://www.cibil.com

data source enriches the CRI default database, and its net effect is to significantly increase the number of defaults for Indian firms from the original 512 to 1,336 as observed in September 2019. However, our PD modeling framework is built on a fundamental time period of one month but the CIBIL only provides the calendar quarter of a default occurrence. In order to utilize these partially observed information, the likelihood function in (12) has to be modified when estimating the default intensity parameters for Indian firms.[2] As of Q1/2022, CIBIL has updated its default occurrence reporting frequency from quarterly to monthly. As such, the treatment outlined for defaults reported by CIBIL below is applicable between Q1/2001 and Q1/2022. Post Q1/2022, monthly reported defaults by CIBIL will require no further treatments and will be treated similarly to other defaults captured in the NUS-CRI system.

We partition the data for Indian firms into two categories to reflect the two types of default information:

$$X = (X_I, X_C),$$

where $X_I = \{X_i\}_{i=1}^{I}$ with X_i containing variables for firm i whose default date (τ_i), other-exit date ($\bar{\tau}_i$), or survival is fully observed, whereas $X_C = \{X_c\}_{c=1}^{C}$ represents the data for defaulted firms reported by the CIBIL and yet not in the CRI's original default list. In other words, we only know the default quarter of firm c, i.e., τ_c is partially observed. Naturally, $I + C$ is the total number of Indian firms.

The likelihood function for defaults of Indian firms can then be written as:

$$\mathcal{L}_{\ell}^{\beta}(\beta;\tau,\bar{\tau},X) = \prod_{m=1}^{N-1}\Big[\prod_{i=1}^{I} P_{\ell}^{\beta}(\beta;\tau_i,\bar{\tau}_i,X_i(m))\prod_{c=1}^{C}\tilde{P}_{\ell}^{\beta}(\beta;\tau_c,\bar{\tau}_c,X_c(m))\Big] \tag{17}$$

where $P_{\ell}^{\beta}(\cdot)$ is the original decomposed likelihood function in (12) applied to all i's, and $\tilde{P}_{\ell}^{\beta}(\cdot)$ is the modified likelihood reflecting partial default information for all c's.

Let t_c^* be the last month of the quarter preceding the reported default quarter of firm c. The modified likelihood function below reflects the fact that at $t_c^* + 3$ the exact default month is still unknown, but the likelihood can be assessed by applying a prior probability distribution over the three months in the defaulting quarter, tallied from other default cases for which we know their defaulting months. Denote this prior probability distribution by w_1, w_2 and w_3.

There are three cases to deal with for this subset of CIBIL reported defaulting firms. To reflect the fact that the default becomes known only at the end of the quarter, the modified likelihood for firm c can be decomposed as:

$$\bar{P}_{\ell}^{\beta}(\beta;\tau_c,\bar{\tau}_c,X_c(m)) = 1_{\{t_{0,c}\le m\le t_c^*+3\ \&\ m+\ell<t_c^*+3\}}P_{\ell}^{\beta}(\beta;\tau_c = t_c^*+3,\bar{\tau}_c,X_c(m)) \tag{18a}$$

$$+\, 1_{\{t_{0,c}\le m\le t_c^*+3\ \&\ m+\ell\ge t_c^*+3\}}\sum_{\kappa=1}^{3} w_\kappa\cdot \mathrm{Prob}_m\{\tau_c = t_c^*+\kappa\} \tag{18b}$$

$$+\, 1_{\{t_{0,c}>m\}}, \tag{18c}$$

where $\mathrm{Prob}_m\{\tau_c = t_c^* + \kappa\}$ denotes the probability at the prediction time m for firm c defaulting at $t_c^* + \kappa$, which can be computed per the forward-intensity model as explained in (8). The second term on the right-hand side, i.e., the equation (18b), reflects the fact that we do not know the exact default month after a default has been reported. The best one can do is to weight the probabilities that firm c defaults in either one of the three months with the prior distribution. The third item in the equation basically addresses firms for which data only become available after the prediction time.

In terms of the CRI implementation[3], we specify the weight w_k in (18b) as the proportion of the observed default months in a quarter. For example, as observed in September 2019,

[2]The likelihood function for other exits of Indian firms remains unchanged.

[3]From 14th October 2019, the CRI-PD model for India has reflected the change in its estimation methodology that incorporates the CIBIL reported default events.

46% of the total default firms is in the third month of the defaulting quarter, whereas each of the remaining two months constitutes approximately 27%. For the CRI website displays, the exact default date for a CIBIL firm is placed as the average day based on the observed sample distribution on defaulting date in a quarter.

1.3 Parameter Estimation

Previously, the CRI system produced default predictions to a horizon of two years (CRI [2012]). An extension of the forecast horizon to five years has been implemented as of the PD released on April 1 2013. This extension to a five-year horizon is done by constraining the term-structure of the parameter estimates to be Nelson-Siegel (Nelson and Siegel [1987]; hereafter NS) functions of the forward-starting time. Horizon-specific parameters β and $\bar{\beta}$ can be obtained from the continuous NS function by using the forward prediction horizon as an input. The term-structures are further constrained so that the effect of risk factors on the forward intensity goes to zero as the horizon increases. This allows tractable and parsimonious extrapolations for horizons beyond five years.

The parameter estimation for the NS functions is based on a new numerical method (a pseudo-Bayesian SMC technique) developed by Duan and Fulop [2013]. The remainder of this section details the new parameter estimation. Subsection 1.3.1 describes the parameterization of the parameters by NS functions. Subsection 1.3.2 explains how a structural break applies to the CRI-PD model parameters for the North America calibration group and Chinese firms. Subsection 1.3.3 gives an overview of the SMC method that is used to estimate the NS functions. Subsection 1.3.4 details the calculation of the confidence intervals for the parameter estimation, and Subsection 1.3.5 describes how the parameters can be re-estimated given new data or updates of old data.

Technically speaking, horizons of arbitrary length can be calculated by extrapolation using the forward-intensity function. However, such a extension is better accompanied by a model calibration including default events being predicted over longer horizons. The current CRI model calibration is limited to default events within five years of a prediction time. Knowing that the CRI data now spanning over 30 years, it is certainly reasonable to calibrate the model with default events up to, say, 10-year prediction horizon if a need for longer-horizon PDs becomes evident.

1.3.1 Smoothed parameters

Duan et al. [2012] formulate the forward-intensity model in which the forward default intensity for a firm is a function of a number of covariates. The forward default intensities for different forward starting periods are computed using different sets of parameters.

In Duan et al. [2012], the sets of parameters are estimated separately for each forward starting time. Parameters at different forward starting times that are associated with each covariate can be approximated by a function of the forward starting time using NS type term structure functions. Duan et al. [2012] show that this approximation by NS functions does not negatively affect prediction performance. The CRI implementation follows Duan and Fulop [2013] to impose the functional restriction during the estimation as opposed to the method used in Duan et al. [2012] of fitting the curve after parameter estimates have been obtained. This is done for two reasons.

First, it will significantly reduce the number of parameters. For example, using 16 covariates for forward default intensities up to 60 months would require a joint estimation of $17 \times 60 = 1020$ parameters. Here, 17 comes from adding an intercept to the intensity function with 16 covariates. If the coefficients corresponding to each covariate are represented by the

NS function of 4 parameters, there will be at most $17 \times 4 = 68$ parameters. In fact, there will be fewer parameters as some of the NS parameters will be constrained to zero.

Second, the NS function will allow extrapolation. For example, the 17 NS functions estimated with predictions up to 60 months can be used for prediction, say, over 72 months.

The NS function with four free parameters is:

$$r(t; \varrho_0, \varrho_1, \varrho_2, d) = \varrho_0 + \varrho_1 \frac{1 - \exp(-t/d)}{t/d} + \varrho_2 \left[\frac{1 - \exp(-t/d)}{t/d} - \exp(-t/d) \right], \tag{19}$$

where t is the forecast horizon (measured in years). In the CRI implementation, the horizon is 60 months (5 years) so that t ranges from 0 to 59/12. Once the four NS parameters are estimated, individual horizon-specific parameters β and $\bar{\beta}$ are obtained from the NS function r using the forecast horizon as input to the NS function. In our current implementation with forecast horizons extending to 60 months (5 years), 120 sets of month specific β and $\bar{\beta}$ are obtained. For all covariates, the restriction $d > 0$ is imposed so that the functions converge to a value for large t. This formulation will be used for forward intensities for both defaults and other types of exit.

For the coefficients of all stochastic covariates, the long-run level ϱ_0 is restricted to zero, because the current value of a stochastic covariate should be uninformative of default or other exits when the forward starting time goes to infinity. In other words, the coefficient of such a stochastic covariate should approach zero when t goes to infinity.

The intercept of the forward-intensity function is of course non-stochastic. Thus, ϱ_0 can have non-zero values for the intercept. With these restrictions on the NS parameters, take the example of 16 covariates and an intercept, there will be a total of $16 \times 3 + 1 \times 4 = 52$ parameters, provided that the calibration group does not carry a structural break.

In the CRI implementation, the NS function is further constrained to be non-positive for certain covariates: liquidity level and trend, and profitability level and trend. Refer to Section 2 for descriptions of these covariates.

For China, we have 15 input variables (an intercept plus 14 covariates) due to the different variable selection specific to the economy (see Subsection 2.1). In addition, we further revise the parameter estimation for the North America calibration group and Chinese firms. For details, refer to Subsection 1.3.2.

1.3.2 Structural break

The North America calibration group (the US and Canada) has incorporated the following two specific changes. First, we include a dummy variable on the intercept for financial firms to account for differences that have not been duly reflected through other covariates. Second, we apply a structural break to this financial-sector intercept dummy to address the change in September 2008 after Lehman Brothers defaulted.

The structural break for the North America calibration group is treated as an impulse response. The key is to allow the different rates of transition, characterized by $\widetilde{\alpha}_1(\tau) > 0$ and $\widetilde{\alpha}_2(\tau) > 0$, before and after the break point t_0 (September 2008), respectively. Before t_0, for example, the coefficient for the financial–sector intercept dummy, $\beta(t, \tau; t_0)$, has the form:

$$\beta(t, \tau; t_0) = \widetilde{\beta}(\tau) + \widetilde{\gamma}(\tau) \times \frac{1}{1 + e^{-\widetilde{\alpha}_1(\tau)(t - t_0)}},$$

where t denotes the default prediction time, and τ denotes a forward starting time ranging from 0 (1 month) to 59/12 (5 years). $\widetilde{\alpha}_1(\tau)$, $\widetilde{\beta}(\tau)$, and $\widetilde{\gamma}(\tau)$ are characterized by the NS function in Eq. (19). After t_0, the coefficient for the financial–sector intercept dummy is governed by

$\widetilde{\alpha}_2(\tau)$ instead of $\widetilde{\alpha}_1(\tau)$:

$$\beta(t,\tau;t_0) = \widetilde{\beta}(\tau) + \widetilde{\gamma}(\tau) \times \frac{1}{1+e^{-\widetilde{\alpha}_2(\tau)(t_0-t)}}.$$

Therefore, $\beta(t,\tau;t_0)$ moves from $\widetilde{\beta}(\tau)$ to $\widetilde{\beta}(\tau)+1/2\widetilde{\gamma}(\tau)$ as t advances toward t_0, and reverts back to $\widetilde{\beta}(\tau)$ as t goes past t_0.

Our treatment on Chinese firms differs from that for the North American calibration group in two aspects. First, we apply a structural break to both the intercept and the DTD level. Second, we model the structural break by a step function allowing for different rates of transition to and away from the break point. As implemented earlier, the treatment is the same for intercept term and the coefficient for the DTD level, but the transition rates are different. Here, we describe generically for one of these two structural breaks. Before t_0 (December 2004), $\beta(t,\tau;t_0)$ has the following form:

$$\beta(t,\tau;t_0) = \widetilde{\beta}(\tau) + \widetilde{\gamma}(\tau) \times \frac{1}{1+e^{-\widetilde{\alpha}_1(\tau)(t-t_0)}},$$

After t_0, the two variables are governed by $\widetilde{\alpha}_2(\tau)$:

$$\beta(t,\tau;t_0) = \widetilde{\beta}(\tau) + \widetilde{\gamma}(\tau) \times \frac{1}{1+e^{-\widetilde{\alpha}_2(\tau)(t-t_0)}}.$$

Therefore, $\beta(t,\tau;t_0)$ smoothly transits from $\widetilde{\beta}(\tau)$ to $\widetilde{\beta}(\tau)+1/2\widetilde{\gamma}(\tau)$ as t moves toward t_0, and then continues to $\widetilde{\beta}(\tau)+\widetilde{\gamma}(\tau)$ as t moves beyond t_0.

1.3.3 Parameter estimation by SMC

Reliably estimating a system involving 52 parameters for 16 covariates and an intercept presents a numerical challenge. Moreover, the number of parameters can be greater than 52 if there are more than 16 covariates or structural breaks. The CRI implementation follows Duan and Fulop [2013] who use the SMC pseudo-Bayesian method for estimation and self-normalized statistics for inference.

Due to decomposability, the analysis can be performed separately on the forward default and other exit intensities. The data in the CRI implementation are refreshed with monthly frequency, and the sample likelihood used in estimation relies on default predictions running from 1 month to 60 months with a one month increment. Naturally, default prediction is subject to data availability. Towards the end of the period with available data, the prediction horizon naturally decreases and stops at one-month predictions.

The following exposition closely follows the appendix in Duan and Fulop [2013]. It is important to note that the CRI implementation uses the model described in Duan and Fulop [2013], which does not contain any latent frailty or partial conditioning variable, and hence is technically much simpler in parameter estimation. For example, there is no nonlinear filtering problem.

According to the current modeling framework, where for a particular economy there are N end of month observations, the input variables of the ith firm in the mth month is given by $X_i(m)$. Let θ denote a set of NS parameters and ℓ denote the forecast horizon ($\ell = 60$). Then the pseudo-likelihood function at step m, denoted by $\mathcal{L}_{m,\min(N-m,\ell)}(\theta)$, takes the form:

$$\mathcal{L}_{m,\min(N-m,\ell)}(\theta) = \prod_{i=1}^{I} P_{\min(N-m,\ell)}\left(\beta(\theta), \bar{\beta}(\theta); \tau_i, \bar{\tau}_i, X_i(m)\right), \tag{20}$$

where I is the number of firms, $\beta(\theta)$ and $\bar{\beta}(\theta)$ are the default and other exit coefficient vectors from Eq. (6) generated from the NS functions with parameter θ, respectively. One may notice that $\mathcal{L}_{m,\min(N-m,\ell)}(\theta)$ is one of the terms in the outer-most product in Eq. (10).

Our objective function at time n after one makes the ℓ-period prediction is:

$$\gamma_n(\theta) \propto \prod_{m=1}^{n-1} \mathcal{L}_{m,\min(N-m,\ell)}(\theta), \text{ for } n = 2, \ldots, N, \tag{21}$$

One can apply the sequential batch-resampling routine of Chopin [2002] together with tempering steps as in Del Moral et al. [2006] to advance the system. For each n, this procedure yields a weighted sample of K particles, $(\theta^{(k,n)}, w^{(k,n)})$ for $k = 1, \ldots, K$, whose empirical distribution function will converge to $\gamma_n(\theta)$ as K increases. In the following paragraphs, the superscript k denotes the particle index. Note that in the CRI implementation, K=1,000.

***Initialization*:** To provide the initial particle cloud from which the algorithm can start, an initial random sample from the normal distribution is drawn $(\theta^{(k,0)} \sim \mathcal{N}(\boldsymbol{\mu}, \Sigma),\ w^{(k,0)} = 1/K)$. Of course, the support of the normal distribution must contain the true parameter value θ_0. In the CRI implementation, $\boldsymbol{\mu}$ and σ are chosen based on cumulative knowledge on parameters' locations and dispersions to speed up optimization.

***Recursions and defining the tempering sequence*:** Assume there is a particle cloud $\left(\theta^{(k,n)}, w^{(k,n)}\right)$ whose empirical distribution represents $\gamma_n(\theta)$. Then, a cloud representing $\gamma_{n+1}(\theta)$ will be reached by combining importance sampling and the Markov Chain Monte Carlo (MCMC) steps. Sometimes moving directly from $\gamma_n(\theta)$ to $\gamma_{n+1}(\theta)$ is too ambitious as the two distributions are too far from each other. This will be reflected in highly variable importance weights if one resorts to direct importance sampling. Hence, following Duan and Fulop [2013] which in turn followed Del Moral et al. [2006], a tempered bridge is built between the two densities and the particles are evolved through the resulting sequence of densities. In particular, assume that at time $n+1$, there are P_{n+1} intermediate densities:

$$\overline{\gamma}_{n+1,p}(\theta) \propto \gamma_n(\theta) \mathcal{L}^{\xi_p}_{n,\min(N-n,\ell)}(\theta), \text{ for } p = 0, \ldots, P_{n+1}. \tag{22}$$

This construction defines an appropriate bridge: $\xi_0 = 0$ so that $\overline{\gamma}_{n+1,0}(\theta) = \gamma_n(\theta)$, and $\xi_{P_{n+1}} = 1$ so that $\overline{\gamma}_{n+1,P_{n+1}}(\theta) = \gamma_{n+1}(\theta)$. For p between 0 and P_{n+1}, ξ_p is chosen from a grid of points to evenly distribute the weights, as described below. A particle cloud representing $\overline{\gamma}_{n+1,0}(\theta)$ can be initialized as $(\overline{\theta}^{(k,n+1,0)}, \overline{w}^{(k,n+1,0)}) = (\theta^{(k,n)}, w^{(k,n)})$. Then, for $p = 1, \ldots, P_{n+1}$ the sequence proceeds as follows:

- *Reweighting Step:* At the beginning of each tempering step, p, a reweighting procedure is run:

$$\overline{w}^{(k,n+1,p-1)} \times \mathcal{L}^{\xi_p - \xi_{p-1}}_{n,\min(N-n,\ell)}(\overline{\theta}^{(k,n+1,p)}), \tag{23}$$

  where ξ_p is chosen to ensure that a minimum effective sample size (ESS) is maintained, where ESS is defined as

$$\text{ESS} = \frac{\left(\sum_{k=1}^{K} \overline{w}^{(k,n+1,p)}\right)^2}{\sum_{k=1}^{K} \left(\overline{w}^{(k,n+1,p)}\right)^2}. \tag{24}$$

  The minimum ESS is set as 50% of the sample size, which equals 500 with the CRI's use of the SMC sample for 1,000 parameter particles. This is done by a grid search, where the ESS is evaluated at a grid of candidate values for ξ_p. The one that produces the ESS that is larger than and closest to 500 is chosen.

In order to arrive at a representation of $\overline{\gamma}_{n+1,p}(\theta)$, the particles representing $\overline{\gamma}_{n+1,p-1}(\theta)$ and the importance sampling principle can be used. This leads to:

$$\overline{\theta}^{(k,n+1,p)} = \overline{\theta}^{(k,n+1,p-1)}, \tag{25}$$

$$\begin{aligned}\overline{w}^{(k,n+1,p)} &= \overline{w}^{(k,n+1,p-1)} \times \frac{\overline{\gamma}_{n+1,p}(\overline{\theta}^{(k,n+1,p)})}{\overline{\gamma}_{n+1,p-1}(\overline{\theta}^{(k,n+1,p)})} \\ &= \overline{w}^{(k,n+1,p-1)} \times \mathcal{L}_{n,\min(N-n,\ell)}^{\xi_p-\xi_{p-1}}(\overline{\theta}^{(k,n+1,p)}).\end{aligned} \tag{26}$$

To avoid particle impoverishment in sequential importance sampling where most of the weights are concentrated in a small number of particles, a resample-move step is run.

- *Resampling Step:* The particles are resampled proportional to their weights. If $I^{(k,n+1,p)} \in (1,\ldots,K)$ are particle indices sampled proportional to $\overline{w}^{(k,n+1,p)}$, the equally weighted particles are obtained as

$$\overline{\theta}^{(k,n+1,p)} = \overline{\theta}^{(I^{(k,n+1,p)},n+1,p)}, \tag{27}$$

$$\overline{w}^{(k,n+1,p)} = \frac{1}{K}. \tag{28}$$

- *Move Step:* Each particle is passed through a Markov kernel $\mathcal{K}_{n+1,p}(\overline{\theta}^{(k,n+1,p)},\cdot)$ that leaves $\overline{\gamma}_{n+1,p}(\theta)$ invariant, typically a Metropolis-Hastings kernel:

  1. Propose $\theta^{*(k)} \sim \mathcal{Q}_{n+1,p}\left(\cdot \;\middle|\overline{\theta}^{(k,n+1,p)}\right)$.
  2. Compute the acceptance rate α, where:

$$\alpha = \min\left(1, \frac{\overline{\gamma}_{n+1,p}(\theta^{*(k)})\mathcal{Q}_{n+1,p}(\overline{\theta}^{(k,n+1,p)} \mid \theta^{*(k)})}{\overline{\gamma}_{n+1,p}(\overline{\theta}^{(k,n+1,p)})\mathcal{Q}_{n+1,p}(\theta^{*(k)} \mid \overline{\theta}^{(k,n+1,p)})}\right). \tag{29}$$

  3. With probability α, set $\overline{\theta}^{(k,n+1,p)} = \theta^{*(k)}$, otherwise keep the old particle.

This step will enrich the support of the particle cloud while conserving its distribution. If the particle set is a poor representation of the target distribution, the move step can also help adjust the location of the support. Crucially, given the importance of the sampling setup, the proposal distribution $Q_{n+1,p}(\cdot \mid \overline{\theta}^{(k,n+1,p)})$ can be adapted using the existing particle cloud.

In the CRI implementation, we define three (or four) NS parameters corresponding to each covariate as one block. A mixture distribution is designed to combine with equal probabilities: (1) a block independent normal distribution using the means and the standard deviations derived from the existing particle set, and (2) a random walk proposal based on a scaled-down covariance matrix used in the block independent proposal; that is,

$$\theta^{*(k)} \sim \frac{1}{2}\mathcal{N}(\boldsymbol{\mu},\Sigma) + \frac{1}{2}\mathcal{N}\left(\overline{\theta}^{(k,n+1,p)},\Sigma^*\right),$$

where $\boldsymbol{\mu}$ is the sample mean vector of $\overline{\theta}^{(k,n+1,p)}$ and Σ is the covariance matrix with a block diagonal structure, i.e., the covariances across blocks are all zero. $\sigma_{i,j}^{*2}$, which is the (i,j)–th element of Σ^*, is set to be $(0.2\sigma_{i,j})^2$ (the (i,j)–th element of Σ), to propose around the original values. Mixing the independent and random walk proposals can effectively boost the support (i.e., a higher ESS) by offering local alternatives to those parameters with already high likelihood, especially when there exists discrepancies between the true distribution and its approximating normal distribution.

Moreover, we do not propose to replace an entire parameter particle, and implement a random block proposal. For each particle, say, comprising sixteen blocks (i.e., covariates), we randomly select a random number of blocks (from three to seven) and only propose new values for the selected blocks, while keeping the remaining blocks at their original values. This design can increase the acceptance rate and still offer rich enough replacements. To ensure a good replacement for every block, we perform multiple such Metropolis-Hastings steps each time until the accumulated acceptance rate exceeds 200% and the ESS reaches at least 75% of sample size.

Finally, proposed particles must satisfy some pre-defined constraints. First, the NS parameter d must be positive. Second, particles must produce an increasing or decreasing structure of the NS function for the first five months in order to ensure the smoothness of the term structure of the forward-intensity parameters. Third, the coefficients for some covariates, such as the level and trend of liquidity, are required to be non–positive over all forward starting times.

Using the mixture proposal creates a minor complication. The sampler for the truncated values does not carry the same norming constant due to the inclusion of the random walk proposal so that it cannot be ignored in the importance weight. To address the issue, we treat those sampled parameters violating the above mentioned constraints as if there were legitimate particles, but assign the likelihood $\overline{\gamma}_{n+1,p}(\theta^{*(k)})$ of any such proposed particle a value of 0. In short, such particles will never be accepted.

***Re–initialization*:** Recall that our SMC approach is the expanding–data SMC technique according to the classification in Duan and Fulop [2013]. Although the expanding data approach is more computationally efficient, we noticed that approximation errors may sometimes get accumulated after repeatedly updating the SMC parameter particle set by adding data one month at a time. We thus introduce a parameter re-initialization every 10 sequential updating time steps to remove the potentially accumulated approximation errors. Re-initialization is the same as the initialization at the beginning of the SMC, except that the relevant means and variances are computed with the updated SMC parameter particle set, so that re-initialization can take advantage of updated information on the sampling distribution. To make the procedure more robust, we deploy slightly enlarged variances in this re-initialization.

***Data Cloning*:** After ξ_p reaches 1, a data-cloning step as in Duan et al. [2020] is performed to increase parameter precision. Reinitialize to generate a set of particles using the means and variances derived from the final SMC parameter particle set. Then tempering steps are re-run with the target density powered up to 4; that is, $(\gamma_n(\theta))^4$.

1.3.4 Statistical inference

The full sample size has N time series data points, but one can only make default prediction at $N-1$ time points; for example, at time point 2, the data is only available for making one-period default prediction at time point 1. Denote the pseudo-posterior mean of the parameter of the whole sample by $\hat{\theta}_N$. And for $n = 2, \cdots, N$,

$$\hat{\theta}_n = \frac{1}{\sum_{k=1}^{K} w^{(k,n)}} \sum_{k=1}^{K} w^{(k,n)} \theta^{(k,n)}. \tag{30}$$

Note that $(\overline{\theta}^{(k,n+1,0)}, \overline{\omega}^{(k,n+1,0)}) = (\theta^{(k,n)}, \omega^{(k,n)})$ is not a true posterior because the likelihood function in Eq. (21) is not a true likelihood function. Thus, it cannot directly provide valid Bayesian inference. But following Duan and Fulop [2013] - which is in turn based on

Shao's self-normalized statistic (Shao [2010]) - inference can be performed using the t-like statistic in the full-sample run. To test, for example, the hypothesis of the kth element of $\overline{\theta}^{(k,n+1,p)} = \overline{\theta}^{(I^{(k,n+1,p)},n+1,p)}$, denoted by $\overline{\omega}^{(k,n+1,p)} = \frac{1}{K}$, equal to a, one has:

$$t^* = \frac{\sqrt{N-1}\left(\hat{\theta}_N^{(k)} - a\right)}{\sqrt{\hat{\delta}_{k,N}}} \xrightarrow{d} \frac{W(1)}{\left[\int_0^1 (W(r) - rW(1))^2 dr\right]^{1/2}}, \tag{31}$$

where $W(r)$ is a Wiener process, $\hat{\delta}_{k,N}$ is the kth diagonal element of $\hat{C}_N$, and

$$\hat{C}_N = \frac{1}{(N-1)^2} \sum_{n=2}^{N} n^2 (\hat{\theta}_n - \hat{\theta}_N)(\hat{\theta}_n - \hat{\theta}_N)'. \tag{32}$$

The statistical inference on the structural break parameters are again based on Shao's self-normalized statistic (see Subsection 1.3.2). Since the parameters in connection with the structural break cannot be identified using the data before the break point, the sequence of parameter estimates used in Shao's self-normalized statistic can only start from the break point onward. In the CRI implementation, all parameter estimates, break or non-break related, start from the break point. Denote by T the endpoint of the data set and t_0 again the structural break point. The number of points in the sequence, N, used to compute the norming matrix and the confidence intervals (see Eq. (32)) therefore equals $T - t_0 + 1$.

The right-hand-side random variable for t^* in Eq. (31) does not have a known distribution, but can be easily simulated. Kiefer et al. [2000] reported that the 95% quantile is 5.374 and the 97.5% quantile is 6.811. These values can also be used to set up confidence intervals.

1.3.5 Periodic updating

In reality, portfolio credit risk models need to be updated periodically as new data arrive and/or old data are revised. With one new month of data, this means that the final date index N is increased to $N + 1$. For this monthly real-time updating procedure, we always apply re-initialization, where the relevant means and variances–covariances used to generate the initial particle cloud are computed with the updated SMC parameter particle set from the previous run up to time N. Then one can apply the same recursive procedure, as described in Subsection 1.3.3. Furthermore, one can update all self-normalized statistics shown in Subsection 1.3.4 to reflect the additional one more pseudo-posterior means to the sequence.

As for this technical report, the initial parameter estimation by SMC is carried out for all calibration groups on May 2023 using (April calibration) the data up to the end of April 2023. Additional implementation details on the calibration are given in Section 3.

2 Input Variables and Data

Subsection 2.1 describes the input variables used in the quantitative model. In principle, the same set of input variables is common to most of the economies under the CRI's coverage. Going further, the CRI system starts to identify different input variables specific to different economies (e.g., China and India). The effect of each of the variables on the PD output will be discussed in the empirical analysis of Section 4.

Subsection 2.2 gives the data sources and relevant details of the data sources. There are two categories of data sources: current and historical. Data sources used for current data need to be updated in a timely manner so that daily updates of PD forecasts are meaningful. They also need to be comprehensive in their current coverage of firms. Data sources that are comprehensive for current data may not necessarily have comprehensive historical coverage for different economies. Thus, other data sources are merged in order to obtain comprehensive coverage of historical and current data.

Subsection 2.3 indicates the fields from the data sources that are used to construct the input variables. For some of the fields, proxies need to be used for a firm if the preferred field is not available for that firm.

Subsection 2.4 discusses the definition and sources of defaults and of other exits used in the CRI.

2.1 Input Variables

Following the notation that was introduced in Section 1, firm i's input variables at time $t = n\Delta t$ are represented by the vector $X_i(n) = (W(n), U_i(n))$ consisting of a vector $W(n)$ that is common to all firms in the same economy, and a firm-specific vector $U_i(n)$ which is observable from the date the firm's first FS is released, until the month end before the month in which the firm exits, if it does exit.

In Duan et al. [2012], different variables that are commonly used in the literature were tested as candidates for the elements of $W(n)$ and $U_i(n)$: the 2 common variables and 10 firm-specific variables were selected as having the greatest predictive power for corporate defaults in the United States. In the current stage of development, the set of 16 covariates beyond the past 12 variables, as described below, is generally used for all economies but China. In an ongoing effort, future development will include variable selection for firms in different economies.

- Common variables

  The vector $W(n)$ contains four elements, which are:

  1. Stock index return: the trailing one-year simple return on a major stock index of the economy;
  2. Interest rate: a representative 3-month short-term interest rate standardized from the data available point until now;
  3. Financial Aggregate DTD: median DTD of financial firms, which include real estate firms under the NUS-CRI 2020 industry classification, in each economy/country inclusive of those foreign financial firms whose primary stock exchange is in this economy/country;
  4. Non–financial Aggregate DTD: median DTD of non–financial firms in each economy/country inclusive of those foreign financial firms whose primary stock exchange is in this economy/country.

Stock index return incorporates the following two treatments. First, we use unified currencies for 6 groups of economies: China (CNY), India (INR), Asia-Pacific Developed (USD), Emerging Market (USD), Europe (EUR), and North America (USD). Second, we winsorize the unified return over the range of $[5\%, 95\%]$ for 3 groups of economies: Asia-Pacific Developed, Emerging Market, and Europe.

Interest rate is standardized in the way of demeaning each series and then scaling the demeaned values so that the standard deviation equals one, except for China and India. The treatment specific to the Eurozone is detailed in Subsection 3.3.

Each of the aggregate DTDs is only applicable to firms in the corresponding category. In short, the number of covariates used for default prediction is 16 including 12 firm–specific variables, as will be discussed below.

China, however, differs from other economies/countries where the two aggregate DTDs are not applicable, because they offer no informational value above and beyond what have already been captured. Furthermore, starting from Apr 2021, we introduced a dummy variable for Chinese SOEs to account for the potential difference between SOEs and non-SOEs that has not been duly captured by other covariates. A firm's SOE status is obtained based on the Chinese government's official enterprise information that is publicly available. The SOEs are generally perceived by the market to be "safer" as compared to their non-SOE counterparts because of the governmental backing. This additional variable has delivered improvement in the predicted number of defaults versus the subsequently realized number for both SOEs and non-SOEs.

- Firm-specific variables

  The 12 firm-specific input variables are transformations of measures of 6 different firm characteristics. The 6 firm characteristics are:

  1. volatility-adjusted leverage;
  2. liquidity;
  3. profitability;
  4. relative size;
  5. market mis-valuation/future growth opportunities; and
  6. idiosyncratic volatility.

Volatility-adjusted leverage is measured as the DTD in a Merton-type model. The calculation of DTD used by the CRI allows a meaningful DTD for financial firms, a critical sector that must be excluded from most DTD computations. This calculation is detailed in Section 3.

Liquidity is measured as a log ratio of cash and short-term investments to total assets for financial firms and a log ratio of current assets to current liabilities for non–financial firms. Under NUS-CRI 2020 industry classification, availability of the former metric is limited for real estate firms and is thus substituted with the latter for this sector, a treatment that is in line with the nature of real estate firms in the sample. Profitability is measured as a ratio of net income to total assets. Relative size is measured as a log ratio of market capitalization to the economy's median market capitalization.

Duan et al. [2012] transformed these first four characteristics into level and trend versions of the measures. For each of these characteristics, the level is computed as the one-year average of the measure, and the trend is computed as the current value of the measure minus the one-year average of the measure. The level and trend of a measure have seldom been used in the academic or industry literature for default prediction, and Duan et al. [2012] found that using the level and trend significantly improves the predictive power of the model for short-term horizons.

To understand the intuition behind using level and trend of a measure as opposed to using just the current value, consider the case of two firms with the same current value for all measures. If the level and trend transformations were not performed, only the current values would be used and the two firms would have identical PD. Suppose that for the first firm the DTD had reached its current level from a high level, and for the second firm the DTD had reached its current level from a lower level (see Fig. 2). The first firm's leverage is increasing (worsening) and the second firm's leverage is decreasing (improving). If there is a momentum effect in DTD, then firm 1 should have a higher PD than firm 2.

Duan et al. [2012] found evidence of the momentum effect in DTD, liquidity, profitability and size. For the other two firm characteristics, applying the level and trend transformation did not improve the predictive power of the model.

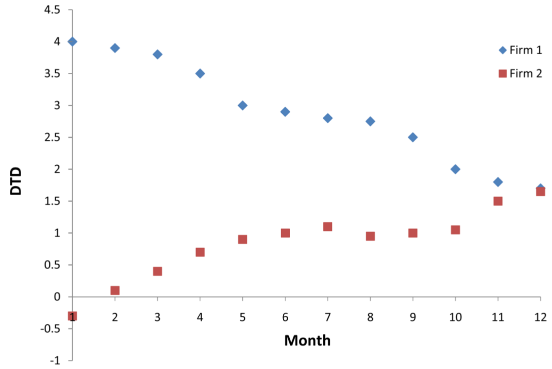

Figure 2: Two firms with all current values equal to each other, but DTD trending in the opposite direction.

As of this technical report, we further conduct additional treatments on liquidity and size. First, the level and trend of liquidity are respectively allowed to be sector–specific: financial firms, and non–financial firms. For financial firms, we take natural logarithm on the existing liquidity definition: log[(Cash + Short–term investments) / Total assets]. For non–financial firms, we refine liquidity as log(Current assets / Current liabilities) with the two current items in their financial statements. Second, size is redefined through the unified currency discussed above and then divided by the economy's median market capitalization over the past one year.

One of the remaining two firm characteristics is the market mis-valuation/future growth opportunities characteristic. This measure is taken as the "relative" market–to–book asset ratio (M/B) in the way of Individual firm's M/B divided by Economy M/B median at the same day that the individual M/B is calculated. In the CRI implementation, market–to–book asset ratio (M/B) is measured as a ratio of market capitalization and total liabilities to total assets. One can see whether the market mis-valuation effect or the future growth opportunities effect dominates this measure by looking at whether the parameter for this variable is positive or negative. This will be further discussed in the empirical analysis of Section 4.

The last firm characteristic is the idiosyncratic volatility which is taken as SIGMA, following Shumway [2001]. SIGMA is computed by regressing the daily returns of the firm's market capitalization against the daily returns of the economy's stock index, for the previous 250 days. SIGMA is defined to be the standard deviation of the residuals of this regression. Using daily returns is to ensure that SIGMA provides an accurate and timely measure of idiosyncratic risk of individual companies. Shumway [2001] reasons that SIGMA should be logically related to bankruptcy since firms with more variable cash flows and therefore more variable stock returns relative to a market index are likely to have a higher probability of bankruptcy.

Finally, the vector $U_i(n)$ contains 12 elements, consisting of:

1. Level of DTD.
2. Trend of DTD.
3. Level of log[(Cash + Short–term investments) / Total assets] for financial firms, abbreviated as CASH/TA.
4. Trend of CASH/TA for financial firms.
5. Level of log(Current assets / Current liabilities) for non–financial firms, abbreviated as CA/CL.
6. Trend of CA/CL for non–financial firms
7. Level of Net income / Total assets, abbreviated as NI/TA.

8. Trend of NI/TA.
9. Level of log (Firm market capitalization / Economy's median market capitalization over the past one year), abbreviated as SIZE.
10. Trend of SIZE.
11. Current value of Relative M/B defined as Individual firm's M/B divided by Economy M/B median, abbreviated as M/B.
12. Current value of SIGMA.

Note that every firm should belong to either a financial sector or a non–financial sector. Natually, this classification determines which liquidity ratio between CASH/TA and CA/CL is used (with the exception of real estate firms, for which the liquidity ratio is similar to that of the financial firm). When it comes to one financial firm, for example, we cannot use CA/CL level and trend among the 12 elements. Therefore, default prediction of each firm should depend on the rest of the 10 firm–specific variables. The data fields that are needed to compute DTD and short-term investments are described in Subsection 2.3. The remaining data fields required are straightforward and standard. The computation for DTD is explained in Section 3.

2.2 Data Sources

There are two data sources that are used for the daily PD forecast updates: Thomson Reuters Datastream and the Bloomberg Data License Back Office Product. Many of the common factors such as short-term interest rates and macroeconomic data are retrieved from Datastream.

Firm-specific data come from Bloomberg's Back Office Product which delivers daily update files by region via FTP after respective market closes. All relevant data is extracted from the FTP files and uploaded into the CRI database for storage. From this, the necessary fields are extracted and joined with previous months of data.

The Back Office Product includes daily market capitalization data based on closing share prices and also includes new FSes as companies release them. Firms will often have multiple versions of FSes within the same period, with different accounting standards, filing statuses (most recent, preliminary, original, reclassified or restated), currencies or consolidated/unconsolidated indicators. A major challenge lies in prioritizing these FSes to decide which data should be used. The priority rules are described in section 3.

The firm coverage of the Back Office Product is of sufficient quality that over 43,000 firms can be updated on a daily basis in the 136 economies under the CRI's coverage. While the current coverage is quite comprehensive, historical data from the Back Office Product can be sparse for certain economies. For this reason, various other databases are merged in order to fill out the historical data. The other databases used for historical data are: a database from the Taiwan Economics Journal (TEJ) for Taiwanese firms; a database provided by Korea University for South Korean firms; data from Prowess for Indian firms; and the Compustat for United States.

With all sources being merged, the CRI database has around 92,000 exchange-listed firms in 136 economies. The historical coverage of the firm data goes back to the early 1990s. In order to be included in our coverage, a company needs to have common equity traded on a stock exchange. Of these 136 economies, 88 economies have their own stock exchange (see Table A.2). For the other 48 economies under the CRI coverage, we cover companies domiciled in the economy that are quoted on a foreign exchange, either because those economies do not have a stock exchange or because data issues are preventing us from including the companies listed on the local exchange (see Table A.3).

2.3 Constructing Input Variables

The chosen stock indices and short-term interest rates for the 88 economies with their own stock exchanges under the CRI's current coverage are listed in Tables A.5 and A.6, respectively. All economies are listed by their three letter ISO code given in Table A.4.

Most of the firm-specific variables can be readily constructed from standard fields from firms' FSes in addition to daily market capitalization values. The only two exceptions are the DTD and the liquidity measure.

The calculation for DTD is explained in section 3. In the calculation, several variables are required. One variable is a proxy for a one-year risk-free interest rate, and the choices for each of the 88 economies are listed in Table A.7. Total assets, long-term borrowing and total liabilities are also required, but can be obtained from standard FS fields easily.

Total current liabilities are also required, and due to the relatively large numbers of firms that are missing this value, proxies have to be found. The preferred Bloomberg field for this is BS_CUR_LIAB. If this is missing, then the sum of BS_ST_BORROW, BS_OTHER_ST_LIAB, BS_CUST_ACCPT_LIAB_CUSTDY_SEC (customers' acceptance and liabilities/custody securities) and BS_SEC_SOLD_REPO_AGRMNT is used. If one, two or three of these are missing, zero is inserted into those fields, but at least one of the four fields is required.

The liquidity measure requires different fields for financial and non-financial firms. For non–financial firms, the two elements of "CA/CL" come from BS_CUR_ASSET_REPORT and BS_CUR_LIAB, respectively: log(Current assets / Current liabilities). For financial firms, the numerator of "CASH/TA", (Cash + Short-term investments), is taken as the sum of BS_CASH_NEAR_CASH_ITEM, ARD_SEC_PURC_UNDER_AGR_TO_RESELL (securities purchased under agreement to re-sell), ARD_ST_INVEST, and BS_INTERBANK_ASSET. If one or two of the last three fields are missing, zero is inserted for those fields, but at least one field is required. The "ARD" prefix indicates that these are "as reported" numbers directly from the FSes. As such, for some firms these fields may need to be adjusted to the same units before adding them to other fields.

To summarize, the firm-specific variables include: DTD, Cash/TA, CA/CL, NI/TA, SIZE, M/B, and SIGMA, and the statistics grouped by economy are listed in Table A.8.

2.4 Data for Corporate Events

The CRI database contains 9,383 default events and 48,293 other exits events from 1990 to the end of April 2023. The corporate events come from numerous sources, including Bloomberg, Compustat, CRSP, Moodys reports, TEJ, exchange websites and news sources. Moreover, in order to enhance default coverage, the CRI team has started to use "defaults" reported by major credit rating agencies and CIBIL for Indian defaults as additional data sources.

The default events that are recognized by the CRI can be classified under one of the following events:

(1) Bankruptcy filing, receivership, administration, liquidation or any other legal impasse to the timely settlement of interest and/or principal payments;

(2) A missed or delayed payment of interest and/or principal, excluding delayed payments made within a grace period;

(3) Debt restructuring/distressed exchange, in which debt holders are offered a new security or package of securities that result in a diminished financial obligation (e.g., a conversion of debt to equity, debt with lower coupon or par amount, debt with lower seniority, debt with longer maturity).

The more precise sub-categories of default corporate actions are listed in Table A.9.

Delisting due to other reasons such as failure to meet listing requirements, inactive stock prices or M&A are counted as "other exits" and are not considered as default. Especially, if a firm has stale stock price for more than a year but has no record on experiencing any credit events, we will assume that it has been suspended and exited from its stock exchange. If two credit events of the same type happen in a row or a default event happens followed by another event of either type, we only keep the first event assuming that the series of events arise from the same source of financial distress. However, if firms are delisted from an exchange and then experience a default event within 180 calendar days of the delisting, we will only keep the default event, and any information between the two dates won't be used. Technical defaults such as covenant violations are not included in our definition of default. The exit events that are not considered as defaults in the CRI system are listed in Table A.10.

In addition to the aforementioned events, there are still cases that require special attention and will be assessed on a case-by-case basis, e.g., subsidiary default. As a general rule, the CRI does not consider related party-default (e.g., subsidiary bankruptcy) as a default event. However, when a non-operating holding parent company relies heavily on its subsidiary, bankruptcy by the subsidiary will cause a considerable economic impact on the parent company. Such cases will be reviewed, and final classifications will be made.

Complete statistics of the total number of firms, number of defaults, and number of other exits in each of the 88 economies from 1990 to 2020 are listed in Table A.11.

3 Implementation Details

Section 1 described the modeling framework underlying the current implementation of the CRI system. It focused on theory rather than the details encountered in an operational implementation. The present section describes how the CRI system handles more specific issues.

Subsection 3.1 describes implementation details related to data, mainly dealing with data cleaning and missing data. Subsection 3.2 describes the specific computation of DTD used by the CRI system that leads to meaningful DTD for financial firms. Subsection 3.3 explains how the calibration previously described in Subsection 1.2 can be implemented. Subsection 3.4 gives the implementation details relevant to the daily output. This includes an explanation of the various modifications needed to compute daily PDs so that the daily PDs are consistent with the usual month end PD and a description of the computation of the aggregate PDs provided by the CRI.

3.1 Data Treatment for Calibration

Fitting data to monthly frequency: Historical end of month data for every firm in an economy is required to calibrate the model. For daily data such as market capitalization, interest rates and stock index values, the last day of the month for which there is valid data is used.

Up to the October 2012 calibration, FS variables data were used, starting from the period end of the statement lagged by 3 months. This is to ensure that predictions are made based on information that was available at the time the prediction was made. However, this treatment can be over-conservative, and many companies actually release their FSes quicker than 3 months. Therefore, we implement a new logic, and we start using the values in an FS as soon as its latest revision was put into the CRI database, unless the FS' release was delayed for more than 3 months. If there was no revision to an FS, the originally released FS is used. Whenever the latest revision is available more than 3 months after the period end, we revert to the previous logic. We start including the FS before the latest revision is actually available as a compromise, to avoid situations like later minor revisions of the FS holding back more up-to-date information. It should be noted that the new approach was only applied for FS input into the CRI database after February 2011, as the revision dates were not accurately recorded before this date. The CRI considers FS variables to be valid for one year without restriction, after they were first used.

Priority of FSes with the same period end: As described in Subsection 2.2, data provided in Bloomberg's Back Office Product can include numerous versions of FSes within the same period. If there are multiple FSes with the same period end, priority rules must be followed in order to determine which to use. The formulation and implementation of these rules are major challenges and areas of continuing development.

The first rule is to prioritize by consolidated/unconsolidated status. This rule applies to all economies, however, special treatment is imposed on firms in the "diversified financial services" sector in South Korea and Taiwan. In this sector of the two economies, firms issue unconsolidated FSes more frequently than consolidated ones. As a result, this prioritization rule can lead to cases where the FSes chosen switch between unconsolidated and consolidated ones on a regular basis. In South Korea and Taiwan, where corporate structures are biased toward large holding companies, this switching may substantially distort the DTD calculation for these holding companies. Therefore, as of October 2013 calibration, in the case of South Korea, and November 2013 calibration, in the case of Taiwan, if a company has released at least one consolidated FS over the last 12 months, all unconsolidated FS will be ignored.

If, after the first prioritization rule has been applied, there are still multiple FSes, the second rule is applied. This is prioritization by fiscal period. In most economies, annual statements are required to be audited, whereas other fiscal periods are not necessarily audited. The order of priority from highest to lowest is, therefore: annual, semi-annual, quarterly, cumulative, and finally other fiscal periods. We have observed that the capital structure breakdown reported by Australian domiciled-banks differs between annual and semi-annual reports, leading to DTD calculations that are not meaningful. Because of this, as of October 2013 calibration, we only use data from annual FSes for Australian banks.

The third prioritization rule is based on filing status. The "Most Recent" statement is used before the "Original" statement, which is used before the "Preliminary" statement.

The final prioritization rule is based on the accounting standard. As more and more countries adopt the International Financial Reporting Standards (IFRS) as their mandatory accounting standard, FSes that are reported using IFRS are given higher priority than they were before. The revised rule is implemented from the 2014 October calibration and is described as follows. For the countries with mandatory IFRS adoption, FSes under IFRS are now given the highest priority after their respective mandatory adoption dates. Before the mandatory adoption dates and for countries without mandatory IFRS adoption, FSes under the Generally Accepted Accounting Principles (GAAP) have the highest priority. If an FS does not indicate its accounting standard, it will not be used.

Having all the prioritization descriptors in place, we rank all the FSes available in the database from the highest priority to the lowest. If there are FSes where all the financial information needed in our model is present, the FS with the highest ranking will be chosen. If instead there is no such FS, we will pick the values variable by variable. For example, the total liability is taken from the highest ranked FS with this information available, while the total asset can be from another FS, which ranks the highest among those bearing this information and having the same FS period end. This treatment is to get as much information as possible and to accommodate the fact that Bloomberg occasionally only revises the variables that have changed values, leaving the other fields NaN.

One variable that requires special attention is the net income. Net income is a flow variable and needs to be adjusted based on the fiscal period of the FS. More specifically, we transform the net income into a monthly net income by dividing the net income by the number of months that the FS covers. For example, the monthly net income can be computed from the annual net income divided by 12, the semi-annual net income divided by 6 and the quarterly net income divided by 3. When the monthly net income can be obtained from different sources simultaneously, the quarterly net income will have the highest priority (followed by the cumulative quarterly, semiannual, annual, and others) because it covers a more recent period of time.

Treatment of stale market capitalization prices: The market capitalization of a firm is required in a few input variables: DTD, SIZE, M/B, and SIGMA. For most firms, the market capitalization is available from Bloomberg on a daily basis.

A check on the trading volume of shares is used to remove stale prices. Specifically, if there are more than two consecutive days of identical market capitalization prices, the subsequent identical prices are removed only if the trading volume is equal to zero. Any firms with zero volume more than 10 consecutive working days, the firms will be labelled as *non-trading* firm and its PD shall not be provided. This is to avoid, for example, cases where the shares of a company are under a trading suspension[4] but the market capitalization data is incorrectly carried forward.

An exception is for Indian companies, where it is common for some companies to have market capitalizations reported only once a month with several consecutive months having identical prices and positive trading volume. These prices are very likely not to be accurate reflections of the firms' value. So, the trading volume is not checked for Indian firms and market capitalizations are excluded after more than two repeated prices.

For some firms, the market capitalization data is not available for some periods. To fill in the blanks, we use the shares outstanding obtained from the previously available market capitalization multiplied by the price on that day as a proxy. If the market capitalization data is missing for more than a year, we use the share price multiplied by the shares outstanding listed on the balance sheet and then multiplied again by the adjustment factor that Bloomberg provides to account for splits, dividends, etc. If there is still market capitalization missing in the data, then shares outstanding from other data sources including Compustat and Korean University Database are used.

Currency conversion: Currency conversions are required if the market capitalization or any of the FS variables are reported in a currency different than the currency of the economy. If a currency conversion is required, the foreign exchange rate used is the one reported at the relevant market close. For firms traded in most of the Asian economies and Asia-Pacific, the Tokyo closing rate is used; for firms traded in Europe, Africa, and Middle East, the London closing rate is used; and for firms traded in North and Latin America, the New York closing rate is used. For market capitalizations, the FX rate used is for the date that the market capitalization is reported. For FS variables, the FX rate used is for the date of the period end of the statement.

As of December 2017, we proceed with the unified currency treatment about stock index return for each calibration group of economies: China (CNY), India (INR), Asia-Pacific Developed (USD), Emerging Market (USD), Europe (EUR), and North America (USD). This attempt is made to prevent currency distortion in assessing default prediction. Similarly, we apply the currency adjustment to market capitalization, total liabilities, and total assets, all of which are used to compute the M/B ratio.

Treatment for mergers and acquisitions (M&A): M&A events are common occurrences in the economic world. For our purpose, we define the M&A events as the cases where a firm ("acquirer") acquires partial or full ownership of another firm ("target"). Once an M&A deal is completed, the market capitalization of the acquirer changes immediately, reflecting the

[4]Note that, the information of trading suspension is not fully available in many exchange markets. If the information is publicly available, the firm status will be labelled as suspended firm accordingly.

restructure of the acquirer. However, its FSes do not usually immediately reflect the new situation due to the fact that they are only released on a periodic basis. As a result, the DTD and market-to-book ratio, which are important inputs for the PD computation, will be distorted due to a mismatch in the market capitalization and the FS variables. In order to ensure the accuracy and reliability of our PD estimates, some special treatments are taken for PD calculations to companies whose financials are presumably significantly affected by the M&A events. The treatments are only applied to the acquirers.

The treatment starts with the screening of the important M&A deals. Only the important M&A deals are treated, assuming that the unimportant ones would not significantly affect a firm's corporate structure. An M&A deal is considered important if it satisfies the following three criteria :

1. Upon the deal's completion, the acquirer owns 20% or more of the target company.
2. The size of the deal is material to the acquirer. This is measured in terms of total assets. If α is the percentage of the target that is being acquired, the size is considered material if the product of α and the total assets of the target is greater than or equal to 20% of the total assets of the acquirer.
3. The change in market capitalization is material, with the largest absolute daily market capitalization return, within 20 days of the M&A completion day, larger than or equal to 5%.

One thing to note in implementation is that some targets stopped producing financial statements years before the M&A events. As a result, they may not have a valid value of total asset (needed for testing criterion 2) on the deal completion date. In this case, we use their last available value within 2 years before the deal completion as a substitute. If the last available value is beyond the 2-year range, we think that the data is not informative enough to reflect the financial situation upon deal completion and thus skip this particular case.

In order to mitigate the mismatching problem between the market capitalization and FS variables, we make the simplest and most conservative treatments, which are in line with the fundamental accounting standards. The treatment period will begin on the deal completion date and end when the first financial statement that reflects the post-M&A situation becomes available, which varies across economies and can range from 3 months to a few years. After identifying the important M&A deals, which must have had an ownership level of equal or more than 20%, we treat them in two different ways:

1. If the acquirer owns 20-50% (excluding 50%) of the target upon deal completion, the "Equity Method" is used to treat the financial statement variables. Under the "Equity Method", the total asset of the acquirer will increase by a proportion, which is the percentage of ownership acquired in this deal, of the target's equity. Its net income will increase by the same proportion of the target's net income. In contrast, other financial statement variables will stay the same.
2. If the acquirer owns 50-100% (including 50%) of the target upon deal completion, the "Acquisition Method" is used to adjust the financial statement variables. By using this method, we assume that the financial manager of the acquirer consolidates the financial statements of both entities. As a consequence, the financial statement variables, including total liability, total asset, and cash and marketable securities, take the simple sum of the values from both entities. The net income will still increase by a proportion (the percentage of ownership acquired in this deal) of the target's net income, simply because it is the profit attributed to the shareholders.

After constructing the hypothetical financial statement data in the above-mentioned way, we use them to compute the DTD and the historical monthly PDs wherever applicable. Note that we do not let the hypothetical values enter the model's calibration process. With enough data points in the database to robustly calibrate the model parameters at the economy or region level, we can afford to disregard a small portion of data for the M&A period during which we believe them to be mismatched. After getting the model parameters, however, we not only use the hypothetical values to re-calibrate the firm-specific DTD parameters and re-calculate the DTD values, we also use them to adjust other variables with financial information. This is to guarantee that the PDs during the treatment period are properly calculated.

Treatment for missing values and outliers: Missing values and outliers are dealt with by a three-step procedure. In the first step, the 10 firm-specific input variables are computed for all firms and all months. In this step, the extreme values will be calculated, and the missing values will be determined. In the second step, outliers are eliminated by winsorization. In the final step, missing values are replaced under certain conditions.

The first step is to compute the input variables and to determine which are missing. As mentioned previously, FS variables are carried forward for one year after the date that they are first used. The date that they are first used is generally three months after the period end of the statement. If no FS is available for the company within this year, then the FS variable will be missing. For market capitalization, if there is no valid market capitalization value within the calendar month, then the value is set to missing.

With regard to the level variables, their values in the current and the last 11 months are averaged to compute the level. A minimum of 6 observations in the 12-month range are required to calculate the level variables. If fewer than 6 observations exist in this case, the level variables will bear missing values. However, this condition is not enforced during the initial 6 months after the firm releases the first financial statement.

To compute the trend variables, the level is subtracted from the current month value. If the current month value is missing, the trend variable is set to be the last valid value during the previous one year.

The value of M/B is set to be missing if any of the following values are missing: market capitalization, total liabilities, or total assets of a firm. For the computation of SIGMA, at least 50 valid returns over the last 250 days of possible returns are required for the regression. If there are less than 50 valid returns, SIGMA is set to be missing.

In this way, the 8 trend and level variables as well as M/B and SIGMA are computed and identified as missing or present. Winsorization can then be performed as a second step to eliminate outliers. The volume of outliers is too large to be able to determine whether each one is valid or not, so winsorization applies a floor and a cap on each of the variables. The historical 0.1 percentile and 99.9 percentile for all firms in the economy are recorded for each of the 10 variables. Any values that exceed these levels are set to equal these boundary values.

With a winsorization level of 0.1 and 99.9 percentile, the boundary values still may not be reasonable. For example, NI/TA levels of nearly -25, meaning an monthly net income -25 times larger than the total assets of a firm, has been observed at this stage. In these cases, a more aggressive winsorization level is applied, until the boundary values are reasonable. Thus, the winsorization level is economy- and variable-specific, and will depend on the data quality for that economy and variable. Winsorization levels different from the default of 0.1 percentile and 99.9 percentile are indicated in Table A.8. As for log variables log(x) such as CASH/TA and CA/CL, we should check first whether x is well defined with positive values. Otherwise, we assign the upper and lower bounds of the economy- and variable-specific winsorization level to these firms.

In addition to the special winsorization of the firm–specific variables, we also implement a winsorization of 5 and 95 percentiles for stock index return used as one of the common variables to the 3 groups of economies: Asia-Pacific Developed, Emerging Market, and Europe.

A third and final step can be taken to deal with missing values. If during a particular month, no variable is missing for a particular firm, the PD can then be computed. If 6 or more of these 10 variables are missing, there is deemed to be too many missing observations and no replacement shall be made.

If between 1 and 5 variables are missing out of the 10, the first step is to trace back for at most 12 months to use previous values of these variables instead. If this does not succeed in replacing all of the variables, a replacement by sector medians is done. A firm's sector during a certain month is classified as either financial or non-financial, which is based on its Bloomberg industry sector code during that month. As of January 2015, the sector median replacement is no longer implemented in the calibration process but still in the PD computation. One special case is that the sector replacement is not done if it results in a relative change in the historical PD of 10% or more when the initial PD was at or above 100 bps, or an absolute change in the historical PD of 10 bps or more when the initial PD was below 100 bps.

One thing to note is that in the initial phase of a company - 6 months or even longer after its IPO - the data availability and quality are relatively low due to, for example, the delay in the issuance of FSes or illiquid trading. As observed in our data, replacing the missing values during this period with a sector median sometimes results in extreme spikes and falls in the company's PD. These extreme values are not easily detected, because in the beginning of a company's history, there are not many previous PD values to compare to as can be done later in the company's history. In order to avoid this, as of the 2015 January calibration, we set the rule to start treating the missing values only from the month when both the DTD level and trend are available and finite. By doing so, we make the PDs in the beginning of a company's history more reflective of its true credit quality.

Inclusion/exclusion of companies for calibration: Firms are included within an economy for calibration when the primary listing of the firm is on an exchange in the economy. This ensures that all firms within the economy are subject to the same disclosure and accounting rules. There are a relatively small number of firms that are listed in multiple economies. For example, Bank of China Ltd is listed both in Hong Kong Stock Exchange and China's Shanghai Stock Exchange. Based on Bloomberg's classification of its primary listing, Bank of China Ltd is assigned to the calibration group of Asia-Pacific rather than China.

In the US, firms traded on the OTC markets or the Pink Sheets are not considered as exchange listed so are not included in calibration or in the reporting of PD forecasts. Many of these firms are small or start-up firms. Including this large group of companies would skew the calibration and the aggregate results. The TSX Venture Exchange in Canada also contains only small and start-up firms, so firms listed here are also excluded.

Other exclusions include Taiwan's Taipei Exchange, Vietnam's Hanoi UPCoM, Switzerland's OTC-X BEKB, Brazil's Soma and Romania's RASDAQ. To identify the smaller markets outside of the US and Canada is challenging due to data availability. However, continuing work is being done in the CRI system to exclude firms that are not listed on major exchanges within a country.

Additional ratio treatment for China-domiciled banks: It was observed that some China-domiciled banks had fluctuations in their reported long-term liabilities and current liabilities due to a difference in reporting standards between the banks' quarterly and (semi) annual financial statements. This was causing an unwarranted periodic (every 3-months) increase and decrease in their DTD values, and vis-a-vis PD values, despite the underlying credit quality of China-domiciled banks remaining unaffected.

Q2 and Q4 financial statements from China-domiciled banks had an additional disclosure pertaining to the current portion of long-term debt, which was absent from Q1 and Q3 financial statements.

As such, since Sep-2022, additional ratio treatment has been implemented in the calculation of China-domiciled banks. Using (semi) annual financial statements, i.e. those with additional current portion of long-term liabilities disclosure in Q2 and Q4, the ratio of current portion of long term debt to long term debt is calculated. The computation of Q1 and Q3 current portion of long term debt is then calculated by multiplying the ratio by the newly disclosed long term debt position. This treatment reduced the frequent fluctuations in DTD and PD seen for China-domiciled banks.

3.2 Distance-to-Default Computation

The DTD computation used in the CRI system is not a standard one. Standard computations exclude financial firms, which is of course a critical part of any economy. Thus, the standard DTD computation must be extended to give meaningful estimates for financial firms as well. Duan and Wang [2012] have provided a review of different DTD calculations with several examples for financial and non-financial firms.

The description of the specialized DTD computation starts with a brief description of the Merton [1974] model. Merton's model makes the simplifying assumption that firms are financed by equity and a single zero-coupon bond with maturity date T and principal L. The asset value of the firm V_t follows a geometric Brownian motion:

$$\mathrm{d}V_t = \mu V_t \mathrm{d}t + \sigma V_t \mathrm{d}B_t. \tag{33}$$

Here, B_t is the standard Brownian motion, μ is the drift of the asset value in the physical measure, and σ is the volatility of the asset value. Following the Merton [1974] model, the probability of the company's default at time T evaluated at time t is $\Pr_t(V_T \leq L)$, from Eq. (33), we can derive $\Pr_t(V_T \leq L) = N(-\mathrm{DTD}_t)$, where DTD at time t is defined as:

$$\mathrm{DTD}_t = \frac{\log\left(\frac{V_t}{L}\right) + \left(\mu - \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}}. \tag{34}$$

The standard KMV assumptions given in Crosbie and Bohn [2003] are to set the time to maturity $T - t$ at a value of one year, and the principal of the zero-coupon bond L to a value equal to the firm's current liabilities plus one half of its long-term debt. Here, the current liabilities and long-term debt are taken from the firm's FSes. If the firm is missing the current liabilities field, then various substitutes for this field can be used, as described in Subsection 2.3.

This is a poor assumption of the debt level for financial firms, since they typically have large liabilities, such as deposit accounts, that are neither classified as current liabilities nor long-term debt. Thus, using these standard assumptions means ignoring a large part of the debt of financial firms.

To properly account for the debt of financial firms, Duan [2010] included a fraction δ of a firm's other liabilities. The other liabilities are defined as the firm's total liabilities minus both the short and long-term debt. The debt level L then becomes the current liabilities plus half of the long-term debt plus the fraction δ multiplied by the other liabilities, so that the debt level is a function of δ. The standard KMV assumptions are then a special case where $\delta = 0$.

The fraction δ can be optimized along with μ and σ in the transformed-data maximum likelihood estimation method developed in Duan [1994, 2000]. As asset value is unobservable, it has to be implied from market equity value. Note that equity holders receive the excess value of the firm above the principal of the zero-coupon bond and have limited liability, so the equity value at maturity is: $\max(V_T - L, 0)$. This is just a call option payoff on the asset value with a strike value of L. Thus, the Black-Scholes option pricing formula can be used to calculate the equity value at times t before T,

$$E_t = V_t N(d_+) - e^{-r(T-t)} L N(d_-), \tag{35}$$

where r is the risk-free rate, $N(\cdot)$ is the standard normal cumulative distribution function,

$$d_{\pm} = \frac{\log\left(\frac{V_t}{L}\right) + \left(r \pm \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}}, \tag{36}$$

and $L \equiv L(\delta) =$ Current Liabilities $+ 1/2 \cdot$ Long-term Debt $+ \delta \cdot$ Other Liabilities as mentioned before. Then we can express the likelihood function of the observed equity values by viewing the equity values as the transformed data from pricing formula in Eq. (35). It should be noted that the transformation involves the unknown asset volatility. By standard transformation theory, the likelihood of observed equity values must equal the product of the likelihood of the asset values (implied by equity values) and the Jacobian of the inverse transformation (from the equity value back to the asset value). Moreover, following Duan et al. [2012], the firm's market value of assets is standardized by its book value A_t, so that the scaling effect from a major investment or financing by the firm will not distort the time series from which the parameter values are estimated. Thus, the log-likelihood function based on equity prices is:

$$\begin{aligned} \mathcal{L}(\mu, \sigma, \delta) = & -\frac{n-1}{2}\log(2\pi) - \frac{1}{2}\sum_{t=2}^{n}\log(\sigma^2 h_t) - \sum_{t=2}^{n}\log\left(\frac{\hat{V}_t(\sigma,\delta)}{A_t}\right) \\ & - \sum_{t=2}^{n}\log[N(\hat{d}_+(\hat{V}_t(\sigma,\delta),\sigma,\delta))] \\ & - \frac{1}{2\sigma^2}\sum_{t=2}^{n}\frac{1}{h_t}\left[\log\left(\frac{\hat{V}_t(\sigma,\delta)}{A_t} \times \frac{A_{t-1}}{\hat{V}_{t-1}(\sigma,\delta)}\right) - \left(\mu - \frac{\sigma^2}{2}\right)h_t\right]^2, \end{aligned} \tag{37}$$

where n is the number of days with observations of the equity value in the sample, $\hat{V}_t$ is the implied asset value found by solving Eq. (35), $\hat{d}_+$ is computed with Eq. (36) using the implied asset value, and h_t is the number of trading days as a fraction of the year between observations $t-1$ and t. Notice that the implied asset value and $\hat{d}_+$ are dependent on δ by virtue of the dependence of L on δ.

Implementation of DTD computation: The DTD at the end of each month is needed for every firm in order to calibrate the forward intensity model. A moving window, consisting of the last one year of data before each month end is used to compute the month end DTD. Daily market capitalization data based on closing prices is used for the equity value in the implied asset value computation of Eq. (35). If there are fewer than 50 days of valid observations for the DTD input variables (market capitalization, FS variables, and interest rate), the DTD value is set to be missing. An observation is valid if there is positive trading volume that day. If the trading volume is not available, the observation is assumed to be valid if the value for the market capitalization changes often enough. The precise criterion is as follows: if the market capitalization does not change for three days or more in a row, the first day is taken as a valid observation, and the remaining days with the same value are set to be missing.

A straightforward idea for the DTD computation is to first estimate the three variables μ, σ and δ via maximizing the log-likelihood function (37) over $\sigma \geq 0$ and $0 \leq \delta \leq 1$, and then to calculate the DTD from Eq. (34). Let $(\hat{\mu}, \hat{\sigma}, \hat{\delta})$ be an optimal solution to the maximization problem. By direct calculation, it is not hard to see that

$$\hat{\mu} = \frac{\hat{\sigma}^2}{2} + \frac{1}{\sum_{t=2}^{n} h_t}\log\left(\frac{\hat{V}_n(\hat{\sigma},\hat{\delta})}{A_n} \times \frac{A_1}{\hat{V}_1(\hat{\sigma},\hat{\delta})}\right). \tag{38}$$

In view of this, maximizing the three-dimensional function $\mathcal{L}(\mu, \sigma, \delta)$ can be equivalently reduced to maximizing the two-dimensional function $\tilde{\mathcal{L}}(\sigma,\delta)$ taking the form

$$\begin{aligned}\tilde{\mathcal{L}}(\sigma,\delta) = &-\frac{n-1}{2}\log(2\pi) - \frac{1}{2}\sum_{t=2}^{n}\log(\sigma^2 h_t) - \sum_{t=2}^{n}\log\left(\frac{\hat{V}_t(\sigma,\delta)}{A_t}\right) \\ &- \sum_{t=2}^{n}\log N(d_+) - \frac{1}{2\sigma^2}\left\{\sum_{t=2}^{n}\frac{1}{h_t}\times\left[\log\left(\frac{\hat{V}_t(\sigma,\delta)}{A_t}\times\frac{A_{t-1}}{\hat{V}_{t-1}(\sigma,\delta)}\right)\right]^2\right. \\ &\left. - \frac{1}{\sum_{t=2}^{n}h_t}\left[\log\left(\frac{\hat{V}_n(\hat{\sigma},\hat{\delta})}{A_n}\times\frac{A_1}{\hat{V}_1(\hat{\sigma},\hat{\delta})}\right)\right]^2\right\}. \end{aligned} \tag{39}$$

However, with quarterly FSes there will never be more than three changes in the corporate structure (defined in this model by L and A_t) throughout the year, leading to possibly unstable estimates of δ. This problem is mitigated by performing a two-stage optimization for σ and δ.

In the first stage, the maximization of $\tilde{\mathcal{L}}(\sigma,\delta)$ for each firm is performed over both σ and δ. For each firm, at the first month in which DTD can be computed, the maximization is constrained in $\sigma \geq 0$ and $0 \leq \delta \leq 1$. Thereafter, at month n, the maximization is still constrained in $\sigma \geq 0$ while δ is constrained in the interval $[\max(0, \hat{\delta}_{n-1} - 0.05), \min(1, \hat{\delta}_{n-1} + 0.05)]$, where $\hat{\delta}_{n-1}$ is the estimate of δ made in the previous month. In other words, a 10% band around the previous estimate of δ (where that band is floored with 0 and capped with 1) is applied so that the estimates do not fluctuate too much from month to month.

However, for many firms, the estimate of δ would frequently lie on the boundary of the constraining interval, meaning that the estimates of δ were not stable. Therefore, a second stage is implemented to impose greater stability. Within the same calibration group, all firms in the same sector (12 sectors as per the NUS-CRI 2020 industry classification, which is based on BICS 2020 version) are assumed to share the same estimate of δ, chosen to be the average of all its individual estimates. However, for some small economies, especially in their early years, the average of δ is still observed to be not stable due to some sector or even the whole calibration group has only few individual estimates of δ. To well handle such cases, a threshold rule at each time of estimation is applied under the following conditions: a) If a sector has fewer than 10 individual estimates, the shared estimate of δ will be set to the average of whole calibration group instead of the sector average; b) furthermore, if the whole calibration group still has fewer than 10 individual estimates, the shared estimate of δ is deemed not available. Accordingly, with δ being fixed to be the sector average on the calibration group level, the original maximization of $\tilde{\mathcal{L}}(\sigma,\delta)$ is reduced to a one-dimensional maximization in σ for each firm.

However, though this implementation rule did provide some stability to the estimation of δ, in cases where the number of companies in a calibration-sector group frequently fluctuate above and below the 10-company threshold, we still witnessed undesirable jumps in the estimation of δ. Thus, in May 2022, NUS-CRI introduced a new methodology for smoothing δ estimation. The new smoothing treatment mitigates sporadic jumps in δ estimation, especially for those calibration-sector groups that tend to have sample sizes that frequently fluctuate around the 10-company threshold. The new estimate of δ is taken to be the weighted average of the sector estimate δ_{sector} and the calibration group proxy δ_{group}. Therefore, the final δ estimate is given by $\delta = \omega \times \delta_{sector} + (1-\omega) \times \delta_{group}$ where ω (the weight for δ_{sector}) gradually changes value between 0 and 1 depending on the sample size of the sector on MoM basis (i.e. ω will increase by $\frac{1}{12}$ in the each consecutive month when the number of companies in the sector is above 10, and vice versa, decrease by the same amount for each consecutive month when the number of companies in the sector is below 10).

Since the first stage is done to obtain a stable sector-average estimate of δ, the criteria used to include a firm-month is more strict. In the first stage, a two-year window of FS variables, market capitalization, and interest rate is used instead of one year, and a minimum of 250 days of valid observations of the DTD input variables are required instead of 50. If a firm has less than 250 days of valid observations within the last two years of a particular month end, δ will not be estimated for that firm and that month end.

It was found that after applying the two-stage procedure described above, the estimate of μ was frequently unstable and could lower the explanatory power of DTD. For example, suppose a firm has a large drop in its implied asset value in January 2011, so that the estimated μ is negative for the DTD calculation at the end of December 2011. If there is little change in the company in January 2012, then the drop in implied asset value in January 2011 is no longer within the observation window for the DTD calculation at the end of January 2012. There will be a large increase in the estimated μ, resulting in a substantial improvement of the DTD just because of the moving observation window. To avoid this problem, we now set μ to be equal to $\sigma^2/2$. So in calculating DTD, the second term in the numerator of Eq. (34) is eliminated.

In summary, the DTD for each firm is computed using the sector average within a calibration group for δ in that month, and the estimate of σ based on the last year of data for the firm. As of September 2020, σ is calibrated daily in order to reflect in a timely manner any change in asset volatility caused by a shift in capital structure, market capitalization, etc when computing individual firm's daily PD.

Carrying out this two-stage procedure would take about 70 hours of computation time on a single PC, given the millions of firm months that are required. However, each of the stages is parallelizable. In the first stage, the DTD can be computed independently between firms. In the second stage, once the sector averages of the δ have been computed for each month, the DTD can again be computed independently between firms. In the current CRI system, by using the NUS' high-performance computing facility, the DTD computational time has been greatly reduced thanks to the application of parallel computing.

3.3 Calibration

Implementation: As shown in Section 1, the calibration of the forward intensity model involves multiple maximum pseudo-likelihood estimations, where the pseudo-likelihood functions are given in Eq. (15). The maximizations are on the logarithm of these expressions, and the default parameters' maximization is performed independently from the non-default exit parameters. Parameter estimates for the entire horizon up to five years for the default and non-default exits can be obtained directly from the NS function.

A few input variables have an unambiguous effect on a firm's probability of default. Increments of both the level and trend of DTD, CASH/TA, CA/CL, and NI/TA should indicate that a firm is becoming more creditworthy and should lead to a decreasing PD. For large and relatively clean data sets such as the US, an unconstrained optimization leads to parameter values which mostly have the expected sign. For each of the DTD level and trend, CASH/TA level and trend, CA/CL level and trend, and NI/TA level and trend, the default parameters at all horizons are negative. A negative default parameter at a horizon means that if the variable increases, the forward intensity will decrease (based on Eq. (6)), so that the conditional default probability at that horizon will decrease.

Grouping for economies: There are not enough defaults in some small economies and calibrations of these individual economies are not statistically meaningful. In order to ensure that there are enough defaults for calibration, the 88 economies are categorized into groups according to similarities in their stage of development and their geographic locations. Within these groups, the economies are combined and calibrated together.

As of January 2015, Canada and the US remain in the North America calibration group, and the developed economies of Asia-Pacific (Australia, Hong Kong, Japan, Singapore, South Korea, Taiwan and New Zealand) form another calibration group. China and India, the two major emerging economies of Asia-Pacific are each calibrated as individual groups. All the European countries covered by the CRI are in a single calibration group. The other emerging economies of Asia-Pacific, Latin America, Middle-East, and Africa form the “emerging markets” calibration group, which now includes 9 African economies: Botswana, Ghana, Kenya, Malawi, Mauritius, Namibia, Rwanda, Tanzania, and Uganda. Detailed grouping can be found in Table A.4.

All economies in the same calibration group share the same coefficients for all common variables except for the 3-month interest rate variable. In particular, we apply standardization to each economy’s interest rate time series, except for China and India. First, we subtract the historical month-end mean from the 3-month interest rate variable in order to reflect the contemporary change relative to the historical average. We then scale the demeaned values so that the standard deviation equals one. Doing so allows to put all economies on the same scale so that the same interest rate parameter can be reasonably used on firms from different countries/economies.

We allow for a unique coefficient on the interest rate variable for each economy. However, certain treatments and exceptions apply due to various reasons. For New Zealand, Bosnia and Herzegovina, and Montenegro, they do not have enough default events to identify a separate coefficient. In this case, the actual interest rates are replaced with zeros throughout the whole time series. This is to disable the effect of interest rate in the particular calibration, but it will not induce bias based on the nature of the standardized interests. For the Eurozone economies, all of them use the standardized Germany’s 3-month Bubill rate after the Eurozone was launched on January 1st, 1999. This aims to reflect more of the monetary rather than the sovereign credit conditions in those economies. Before joining the Eurozone, each of those economies except Germany uses own standardized interest rates, because none of them has enough default events before that date. Among the non-Eurozone economies, Denmark, Norway, Sweden, and UK have their own respective coefficients on the interest rate variable, but Iceland, Switzerland along with all the others share the same one. In the Emerging Markets group, only Indonesia, Malaysia, the Philippines, and Thailand have their own economy-specific coefficients on the interest rate variable. The Latin American subgroup has a universal coefficient for all the member economies, and all the others in the Emerging Markets group share the same coefficient.

One thing to note is that in addition to the unique coefficient on the interest rate variable, Indonesia also has its own coefficient for the relative size level as of October 2013.

Relative size: For the calibration data set, the median market cap of firms in an economy for each month end includes the market cap from the last trading day of each firm in the month. If a firm does not trade in a particular month, the firm’s market cap is not included in the median. For certain economies, many firms are illiquid and the median market cap experiences large variations due to the change in composition of firms rather than the market value of the firms. Another problem is data quality at the beginning of the historical sample: if a data provider starts including the market cap for a large number of firms in one month compared to the previous, there can be a large jump in the median market cap. Our research also reveals that debt–ridden countries (e.g., Venezuela) are usually susceptible to hyperinflation so that the market value of the firms under the severe economic turmoil is not trustworthy.

To avoid this problem, we use the economy’s median market cap over the past one year as the divisor in the Relative Size variable:

1. We collect the whole market cap data of individual firms in a specific economy over the past one year.
2. We calculate the ratio of individual firm’s market cap to the economy’s median market cap calculated above.
3. We take a natural logarithm to reduce its variability.

3.4 Daily Output

Individual firms' PD: In computing the pseudo-log-likelihood functions in Eq. (15), only the end of month data is needed. The data needs to be extended to daily values in order to produce daily PDs.

For the level variables, the last 12 end-of-month observations (before averaging) are combined with the current value. The current value is scaled by a fraction equal to the current day of the month divided by the number of calendar days in the month. The earliest monthly value is scaled by one minus this fraction. The sum is then divided by the number of valid monthly observations, with the current value and the earliest monthly value jointly having the weight of one observation if either or both are not missing. Not performing this scaling can lead to an artificial jump in PD at the beginning of the month. When performing the scaling, the change in level is more gradual throughout the month.

As of September 2020, DTD is calculated based on daily calibrated σ (so as to react timely and properly to market capitalization changes) and monthly calibrated δ (as δ is structurally much more stable because it is a sector average).

SIGMA is computed by regressing the daily returns of the firm's market capitalization against the daily returns of the economy's stock index for the previous 250 days.

Aggregating PDs: The CRI provides term structures of the probability distributions for the number of defaults as well as the expected number of defaults for different groups of firms. The companies are grouped by their domicile country (using the location of a firm's headquarter), by sector (using the NUS-CRI 2020 industry classificaiton code that is based on the BICS 2020 code) and sectors within economies. However, the dual-listed companies (for example, Rio Tinto) exist as a single corporation, but retain two different legal identities. They may have two different sets of PDs, due to two exchange listings for separate entities, but sharing the same domicile. In such cases, we will override the entity's default domicile country to follow its stock exchange's location.

To compute the probability distribution of the number of defaults, we use an algorithm which was originally reported in Anderson et al. [2003]. It assumes conditional independence and uses a fast recursive scheme to compute the necessary probability distribution. With the individual firms' PDs, the expected number of defaults is trivial to compute and is simply the sum of the individual PDs within each group. Note that while this algorithm is currently used to produce the probability distribution of the number of defaults within an economy or sector, it can easily be generalized to compute loss distributions for a portfolio manager, in which case the portfolio's exposure to each firm should be aggregated.

Since April 2022, NUS-CRI has incorporated default correlations (DC) when producing default-rate and default number distributions. Calculation of DC largely follows the methodology of Duan and Miao [2016]. As can be expected, the incorporation of DC makes the default-rate distributions far more right-skewed, reflecting a much higher chance that obligors in a typical credit portfolio may default together due to the impact of an exogenous common shock. Therefore, ignoring the impact of DCs in credit portfolios can cause a severe under-assessment of the chance for joint defaults to occur in both the short and long term.

Computing default-rate distributions comprises four steps: (1) identify a set of predetermined credit risk factors, estimate the factor model, and produce the factor model residuals; (2) estimate the time series dynamics of the predetermined credit risk factors and individual factor model residuals; (3) construct a sparse correlation matrix for the factor model residuals after taking out their individual time series effect; (4) further calibrate the model to the term structure of PDs at the time of application to take advantage of the information embedded in longer-term PDs.

As of 8th July 2014, the display of the aggregate PDs on the NUS CRI website started to adopt the simple median of the individual PDs within each group. This change will mitigate the effect from extreme outliers and synchronize with the aggregate display of the AS. It should be noted that the aggregate PDs using mean values are still accessible through the data downloading section on the website.

Inclusion of firms in aggregation: As explained in Subsection 3.1, firms are included in an economy for calibration if the firms' primary listing is on an exchange in that economy. This is to ensure that all firms in an economy are subject to the same disclosure and accounting requirements. In contrast, a firm is included in an economy's aggregate results if the firm is domiciled in that economy. This is because users typically associate firms with their economy of domicile rather than the economy where their primary listing is, if they are different. For example, the Bank of China has its primary listing in Hong Kong, but its economy of domicile is China so the Bank of China is included in the aggregation forecasts for China, and is included under China when searching for the individual PDs.

Treatment of companies after a default event: When a company experiences a default event, the CRI system discontinues the PD calculation for that company. However, if the company resumes operations after some time, it will be treated as a new company, and we continue to generate PD. The new company's PDs are not affected by the FS or market cap data prior to the event. So, the PDs calculated are independent of the PDs that were generated before the default event. On our website, the PDs are however displayed on a single graph for the convenience of our users.

3.5 Default Correlations

As of Apr-2022, NUS-CRI has implemented default correlations (DC) on various portfolios to improve the estimate of default-rate and default-number distributions. Though the NUS-CRI system only displays the default-number distributions on the website, the two distributions are interchangable as long as the total number of firms in the portfolio are known for a given time point.

Incorporating DC in the calculation of default-rate distribution goes beyond the previous system that relied on marginal PDs and POEs. The previous system calculated default-rate distribution under the assumption of zero default correlation. As expected, the incorporation of DC makes default-rate distribution far more right skewed, as the impact of an exogenous shock on the credit profile on entities, for example a large move on commodity prices or interest rates, likely causes entities in a credit portfolio to increase their chance of defaulting together.

The methodology deployed in the calculation of DC is largely based on Duan and Miao [2016] except for factor model selection and part of re-calibration. There are four steps required to compute default correlations for a credit portfolio of interest. Namely, they are:

1. Identification of a set of predetermined credit risk factors to estimate the factor model and produce factor model residuals
2. Estimate the time series dynamics of the predetermined credit risk factors and individual factor model residuals
3. Construct a sparse correlation matrix for the factor model residuals after taking out their individual time series effects
4. Further calibrate the model to Period PDs[5] for different horizons at the time of application to take advantage of the information embedded

[5]Period PD is survival probability times Forward PD. We adopt this term to differentiate it from Forward PD, which refers to the PD of a forward period conditional on survival up to the beginning of a period.

Generating the common factor model: The first step is to estimate the factor model using transformed values of one-month PDs and POEs. Let n_t be the total number of firms in the credit portfolio with PDs and POEs at time t, and T be the time point of credit analysis. Let $p_{it}(l)$ and $q_{it}(l)$ denote the l-month PD and POE of firm i at month t for $i = 1, ..., n_t$ and $t = 1, ..., T$. As the PD and POEs are naturally bounded between 0 and 1, the following logit transformation is used to take PDs and POEs back to real numbers.

$$P_{it} = \ln\left\{\frac{p_{it}(1)}{(1-p_{it}(1))}\right\} \quad \text{and} \quad Q_{it} = \ln\left\{\frac{q_{it}(1)}{(1-q_{it}(1))}\right\}$$

A firm's likelihood of default is based on a plethora of factors including global, economy-specific and industry-specific credit risk factors. Logit-transformed credit cycle indices (CCIs) which are the one-month aggregate (median) PDs and POEs for specific economy-industry pairs can be used as common credit factors, naturally these are going to be correlated. Other factors that reflect the macroeconomic environment are also taken into account, such as foreign exchange (FX) rates and interest rates. In total, close to 420 potential common factors are present for every firm-month observation to select from. We use the zero-norm variable selection technique of Duan [2019][6]. For the PD factor model, the global PD-CCI, the industry-specific PD-CCI (the industry to which majority of the companies in the credit portfolio belong to) are "must-include" variables. Similarly, for the POE factor model, the global POE-CCI and the same industry-specific POE-CCI are also "must-include" variables.

For individual firms that are expected to react differently to the common credit risk factors, a regression can be conducted to identify their influence on the above-mentioned logit-transformed one-month PD and one-month POE. The regression would take the following form:

$$P_{i,t} = \beta_{0,i}^{(P)} + \beta_i^{(P)} F_t^{(P)} + \epsilon_{i,t}^{(P)}, \qquad t = 1, ..., T \tag{40}$$

$$Q_{i,t} = \beta_{0,i}^{(Q)} + \beta_i^{(Q)} F_t^{(Q)} + \epsilon_{i,t}^{(Q)}, \qquad t = 1, ..., T \tag{41}$$

where $F_t^{(P)}$ and $F_t^{(Q)}$ refer to the selected common set of factors post the zero-norm variable selection in the PD and POE factor models respectively.

Considering residual time dynamics: The next step is to estimate the time dynamics for the factor residuals using vector auto-regression (VAR) and auto-regression (AR) models. AR(1) is used to account for autocorrelation in the residual dynamics:

$$\epsilon_{i,t}^{(P)} = \mu_i^{(P)} + \rho_i^{(P)} \epsilon_{i,t-1}^{(P)} + e_{i,t}^{(P)}, \qquad t = 1, ..., T \tag{42}$$

$$\epsilon_{i,t}^{(Q)} = \mu_i^{(Q)} + \rho_i^{(Q)} \epsilon_{i,t-1}^{(Q)} + e_{i,t}^{(Q)}, \qquad t = 1, ..., T \tag{43}$$

Modeling factors' time dynamics: For global PD-CCI and POE-CCI factors, the first-order two-dimensional VAR model is used to capture the time dynamics.

$$F_t = AF_{t-1} + E_t, \qquad t = 1, ..., T \tag{44}$$

where F_t represents the global CCI vector, A is the two-by-two time-invariant square matrix and E_t is a vector of two error terms.

[6]This zero-norm variable selection technique is a combinatorial optimization method built upon density/probability-tempered sequential Monte Carlo to find a best stable subset of variables that delivers the highest R^2. It directly addresses the variable selection issue in its natural context and performs measurably better than the L^1-norm based LASSO.

For other factors such as industry/economy specific CCI, FX rates, interest rates, commodity prices etc, an AR(1) model is used to estimate time dynamics.

$$Y_t = b_0 + bY_{t-1} + e_t, \qquad t = 1, ..., T \tag{45}$$

where Y_t denotes the corresponding factor, b_0 is the intercept, b is the coefficient of the 1-period lag term, and e_t is the corresponding error term.

Constructing the sparse residual correlation matrix: To better capture the co-movements of credit risk across firms, supplementary information on co-movements from PD and POE residuals $\epsilon_{i,t}^{(P)}$ and $\epsilon_{i,t}^{(Q)}$ in equation (40) and (41) are also extracted. We stack together all the AR(1) model residual terms estimated in the above-mentioned equations (43) and (44), i.e. $e_{i,t}^{(P)}$ and $e_{i,t}^{(Q)}$, to create a matrix of size $T \times 2n_t$ at time T. Since the initial PD and POE residuals are estimated after employing the common risk factors, we can reasonably assume that the relationship between these residual terms are likely to be uncorrelated in most cases, leading to a sparse correlation matrix.

Due to missing data, only pairwise correlations are available, with simple statistical significance helping to filter out insignificant correlations present. The SCAD-thresholding element-wise method is then applied to achieve both sparsity and postive semi-definiteness.

Calibrating to Period PDs: So far, generating the point estimate of the factor model and residual dynamics only depends on historical time series of one-month PD and POE series. Conceivably, one could utilize the information is the term structure of PDs to re-calibrate the components of the factor model and residual dynamics to make the model more forward-looking. Instead of targeting the term structure of cumulative PDs as in Duan and Miao [2016], we deploy Period PD, which is calculated as the difference in cumulative PDs for two consecutive 1-month horizons. For example, the 3rd month Period PD for an entity will be the entity's 3-month PD minus its 2-month PD. Aiming to match a set of Period PDs rather than cumulative PDs over the horizon yields more stable re-calibration results because it prevents oscillating behavior to appear in the re-calibrated model that still yields smooth cumulative PDs.

The factor model in equations (40) and (41), the factor model residual time dynamics equations in (42) and (43), as well as the factor dynamics themselves in equations (44) and (45) with the sparse correlation matrix can be used together to generate future paths of one-month PDs and POEs for all members of a credit portfolio over any horizon of interest.

With the set of, say, 1000 simulated paths in place, one can compute the average cumulative PDs for different horizons, and use them to produce corresponding Period PDs. In principle, these Period PDs should match their corresponding Period PDs generated by the NUS-CRI PD model. In practice, however, model mis-specifications and estimation errors occur and these two sets are unlikely to match exactly. Nevertheless, re-calibration can be deployed to tune some model parameters in order to minimize their gap.

The current implementation only sets out to re-calibrate the residual dynamics, i.e., those for $\epsilon_{i,t}^{(P)}$ and $\epsilon_{i,t}^{(Q)}$, which involve six parameters for each firm. Specifically, we minimize the mismatch between the Period PDs generated by the DC model and the actual Period PDs released by NUS-CRI. For firm i, the re-calibration is to search for the six unknown parameters in equation (42) and (43); that is, $\theta_i := (\mu_i^{(P)}, \mu_i^{(Q)}, \rho_i^{(P)}, \rho_i^{(Q)}, \sigma_i^{(P)}, \sigma_i^{(Q)})$ with σ_i being the standard deviation of e_i.

Impact on default-rate distributions: Incorporation of DC in the calculation of default-rate distributions suggests that entities in a credit portfolio tend to default together, making the default-rate distribution more right-skewed than when not taking into account default correlations. The long tail suggests that ignoring DCs can cause a severe under-assessment of joint default risk, which should be a concern for any credit portfolio of interest. The prediction of long tail is valid for both the short and the long term.

4 Empirical Analysis

This section presents an empirical analysis of the CRI outputs for the 88 economies with their own exchange that are currently being covered. In Subsection 4.1, an overview is given of the default parameter estimates. Subsection 4.2 explains and provides the accuracy ratios for the different countries under the CRI coverage.

4.1 Parameter Estimates

With 60 months of forecast horizons, 17 variables (16 variables plus an intercept), and 6 different groups of economies, tables of the parameter estimates occupy over 20 pages and are not included in this Technical Report. In Figs. B.1 and B.2, the parameter estimates are from calibrations performed in May 2023 (April calibration) using data until the end of April 2023. As an example, plots of the default parameters for the US are given in Figs. B.1 and B.2 in Appendix B. In this part, a brief overview is given of the general traits and patterns seen in the default parameter estimations of the economies covered by the CRI.

Recall that if a default parameter for a variable at a particular horizon is estimated to be positive (negative) from the maximum pseudo-likelihood estimate, then an increasing value in the associated variable will lead to an increasing (decreasing) value of the forward intensity at that horizon, which in turn means an increasing (decreasing) value for the forward default probability at that horizon.

For the stock index one-year trailing return variable, most groups have default parameters that are slightly negative in the shorter horizons and then become positive in the longer horizons. When the equity market performs well, this is only a short-term positive for firms and in the longer term, firms are actually more likely to default. This seemingly counterintuitive result could be due to correlation between the market index and other firm-specific variables. For example, Duffie et al. [2009] suggested that a firm's DTD can overstate its creditworthiness after a strong bull market. If this is the case, then the stock index return serves as a correction to the DTD levels at these points in time.

As expected, we observe the different relationships between the short-term interest rate and default across economies. This observation possibly indicates different lead-lag relationships between credit conditions and the raising and cutting of short-term interest rates.

DTD is a measure of the volatility-adjusted leverage of a firm. Low or negative DTD indicates high leverage and high DTD indicates low leverage. Therefore, PD would be expected to increase with decreasing DTD. Indeed, the DTD level has negative default parameters across calibration groups.

Aggregate DTD can measure the overall degree of the volatility-adjusted leverage in an economy. As mentioned in Subsection 2.1, we use two kinds of sector–specific aggregate DTDs: one for financial firms, and the other for non–financial firms. In each economy, the default parameters for the two aggregate DTDs usually display different patterns. Such patterns may reflect different credit risk profiles of the economy–wide business environments.

The log ratio of the sum of cash and short-term investments to total assets (CASH/TA) measures liquidity of a financial firm. Likewise, the log ratio of current assets to current liabilities (CA/CL) stands for liquidity of a non–financial firm. These two ratios indicate the availability of a firm's funds and its ability to make interest and principal payments. On the whole, almost all economies have negative default parameters for such liquidity ratios, although the short–term and long–term effects differ across each calibration group.

The ratio of net income to total assets (NI/TA) measures profitability of a firm. The relationship between PD and NI/TA is as expected: the default parameters for NI/TA level is negative for all economies and all horizons.

The logarithm of the market capitalization of a firm over the median market capitalization of firms over the past one year within the economy (SIZE) does not have a consistent effect on PD across different economies. For example, in the US the default parameters for SIZE level are positive for almost all horizons, suggesting that the complexity of larger firms outweighs the potential benefits, such as diversified business lines and funding sources. On the other hand, in China the default parameters for SIZE level are negative across almost all horizons. The lack of similarity may reflect the different business environments in such respective economies.

The default parameters associated with DTD Trend, CASH/TA Trend, CA/CL Trend, SIZE Trend and NI/TA Trend are negative across almost all economies and horizons. The trend variables reflect momentum. The momentum effect is a short-term effect, and evidence of this is seen in the lower magnitude of the default parameters at longer horizons than at shorter horizons. The exception is the NI/TA Trend, which for some calibration groups has a higher magnitude at longer horizons.

The ratio of the individual firm's M/B to the economy M/B median (M/B) can either indicate the market mis-valuation effect or the future growth effect. This default parameter is negative for the US in the shorter term, indicating that higher M/B implies lower PD, and the future growth effect dominates during this period. On the other hand, in China and in the Developed Asia-Pacific calibration group, the default parameter for M/B is positive, indicating that for these economies, the market mis-valuation effect dominates.

Shumway [2001] argued that a high level of the idiosyncratic volatility (SIGMA) indicates highly variable stock returns relative to the market index, which is equivalent to highly variable cash flows. Empirically, the sign on SIGMA is different across countries and across prediction horizons.

4.2 Prediction Accuracy

In-sample testing: Various tests are carried out to test the prediction accuracy of the NUS-CRI PD forecasts. These tests are conducted in-sample.

A single calibration is conducted for the in-sample tests, using data until the end of the data sample. As an example, one-year PD forecasts are made for 31 December, 2000 by using the data at or before 31 December, 2000 and the parameters from the calibration. These PD forecasts can be compared to actual defaults that occurred at any time in 2001.

Accuracy ratio: The accuracy ratio (AR) is one of the most popular and meaningful measures of the discriminatory power of a rating system (BCBS, 2005). The AR and the equivalent Area Under the Receiver Operating Characteristic (AUROC) are described in Duan and Shrestha [2011]. In short, if defaulting firms had been assigned among the highest PD of all firms before they defaulted, then the model has discriminated well between safe and distressed firms. This leads to higher values of AR and AUROC. The range of possible AR values is in [0,1], where 0 indicates a completely random rating system and 1 stands for a perfect rating system. The range of possible AUROC values is in [0.5, 1]. AUROC and AR values are related by: AR = $2\times$AUROC - 1.

The AR and AUROC values for different horizons are available in Table B.1. Only economies with more than 20 defaults entering into the AR and AUROC computation are listed.

The AUROC values have been provided only for the purpose of comparison, if other rating systems report their results in terms of AUROC. The discussion will focus only on AR. The model is able to achieve strong AR results mostly greater than 0.80 at the one and six-month horizons for developed economies. There is a drop in AR at one and two-year horizons, but the AR are still mostly acceptable.

The AR in some emerging market economies such as China, India, Indonesia, and the Philippines are noticeably weaker than the results in the developed economies. This can be due to a number of issues. The quality of data is worse in emerging markets, in terms of availability and data errors. This may be due to lower reporting and auditing standards. Also, variable selection is likely to play a more important role in emerging markets. The variables are selected based on the predictive power in the US. Performing variable selections specific to the calibration group are expected to improve predictive accuracy, especially in emerging market economies. Finally, there could be structural differences in how defaults and bankruptcies occur in emerging market economies. If the judicial system is weak and there are no repercussions for default, firms may be less reluctant to default.

Aggregate defaults: The time series of aggregate predicted number of defaults and actual number of defaults in each calibration group are also available in Figs. B.4 to B.14. For India in particular, these figures show that there is room for improvement in the predictive power of the model.

Forward-looking prediction accuracy: A regression analysis comparing the forward realized default rate against the PD corresponding to the forward period, repeated at different time points and for various lengths of forward period can be used to measure the accuracy of the PD model's prediction. For example, by regressing a 6-month ahead 1-year realized default rate against the 6-month forward 1-year Period PD at different time points[7], prediction accuracy can be measured for this combination. Since one can only meaningfully compute realized default rates for a credit portfolio of reasonable size, their corresponding Period PDs should be understood as average Period PDs of the portfolio.

Simply put, the regression takes the following form:

$$\text{Realized Default Rate}_{(t,\tau,d)} = \alpha_{(\tau,d)} + \beta_{(\tau,d)} \times \text{Period PD}_{(t,\tau,d)} + \epsilon_{(t,\tau,d)}$$

where t is the prediction time, τ is the forward time, and d is the length of the period. Results of the regression are available from Table B.2 to B.6.

In an ideal model, α and β should equal 0 and 1, respectively. However, it is unlikely that the prediction accuracy is perfect given that both common macro-financial variables and firm-specific company fundamentals changes over, say, a 12-month period. However, this exercise can help determine the efficacy of the NUS-CRI PD model in creating accurate term structures of forward-looking default probabilities. Prediction accuracy for most calibration groups is strong.

5 Corporate Vulnerability Index

In July 2012, CRI launched the Corporate Vulnerability Index (CVI), which is a new suite of indices to produce bottom-up measures of credit risk in economies, regions and portfolios of special interest. The suite of CVIs is available in three distinctive types:

1. Value-weighted CVI (CVI_{vw}) NUS CRI PDs are aggregated with each firm weighted by its market capitalization so that the size of each firm is taken into account.

[7] Period PD has been previously defined as the Forward PD times the survival probability up to the beginning of a forward period.

2. Equally-weighted CVI (CVI_{ew}) NUS CRI PDs are aggregated with each firm equally weighted. This captures the prevalence of credit risk by focusing on the number of firms at risk.
3. Tail CVI (CVI_{tail}) In taking the 5th percentile of the highest NUS CRI PDs, the most vulnerable firms in a group are measured.

The CVIs are a set of indicators that gauge economic and financial environments in a new dimension. They are best viewed as stress indicators that reflect heightened credit risks in the corporate sector from three different angles.

Index Construction The primary inputs to the CVI are NUS CRI 1-year PDs for individual exchange-listed firms.

- Value-weighted CVI (CVI_{vw}) CVI_{vw} is an aggregation of individual PDs weighted by each firm's market capitalization. In other words, at time t, given an interested group or portfolio G,

$$\text{CVI}_{\text{vw}}(t) = \sum_{i=1}^{I} \omega_{it} p_i(t, 12),$$

  where $p_i(t, 12)$ is firm i's default probability within 12 months viewed from t, $i \in \{1, 2, ..I\}$. Also, the weight for firm i at time t is ω_{it}, and $\omega_{it} = \frac{MC_{it}}{\sum_{i=1}^{I} MC_{it}}$, in which, MC_{it} is firm i's market capitalization at time t. If a firm does not trade on a particular day, the market capitalization from the previous valid day (within 20 trading days) is used. The market-capitalization weighting is applied to all economies and groups of economies, but is not applied to portfolios such as the S&P 500 index. The S&P 500 index is a float-adjusted index where the shares available to investors are used instead of the total shares outstanding, and our weighting scheme of CVI_{vw}(SPP) is consistent with the S&P 500 index.

- Equally-weighted CVI (CVI_{ew}) The equally-weighted CVI is computed by aggregating each firm's PD with equal weights applied to each firm. In other words,

$$\text{CVI}_{\text{ew}} = \frac{1}{I} \sum_{i=1}^{I} p_i(t, 12).$$

- Tail CVI (CVI_{tail}) The tail CVI provides a measure of the relatively more distressed firms in a group. It is the highest 5th percentile of PDs. The tail CVI can also be interpreted as the conditional median of the 10 percent tail, which is a more robust measure of "tail average" than the conditional mean of the 10 percent tail.

Inclusion of Firms: A firm's PD is computed with the model parameters from its primary exchange. The construction of CVI, however, is based on the firm's country of domicile. In regions like the Eurozone, some of the public holidays do not coincide. In this case, the aggregation is computed by using PDs from the previous trading day for firms that are listed in countries that have a public holiday, and PDs from the current trading day for firms that are listed in countries that do not have a public holiday. And firms are included in the Eurozone CVI only if their countries of domicile are part of the Eurozone at time t. For CVI of the S&P 500 portfolio, the constituents typically coincide with the constituents of the S&P 500 index for each point in time, and any missing PD value for a company in the S&P 500 is filled in with the most recently available PD.

6 Actuarial Spread

In July 2014, CRI launched a new credit risk measure, the Actuarial Spread (AS), which is the counterpart of market credit default swap (CDS) with contract horizons ranging from 1 year to 5 years but valued based on NUS CRI's PDs in the forward horizons. Since then, the computation and publication of the AS have been implemented on a daily basis in addition to those of the PDs. Much like the par spread in a standard credit default swap (CDS) contract, the AS leverages the term structure of the physical PDs of the CRI and is essentially the premium rate that purely reflects the actuarial present value of a default protection. It provides a new metric of credit risk that the financial practitioners are more familiar with.

The construction of the AS relies on the features of a standard CDS contract. To fulfill a CDS contract, the protection buyer pays premiums on a regular basis to the seller until the contract matures or the reference entity defaults. In exchange, the protection buyer receives at the default time a contingent lump sum payment, the amount of which is based on the recovery rate of the reference instrument. Such a CDS contract terminates on its maturity date if there is no default up to its maturity; otherwise, it ceases on a default day, if any. Note that, if a default occurs during a payment period, the premium for the protection from the first accrual day to the default day is also assumed to be paid by the CDS buyer on the default day. Considering no effect from the market liquidity and using the physical PDs that CRI generates, the AS is calculated in a way that the expected present value of the contingent claim upon default is equal to the expected present value of the series of premiums up until the stop of a CDS contract. To familiarize the details of its theoretical formulation, please refer to Duan [2014]. As opposed to the continuous model introduced in Duan [2014], this technical report provides a discrete representation of the model for implementation purpose. For easy comparison, it adopts the same notations in the journal article as much as it possibly can.

A typical CDS contract adopts one day as the fundamental period of time. For this, we abbreviate the interval $((d-1)\cdot\Delta t,\, d\cdot\Delta t]$ in a forward time axis by the term day $d \in \mathbb{N}$ where $\Delta t = 1/365$ reflects the 365 day count convention. Consider t is the trading day of a CDS contract terminating on the day $T > t$. If the reference entity defaults at a random day τ where $t+1 \leq \tau \leq T$, he will in return get a lump sum payment, which is 1 minus the recovery rate R_τ, from a unit-notional CDS and cease to make the scheduled payment beyond the default point. We assume the premiums are scheduled to be paid on the days $t_1, t_2, ..., t_k$ with $t_k = T$, where each payment period is roughly three months. Note that a payment day t_{i-1} is also the first day of the coming accrual period, which ends on the day before next payment day, denoted and defined by $t'_i = t_i - 1$. However, a trading day t may also occur after a payment day, say t_{i-1}, and we denote the exact start date of its remaining accrual period by $t_{i-1} \vee (t+1) = \max\{t_{i-1}, t+1\}$ for a general purpose.

Another actual/360 day count convention is usually adopted to define the length in year of an accrual period, for which we denote $A(s,q)$ the period length in year from the day s to the day $q > s$ (both inclusive). For example, if a quarterly accrual period from t_{i-1} to t'_i (both inclusive) has 91 days, then $A(t_{i-1}, t'_i) = 91/360$ is applicable.

Compared to the risk-neutral probability measure used in the CDS pricing, the AS is essentially its counterpart based on a physical probability measure P. We denote it by $S_t^{(a)}(T-t)$ with its days to maturity $(T-t)$. Following the assumption that there is no arbitrage for CDS buyer and seller, the AS is defined to satisfy the equation:

$$
\begin{aligned}
& E_t^p\left[(1-R_\tau)D_t(\tau-t)\cdot\mathbb{1}_{\{t<\tau\leq t'_k\}}\right] \\
= \; & S_t^{(a)}(T-t)\sum_{i=1}^{k}\Big\{A(t_{i-1}\vee(t+1),t'_i)\cdot E_t^p\left[D_t(t_i-t)\cdot\mathbb{1}_{\{t'_i<\tau\}}\right] \\
& \qquad +E_t^p\left[A(t_{i-1}\vee(t+1),\tau)\cdot D_t(\tau-t)\cdot\mathbb{1}_{\{t'_{i-1}<\tau\leq t'_i\}}\right]\Big\},
\end{aligned}
$$

where E_t^P is an expectation operator with respect to the physical probability measure P, τ refers to the random default day, $D_t(\tau - t)$ is the random money market discount factor starting from the day t to another day τ and k is the number of the CDS premium payments.

Historically, the NUS-CRI system has utilised LIBOR and associated swap rates to generate a term structure of discount factors that can be utilized to compute the AS of a reference entity. In line with industry standards where fewer contracts are being based on LIBOR as the industry transitions to a more apt benchmark rate, the NUS-CRI system has shifted to the Secured Overnight Financing Rate (SOFR) to generate the risk-free discount rates used in the computation of AS. The real-time SOFR rates up to one year and Swap rates beyond are becoming readily available from the market. The change from LIBOR to SOFR will be available on the website from Jul-2023.

With the combination, one can bootstrap the implied SOFR rates beyond one year. As the AS is calculated based on days, a linear interpolation is further performed to obtain the implied SOFR rates up to each forward day (in continuously compounded annualized form), which then serve the role of the discount factor $D_t(\cdot)$. Let $r_t(s,q)$ be the day-t risk-free annualized forward discount rate between the day $t+s$ and the day $t+q$ (both inclusive) with $q \geq s \geq 1$. In particular, $r_t(1,q)$ refers to the day-t risk-free spot discount rate covering the days $t+1, \ldots, t+q$. The standard term structure theory implies that

$$r_t(1,q) = -\frac{1}{q} \ln \left\{ E_t^P \left[D_t(q) \right] \right\}.$$

Further we let $r_t(q,q) = r_t(1,q) \cdot q - r_t(1,q-1) \cdot (q-1)$ for $q \geq 2$, which refers to the day-t instantaneous forward rate for the day $t+q$. As will be seen later, defining $r_t(s,q)$ this way is to make it consistent with the definition of the forward default/other exit intensity in terms of the day count convention. With the NUS CRI PDs serving as the physical probability measure P and the use of a standard recovery rate of $\bar{R}_t = 40\%$, the AS is rewritten as

$$\begin{aligned} S_t^{(a)}(T-t) = {} & (1-\bar{R}_t) \cdot E_t^p \left[e^{-r_t(1,\tau-t)(\tau-t)/365} \cdot \mathbb{1}_{\left\{t<\tau\leq t_k'\right\}} \right] \\ & \times \left[\sum_{i=1}^{k} \left\{ A(t_{i-1} \vee (t+1), t_i') \cdot e^{-r_t(1,t_i-t)(t_i-t)/365} \cdot E_t^p \left[\mathbb{1}_{\left\{t_i'<\tau\right\}} \right] \right. \right. \\ & \left. \left. + E_t^p \left[A(t_{i-1} \vee (t+1), \tau) \right] \cdot e^{-r_t(1,\tau-t)(\tau-t)/365} \cdot \mathbb{1}_{\left\{t_{i-1}'<\tau\leq t_i'\right\}} \right\} \right]^{-1} \end{aligned} \tag{46}$$

where the actual/365 day count convention is used for the discount factor and integration.

To obtain the physical probability of defaults and their term structures, we apply CRI's forward intensity model. Define $f_t(u)$ to be the day-t forward default intensity over the day $t+u$, which will be used to calculate the probability of default of a firm conditioning on its survival up to the day $t+(u-1)$. The forward intensity for other exits, or $h_t(u)$, can be similarly defined. These two intensities are expressed as exponential linear functions of 17 variables in general, including an intercept term, 4 common covariates and 12 firm-specific covariates, in the form of

$$f_t(u) = \exp\{\alpha_0(u) + \alpha_1(u)x_{1,t} + \ldots + \alpha_{16}(u)x_{16,t}\},$$

and

$$h_t(u) = \exp\{\beta_0(u) + \beta_1(u)x_{1,t} + \ldots + \beta_{16}(u)x_{16,t}\}.$$

In this similar manner, 15 variables for China apply to the two intensities (see Subsection 2.1). The coefficients $\alpha_i(u)$ and $\beta_i(u)$ are functions of forward starting time, which are further modelled by Nelson-Siegel term structure functions, such as

$$\begin{aligned}\alpha_i(u;\varrho_{i,0},\varrho_{i,1},\varrho_{i,2},d_i) = \varrho_{i,0} + \varrho_{i,1}\frac{1-\exp(-u\Delta t/d_i)}{u\Delta t/d_i} \\ + \varrho_{i,2}\left[\frac{1-\exp(-u\Delta t/d_i)}{u\Delta t/d_i} - \exp(-u\Delta t/d_i)\right],\end{aligned} \tag{47}$$

for $i = 0, 1, 2, \ldots, 16$. Recall that, except for the intercept terms $\alpha_0(u)$ and $\beta_0(u)$, the other covariates are stochastic and their long-term levels are restricted to zeros; namely, $\varrho_{i,0} = 0$ for $i = 1, 2, \ldots, 16$. With $f_t(u)$ and $h_t(u)$ in place, we are ready to define $\psi_t(s,q) = \frac{\sum_{u=s}^{q}[f_t(u)+h_t(u)]}{q-(s-1)}$, for $q \geq s \geq 1$, which is a standardized forward termination intensity covering the days $t+s, \ldots, t+q$.

One important feature of the CDS is that when the reference entity ceases to exist due to reasons other than default, such as mergers and acquisitions, the CDS protection is typically shifted to the merged or acquiring entity. Naturally, we should take into account the fact that the successor entity will then face subsequent default or other exits. There indeed are a number of ways to model the relationship between the termination probability of the reference entity and the successor entity (see [Duan, 2014]). In CRI's implementation, we further assume that the successor has the forward default and other exit intensities identical to those of the original reference entity.

Let $P_t(s,q;r_t(1,u), s \leq u \leq q)$ denote the day-t discounted forward probability of the reference entity of the CDS being terminated, including successions, over the days $t+s, \ldots, t+q$. Under the assumptions above, Duan [2014] has derived its analytical solution, which can be re-written in the discrete form below

$$P_t(s,q;r_t(1,v), s \leq v \leq q) = \sum_{v=s}^{q} e^{-\sum_{u=s}^{v}[r_t(u,u)+f_t(u)]\Delta t} f_t(v)\Delta t. \tag{48}$$

By temporarily setting the forward interest rate to 0 in Eq. (48), the first term of denominator in Eq. (46) can be presented in the form of

$$E_t^P(1_{\{t_i'<\tau\}}) = 1 - P_t(1, t_i' - t; r_t(1,u) = 0 \text{ for } 1 \leq u \leq t_i' - t). \tag{49}$$

The solutions to the two remaining two terms of Eq. (46) can be expressed as

$$\begin{aligned}&E_t^p\left[e^{-r_t(1,\tau-t)(\tau-t)/365}\cdot \mathbb{1}_{\left\{t<\tau\leq t_k'\right\}}\right] \\ &= \sum_{q=1}^{t_k'-t} e^{-[r_t(1,q)+\psi_t(1,q)]\cdot(q/365)}\cdot f_t(q)\cdot\Delta t \\ &+ \sum_{q=1}^{t_k'-t} e^{-[r_t(1,q)+\psi_t(1,q)]\cdot(q/365)}\cdot h_t(q)\cdot P_t(q, t_k'-t; r_t(1,v), q \leq v \leq t_k'-t)\cdot\Delta t\end{aligned}$$

;and

$$\begin{aligned}&E_t^p\left[A(t_{i-1}\vee(t+1),\tau)\right]\cdot e^{-r_t(1,\tau-t)(\tau-t)/365}\cdot\mathbb{1}_{\left\{t_{i-1}'<\tau\leq t_i'\right\}} \\ &= \sum_{q=t_{i-1}\vee(t+1)}^{t_i'} A(t_{i-1}\vee(t+1),q)\cdot e^{-[r_t(1,q-t)+\psi_t(1,q-t)]\cdot(q-t)/365}\cdot f_t(q-t)\cdot\Delta t \\ &+ \sum_{q=t_{i-1}\vee(t+1)}^{t_i'} A(t_{i-1}\vee(t+1),q)\cdot e^{-[r_t(1,q-t)+\psi_t(1,q-t)]\cdot(q-t)/365}\cdot h_t(q-t) \\ &\qquad \cdot P_t(q-t, t_i'-t; r_t(1,v), q-t \leq v \leq t_i'-t)\cdot\Delta t\end{aligned}$$

With the formulas mentioned above, we compute the AS, or $S_t^{(a)}(T-t)$, and provide it to the public on a daily basis.

7 CriSIFI

In August 2017, the CRI launched the CRI Systemically Important Financial Institution (CriSIFI) on its website (`http://nuscri.org/srt`). The CriSIFI aims to identify systemic risks of those banks and insurers by capturing their tendency to default together (i.e., too connected to fail) along with their respective asset sizes (i.e., too big to fail). For example, a financial institution with a higher ranking (e.g., 10 is a higher ranking than 20) is likely to pose a higher risk to the financial system and thus has greater systemic importance than does a lower ranked firm. In short, the CriSIFI relies on a novel way to construct a proper financial network which combines nodes and edges of a network.

- Node: firm characteristics captured by the ratio of individual financial institution's assets over the network's total assets
- Edge: network configuration reflected through partial default correlations of financial institutions

Since June 2023, the CRI launched an updated version of CriSIFI, named CriSIFI v2.0. The update incorporates the new default correlation methodology, detailed in Section 3. This update continues to use the NUS-CRI 2020 industry classification system to determine the sample of financial institutions to be taken into account in the computation of global rankings. The use of the NUS-CRI 2020 industry classification increases the number of banks included in the rankings by 900, while the number of insurance firms remains relatively unchanged. Although users of the NUS-CRI website have the option to select between the NUS-CRI 2007 and NUS-CRI 2020 industry classification systems, the new DC methodology has only been implemented on the sample of financial institutions in the NUS-CRI 2020 industry classification system.

The CriSIFI data panel is monthly updated and starts from January 2000. The CriSIFI is updated monthly on the CRI website where all exchanged-traded banks (banks and investment banks) and insurers globally are included. For details, see Table A.1 for the CRI coverage. The new DC methodology update is already available for CriSIFI rankings from Jan-2023 to present. Historical refresh for rankings prior to Jan-2023 will be gradually updated by the NUS-CRI Team. The CriSIFI can be used to track and monitor systemic risk of each financial institution in the global financial system. Apart from the CriSIFI, the CRI reports "the CRI Systemically Important Bank (CriSIB)" and "the CRI Systemically Important Insurer (CriSII)" globally, or within a local community such as region (e.g., North America and Asia-Pacific Developed economies) and economy (e.g., U.S. and Singapore). All three systemic importance indicators can help identify potential systemic risk via financial institutions' connectedness in the global financial network. Next, we explain how to construct the CriSIFI.

7.1 Constructing the forward-looking PD partial correlation matrix

A primary input to the CriSIFI is the forward–looking PD (probability of default) partial correlation matrix, which is used to measure connectedness between financial institutions in the network. This partial correlation matrix is generated from the forward–looking PD total correlation matrix using the model of Duan and Miao [2016], which is a factor model along with sparsely correlated residuals for PDs and POEs (probabilities of other exist) of all firms considered. It is worth noting that POE is a crucial element for properly estimating multiple–period default probabilities, because suitable survival probability of a firm in a multiperiod context cannot be determined without POE (see Duan et al. [2012]). Omitting POE is particularly troublesome when knowing that POEs are empirically many folds larger than PDs.

The construction of forward-looking PD partial correlation matrix follows the new DC methodology detailed in Section 3. The key differences in the new methodology include the incorporation of employing a new factor model that performs variable selection based on the zero-norm variable selection technique proposed in Duan [2019], as well as re-calibrating the DC model generated Period PDs to the Period PDs generated by NUS-CRI. This new methodology follows and builds upon the one detailed in Chan-Lau et al. [2016], which is largely based on Duan and Miao [2016]. Details of the old methodology can be found in Appendix D.

Importantly, we focus on the forward–looking default correlation via simulation, not on the historical average available from the time series of PDs in the CRI database. The reason is that this average measure represents backward-looking comovements, which does not represent the future when one goes through different phases of a credit cycle. In contrast, the forward-looking correlations reflect the currently available information and should better gauge the potential riskiness going forward. Readers who are interested in comparing the forward-looking and backward-looking results are referred to Chan-Lau et al. [2016]. Other practical considerations also favor forward-looking default correlations over historical default correlations. For example, considering 1–year PD correlations over a period of six months instead of one month would see a dramatic reduction in usable sample size by a factor of six.

Apart from the use of the forward–looking PDs, we focus on "partial" not "total" correlations. Partial correlation is the residual correlation after removing any indirect connections through other parties in the network. Conceptually, partial correlation rightfully captures the direct default connection between any two financial institutions. Of course, indirect connections are also of interest for network analysis, but they are already reflected through the network configuration represented by many direct bilateral linkages. We obtain the partial default correlation matrix through a regularization technique.

We use the CONCORD (CONvex CORrelation selection methoD) algorithm of Khare et al. [2015] and Oh et al. [2014]. Conceptually, it amounts to imposing zero partial correlations on pairs with weak ties. The CONCORD algorithm also ensures convergence because it preserves convexity through an appropriate selection of weights and a particular design of the penalty term on the concentration matrix rather than on the partial correlation matrix. In addition, the high dimensional data calls for regularization, simply because high dimensionality left un-regularized may deliver a highly unstable partial correlation matrix. As a result, the globally connected and regularized network will be more stable and does not generate an overwhelmingly large number of systemic firms.

Specifically, the CONCORD objective is to minimize

$$Q_{con}(\Omega) = \frac{N}{2}\left[-\ln\left[\det(\Omega_D^2)\right] + \mathrm{tr}(S_N\Omega^2) + \lambda||\Omega_X||_1\right],$$

where $\det(\cdot)$ denotes the determinant operator; $\mathrm{tr}(\cdot)$ denotes the trace operator; S_N is the sample correlation matrix computed with a sample size of N; $\Omega = \Omega_D + \Omega_X$ is the concentration matrix (i.e., the inverse of the correlation matrix); $\lambda > 0$ is the tuning parameter used to determine the shrinkage rate or how aggressively one penalizes the non–zero entries in Ω_X; $\lambda||\Omega_X||_1 = \lambda\sum_{i\neq j}|\omega_{ij}|$ is the L_1–penalty term; and ω_{ij} is the off–diagonal element in Ω_X. Here, we select a λ below which totally isolated firms in the network begin to emerge. The tolerance error for finding the optimal λ and the partial correlation precision are respectively set to 10^{-3} and 10^{-4}. For technical details, see Chan-Lau et al. [2016].

7.2 Computing the CriSIFI

The CriSIFI is a network centrality indicator used to assess the relative importance of a financial institution in the network, and is the appropriate entry in the non-negative eigenvector of $Q|\bar{P}_{X,t}|Q$ that corresponds to the largest eigenvalue. $|\bar{P}_{X,t}|$ is the absolute value of $\bar{P}_{X,t}$ and $\bar{P}_{X,t}$ denotes the 12–month moving average of $P_{X,t}$, the regularized partial correlation matrix at time t after setting its diagonal elements to 0. Deploying the 12-month moving average is to remove the excessive noise. Q is a diagonal matrix with q_i as its i–th diagonal element where q_i is the size of a financial institution over the total size of the network, measured in USD; Technically, $Q|\bar{P}_{X,t}|Q$ is a non–negative matrix, and the Perron–Frobenius theorem ensures the existence of such a non–negative eigenvector.

The CriSIFI captures both the node (the firm's asset size) and edge (the strength of connectedness reflected in the partial correlation) characteristics in the financial network. We contend that our forward-looking systematic risk ranking, combining both the edge and node characteristics, is much more comprehensive than the alternatives: (1) a backward-looking ranking measure, and (2) any measure that only factors in one of the two characteristics. Therefore, under the CriSIFI small financial institutions being connected to large ones may present significant systemic risks simply due to the feedback effect from their connected larger counter–parties. Chan-Lau et al. [2016] also compare the performance of the CriSIFI with those of other measures such as Global Systemically Important Banks (G-SIBs) released by the Financial Stability Board (FSB). They find that the G-SIBs are likely to be biased toward singling out large financial institutions in the system, and overall connectivity only plays a rather minor role.

8 Probability of Default implied Rating (PDiR)

The CRI team has developed a generic technique that can translate the CRI-PD or any granular PD system into a credit rating/scoring system. The need for such reverse engineering is rather obvious in terms of business applications. The long tradition of credit rating practice has developed a deeply entrenched management infrastructure (business conventions, regulatory regimes and reference knowledge) around it. A credit rating of, say, S&P BBB- and above is known as an investment-grade obligor meeting certain regulatory and/or fiduciary requirements. Merely providing a PD value, regardless of its granularity and scientific quality, simply will not meet usage requirements under many circumstances. In short, a PD system critically needs a rating-equivalent interpretation for its outputs in order to facilitate its business and regulatory adoption.

First introduced by the CRI in 2011, the Probability of Default Implied Rating (PDiR) complements the CRI-PD system by mapping its one-year PD to letter grades used by major rating agencies. The original PDiR method aims to match the expected default rates predicted by the CRI-PD and the average historical default rates of the S&P or Moody's global corporate rating pool. However, due to the lack of realized defaults for top categories like AAA and AA+ for the S&P rating pool, proxy values from a linear extrapolation are adopted which are arguably arbitrary. Moreover, a recent effort to tally the proportion of the firms in the CRI sample falling into each of the rating categories suggests that there have been too many firms in the AAA category as compared to the experience of the S&P or Moody's global corporate rating pool. These two considerations have led to the revision effort to roll out PDiR2.0 based on the work of Duan and Li [2021]. PDiR2.0 has been implemented by the CRI starting April 13, 2020. It enhances the PD mapping by targeting the average realized credit rating migration experienced by the S&P or Moody's global corporate rating pool instead of relying solely on the reported default rates of the pool.

PDiR2.0 determines the suitable boundary CRI-PD levels for each of the rating categories used by rating agencies, and defines the migration rule with buffer zones built in to reflect rating stickiness. Currently, we provide the mapping tables of 1-year PD to PDiR calibrated to the realized credit rating migration history of the S&P and Moody's global rating pool. See Tables C.1 and C.2 for the results as of April 13, 2020. We assign the initial ratings for any firms by mapping its 10-business day moving average PD against the upper and lower bounds in the first 2 columns of the tables. The upper and lower bounds for upgrade/downgrade to a specific cohort are defined in the last 4 columns. The design with migration buffer zones creates latency in rating changes, intending to mimic the commercial credit rating practice. For example, a firm is upgraded from A+ to AA only if its moving average PD is smaller than AA's lower bound defined in the initial assignment. The methodology to estimate the boundary PD values is briefly sketched below.

Step 1: Obtain target rating migration matrix

We obtain the S&P average realized one-year migration matrix over the 18-year sample period (from 2000 to 2017). [8] Our data source (European Securities and Markets Authority's central repository) provides data on the 9 consolidated rating cohorts from the original scale of 21 rating categories by lumping together those with a plus/minus modifier. We then construct rating migration matrix of dimension 9 by 10 with the last column holding the default rates corresponding to the 9 rating cohorts. To account for the substantially different other-exit rates facing S&P and CRI, we gross up each row of the migration matrix with the one minus other-exit rate unique to each rating cohort so that each row of the adjusted migration matrix has a row sum equal to 1. The grossed-up average realized rating migration matrix is our target matrix denoted by $\hat{M}$

Step 2: Obtain PD implied migration matrix

The upper PD bound for a rating category simultaneously serves as the lower bound of the adjacent category of less credit quality. Therefore, 8 cutoff values along with two natural PD bounds of 0 and 1 define the 9 consolidated rating categories. These 8 PD upper bounds are denoted by $\theta = (U_{AAA}, U_{AA}, U_A, U_{BBB}, U_{BB}, U_B, U_{CCC}, U_{CC})$, and they must be increasing in values. We divide each PD segment defined by θ into four subsegments. The top (bottom) 25% subsegment (measured as the percentage of PDs) is reserved for the rating with a minus (plus) modifier, which also help define the migration buffer zones. After the initial rating assignment of a firm, migration to another category only occurs if its 10-day moving average PD crosses beyond a complete finer rating category. That is, an A obligor is downgraded to BBB+ only if its PD moves into the interval defined by BBB. Likewise, to upgrade a BBB+ obligor to A, its PD must move into the interval defined by A+. Category AAA, CC and C do not carry a rating modifier, but they still need buffer zones for migration assignments. To upgrade a firm to AAA (or CC), the 10-day moving average PD must be lower than the PD level corresponding to 75% of the AAA (or CC) interval. To downgrade a firm to CC (or C), the same logic applies, but is instead at the 25% level of the relevant segment.

After assigning firms into the 21 finer rating categories for the CRI sample over the 18-year sample period, we group all firms into the 9 consolidated rating categories, tally the results, and gross up by the other-exit rates to generate the model's implied 9 by 10 average realized migration matrix. Denote the model's final implied rating migration matrix by $M(\theta)$.

Step 3: Calibrate PD boundaries defining PDiR classes

The calibration objective is to find the value of θ that minimizes the sum of squared differences between the S&P observed and PD-implied rating migration matrices, i.e., $\hat{M}$ and $M(\theta)$.

[8] Our data source is European Securities and Markets Authority (ESMA)'s central repository (CEREP).

However, we include only three components in the calibration target. They are the diagonal, two immediate off-diagonal terms (one in each direction) and the 10th column holding default rates. Other elements of the 9 by 10 matrix are ignored because their values are small and prone to sampling errors. In addition to the constraint of increasing values placed on the elements of θ, we require the proportion of AAA firms in the CRI sample to be no less than 1.5%, a level comparable to that of the S&P global corporate rating pool. Without it, we would have substantially fewer AAA firms. Mathematically, we are solving the following minimization problem,

$$\min_{\theta} \sum_{i=1}^{9} \sum_{j \in A_i} (M_{i,j}(\theta) - \hat{M}_{i,j})^2$$
$$subject\ to \begin{cases} \theta\ satisfies\ \ 0 < U_{AAA} < U_{AA} < \cdots < U_{CC} < 1 \\ P_{AAA}(\theta) \geq P_{AAA}(S\&P) = 1.5\% \end{cases}$$

where

$$A_i = \begin{cases} 1, 2, 10 & i = 1 \\ i-1, i, i+1, 10 & 2 \leq i \leq 8 \\ 8, 9, 10 & i = 9 \end{cases}$$

defines the element/column indices included in the objective function. $P_{AAA}(\theta)$ is the percentage of firms classified as AAA according to the PD cutoff values while $P_{AAA}(S\&P)$ is the observed percentage of AAA firms under the S&P global rating pool. The minimization is executed by adopting the density-tempered sequential Monte Carlo (SMC) technique of Duan and Fulop [2015], which is detailed in Duan and Li [2021].

9 Ongoing Developments

The CRI can develop in several directions. We now comment on obvious ones that in our view are likely to bring meaningful and measurable benefits. Besides modifications to the current modeling framework based on forward intensities, a change to the CRI platform will be undertaken if another approach proves to be more promising in terms of accuracy and robustness of results. For that to occur, we rely on the collective efforts by the worldwide credit research community to challenge and improve the existing modeling platform.

Within the current framework, the CRI team has constantly been working on implementing more comprehensive data treatments inclusive of how missing data are handled. The team is also involved in several challenging projects including, for example, (1) implementing a novel DTD estimation based on a density-tempered expanding-data sequential Monte Carlo method, (2) creating/implementing variable and structural-break selections where Artificial Intelligence automatically and smartly identifies time window, crucial risk drivers, and breakpoints to better model defaults, (3) deploying Natural Language Processing to extract media sentiments in business press for the purpose of complementing the vast amount of structural data already in the CRI database, and (4) developing a mixed-frequency calibration of the forward-intensity model where corporate events are measured down to a calendar day but default predictions are conducted on a monthly frequency over the data period.

Finally, a series of applications and tools using the CRI-PDs as an input have already been or will be developed. The CRI team is actively working with users to explore different possibilities of taking advantage of the world-class research infrastructure at the National University of Singapore to propagate real-world applications of cutting-edge credit analytics. As a concrete example, the CRI team has been regularly improving the bottom-up aggregation toolkit, developed in 2015 in collaboration with the International Monetary Fund, for stress testing financial stability of economies around the world. In summary, the CRI team remains committed to making its vast resources current and easily accessible for academic research and industry usage.

Acknowledgements

The NUS Credit Research Initiative is premised on the concept of credit ratings as a "public good". Being a non-profit undertaking allows a high level of transparency and collaboration that other commercial credit rating systems cannot replicate. The research and support infrastructure is in place and researchers from around the world are invited to contribute to this initiative. Any methodological improvements that researchers develop will be incorporated into the CRI system. In essence, the initiative operates as a "selective wikipedia" where many can contribute but implementation control is retained.

If you have feedback on this technical report or wish to work with us in this endeavor, please contact us at nuscri@nus.edu.sg.

A APPENDIX: DATA

Table A.1: All economies under the CRI coverage

Region	Economy
Asia Pacific (Developed) (7)	Australia, Hong Kong, Japan, New Zealand, Singapore, South Korea, Taiwan.
Asia Pacific (Emerging) (17)	Bangladesh, Cambodia, China, India, Indonesia, Kazakhstan, Laos, Macau, Malaysia, Mongolia, Myanmar, Pakistan, Papua New Guinea, Philippines, Sri Lanka, Thailand, Vietnam.
North America (4)	Bermuda, Canada, Greenland, United States.
Western Europe (28)	Austria, Belgium, Cyprus, Denmark, Faeroe Islands, Finland, France, Germany, Gibraltar, Greece, Guernsey, Iceland, Ireland, Italy, Isle of Man, Jersey, Liechtenstein, Luxembourg, Malta, Monaco, Netherlands, Norway, Portugal, Reunion, Spain, Sweden, Switzerland, United Kingdom.
Eastern Europe (21)	Azerbaijan, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Georgia, Hungary, Latvia, Lithuania, Macedonia, Moldova, Montenegro, Poland, Romania, Russian Federation, Serbia, Slovakia, Slovenia, Turkey, Ukraine.
Latin America & Caribbean (23)	Argentina, Bahamas, Barbados, Belize, Brazil, British Virgin Islands, Cayman Islands, Chile, Colombia, Costa Rica, Curacao, Dominican Republic, Falkland Islands, French Guiana, Jamaica, Mexico, Peru, Panama, Puerto Rico, Turks And Caicos Islands, Uruguay, U.S. Virgin Islands, Venezuela.
Middle East & Africa (33)	Angola, Bahrain, Botswana, Cameroon, Egypt, Gabon, Ghana, Iraq, Israel, Jordan, Kenya, Kuwait, Madagascar, Malawi, Mauritius, Morocco, Mozambique, Namibia, Nigeria, Niger Republic, Oman, Qatar, Rwanda, Saudi Arabia, Sierra Leone, South Africa, Sudan, Tanzania, Togo, Tunisia, Uganda, United Arab Emirates, Zambia.

Table A.2: The 88 economies under the CRI coverage for which we cover companies listed on the exchange.

Region	**Economy**
Asia Pacific (Developed) (7)	Australia, Hong Kong, Japan, New Zealand, Singapore, South Korea, Taiwan.
Asia Pacific (Emerging) (11)	Bangladesh, China, India, Indonesia, Kazakhstan, Malaysia, Pakistan, Philippines, Sri Lanka, Thailand, Vietnam.
North America (2)	Canada, United States.
Western Europe (20)	Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom.
Eastern Europe (18)	Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Macedonia, Montenegro, Poland, Romania, Russian Federation, Serbia, Slovakia, Slovenia, Turkey, Ukraine.
Latin America & Caribbean (8)	Argentina, Brazil, Colombia, Chile, Jamaica, Mexico, Peru, Venezuela.
Middle East & Africa (22)	Bahrain, Botswana, Egypt, Ghana, Israel, Jordan, Kenya, Kuwait, Malawi, Mauritius, Morocco, Namibia, Nigeria, Oman, Qatar, Rwanda, Saudi Arabia, South Africa, Tunisia, Uganda, United Arab Emirates, United Republic of Tanzania.

Table A.3: The 48 economies under the CRI coverage for which we cover companies domiciled in the economy but listed on a foreign exchange included in Table A.2. The gray boxes indicate that these economies also have their own local stock exchange.

Angola	Gambia	Monaco
Azerbaijan	Gabon	Mozambique
Bahamas	Georgia	Marshall Island
Barbados	Gibraltar	Panama
Belize	Greenland	Papua New Guinea
Bermuda	Guernsey	Puerto Rico
British Virgin Islands	Iraq	Reunion
Cambodia	Isle of Man	Senegal
Cameroon	Jersey	Sierra Leone
Cayman Islands	Laos	Sudan
Costa Rica	Liechtenstein	Togolese Republic
Curacao	Macau	Trinidad and Tobago
Democratic Republic of the Congo	Madagascar	Turks And Caicos Islands
Faeroe Islands	Myanmar	United States Virgin Islands
Falkland Islands	Moldova	Uruguay
French Guiana	Mongolia	Zimbabwe

Table A.4: The ISO codes of 88 economies covered by the CRI and the corresponding calibration groups and stock exchanges.

ISO Code	Economy	Calibration Group	Stock Exchange
ARE	United Arab Emirates	Emerging	Abu Dhabi Securities Exchange
			Dubai Financial Market
			National Association of Securities Dealers
ARG	Argentina	Emerging	Buenos Aires Stock Exchange
AUS	Australia	Developed Asia-Pacific	Australian Securities Exchange
			National Stock Exchange of Australia
			SIM Venture Securities Exchange
AUT	Austria	Europe	Vienna Stock Exchange
BEL	Belgium	Europe	Brussels Stock Exchange
BGD	Bangladesh	Emerging	Dhaka Stock Exchange
BGR	Bulgaria	Europe	Bulgarian Stock Exchange
BHR	Bahrain	Emerging	Bahrain Stock Exchange
BIH	Bosnia and Herzegovina	Europe	Banja Luka Stock Exchange
			Sarajevo Stock Exchange
BRA	Brazil	Emerging	BM&FBOVESPA
BWA	Botswana	Emerging	Botswana Domestic Companies Index
CAN	Canada	North America	Canadian Securities Exchange
			TSX Venture Exchange
			Toronto Stock Exchange
CHE	Switzerland	Europe	Berne Stock Exchange
			Six Swiss Exchange
CHL	Chile	Emerging	Santiago Stock Exchange
CHN	China	China	Shanghai Stock Exchange
			Shenzhen Stock Exchange
COL	Colombia	Emerging	Colombia Stock Exchange
CYP	Cyprus	Europe	Cyprus Stock Exchange
CZE	Czech Republic	Europe	Prague Stock Exchange
DEU	Germany	Europe	Berlin Stock Exchange
			BOAG Borsen AG
			Dusseldorf Stock Exchange
			Frankfurt Stock Exchange
			Munich Stock Exchange
			Stuttgart Stock Exchange
DNK	Denmark	Europe	Copenhagen Stock Exchange
			First North Denmark
EGY	Egypt	Emerging	Egyptian Exchange
			Nile Stock Exchange
ESP	Spain	Europe	Barcelona Stock Exchange
			Madrid Stock Exchange
EST	Estonia	Europe	Tallinn Stock Exchange

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Table A.4 – *Continued from previous page*

ISO Code	Economy	Calibration Group	Stock Exchange
FIN	Finland	Europe	Helsinki Stock Exchange
			NASDAQ OMX NORDIC
FRA	France	Europe	Euronext Paris
GBR	United Kingdom	Europe	Icap Securities and Derivatives Exchange
			London International Financial Futures and Options Exchange
			London Stock Exchange
			Professional Liability Underwriting Society Market Group
GHA	Ghana	Emerging	GSE Composite Index
GRC	Greece	Europe	Alternative Market of Athens Exchange
			Athens Stock Exchange
HKG	Hong Kong	Developed Asia-Pacific	Hong Kong Exchanges and Clearing Limited
HRV	Croatia	Europe	Zagreb Stock Exchange
HUN	Hungary	Europe	Budapest Stock Exchange
IDN	Indonesia	Emerging	Indonesian Stock Exchange
IND	India	India	Bombay Stock Exchange
			MCX Stock Exchange Limited
			National Stock Exchange of India Limited
IRL	Ireland	Europe	Irish Stock Exchange
ISL	Iceland	Europe	Iceland Stock Exchange
ISR	Israel	Europe	Tel Aviv Stock Exchange
ITA	Italy	Europe	Borsa Italiana S.p.A
			Hi-Multilateral Trading Facilities Sim S.p.A
JAM	Jamaica	Emerging	Jamaica Stock Exchange
JOR	Jordan	Emerging	Amman Stock Exchange
JPN	Japan	Developed Asia-Pacific	Fukuoka Stock Exchange
			JASDAQ Securities Exchange
			Nagoya Stock Exchange
			Osaka Securities Exchange
			Sapporo Stock Exchange
			Tokyo Stock Exchange
KAZ	Kazakhstan	Emerging	Kazakhstan Stock Exchange JSC
KEN	Kenya	Emerging	Kenya Nairobi Stock Exchange Index
KOR	South Korea	Developed Asia-Pacific	Korea New Exchange
			Korea Stock Exchange
			Korean Securities Dealers Automated Quotations
KWT	Kuwait	Emerging	Kuwait Stock Exchange
			Bloomberg Kuwait Premier Market Total Return Index
LKA	Sri Lanka	Emerging	Colombo Stock Exchange
LTU	Lithuania	Europe	OMX Vilnius Stock Exchange

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Table A.4 – *Continued from previous page*

ISO Code	Economy	Calibration Group	Stock Exchange
LUX	Luxembourg	Europe	Luxembourg Stock Exchange
LVA	Latvia	Europe	OMX Riga Stock Exchange
MAR	Morocco	Emerging	Casablanca Stock Exchange
MEX	Mexico	Emerging	Mexican Stock Exchange
MKD	Macedonia	Europe	Macedonian Stock Exchange Inc.
MLT	Malta	Europe	Malta Stock Exchange
MNE	Montenegro	Europe	Montenegro Stock Exchange
MUS	Mauritius	Emerging	Mauritius Stock Exchange SEMDEX Index
MWI	Malawi	Emerging	Malawi All Share Index
MYS	Malaysia	Emerging	Kuala Lumpur Stock Exchange
NAM	Namibia	Emerging	Namibia Overal Index
NGA	Nigeria	Emerging	Nigerian Stock Exchange
NLD	Netherlands	Europe	Euronext Amsterdam Stock Exchange
NOR	Norway	Europe	Oslo Stock Exchange
NZL	New Zealand	Developed Asia-Pacific	New Zealand Exchange
OMN	Oman	Emerging	Muscat Securities Market
PAK	Pakistan	Emerging	Karachi Stock Exchange
			Pakistan Stock Exchange
PER	Peru	Emerging	Lima Stock Exchange
PHL	Philippines	Emerging	Philippine Stock Exchange
POL	Poland	Europe	Warsaw Stock Exchange
PRT	Portugal	Europe	Euronext Lisbon Stock Exchange
QAT	Qatar	Emerging	Qatar Exchange (QE) Index
ROM	Romania	Europe	Bucharest Stock Exchange
			Sibiu Stock Exchange
RUS	Russian Federation	Europe	Moscow Exchange
			Moscow Interbank Currency Exchange
			Russian Trading System
RWA	Rwanda	Emerging	Rwanda Stock Exchange All Share Index
SAU	Saudi Arabia	Emerging	Saudi Stock Exchange
SGP	Singapore	Developed Asia-Pacific	Singapore Exchange
SRB	Serbia	Europe	Belgrade Stock Exchange
SVK	Slovakia	Europe	Bratislava Stock Exchange
SVN	Slovenia	Europe	Ljubljana Stock Exchange
SWE	Sweden	Europe	AktieTorget Stock Exchange
			First North Stockholm
			Nordic Growth Market
			Stockholm Stock Exchange
THA	Thailand	Emerging	Stock Exchange of Thailand
TUN	Tunisia	Emerging	Tunis Stock Exchange
TUR	Turkey	Europe	Istanbul Stock Exchange

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Table A.4 – *Continued from previous page*

ISO Code	Economy	Calibration Group	Stock Exchange
TWN	Taiwan	Developed Asia-Pacific	Taiwan Stock Exchange
TZA	United Republic of Tanzania	Emerging	Tanzania Share (TSI) Index
UGA	Uganda	Emerging	Uganda SE All Share Index
UKR	Ukraine	Europe	First Stock Trading System
			Russian Trading System Ukraine
USA	United States	North America	NASDAQ Capital Market
			NASDAQ Global Market
			NASDAQ Global Select Market
			New York Stock Exchange
			NYSE Arca
			NYSE MKT LLC
			Bats Stock Exchange
VEN	Venezuela	Emerging	Caracas Stock Exchange
VNM	Vietnam	Emerging	Hanoi Stock Exchange
			Ho Chi Minh City Stock Exchange
ZAF	South Africa	Emerging	Johannesburg Stock Exchange

The stock exchanges covered by the CRI database are collected from Bloomberg system and labeled as primary exchange.

Table A.5: The stock indices used for each economy in computing the first common variable.

Economy	Stock Index	Period Used*
ARE	FTSE NASDAQ DUB UAE 20	06/28/2006 - Present
ARG	Buenos Aires Stock Exchange Merval Index	
AUS	All Ordinaries Index	
AUT	Austrian Traded ATX Index	
BEL	Belgian Stk Mkt Ret Index	
BGD	DSEX Index	01/28/2013 - Present
	Dhaka Stock Exchange General I	- 01/27/2013
BGR	Bulgaria Stock Exchange Sofix Index	10/24/2000 - Present
BHR	BB All Share Index	07/08/2004 - Present
BIH	SASE Free Market 10 Index	12/31/2004 - Present
BRA	Brazil Bovespa Stock Index	
BWA	Botswana Domestic Companies Index	06/30/1989 - Present
CAN	S&PTSX Composite Index	
CHE	SPI Swiss Performance Index	
CHL	Santiago Stock Exchange IPSA Index	
CHN	Shanghai SE Composite Index	12/19/1990 - Present
COL	FTSE All World Series Colombia Local	01/01/1999 - Present
CYP	Cyprus Stock Exchange General Index	09/03/2004 - Present
	Cyprus Stock Exchange General	04/02/1996 - 09/02/2004
CZE	Prague Stock Exchange Index	04/05/1994 - Present
DEU	CDAX Performance Index	
DNK	OMX Copenhagen 20 Index	
EGY	EGX 100EW Index	10/05/2020 - Present
	EGX 100 Index	05/01/2006 - 09/05/2020
ESP	IBEX 35 Index	
EST	OMX Tallinn OMXT	06/03/1996 - Present
FIN	OMX Helsinki Index	
FRA	CAC 40 Index	
GBR	FTSE 100 Index	
GHA	GSE Composite Index	12/31/2010 - Present
GRC	Athex Composite Share Price Index	
HKG	Hang Seng Index	
HRV	Croatia Zagreb CROBEX	06/14/2002 - Present
HUN	Budapest Stock Exchange Index	01/02/1991 - Present
IDN	Jakarta Composite Index	
IND	BSE Sensex 30 Index	
IRL	ISEQ Overall Index	
ISL	OMX Iceland All-Share PR	12/31/1992 - Present
ISR	Tel Aviv 100 Index	12/31/1991 - Present
ITA	FTSE Italia All-share Index	11/02/2020 - Present
	Italy Stock Market BCI Comit Globale	- 10/02/2020
JAM	Jamaica Stock Exchange Market Index	
JOR	MSCI Jordan Index	
JPN	Nikkei 500	
KAZ	Kazakhstan Stock Exchange Index KASE	07/12/2000 - Present
KEN	Keyna Nairobi Stock Exchange Index	01/11/1990 - Present
KOR	KOSPI Index	
KWT	Bloomberg Kuwait Premier Market Total Return Index	04/01/2018 - Present
	Kuwait SE Weighted Index	01/02/2012 - 03/31/2018

Continued on next page

Table A.5 – *Continued from previous page*

Economy	Stock Index	Period Used*
	Kuwait Global General Index	- 01/01/2012
LKA	Sri Lanka Colombo Stock Exchange All-Share Index	
LTU	OMX Vilnius OMXV	01/04/2000 - Present
LUX	Luxembourg Stock Exchange Luxx Index	01/04/1999 - 01/04/1999
	Luxembourg Stock Exchange 13 'Dead'	01/02/1998 - 01/03/1999
LVA	OMX Riga OMXR	01/03/2000 - Present
MAR	MASI Free Float All Shares Index	03/31/1995 - Present
	CFG 25 CFG 25	12/31/1993 - 03/30/1995
MEX	Mexico Bolsa Index	01/19/1994 - Present
MKD	Macedonian Stock Exchange MBI 10	12/30/2004 - Present
MLT	Malta Stock Exchange	12/27/1995 - Present
MNE	Montenegro Stock Exchange Index	01/04/2015 - Present
	Montenegro Stock Exchange 20	03/03/2003 - 03/31/2015
MUS	Mauritius Stock Exchange SEMDEX Index	07/05/1989 - Present
MWI	Malawi All Share Index	11/15/1996 - Present
MYS	FTSE Bursa Malaysia KLCI	
NAM	Namibia Overall Index	12/19/2003 - Present
NGA	Nigeria Stock Exchange All Share	01/30/1998 - Present
NLD	AEX-Index	
NOR	OBX Price Index	
NZL	NZX All Index	03/30/1992 - Present
OMN	MSM30 Index	03/31/1992 - Present
PAK	Karachi All Share Index	03/11/1998 - Present
PER	S&PBVL Peru General Index TR PEN	01/05/2015 - Present
	Bolsa de Valores de Lima General Sector Index	01/02/1990 - 04/30/2015
PHL	Philippine Stock Exchange Index	
POL	WSE WIG Index	04/16/1991 - Present
PRT	PSI General Index	
QAT	Qatar Exchange (QE) Index	08/10/1998 - Present
ROM	Bucharest BET Plus Index	06/23/2014 - Present
	BSE Composite Index	04/17/1998 - 06/22/2014
RUS	MICEX Index	09/22/1997 - Present
RWA	Rwanda Stock Exchange All Share Index	01/10/2013 - Present
SAU	Tadawul All Share Index	01/31/1994 - Present
SGP	Straits Times Index	1/10/2008 - Present
	Straits Times Old Index	01/04/1985 - 01/09/2008
SRB	BELEXline Index	10/01/2004 - Present
SVK	Slovak Share Index	09/14/1993 - Present
SVN	HSBC Slovenia Dollar	12/29/1995 - Present
SWE	OMX Stockholm All-Share	
THA	Stock Exchange Of Thai Index	
TUN	Tunis SE TUNINDEX	04/30/1999 - Present
TUR	Istanbul Stock Exchange National 100 Index	
TWN	Taiwan Stock Exchange Weighted Index	
TZA	Tanzania Share (TSI) Index	04/03/2009 - Present
UGA	Uganda SE All Share Index	10/28/2003 - Present
UKR	Ukraine PFTS Index	01/12/1998 - Present
USA	S&P 500 Index	
VEN	Caracas Stock Exchange Stock Market Index	12/30/1993 - Present
VNM	Ho Chi Minh Stock Index	07/28/2000 - Present
ZAF	MSCI South Africa Index	12/31/1992 - Present

* A blank Period Used column indicates that there is only a single index that is used throughout the whole period.

Table A.6: The interest rates used for each economy as the second common variable.

Economy	Short-Term Interest Rate	Period Used*
ARE	UAE Ibor 3 Month	05/15/2000 - Present
ARG	Argentina Deposit Tate 90 Day	04/01/1991 - Present
AUS	Australia Dealer Bill 90 Day	
AUT	Germany 3 Month Bubill	01/01/1999 - Present
	AUSTRIA VIBOR 3 MONTH	06/10/1991 - 12/31/1998
BEL	Germany 3 Month Bubill	01/01/1999 - Present
	BELGIUM TREASURY BILL 3 MONTH	01/30/1991 - 12/31/1998
BGD	Bangladesh 3 Month Bill Auction Cut Off Yield	
BGR	Bulgaria Interbank 3 Month	02/17/2003 - Present
BHR	Bahrain Ibor 3 Month	12/14/2006 - Present
BIH	-	
BRA	Andima Brazil Govt Bond Fixed Rate 3 Months	04/03/2000 - Present
	Brazil CDB (Up To 30 Days)	10/10/1994 - 04/02/2000
BWA	Botswana 3 Month T-Bill Auction Average Yield	1/04/2020 - Present
	Botswana, Treasury Bills, Nominal Yield, 3 Month Average	11/01/2004 - 31/01/2020
CAN	Canada Treasury Bill 3 Month	01/02/1990 - Present
CHE	Swiss Interbank 3m (ZRC:SNB)	
CHL	Chile Overnight Interbank Interest Rate	05/29/1995 - Present
	Chile TAB UF Interbank Rate 90 Days	11/02/1992 - 05/28/1995
CHN	China Time Deposit Rate, 3 Month	05/17/1993 - Present
COL	Colombia CD Rate 90-Day	
CYP	Germany 3 Month Bubill	01/01/2008 - Present
	Cyprus, TREASURY BILL RATE - 13 WEEK	01/15/1993 - 12/31/2007
CZE	Czech Republic Interbank 3 Month	04/22/1992 - Present
DEU	Germany 3 Month Bubill	05/25/1993 - Present
	Germany Interbank 3 Month	01/02/1986 - 05/24/1993
DNK	Denmark Interbank 3 Month	
EGY	Egypt 91 Day T-Bill	07/06/2004 - Present
ESP	Germany 3 Month Bubill	01/01/1999 - Present
	Spain 3 Month Treasury Bill Yield	11/30/1992 - 12/31/1998
	SPAIN INTERBANK 3 MONTH	12/19/1991 - 11/29/1992
EST	Germany 3 Month Bubill	01/01/2011 - Present
	Estonia, Interest Rates, Prices, Production, & Labour, Interest Rates, DEPOSIT RATE	02/15/1993 - 12/31/2010
FIN	Germany 3 Month Bubill	01/01/1999 - Present
	FINLAND INTERBANK CLOSE 3 MONT	04/01/1992 - 12/31/1998
FRA	Germany 3 Month Bubill	01/01/1999 - Present
	France Treasury Bills 3 Month Intraday	12/29/1995 - 12/31/1998
GBR	UK Treasury Bill Tender 3 Month	01/04/1995 - Present
GHA	Ghana 12 Month T-Bill Auction Average Yield	11/02/2020 - Present
	Ghana 3 Month Bill Auction Average Yield	11/02/2007 - 10/02/2020
GRC	Germany 3 Month Bubill	01/01/2000 - Present
	GREECE TREASURY BILL 3 MONTH	01/02/1990 - 12/31/1999
HKG	Hong Kong Exchange Fund Bill 3 Month	06/10/1991 - Present
HRV	Croatia Zibor Rate 3 Month	06/02/1997 - Present
HUN	Hungary Interbank 3 Month	09/07/1995 - Present

Continued on next page

Table A.6 – *Continued from previous page*

Economy	Short-Term Interest Rate	Period Used*
IDN	Indonesia Interbank 3 Months	07/10/2003 - Present
	Indonesia SBI/DISC 90 Day'dead'	- 07/09/2003
IND	India Treasury Bill 3 Month	05/20/2013 - Present
	India T-Bill Secondary 91 Day	01/15/1993 - 05/19/2013
IRL	Germany 3 Month Bubill	01/01/1999 - Present
	IRELAND INTERBANK 3 MONTH	01/20/1984 - 12/31/1998
ISL	Iceland Interbank 3 - Month	08/04/1998 - Present
	Iceland 90 - Day Cb Notes	- 08/03/1998
ISR	Israel T-Bill Secondary 3 Mnth	05/30/1995 - Present
ITA	Germany 3 Month Bubill	01/01/1999 - Present
	Italy Bots Treasury Bill 3 Month Intraday Gross Yields	09/05/1994 - 12/31/1998
	ITALY T-BILL AUCT. GROSS 3 MONTH	01/15/1988 - 09/04/1994
JAM	Bloomberg Bank of Jamaica 3 Month Treasury Bill Yield	11/30/2010 - Present
	Jamaica 3 Months Repo Rate	07/17/2008 - 11/29/2010
JOR	Jordanian Dinar Interbank Offered Rate 3 Months	09/20/2006 - Present
	Jordan Re-discount rate	03/12/2001 - 09/19/2006
JPN	Japan Treasury Discount Bills 3 Month	07/10/1992 - Present
	Japan Government Bond Interest Rate - 1 Year	- 07/09/1992
KAZ	Kazakhstan KEY MONETARY POLICY INSTRUMENT: BASE RATE	09/04/2021 - Present
	Kazakhstan KIBOR/KIBID 90 Days Interbank	09/29/2001 - 09/04/2021
KEN	Thomson Reuters Kenya GVT BMK Bid Yield 3 Months	05/26/2009 - Present
KOR	Korea Commercial Paper 91d	06/14/1993 - Present
KWT	Kuwait Interbank 3 Month	
LKA	Sri Lanka Treasury Bill 3 Month	
LTU	Germany 3 Month Bubill	01/01/2015 - Present
	VILNIUS INTERBANK THREE MONTH	01/06/1999 - 12/31/2014
LUX	Germany 3 Month Bubill	01/01/1999 - Present
	LONG TERM GOVERNMENT BOND YIELDS - MAASTRICHT DEFINITION (AVG.)	01/15/1985 - 12/31/1998
LVA	Germany 3 Month Bubill	01/01/2014 - Present
	TREASURY BILL RATE 3 MONTH	05/11/1994 - 12/31/2013
MAR	Morocco Deposit Rate 3 Month	06/06/2003 - Present
MEX	Mexico Cetes 2nd Mkt. 90 Day	06/26/1996 - Present
	Mexico CETES 91 Day Avg.Ret.At Auc.	- 06/25/1996
MKD	Macedonia Skibor 3 Months	07/02/2007 - Present
MLT	Germany 3 Month Bubill	01/01/2008 - Present
	LONG TERM GOVERNMENT BOND YIELDS - MAASTRICHT DEFINITION (AVG.)	01/15/1985 - 12/31/2007
MNE	-	
MUS	Thomson Reuters Mauritius GVT BMK Bid Yield 1 Year	05/26/2010 - Present
MWI	Malawi 3 Month T-Bill Auction Average Yield	01/02/2009 - Present
MYS	Malaysia Deposit 3 Month	
NAM	Namibia, Treasury Bills, Effective Yield, 3 Month	05/01/1991 - Present
NGA	Nigeria Interbank Offered Rate 3 Month	01/30/2004 - Present
NLD	Germany 3 Month Bubill	01/01/1999 - Present

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Table A.6 – *Continued from previous page*

Economy	Short-Term Interest Rate	Period Used*
	Netherlands Interbank 3 Month	01/02/1979 - 12/31/1998
NOR	Norway Govt Treasury Bills 3 Month	06/27/1995 - Present
	Norway Interbank 3 Month (Effective)	- 06/26/1995
NZL	-	
OMN	OMR 3 Month Deposit	07/16/2002 - Present
PAK	Reuters Pakistan Repo 3 Month Rate	01/02/2002 - Present
	PKR 3 Month Repo	10/29/1999 - 01/01/2002
PER	Bloomberg Asbanc Peru 3 Months Nominal Rate	09/30/2002 - Present
	Peru Savings Rate	07/01/1991 - 09/29/2002
PHL	Philippine Treasury Bill 91d	
POL	Poland Interbank 3 Month (EOD)	06/04/1993 - Present
PRT	Germany 3 Month Bubill	01/01/1999 - Present
	Portugal 1–year - LISBOB - Act/365 Day convention	- 12/31/1998
QAT	Qatar 3 Month T–Bill Auction Average Yield	05/08/2012 - Present
ROM	Romanian Interbank 3 Month	08/01/1995 - Present
RUS	MosPime 3 Months Rate	04/18/2005 - Present
	Russia Moscow Interbank Non Co	08/14/2000 - 04/17/2005
	Russia Interbank 31 To 90 Day	09/01/1994 - 08/13/2000
RWA	Rwanda 3 Month Bill Auction Average Yield	04/22/2009 - Present
SAU	Saudi Interbank 3 Month	
SGP	Monetary Authority of Singapore Benchmark Govt Bill Yield 3 Month	09/20/2013 - Present
	Singapore T-Bill 3 Month	- 09/19/2013
SRB	National Bank of Serbia Belibor 3M Rate (Interbank Rate)	01/28/2005 - Present
SVK	Germany 3 Month Bubill	01/01/2009 - Present
	SLOVAK REP. INTERBANK 3 MTH	06/23/1994 - 12/31/2008
SVN	Germany 3 Month Bubill	01/01/2007 - Present
	SLOVENIA TREASURY BILL 3 MONTH’DEAD’	10/29/1998 - 12/31/2006
SWE	Sweden T Bill 3 Month	05/25/1993 - Present
	Sweden Treasury Bill 90 Day	- 05/24/1993
THA	Thailand Bibor Fixings 3 Month	05/30/2002 - Present
	Thailand Repo 3 Month (BOT)’Dead’	03/11/1994 - 05/29/2002
TUN	Tu Policy Rates: TMM (Avg.)	12/15/1994 - Present
TUR	Turkish Interbank 3 Month	08/01/2002 - Present
TWN	Taiwan Money Market 90 Day	
TZA	Tanzania 3 Month Bill Auction Average Yield	01/02/2003 - Present
UGA	Uganda 3 Month Bill Auction Average Yield	01/05/2005 - Present
UKR	Ukraine Interbank 3 Months	03/01/2001 - Present
USA	US Generic Govt 3 Month Yield	
VEN	Venezuela 90 Day Deposit Rate	01/10/1997 - Present
	Venezuela Overnight	11/28/1994 - 01/09/1997
VNM	Vietnam Interbank 3 Month	12/11/1998 - Present
ZAF	SA T-Bill 91 Days (Tender Rates)	

* A blank Period Used column indicates that there is only a single interest rate that is used throughout the whole period.

Table A.7: The interest rates used for each economy in the DTD calculation.

Economy	Interest Rate Name	Period Used*
ARE	UAE IBOR 1 Year	05/15/2000 - Present
ARG	Argentina Deposit 90 Day (PA.)	04/01/1991 - Present
AUS	Australia Govt Bonds Generic Mid Yield 1 Year	
AUT	German Government Bonds 1 Year BKO	01/01/1999 - Present
	Austria VIBOR 12 Month	06/10/1991 - 12/31/1998
BEL	German Government Bonds 1 Year BKO	01/01/1999 - Present
	Belgium Treasury Bill 1 Year	04/02/1991 - 12/31/1998
BGD	Bangladesh 12 Month Bill Auction Cut Off Yield	
BGR	Bulgaria Interbank 3 Month	02/17/2003 - Present
BHR	Bahrain IBOR 1 Year	12/14/2006 - Present
BIH	Reuters Bosnia and Herzegovina, Interest Rates, Deposite Rate	09/14/1998 - Present
	BP Real Interest Rate (%) NADJ	06/30/1998 - 09/13/1998
BRA	Andima Brazil Govt Bond Fixed Rate 1 Year	04/03/2000 - Present
	Brazil CDB (Up To 30 Days)	10/10/1994 - 04/02/2000
BWA	Thomson Reuters Botswana Pula 1 Year Deposit	07/27/2010 - Present
CAN	Canada Treasury Bill 1 Year	01/02/1990 - Present
CHE	Swiss Interbank 1 Year (ZRC:SNB)	
CHL	Chile Overnight Interbank Interest Rate	05/29/1995 - Present
	Chile Tab UF Interbank Rates 90 Days	11/02/1992 - 05/28/1995
CHN	China Household Savings Deposits 1 Year Rate	01/02/1992 - Present
COL	Colombia Government Generic Bond 1 Year Yield	01/03/2001 - Present
	Colombia CD Rate 360-Day	07/12/1993 - 01/02/2001
CYP	German Government Bonds 1 Year BKO	01/01/2008 - Present
	Cyprus, Treasury Bill Rate - 13 Week	01/15/1993 - 12/31/2007
CZE	Czech Republic Interbank 3 Month	04/22/1992 - Present
DEU	German Government Bonds 1 Year BKO	01/10/1995 - Present
	Germany Interbank 12 Month	11/02/1990 - 01/09/1995
DNK	Denmark Government Bonds 1 Year Note Generic Bid Yield	06/19/2008 - Present
	Denmark Euro-Krone 1 Year (FT/ICAP/TR)	06/14/1985 - 06/18/2008
EGY	Egypt 364 Day T-Bill	07/06/2004 - Present
ESP	German Government Bonds 1 Year BKO	01/01/1999 - Present
	Spain 12 Month Treasury Bill Yield	11/30/1992 - 12/31/1998
	Spain Interbank 12 Month	12/19/1991 - 11/29/1992
EST	German Government Bonds 1 Year BKO	01/01/2011 - Present
	Estonia, Interest Rates, Prices, Production, & LABOUR, Interest Rates, Deposit Rate	02/15/1993 - 12/31/2010
FIN	German Government Bonds 1 Year BKO	01/01/1999 - Present
	Finland Interbank Close 12 Month	04/02/1992 - 12/31/1998
FRA	German Government Bonds 1 Year BKO	01/01/1999 - Present
	France Treasury Bill 1 Year Intraday	- 12/31/1998
GBR	UK Govt Bonds 1 Year Note Gene	09/12/2001 - Present
	UK Govt. Liab. Nom. Spot Curve 12 Month	- 09/11/2001
GHA	Ghana 1YR Note Auction Average Yield	11/02/2007 - Present
GRC	German Government Bonds 1 Year BKO	01/01/2001 - Present
	Greece Treasury Bill 1 Year	01/02/1990 - 12/31/2000
HKG	HKMA Hong Kong Exchange Fund Bills 12 Month	10/28/1991 - Present
HRV	Croatia ZIBOR Rate 3 Month	06/02/1997 - Present
HUN	Hungary Central Bank Base Rate	10/15/1990 - Present

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Table A.7 – *Continued from previous page*

Economy	Interest Rate Name	Period Used*
IDN	INDONESIA SBI 90 DAY	07/10/2003 - Present
	INDONESIA SBI/DISC 90 DAY'DEAD'	01/01/1985 - 07/09/2003
IND	India Treasury Bill 1 Year	05/20/2013 - Present
	INDIA T-BILL SECONDARY 1 YEAR	01/01/1993 - 05/19/2013
IRL	German Government Bonds 1 Year BKO	01/01/1999 - Present
	Dublin Interbank Offered Rates	04/10/1991 - 12/31/1998
ISL	Iceland Interbank 12 - Month	02/01/2000 - Present
	Iceland Interbank 3 - Month	08/04/1998 - 01/31/2000
	Iceland 90 - Day CD Notes	- 08/03/1998
ISR	Israel T-Bill Secondary 1 Year	11/15/1994 - Present
ITA	German Government Bonds 1 Year BKO	01/01/1999 - Present
	Italy Bots Treasury Bill 12 Month Gross Yields	09/05/1994 - 12/31/1998
	Italy T-Bill Auct. Gross 12 Month	- 09/04/1994
JAM	Bloomberg Bank of Jamaica 6 Month Treasury Bill Yield	03/13/2017 - Present
	Jamaica 12 Months Repo Rate	07/17/2008 - 03/12/2017
JOR	Bllomberg Jordanian Dinar Interbank Offered Rate 1 Year	09/20/2006 - Present
	Jordan Re-Discount Rate	03/12/2001 - 09/19/2006
JPN	Japan Treasury Bills 12 Month	12/14/1999 - Present
KAZ	Kazakhstan KEY MONETARY POLICY INSTRUMENT: BASE RATE	09/04/2021 - Present
	Kazakhstan KIBOR/KIBID 90 Days Interbank	09/29/2001 - 09/04/2021
KEN	Thomson Reuters Kenya GVT BMK Bid Yield 1 Year	05/26/2009 - Present
KOR	Korea Monetary Stab. Bonds 1 Year	01/03/1992 - Present
KWT	Kuwait Interbank 1 Year	
LKA	Sri Lanka Fixed Deposit 1 Year	
LTU	German Government Bonds 1 Year BKO	01/01/2015 - Present
	Vilnius Interbank 12 Month	03/29/2000 - 12/31/2014
LUX	German Government Bonds 1 Year BKO	01/01/1999 - Present
	Long Term Government Bond Yields - Maastricht Definition (Avg.)	- 12/31/1998
LVA	German Government Bonds 1 Year BKO	01/01/2014 - Present
	Treasury Bill Rate 1 Year	04/03/1996 - 12/31/2013
MAR	Morocco Deposit Rate 1 Year	06/06/2003 - Present
MEX	Mexico Cetes 2nd Mkt. 360 Day	06/26/1996 - Present
	Mexico Cetes 91 Day Avg.Ret.At Auc.	- 06/25/1996
MKD	Macedonia SKIBOR 3 Months	07/02/2007 - Present
MLT	German Government Bonds 1 Year BKO	01/01/2008 - Present
	Long Term Government Bond Yields - Maastricht Definition (Avg.)	01/15/1985 - 12/31/2007
MNE	Montenegro INTEREST RATES: Government Securities	09/04/2021 - Present
	Treasury Bill Rate - 182-Day (EP)	07/16/2004 - 09/04/2021
MUS	Thomson Reuters Mauritius GVT BMK Bid Yield 1 Year	05/26/2010 - Present
MWI	MALAWI 12 Month Bill Auction Average Accepted Yield	03/06/2012 - Present
MYS	Bank Negara Malaysia 1 Year Govt Securities Indicative YTM	06/21/2005 - Present
	Malaysia Deposit 1 Year	- 06/20/2005
NAM	Namibia 12 Month Bill Auction Average Yield	03/13/2002 - Present
NGA	Nigeria Interbank Offered Rate 12 Month	09/29/2011 - Present
	Nigeria Interbank Offered Rate 3 Month	01/30/2004 - 09/28/2011

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Table A.7 – *Continued from previous page*

Economy	Interest Rate Name	Period Used*
NLD	German Government Bonds 1 Year BKO	01/01/1999 - Present
	Netherland Interbank 1 Year	- 12/31/1998
NOR	Norway Govt Treasury Bills 12 Month	07/01/1997 - Present
	Norway Interbank 1 Year	- 06/30/1997
NZL	New Zealand Dollar Deposit 1 Year	
OMN	OMR 12 Month Deposit	07/16/2002 - Present
PAK	Bloomberg State Bank of Pakistan KIBOR Fixing 12 Month Rate	04/19/2004 - Present
	PKR 12 Month Repo	10/29/2004 - 04/18/2004
PER	Bloomberg Asbanc Peru 1 Year Nominal Rate	09/30/2002 - Present
	Peru Savings Rate	07/01/1991 - 09/29/2002
PHL	Philippine Treasury Bill 364d	
POL	Poland Interbank 1 Year (EOD)	10/11/1995 - Present
PRT	German Government Bonds 1 Year BKO	01/01/1999 - Present
QAT	Qatar 3 Month T–Bill Auction Average Yield	05/08/2012 - Present
ROM	Romanian Interbank 12 Month	08/01/1995 - Present
RUS	Mospime 3 Months Rate	04/18/2005 - Present
	Russia Moscow Interbank Non Co	08/14/2000 - 04/17/2005
	Russia Interbank 31 To 90 Day	09/01/1994 - 08/13/2000
RWA	Rwanda 12 Month Bill Auction Average Yield	05/12/2010 - Present
SAU	Saudi Interbank 1 Year	
SGP	Monetary Authority of Singapore Benchmark Govt Bill Yield 3 Month	09/20/2013 - Present
	Singapore T-Bill 3 Month	- 09/19/2013
SRB	Bloomberg National Bank of Serbia BELIBOR 6M Rate	01/28/2005 - Present
	Serbia Treasury Bill Auction Results 12 Months Average Accepted Yield	08/26/2009 - 01/27/2005
SVK	German Government Bonds 1 Year BKO	01/01/2009 - Present
	Slovak Rep. Interbank 1 Year	08/09/1994 - 12/31/2008
SVN	German Government Bonds 1 Year BKO	01/01/2007 - Present
	Slovenia Treasury Bill 3 Month'dead'	10/29/1998 - 12/31/2006
SWE	Sweden T Bill 3 Month	05/25/1993 - Present
	Sweden Treasury Bill 90 Day	- 05/24/1993
THA	Thailand Govt Bond 1 Year Note	08/07/2000 - Present
	Thailand Deposit 12 Month (KT)	01/02/1991 - 08/06/2000
TUN	TU BCT Key Interest Rate	12/15/1994 - Present
TUR	Turkish Interbank 12 Month	08/01/2002 - Present
TWN	Taiwan Deposit 12 Month	
TZA	Tanzania 12 Month Bill Auction Average Yield	01/02/2003 - Present
UGA	Uganda 12 Month Bill Auction Average Yield	01/05/2005 - Present
UKR	Ukraine Interbank 3 Months	03/01/2001 - Present
USA	US Treasury Constant Maturities 1 Year	
VEN	Venezuela Savings Deposit Rate	01/03/2000 - Present
	Venezuela Overnight	11/28/1994 - 01/02/2000
VNM	Vietnam Interbank 3 Month	12/11/1998 - Present
ZAF	South African Prime Overdraft 1 Year Rate	

* A blank Period Used column indicates that there is only a single interest rate that is used throughout the whole period.

Table A.8: Summary Statistics of input variables (based on data from January 1990 to April 2023).

			DTD Level					
Country	Min	25%	Median	75%	Max	Mean	StdDev	Observations
Argentina	-1.78	0.87	2.11	3.63	39.98	2.52	2.42	20610
Australia	-1.28	1.8	3.03	4.58	34.35	3.49	2.53	449829
Austria	-3.24	2.08	3.57	5.66	43.27	4.82	6.06	27941
Bahrain	-1.29	1.95	3.82	7.38	24.39	5.1	4.36	3462
Bangladesh	-2.22	2.07	3.32	4.95	39.98	3.78	2.69	38308
Belgium	-3.24	2.79	4.77	7.41	43.27	5.66	4.85	42995
Bosnia and Herzegovina	-3.24	1.6	2.83	5.16	41.26	3.79	3.58	4606
Botswana	0.03	6.9	10.78	17.84	39.98	13.55	9.57	2139
Brazil	-2.22	0.73	2.29	4.15	39.98	2.74	2.96	77519
Bulgaria	-1.92	1.32	2.55	4.5	43.27	3.51	3.8	13317
Canada	-1.11	1.75	3.21	5.16	69.08	3.79	2.96	333225
Chile	-1.55	3.24	5.36	8.12	39.98	6.34	4.88	36350
China	0.06	3.22	4.35	5.92	17.32	4.79	2.26	632527
Colombia	-2.22	2.21	3.92	6.09	37.1	4.42	3.19	8150
Croatia	-2.9	1.18	2.7	4.91	23.61	3.3	2.95	17199
Cyprus	-1.4	0.91	1.78	3.17	43.27	2.53	2.92	17166
Czech Republic	-3.24	1.46	2.96	5.12	43.27	3.47	2.99	6849
Denmark	-3.24	2.04	3.6	5.54	43.27	4.23	3.63	58121
Egypt	-2.22	1.55	2.69	4.13	25.78	3.08	2.36	38235
Estonia	-1.57	2.09	3.99	6.89	23.97	4.85	3.79	4477
Finland	-3.24	2.59	4.01	5.74	43.27	4.32	2.57	44657
France	-3.24	1.98	3.41	5.25	43.27	3.98	3.34	228801
Germany	-3.24	1.76	3.25	5.1	43.27	3.78	3.18	258804
Ghana	-2.22	0.63	2.24	4.16	19.52	2.97	3.49	2227
Greece	-3.24	1.17	2.33	3.83	43.27	2.73	2.72	73127
Hong Kong	-1.28	1.67	2.79	4.34	34.35	3.34	2.63	426748
Hungary	-3.24	1.51	2.81	4.66	34.83	3.54	3.46	10801
Iceland	-3.24	1.97	3.6	5.25	17.97	3.69	2.7	5666
India	-3.6	0.97	2.07	3.57	26.71	2.65	2.78	813103
Indonesia	-2.22	1.12	2.3	4.0	39.98	3.14	3.87	120635
Ireland	-1.28	2.02	3.67	5.45	35.26	4.02	2.86	11131
Israel	-3.24	1.48	2.84	4.49	43.27	3.26	2.71	115863
Italy	-3.24	1.85	3.22	4.93	43.27	3.67	3.42	95935
Jamaica	-2.22	1.38	2.36	3.52	18.25	2.66	1.99	11003
Japan	-1.28	2.42	3.64	5.28	34.35	4.14	2.6	1213815
Jordan	-1.09	2.56	3.92	5.9	25.26	4.55	2.87	39146
Kazakhstan	-2.22	0.31	2.26	5.35	39.98	3.32	4.49	1790
Kenya	-2.22	1.42	2.59	4.14	39.98	3.1	2.73	8562
Kuwait	-1.97	2.21	3.39	5.02	39.98	3.92	2.58	37473
Latvia	-1.16	1.18	2.8	4.77	36.67	3.4	3.15	3596
Lithuania	-1.31	1.82	3.78	6.11	20.71	4.41	3.6	7198
Luxembourg	-3.24	2.85	4.86	8.76	35.53	6.57	5.34	3483
Macedonia	-1.62	1.76	2.94	5.52	24.9	4.33	3.9	3734
Malawi	-2.22	0.94	2.71	5.09	37.93	4.08	5.59	887
Malaysia	-2.22	1.74	3.08	5.14	39.98	3.94	3.36	287077
Malta	-0.54	2.96	4.65	7.47	23.06	5.68	3.75	2957
Mauritius	-0.55	3.83	6.23	10.23	39.98	8.27	7.15	5032
Mexico	-2.22	2.23	4.23	6.85	39.98	5.01	4.36	30514
Montenegro	-1.01	1.41	2.63	3.88	43.27	3.0	3.22	2228
Morocco	-1.19	2.53	3.83	5.72	24.85	4.35	2.83	14298
Namibia	0.75	4.98	7.01	9.99	39.98	8.57	6.28	844
Netherlands	-3.24	2.61	4.27	6.35	43.27	4.76	3.36	47060
New Zealand	-1.11	3.04	5.3	7.94	34.35	5.92	4.05	29912
Nigeria	-2.22	0.69	1.97	3.48	39.98	2.64	3.65	26920
Norway	-2.83	1.43	2.75	4.37	31.35	3.1	2.49	66243
Oman	-1.33	2.64	4.21	7.32	39.98	5.52	4.46	8593
Pakistan	-2.22	0.88	2.38	4.05	39.98	2.7	2.67	49117
Peru	-2.22	1.96	3.55	5.45	39.98	4.16	3.31	13860
Philippines	-2.22	1.58	3.01	4.95	39.98	3.67	3.25	63577
Poland	-2.86	1.43	2.54	3.84	43.27	2.82	2.11	109473
Portugal	-3.24	0.93	2.32	4.25	43.27	2.82	3.04	17534
Qatar	0.69	3.73	5.59	8.29	23.85	6.6	3.97	5757
Romania	-3.24	1.16	2.43	4.22	31.53	3.0	2.87	17782
Russian Federation	-3.24	0.59	1.77	3.37	43.27	2.26	2.71	36522
Rwanda	-1.41	3.75	5.09	17.51	38.31	9.49	9.62	287
Saudi Arabia	-0.89	3.99	5.76	8.52	39.98	6.71	4.04	35652
Serbia	-2.8	0.77	1.8	3.22	43.27	2.58	3.28	9192
Singapore	-1.28	1.53	2.86	4.82	34.35	3.55	2.92	177825
Slovakia	-2.53	1.24	2.41	3.83	43.27	4.69	8.37	1758
Slovenia	-2.43	1.82	3.83	6.39	43.27	4.62	4.73	7513
South Africa	-2.22	1.29	2.88	5.07	39.98	3.6	3.53	104423
South Korea	-1.28	1.64	2.74	4.18	34.35	3.36	3.42	530811
Spain	-3.24	2.06	3.68	5.62	43.27	4.42	4.48	51058
Sri Lanka	-2.22	1.44	2.61	4.25	39.98	3.21	2.98	45755
Sweden	-3.24	1.96	3.41	5.18	43.27	3.88	2.97	161168
Switzerland	-3.24	2.8	4.61	6.89	40.7	5.14	3.46	77560
Taiwan	-1.25	3.16	4.4	6.13	34.35	5.11	3.45	244153
Tanzania	0.1	2.37	5.94	10.16	39.98	7.77	7.27	1346
Thailand	-1.75	2.22	3.66	5.72	39.98	4.56	4.2	175150
Tunisia	-2.22	2.05	3.53	5.7	23.62	4.17	3.15	14136
Turkey	-3.24	1.58	2.8	4.58	43.27	3.52	3.42	87325
UK	-3.24	2.3	3.96	6.28	43.27	4.82	4.07	517654
US	-1.11	1.97	3.34	5.17	110.72	4.25	6.29	1983455
Uganda	-0.04	1.39	2.14	4.03	39.98	3.85	5.67	913
Ukraine	-3.24	0.35	1.33	2.51	28.11	1.61	2.16	4824
United Arab Emirates	-0.85	1.95	3.07	4.65	35.55	3.69	2.75	13468
Venezuela	-2.22	1.0	4.13	9.66	39.98	6.63	7.42	3827
Vietnam	-1.85	1.36	2.3	3.64	39.98	2.8	2.23	109290

DTD Trend

Country	Min	25%	Median	75%	Max	Mean	StdDev	Observations
Argentina	-11.99	-0.49	-0.0	0.43	10.43	-0.06	1.08	20610
Australia	-8.54	-0.55	-0.03	0.44	6.57	-0.07	1.09	449829
Austria	-13.88	-0.7	-0.05	0.53	9.47	-0.19	2.23	27941
Bahrain	-6.91	-0.54	0.0	0.6	10.43	0.04	1.5	3462
Bangladesh	-11.99	-0.43	-0.0	0.46	10.43	0.02	1.04	38308
Belgium	-13.88	-0.76	-0.04	0.65	9.47	-0.1	1.82	42995
Bosnia and Herzegovina	-13.88	-0.53	-0.02	0.35	9.47	-0.06	1.34	4606
Botswana	-11.99	-2.43	-0.06	1.72	10.43	-0.14	4.75	2139
Brazil	-11.99	-0.46	-0.01	0.4	10.43	-0.04	1.07	77519
Bulgaria	-13.88	-0.52	0.0	0.42	9.47	-0.08	1.4	13317
Canada	-27.71	-0.59	-0.05	0.45	14.56	-0.09	1.23	333225
Chile	-11.99	-0.9	-0.04	0.73	10.43	-0.08	2.17	36350
China	-5.74	-0.6	-0.04	0.48	5.39	-0.08	1.07	632527
Colombia	-11.99	-0.72	-0.05	0.63	9.25	-0.06	1.49	8150
Croatia	-8.09	-0.58	-0.03	0.41	9.47	-0.07	1.13	17199
Cyprus	-13.88	-0.4	-0.05	0.28	9.47	-0.12	1.05	17166
Czech Republic	-13.88	-0.61	-0.05	0.42	9.47	-0.14	1.35	6849
Denmark	-13.88	-0.64	-0.03	0.51	9.47	-0.08	1.46	58121
Egypt	-11.7	-0.52	-0.04	0.44	10.43	-0.04	1.08	38235
Estonia	-8.82	-0.69	0.03	0.71	9.47	0.0	1.5	4477
Finland	-13.88	-0.59	0.0	0.59	9.35	-0.02	1.17	44657
France	-13.88	-0.59	-0.02	0.5	9.47	-0.06	1.34	228801
Germany	-13.88	-0.58	-0.04	0.47	9.47	-0.07	1.3	258804
Ghana	-7.83	-0.67	-0.09	0.35	9.39	-0.2	1.42	2227
Greece	-13.88	-0.5	-0.05	0.37	9.47	-0.06	1.08	73127
Hong Kong	-8.54	-0.57	-0.06	0.41	6.57	-0.09	1.07	426748
Hungary	-13.88	-0.48	0.0	0.46	9.47	-0.04	1.31	10801
Iceland	-9.63	-0.72	-0.01	0.53	9.47	-0.09	1.3	5666
India	-9.45	-0.39	-0.01	0.39	6.66	-0.02	1.0	813103
Indonesia	-11.99	-0.43	0.0	0.42	10.43	-0.04	1.49	120635
Ireland	-13.88	-0.62	-0.01	0.54	8.57	-0.1	1.3	11131
Israel	-13.88	-0.55	-0.02	0.48	9.47	-0.05	1.19	115863
Italy	-13.88	-0.61	-0.04	0.47	9.47	-0.1	1.27	95935
Jamaica	-10.15	-0.44	-0.01	0.38	10.43	-0.01	1.0	11003
Japan	-8.54	-0.51	0.0	0.51	6.57	0.0	1.02	1213815
Jordan	-11.99	-0.5	-0.02	0.44	10.43	-0.04	1.12	39146
Kazakhstan	-11.99	-0.51	0.0	0.46	10.43	-0.09	1.78	1790
Kenya	-11.99	-0.49	-0.08	0.31	7.18	-0.1	0.96	8562
Kuwait	-11.99	-0.53	-0.02	0.46	10.43	-0.06	1.14	37473
Latvia	-13.88	-0.51	0.0	0.48	6.86	-0.06	1.26	3596
Lithuania	-10.53	-0.67	0.0	0.61	9.47	-0.02	1.55	7198
Luxembourg	-11.08	-0.76	0.0	0.63	9.47	-0.07	1.81	3483
Macedonia	-12.68	-0.55	-0.02	0.51	9.24	-0.03	1.42	3734
Malawi	-11.99	-0.48	0.1	0.84	10.43	0.07	2.42	887
Malaysia	-11.99	-0.52	-0.01	0.46	10.43	-0.05	1.21	287077
Malta	-10.87	-0.85	-0.11	0.56	9.47	-0.12	1.74	2957
Mauritius	-11.99	-1.03	-0.08	0.79	10.43	-0.18	2.95	5032
Mexico	-11.99	-0.68	-0.01	0.62	10.43	-0.08	1.68	30514
Montenegro	-13.88	-0.31	-0.0	0.27	9.47	-0.0	0.9	2228
Morocco	-11.88	-0.57	-0.02	0.46	10.43	-0.08	1.15	14298
Namibia	-11.99	-1.5	-0.17	1.11	10.43	-0.1	3.72	844
Netherlands	-13.88	-0.74	-0.04	0.62	9.47	-0.08	1.38	47060
New Zealand	-8.54	-0.79	-0.03	0.68	6.57	-0.09	1.63	29912
Nigeria	-11.99	-0.47	-0.02	0.39	10.43	-0.07	1.56	26920
Norway	-13.88	-0.58	-0.03	0.44	9.47	-0.09	1.08	66243
Oman	-11.99	-0.65	-0.02	0.55	10.43	-0.05	1.83	8593
Pakistan	-11.99	-0.43	-0.01	0.36	7.4	-0.04	0.87	49117
Peru	-11.99	-0.6	-0.0	0.57	10.43	-0.01	1.52	13860
Philippines	-11.99	-0.51	-0.01	0.46	10.43	-0.04	1.33	63577
Poland	-13.88	-0.49	-0.04	0.38	9.47	-0.07	0.9	109473
Portugal	-13.88	-0.48	-0.02	0.41	9.47	-0.04	1.05	17534
Qatar	-6.96	-0.91	-0.09	0.55	10.43	-0.18	1.46	5757
Romania	-13.88	-0.44	0.0	0.43	9.47	-0.01	1.06	17782
Russian Federation	-13.88	-0.47	0.0	0.42	9.47	-0.09	1.24	36522
Rwanda	-11.99	-0.68	0.05	0.82	10.43	-0.17	3.7	287
Saudi Arabia	-11.99	-0.96	-0.02	0.86	10.43	-0.1	1.93	35652
Serbia	-13.88	-0.42	0.0	0.31	9.47	-0.1	1.15	9192
Singapore	-8.54	-0.53	-0.02	0.44	6.57	-0.06	1.12	177825
Slovakia	-13.88	-0.49	0.0	0.43	9.47	-0.3	2.72	1758
Slovenia	-13.88	-0.74	-0.09	0.46	9.47	-0.24	1.85	7513
South Africa	-11.99	-0.58	-0.05	0.44	10.43	-0.11	1.34	104423
South Korea	-8.54	-0.48	-0.01	0.43	6.57	-0.05	1.13	530811
Spain	-13.88	-0.59	0.0	0.57	9.47	-0.06	1.7	51058
Sri Lanka	-11.99	-0.46	-0.04	0.38	10.43	-0.05	1.18	45755
Sweden	-13.88	-0.61	-0.05	0.46	9.47	-0.08	1.18	161168
Switzerland	-13.88	-0.72	0.0	0.68	9.47	-0.03	1.45	77560
Taiwan	-8.54	-0.61	0.0	0.6	6.57	-0.02	1.26	244153
Tanzania	-11.99	-1.16	-0.12	0.67	10.43	-0.26	3.25	1346
Thailand	-11.99	-0.6	-0.0	0.56	10.43	-0.05	1.41	175150
Tunisia	-11.99	-0.61	-0.08	0.43	10.43	-0.1	1.24	14136
Turkey	-13.88	-0.56	-0.0	0.54	9.47	-0.02	1.31	87325
UK	-13.88	-0.82	-0.07	0.58	9.47	-0.2	1.83	517654
US	-27.71	-0.56	-0.02	0.48	14.56	-0.08	1.68	1983455
Uganda	-11.99	-0.46	-0.04	0.51	10.43	-0.14	2.48	913
Ukraine	-13.88	-0.51	-0.01	0.37	6.48	-0.12	1.08	4824
United Arab Emirates	-11.99	-0.53	-0.04	0.38	10.43	-0.12	1.11	13468
Venezuela	-11.99	-0.84	-0.04	0.66	10.43	-0.16	2.83	3827
Vietnam	-11.99	-0.45	-0.03	0.35	10.22	-0.05	0.88	109290

CA/CL Level

Country	Min	25%	Median	75%	Max	Mean	StdDev	Observations
Argentina	-3.89	-0.14	0.24	0.6	2.62	0.22	0.67	19120
Australia	-3.35	0.19	0.8	1.85	5.42	1.01	1.34	433814
Austria	-3.48	0.01	0.28	0.58	4.08	0.3	0.63	20803
Bahrain	-0.44	0.41	0.76	1.46	5.03	1.03	0.85	2850
Bangladesh	-3.12	0.01	0.39	0.88	4.27	0.47	0.85	27103
Belgium	-3.61	0.03	0.32	0.69	5.4	0.38	0.74	31424
Bosnia and Herzegovina	-2.7	-0.1	0.57	1.42	5.4	0.66	1.18	12314
Botswana	-4.22	0.14	0.48	0.82	4.28	0.5	0.71	2903
Brazil	-4.7	-0.11	0.31	0.71	5.03	0.19	0.99	77573
Bulgaria	-3.61	0.1	0.48	1.08	5.4	0.58	0.96	13688
Canada	-4.14	-0.01	0.55	1.29	4.78	0.65	1.31	305735
Chile	-4.7	0.08	0.41	0.82	5.03	0.47	0.7	35395
China	-2.68	0.11	0.5	1.03	4.01	0.61	0.81	594935
Colombia	-4.27	-0.04	0.27	0.66	1.87	0.29	0.53	7001
Croatia	-3.61	-0.34	0.21	0.69	5.4	0.18	1.15	22612
Cyprus	-3.61	-0.31	0.24	0.79	5.4	0.23	0.91	13931
Czech Republic	-2.23	-0.09	0.18	0.67	5.4	0.35	0.79	8192
Denmark	-3.61	0.12	0.44	0.8	5.4	0.49	0.77	40115
Egypt	-3.12	0.05	0.39	0.85	5.03	0.49	0.82	27809
Estonia	-2.61	0.0	0.43	0.85	2.9	0.48	0.68	3657
Finland	-1.9	0.11	0.38	0.72	4.15	0.43	0.58	40948
France	-3.61	0.08	0.35	0.68	5.4	0.42	0.63	195862
Germany	-3.61	0.09	0.45	0.9	5.4	0.52	0.83	203285
Ghana	-2.49	-0.24	0.02	0.5	1.96	0.07	0.73	2154
Greece	-3.61	0.05	0.39	0.75	5.4	0.41	0.69	67049
Hong Kong	-3.35	0.16	0.54	1.07	5.42	0.63	0.86	325727
Hungary	-3.11	-0.06	0.33	0.81	5.4	0.45	0.82	8891
Iceland	-1.11	0.01	0.27	0.51	2.84	0.28	0.44	5631
India	-5.21	0.13	0.57	1.22	6.72	0.7	1.23	934494
Indonesia	-4.7	0.01	0.4	0.88	5.03	0.43	0.97	99955
Ireland	-3.61	0.14	0.43	0.81	4.4	0.5	0.75	9655
Israel	-3.61	0.11	0.46	0.98	5.4	0.59	1.09	81725
Italy	-2.84	0.0	0.3	0.62	5.4	0.32	0.61	74019
Jamaica	-1.83	0.43	0.76	1.16	3.76	0.82	0.69	8114
Japan	-3.35	0.12	0.47	0.9	5.2	0.53	0.66	1119458
Jordan	-4.61	-0.01	0.49	1.03	5.03	0.54	0.92	25344
Kazakhstan	-2.71	0.21	0.78	1.25	5.03	0.71	1.01	1598
Kenya	-2.63	0.05	0.4	0.79	4.07	0.44	0.71	9142
Kuwait	-3.44	0.08	0.53	1.21	4.17	0.63	0.95	17327
Latvia	-2.7	0.28	0.77	1.48	5.4	0.92	0.99	5846
Lithuania	-2.71	-0.11	0.28	0.68	2.61	0.29	0.66	6499
Luxembourg	-2.27	-0.26	0.18	0.77	4.18	0.24	1.06	1615
Macedonia	-2.97	0.07	0.64	1.11	3.9	0.66	0.95	4404
Malawi	-1.9	-0.41	-0.09	0.4	0.94	-0.04	0.56	750
Malaysia	-4.7	0.15	0.57	1.12	5.03	0.67	0.89	235290
Malta	-1.19	-0.11	0.24	0.44	1.49	0.14	0.5	1575
Mauritius	-4.15	-0.28	0.07	0.4	2.8	0.05	0.68	6474
Mexico	-3.96	0.08	0.46	0.9	3.97	0.48	0.76	29707
Montenegro	-3.61	-0.62	0.22	1.11	5.4	0.19	1.26	4881
Morocco	-1.44	0.11	0.44	0.75	2.46	0.43	0.51	12603
Namibia	-0.57	0.39	0.56	0.96	1.28	0.59	0.4	467
Netherlands	-3.61	0.07	0.34	0.61	5.4	0.37	0.61	39111
New Zealand	-3.35	-0.03	0.42	0.88	5.42	0.43	0.92	26533
Nigeria	-4.7	-0.34	0.11	0.48	3.99	-0.03	1.0	21948
Norway	-3.61	0.13	0.49	0.98	5.4	0.63	0.89	57104
Oman	-4.06	0.0	0.29	0.82	4.52	0.41	0.78	16014
Pakistan	-4.7	-0.07	0.18	0.54	5.03	0.22	0.69	42981
Peru	-2.9	-0.06	0.33	0.73	4.13	0.35	0.76	19105
Philippines	-4.7	-0.1	0.39	0.99	5.03	0.47	1.38	44463
Poland	-3.61	0.1	0.39	0.82	5.4	0.47	0.79	92008
Portugal	-3.61	-0.42	-0.03	0.32	5.4	-0.05	0.7	17166
Qatar	-1.21	0.19	0.57	1.02	5.03	0.7	0.85	4560
Romania	-3.61	0.02	0.45	0.99	5.4	0.51	0.91	22072
Russian Federation	-3.61	-0.02	0.32	0.79	5.4	0.47	0.94	45539
Rwanda	-0.66	-0.59	-0.5	-0.37	-0.23	-0.47	0.14	121
Saudi Arabia	-4.7	0.13	0.49	0.97	4.68	0.54	0.78	24222
Serbia	-3.61	-0.05	0.36	0.88	3.55	0.38	0.95	19888
Singapore	-3.35	0.19	0.54	1.01	5.42	0.62	0.76	150539
Slovakia	-1.53	-0.09	0.3	0.69	4.74	0.47	0.94	3107
Slovenia	-2.27	-0.09	0.23	0.62	3.07	0.29	0.71	8671
South Africa	-4.7	0.13	0.41	0.75	5.03	0.47	0.73	85199
South Korea	-3.35	0.04	0.45	1.01	5.42	0.59	0.87	493456
Spain	-3.61	-0.03	0.2	0.52	3.84	0.24	0.57	43898
Sri Lanka	-4.37	-0.11	0.3	0.8	5.03	0.34	0.91	32285
Sweden	-3.61	0.14	0.56	1.04	5.4	0.65	0.84	141041
Switzerland	-3.61	0.3	0.59	0.94	5.4	0.65	0.64	59961
Taiwan	-3.35	0.24	0.54	0.92	5.42	0.6	0.64	216361
Tanzania	-4.58	-0.1	0.46	0.87	1.75	0.26	0.9	1166
Thailand	-4.7	-0.05	0.36	0.92	5.03	0.44	0.87	141749
Tunisia	-1.74	0.04	0.43	0.8	3.04	0.42	0.66	9022
Turkey	-3.61	0.05	0.38	0.78	5.4	0.42	0.78	80757
UK	-3.61	0.01	0.38	0.88	5.4	0.51	0.96	452315
US	-4.14	0.31	0.75	1.28	4.78	0.83	0.84	1559184
Uganda	-0.76	-0.14	0.35	1.26	2.31	0.49	0.8	584
Ukraine	-3.61	-0.16	0.2	0.62	5.4	0.25	0.73	8783
United Arab Emirates	-2.49	0.15	0.56	1.07	5.03	0.68	0.92	8159
Venezuela	-2.03	0.12	0.33	0.53	1.96	0.3	0.56	2676
Vietnam	-4.2	0.11	0.38	0.84	4.86	0.52	0.68	101189

CA/CL Trend

Country	Min	25%	Median	75%	Max	Mean	StdDev	Observations
Argentina	-2.12	-0.08	0.0	0.07	2.24	-0.0	0.24	19120
Australia	-2.58	-0.24	-0.0	0.14	2.53	-0.04	0.6	433814
Austria	-2.5	-0.06	0.0	0.05	2.55	-0.01	0.2	20803
Bahrain	-2.12	-0.1	0.0	0.11	2.24	-0.01	0.3	2850
Bangladesh	-2.12	-0.05	0.0	0.04	2.24	-0.01	0.2	27103
Belgium	-2.57	-0.05	0.0	0.04	2.55	-0.01	0.22	31424
Bosnia and Herzegovina	-2.57	-0.07	0.0	0.07	2.55	-0.0	0.29	12314
Botswana	-2.12	-0.07	0.0	0.07	2.24	0.0	0.3	2903
Brazil	-2.12	-0.1	-0.0	0.08	2.24	-0.01	0.28	77573
Bulgaria	-2.57	-0.06	0.0	0.06	2.55	0.0	0.23	13688
Canada	-2.55	-0.19	-0.0	0.12	2.67	-0.04	0.56	305735
Chile	-2.12	-0.09	-0.0	0.08	2.24	-0.0	0.28	35395
China	-1.46	-0.09	-0.01	0.05	1.45	-0.02	0.21	594935
Colombia	-2.12	-0.08	-0.0	0.07	2.24	-0.01	0.24	7001
Croatia	-2.42	-0.13	-0.0	0.09	2.55	-0.01	0.36	22612
Cyprus	-2.57	-0.08	0.0	0.03	2.55	-0.02	0.26	13931
Czech Republic	-2.57	-0.06	0.0	0.04	2.55	0.0	0.29	8192
Denmark	-2.57	-0.08	0.0	0.05	2.55	-0.02	0.32	40115
Egypt	-2.12	-0.09	-0.0	0.07	2.24	-0.0	0.28	27809
Estonia	-1.04	-0.08	0.0	0.07	2.55	0.0	0.23	3657
Finland	-2.57	-0.08	-0.0	0.05	2.55	-0.01	0.2	40948
France	-2.57	-0.05	0.0	0.03	2.55	-0.01	0.19	195862
Germany	-2.57	-0.07	0.0	0.05	2.55	-0.01	0.3	203285
Ghana	-1.7	-0.1	-0.01	0.06	1.28	-0.02	0.22	2154
Greece	-2.57	-0.1	-0.01	0.05	2.55	-0.02	0.26	67049
Hong Kong	-2.58	-0.09	-0.0	0.06	2.53	-0.02	0.31	325727
Hungary	-2.57	-0.08	0.0	0.07	2.55	0.0	0.32	8891
Iceland	-1.07	-0.07	0.0	0.05	1.07	-0.01	0.18	5631
India	-3.19	-0.09	0.0	0.06	3.01	-0.02	0.41	934494
Indonesia	-2.12	-0.1	-0.0	0.07	2.24	-0.01	0.32	99955
Ireland	-2.57	-0.07	0.0	0.06	2.55	-0.02	0.32	9655
Israel	-2.57	-0.09	-0.0	0.06	2.55	-0.02	0.42	81725
Italy	-2.57	-0.07	-0.0	0.05	2.55	-0.01	0.25	74019
Jamaica	-2.07	-0.08	0.0	0.08	2.19	-0.01	0.24	8114
Japan	-2.58	-0.04	0.0	0.05	2.53	0.0	0.14	1119458
Jordan	-2.12	-0.09	-0.0	0.07	2.24	-0.01	0.28	25344
Kazakhstan	-1.57	-0.11	0.0	0.15	1.41	0.01	0.31	1598
Kenya	-2.12	-0.07	0.0	0.04	2.24	-0.01	0.24	9142
Kuwait	-2.12	-0.1	0.0	0.09	2.24	-0.01	0.33	17327
Latvia	-2.57	-0.12	-0.0	0.09	2.55	-0.02	0.3	5846
Lithuania	-1.86	-0.1	0.0	0.09	1.32	-0.01	0.24	6499
Luxembourg	-2.57	-0.07	0.0	0.07	2.55	0.01	0.28	1615
Macedonia	-2.57	-0.06	0.0	0.05	2.05	-0.01	0.27	4404
Malawi	-1.43	-0.05	0.0	0.06	2.01	0.0	0.22	750
Malaysia	-2.12	-0.08	0.0	0.07	2.24	-0.01	0.26	235290
Malta	-0.74	-0.05	0.0	0.05	2.15	0.01	0.2	1575
Mauritius	-2.12	-0.06	0.0	0.06	2.24	0.0	0.27	6474
Mexico	-2.12	-0.1	-0.0	0.07	2.24	-0.01	0.24	29707
Montenegro	-2.57	-0.06	0.0	0.08	2.55	0.02	0.36	4881
Morocco	-2.12	-0.06	-0.0	0.05	1.19	-0.01	0.15	12603
Namibia	-0.36	-0.04	0.0	0.07	0.56	0.01	0.12	467
Netherlands	-2.57	-0.06	0.0	0.05	2.55	-0.01	0.23	39111
New Zealand	-2.58	-0.11	0.0	0.1	2.53	-0.01	0.37	26533
Nigeria	-2.12	-0.08	0.0	0.06	2.24	-0.01	0.33	21948
Norway	-2.57	-0.13	-0.0	0.08	2.55	-0.03	0.38	57104
Oman	-2.12	-0.08	0.0	0.08	2.24	0.0	0.25	16014
Pakistan	-2.12	-0.05	0.0	0.05	2.24	0.0	0.18	42981
Peru	-2.12	-0.09	0.0	0.08	2.24	-0.0	0.26	19105
Philippines	-2.12	-0.11	-0.0	0.08	2.24	-0.01	0.42	44463
Poland	-2.57	-0.09	-0.0	0.06	2.55	-0.02	0.3	92008
Portugal	-2.57	-0.08	0.0	0.06	2.22	-0.0	0.25	17166
Qatar	-2.12	-0.13	-0.01	0.1	2.24	-0.03	0.37	4560
Romania	-2.57	-0.09	0.0	0.08	2.55	0.0	0.3	22072
Russian Federation	-2.57	-0.11	0.0	0.11	2.55	0.0	0.47	45539
Rwanda	-0.26	-0.02	0.0	0.03	0.15	-0.01	0.08	121
Saudi Arabia	-2.12	-0.1	-0.0	0.08	2.24	-0.01	0.27	24222
Serbia	-2.57	-0.03	0.0	0.02	2.55	-0.0	0.24	19888
Singapore	-2.58	-0.08	0.0	0.07	2.53	-0.01	0.29	150539
Slovakia	-2.11	-0.07	0.0	0.04	2.55	-0.01	0.33	3107
Slovenia	-1.97	-0.06	0.0	0.06	2.05	-0.01	0.22	8671
South Africa	-2.12	-0.06	0.0	0.05	2.24	-0.01	0.3	85199
South Korea	-2.58	-0.1	0.0	0.08	2.53	-0.02	0.32	493456
Spain	-2.57	-0.06	0.0	0.06	2.55	-0.01	0.21	43898
Sri Lanka	-2.12	-0.09	0.0	0.09	2.24	-0.0	0.3	32285
Sweden	-2.57	-0.13	-0.0	0.08	2.55	-0.03	0.39	141041
Switzerland	-2.57	-0.06	0.0	0.06	2.55	-0.01	0.23	59961
Taiwan	-2.58	-0.08	0.0	0.08	2.53	0.0	0.21	216361
Tanzania	-1.42	-0.08	0.0	0.07	2.24	-0.01	0.3	1166
Thailand	-2.12	-0.09	0.0	0.08	2.24	-0.0	0.27	141749
Tunisia	-1.83	-0.07	-0.0	0.03	1.34	-0.02	0.16	9022
Turkey	-2.57	-0.1	-0.01	0.08	2.55	-0.01	0.29	80757
UK	-2.57	-0.09	0.0	0.06	2.55	-0.02	0.37	452315
US	-2.55	-0.11	-0.0	0.08	2.67	-0.02	0.31	1559184
Uganda	-0.97	-0.05	0.0	0.04	1.02	-0.0	0.18	584
Ukraine	-2.57	-0.06	0.0	0.05	2.55	-0.0	0.28	8783
United Arab Emirates	-2.12	-0.12	-0.01	0.07	2.24	-0.03	0.31	8159
Venezuela	-2.12	-0.05	0.0	0.04	1.46	-0.01	0.22	2676
Vietnam	-2.12	-0.07	0.0	0.07	2.24	0.0	0.25	101189

NI/TA Level

Country	Min	25%	Median	75%	Max	Mean	StdDev	Observations
Argentina	-0.04	-0.0	0.0	0.01	0.03	0.0	0.01	22886
Australia	-0.7	-0.03	-0.01	0.0	0.11	-0.03	0.08	493047
Austria	-0.64	0.0	0.0	0.0	0.12	-0.0	0.02	30717
Bahrain	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	7385
Bangladesh	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	42386
Belgium	-0.95	0.0	0.0	0.01	0.12	0.0	0.03	47949
Bosnia and Herzegovina	-0.04	-0.0	0.0	0.0	0.04	0.0	0.01	13852
Botswana	-0.04	0.0	0.01	0.01	0.03	0.01	0.01	5599
Brazil	-0.04	-0.0	0.0	0.01	0.03	0.0	0.01	94694
Bulgaria	-0.32	-0.0	0.0	0.01	0.12	0.0	0.01	20802
Canada	-1.26	-0.01	-0.0	0.0	0.21	-0.03	0.12	350392
Chile	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	50630
China	-0.07	0.0	0.0	0.01	0.08	0.0	0.01	644060
Colombia	-0.04	0.0	0.0	0.0	0.03	0.0	0.01	11385
Croatia	-0.34	-0.0	0.0	0.0	0.12	0.0	0.02	26137
Cyprus	-0.95	-0.0	0.0	0.0	0.12	-0.01	0.05	22689
Czech Republic	-0.29	0.0	0.0	0.01	0.04	0.0	0.01	9352
Denmark	-0.95	-0.0	0.0	0.0	0.12	-0.0	0.04	64252
Egypt	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	40641
Estonia	-0.09	-0.0	0.0	0.01	0.05	0.0	0.01	4610
Finland	-0.48	0.0	0.0	0.01	0.12	0.0	0.02	46746
France	-0.95	-0.0	0.0	0.0	0.12	-0.0	0.03	241286
Germany	-0.95	-0.0	0.0	0.0	0.12	-0.0	0.03	272349
Ghana	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	3461
Greece	-0.95	-0.0	0.0	0.0	0.12	0.0	0.02	76488
Hong Kong	-0.7	-0.0	0.0	0.01	0.11	-0.0	0.03	436521
Hungary	-0.95	-0.0	0.0	0.01	0.07	-0.01	0.08	11966
Iceland	-0.07	0.0	0.0	0.01	0.12	0.0	0.01	7266
India	-0.06	-0.0	0.0	0.01	0.03	0.0	0.01	1113698
Indonesia	-0.04	-0.0	0.0	0.01	0.03	0.0	0.01	136400
Ireland	-0.81	-0.0	0.0	0.01	0.12	-0.0	0.03	12344
Israel	-0.95	-0.0	0.0	0.0	0.12	-0.01	0.08	123178
Italy	-0.95	-0.0	0.0	0.0	0.12	0.0	0.01	99740
Jamaica	-0.04	0.0	0.0	0.01	0.03	0.01	0.01	12584
Japan	-0.7	0.0	0.0	0.0	0.11	0.0	0.01	1234669
Jordan	-0.04	-0.0	0.0	0.0	0.03	0.0	0.01	49716
Kazakhstan	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	3146
Kenya	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	13683
Kuwait	-0.04	-0.0	0.0	0.01	0.03	0.0	0.01	43096
Latvia	-0.12	-0.0	0.0	0.01	0.12	0.0	0.01	6223
Lithuania	-0.04	0.0	0.0	0.01	0.04	0.0	0.01	7681
Luxembourg	-0.04	0.0	0.0	0.01	0.11	0.0	0.01	4585
Macedonia	-0.5	0.0	0.0	0.0	0.12	-0.0	0.03	5883
Malawi	-0.02	0.0	0.0	0.01	0.03	0.01	0.01	1999
Malaysia	-0.04	-0.0	0.0	0.01	0.03	0.0	0.01	294450
Malta	-0.02	0.0	0.0	0.0	0.04	0.0	0.0	4094
Mauritius	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	10001
Mexico	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	37502
Montenegro	-0.06	-0.0	0.0	0.0	0.02	-0.0	0.01	5512
Morocco	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	19179
Namibia	-0.01	0.0	0.0	0.01	0.03	0.01	0.01	1474
Netherlands	-0.95	0.0	0.0	0.01	0.12	-0.0	0.05	48451
New Zealand	-0.7	-0.0	0.0	0.01	0.11	-0.01	0.06	32694
Nigeria	-0.04	-0.0	0.0	0.01	0.03	0.0	0.01	33157
Norway	-0.95	-0.0	0.0	0.0	0.12	-0.0	0.03	72519
Oman	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	24538
Pakistan	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	54888
Peru	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	22413
Philippines	-0.04	-0.0	0.0	0.0	0.03	0.0	0.01	72372
Poland	-0.95	-0.0	0.0	0.01	0.12	-0.0	0.04	113073
Portugal	-0.22	-0.0	0.0	0.0	0.12	0.0	0.01	21362
Qatar	-0.01	0.0	0.0	0.01	0.03	0.0	0.01	9475
Romania	-0.95	-0.0	0.0	0.01	0.12	0.0	0.03	24805
Russian Federation	-0.95	0.0	0.0	0.01	0.12	0.0	0.03	50104
Rwanda	-0.01	0.0	0.0	0.0	0.01	0.0	0.0	361
Saudi Arabia	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	36593
Serbia	-0.12	-0.0	0.0	0.01	0.07	0.0	0.01	22203
Singapore	-0.7	-0.0	0.0	0.01	0.11	-0.0	0.03	190708
Slovakia	-0.05	-0.0	0.0	0.0	0.05	0.0	0.01	4491
Slovenia	-0.07	-0.0	0.0	0.0	0.09	0.0	0.01	11374
South Africa	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	112722
South Korea	-0.7	-0.0	0.0	0.01	0.11	-0.0	0.02	540678
Spain	-0.95	0.0	0.0	0.0	0.12	0.0	0.02	62128
Sri Lanka	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	47534
Sweden	-0.95	-0.02	0.0	0.01	0.12	-0.01	0.04	167260
Switzerland	-0.95	0.0	0.0	0.01	0.12	0.0	0.02	83038
Taiwan	-0.37	0.0	0.0	0.01	0.06	0.0	0.01	246000
Tanzania	-0.04	0.0	0.0	0.01	0.03	0.01	0.01	1872
Thailand	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	182518
Tunisia	-0.04	0.0	0.0	0.0	0.03	0.0	0.01	15236
Turkey	-0.95	-0.0	0.0	0.01	0.12	0.0	0.02	107443
UK	-0.95	-0.01	0.0	0.01	0.12	-0.01	0.06	560696
US	-1.26	-0.0	0.0	0.01	0.21	-0.0	0.04	2085641
Uganda	-0.01	0.0	0.0	0.0	0.02	0.0	0.0	1217
Ukraine	-0.1	-0.0	0.0	0.01	0.11	0.0	0.01	9834
United Arab Emirates	-0.04	0.0	0.0	0.0	0.03	0.0	0.01	19242
Venezuela	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	5335
Vietnam	-0.04	0.0	0.0	0.01	0.03	0.0	0.01	117862

NI/TA Trend

Country	Min	25%	Median	75%	Max	Mean	StdDev	Observations
Argentina	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	22886
Australia	-0.49	-0.0	0.0	0.0	0.42	-0.0	0.06	493047
Austria	-0.49	-0.0	0.0	0.0	0.45	-0.0	0.02	30717
Bahrain	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.0	7385
Bangladesh	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.0	42386
Belgium	-0.49	-0.0	0.0	0.0	0.47	0.0	0.02	47949
Bosnia and Herzegovina	-0.19	-0.0	0.0	0.0	0.04	-0.0	0.0	13852
Botswana	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.0	5599
Brazil	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	94694
Bulgaria	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.02	20802
Canada	-0.58	-0.0	0.0	0.0	0.61	0.0	0.08	350392
Chile	-0.03	-0.0	-0.0	0.0	0.03	-0.0	0.01	50630
China	-0.09	-0.0	-0.0	0.0	0.08	-0.0	0.01	644060
Colombia	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.0	11385
Croatia	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.03	26137
Cyprus	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.03	22689
Czech Republic	-0.27	-0.0	0.0	0.0	0.26	0.0	0.01	9352
Denmark	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.02	64252
Egypt	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	40641
Estonia	-0.31	-0.0	0.0	0.0	0.16	0.0	0.01	4610
Finland	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.02	46746
France	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.02	241286
Germany	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.02	272349
Ghana	-0.03	-0.0	-0.0	0.0	0.03	-0.0	0.01	3461
Greece	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.02	76488
Hong Kong	-0.49	-0.0	0.0	0.0	0.42	-0.0	0.03	436521
Hungary	-0.49	-0.0	0.0	0.0	0.47	0.0	0.04	11966
Iceland	-0.08	-0.0	0.0	0.0	0.45	0.0	0.01	7266
India	-0.37	-0.0	0.0	0.0	0.35	-0.0	0.02	1113698
Indonesia	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	136400
Ireland	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.03	12344
Israel	-0.49	-0.0	-0.0	0.0	0.47	0.0	0.06	123178
Italy	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.01	99740
Jamaica	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	12584
Japan	-0.49	-0.0	0.0	0.0	0.42	-0.0	0.01	1234669
Jordan	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	49716
Kazakhstan	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	3146
Kenya	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.0	13683
Kuwait	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	43096
Latvia	-0.29	-0.0	0.0	0.0	0.47	-0.0	0.02	6223
Lithuania	-0.13	-0.0	0.0	0.0	0.12	-0.0	0.01	7681
Luxembourg	-0.12	-0.0	0.0	0.0	0.15	0.0	0.01	4585
Macedonia	-0.43	-0.0	0.0	0.0	0.34	-0.0	0.02	5883
Malawi	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.0	1999
Malaysia	-0.03	-0.0	-0.0	0.0	0.03	-0.0	0.01	294450
Malta	-0.05	-0.0	0.0	0.0	0.03	-0.0	0.0	4094
Mauritius	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	10001
Mexico	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	37502
Montenegro	-0.08	-0.0	0.0	0.0	0.06	0.0	0.0	5512
Morocco	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.0	19179
Namibia	-0.02	-0.0	0.0	0.0	0.01	-0.0	0.0	1474
Netherlands	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.03	48451
New Zealand	-0.49	-0.0	0.0	0.0	0.42	0.0	0.04	32694
Nigeria	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	33157
Norway	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.03	72519
Oman	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	24538
Pakistan	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.0	54888
Peru	-0.03	-0.0	0.0	0.0	0.03	0.0	0.01	22413
Philippines	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	72372
Poland	-0.49	-0.0	0.0	0.0	0.47	0.0	0.03	113073
Portugal	-0.49	-0.0	0.0	0.0	0.22	-0.0	0.01	21362
Qatar	-0.03	-0.0	-0.0	0.0	0.03	-0.0	0.0	9475
Romania	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.02	24805
Russian Federation	-0.49	-0.0	0.0	0.0	0.47	0.0	0.02	50104
Rwanda	-0.01	-0.0	0.0	0.0	0.01	-0.0	0.0	361
Saudi Arabia	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	36593
Serbia	-0.13	-0.0	0.0	0.0	0.16	-0.0	0.01	22203
Singapore	-0.49	-0.0	-0.0	0.0	0.42	-0.0	0.03	190708
Slovakia	-0.06	-0.0	0.0	0.0	0.07	-0.0	0.01	4491
Slovenia	-0.1	-0.0	0.0	0.0	0.11	-0.0	0.01	11374
South Africa	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	112722
South Korea	-0.49	-0.0	0.0	0.0	0.42	-0.0	0.02	540678
Spain	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.02	62128
Sri Lanka	-0.03	-0.0	-0.0	0.0	0.03	-0.0	0.01	47534
Sweden	-0.49	-0.0	0.0	0.0	0.47	-0.0	0.03	167260
Switzerland	-0.49	-0.0	0.0	0.0	0.47	0.0	0.01	83038
Taiwan	-0.49	-0.0	-0.0	0.0	0.37	-0.0	0.01	246000
Tanzania	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	1872
Thailand	-0.03	-0.0	-0.0	0.0	0.03	-0.0	0.01	182518
Tunisia	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.0	15236
Turkey	-0.49	-0.0	-0.0	0.0	0.47	-0.0	0.02	107443
UK	-0.49	-0.0	0.0	0.0	0.47	0.0	0.04	560696
US	-0.58	-0.0	0.0	0.0	0.61	-0.0	0.03	2085641
Uganda	-0.02	-0.0	0.0	0.0	0.02	0.0	0.0	1217
Ukraine	-0.2	-0.0	0.0	0.0	0.16	-0.0	0.01	9834
United Arab Emirates	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	19242
Venezuela	-0.03	-0.0	0.0	0.0	0.03	-0.0	0.01	5335
Vietnam	-0.03	-0.0	-0.0	0.0	0.03	-0.0	0.01	117862

SIZE Level

Country	Min	25%	Median	75%	Max	Mean	StdDev	Observations
Argentina	-5.99	-1.55	-0.02	1.35	6.1	-0.08	1.99	23021
Australia	-4.22	-1.17	-0.02	1.59	7.18	0.38	2.09	516522
Austria	-7.29	-1.32	-0.0	1.48	4.83	-0.01	2.06	33313
Bahrain	-3.38	-0.82	0.01	1.28	3.83	0.19	1.38	6254
Bangladesh	-4.42	-0.83	0.03	1.33	6.17	0.23	1.58	46917
Belgium	-7.29	-1.47	0.02	1.62	7.5	0.01	2.32	56624
Bosnia and Herzegovina	-7.29	-1.15	-0.02	1.12	5.63	0.07	1.86	17114
Botswana	-5.99	-0.87	0.01	1.01	5.49	0.05	1.42	5219
Brazil	-5.99	-1.67	0.01	1.38	6.47	-0.15	2.35	96084
Bulgaria	-7.29	-1.4	0.0	1.18	7.5	-0.11	1.83	31525
Canada	-6.18	-1.56	-0.04	1.61	6.74	0.05	2.35	389632
Chile	-5.99	-1.18	-0.01	1.21	6.22	-0.04	1.79	48490
China	-2.07	-0.46	0.01	0.64	4.7	0.17	0.92	677845
Colombia	-4.79	-1.44	0.03	1.09	4.45	-0.23	1.7	11022
Croatia	-7.29	-1.21	-0.02	1.18	5.74	0.03	1.83	24802
Cyprus	-7.29	-1.06	-0.08	0.98	6.58	-0.01	1.56	24526
Czech Republic	-6.53	-1.28	-0.1	1.19	5.5	-0.01	1.91	10100
Denmark	-7.29	-1.19	-0.01	1.41	7.5	0.24	2.06	66962
Egypt	-5.99	-1.25	-0.06	1.42	5.74	0.09	1.87	42388
Estonia	-3.75	-1.11	-0.02	1.18	4.79	0.04	1.68	4933
Finland	-6.22	-1.34	-0.05	1.43	7.41	0.08	1.97	48636
France	-7.29	-1.46	-0.04	1.74	7.5	0.24	2.39	281108
Germany	-7.29	-1.62	-0.03	1.6	7.5	0.02	2.61	326355
Ghana	-5.99	-1.6	-0.02	1.12	3.77	-0.4	2.06	3288
Greece	-7.21	-0.95	-0.02	1.23	6.73	0.25	1.76	78977
Hong Kong	-4.22	-1.08	-0.02	1.43	7.18	0.3	1.91	471713
Hungary	-7.29	-1.6	-0.01	1.49	7.5	0.17	2.43	12819
Iceland	-6.41	-0.66	0.06	0.76	3.64	0.01	1.29	7679
India	-5.11	-1.46	0.02	1.94	8.52	0.38	2.44	948720
Indonesia	-5.99	-1.26	-0.01	1.29	6.47	0.09	1.87	135517
Ireland	-5.87	-1.15	0.0	1.59	5.38	0.17	2.01	13378
Israel	-7.29	-1.08	-0.03	1.25	7.5	0.14	1.8	142021
Italy	-7.29	-1.2	-0.04	1.51	6.72	0.19	1.99	106475
Jamaica	-5.99	-1.1	-0.01	1.12	6.47	-0.01	1.78	13452
Japan	-4.22	-1.05	-0.05	1.22	7.18	0.21	1.72	1284009
Jordan	-3.81	-0.89	-0.01	1.1	6.47	0.23	1.55	48720
Kazakhstan	-5.99	-1.79	0.02	1.2	4.16	-0.28	1.92	2877
Kenya	-5.99	-1.24	-0.0	1.25	6.34	-0.04	1.86	14836
Kuwait	-5.99	-0.81	-0.02	0.91	5.59	0.16	1.42	42438
Latvia	-6.25	-1.21	-0.02	2.25	6.21	0.46	2.2	6288
Lithuania	-4.88	-1.12	0.04	1.03	3.97	-0.01	1.56	9016
Luxembourg	-7.29	-1.39	0.01	0.71	5.62	-0.22	1.87	5218
Macedonia	-7.08	-1.38	-0.01	1.04	4.88	-0.1	1.8	8195
Malawi	-5.75	-1.18	-0.02	1.06	6.25	-0.15	1.71	2009
Malaysia	-5.48	-0.87	-0.02	1.08	6.47	0.24	1.57	309444
Malta	-4.2	-0.94	-0.05	1.03	2.49	-0.06	1.33	4404
Mauritius	-4.45	-0.8	0.05	0.8	3.54	0.0	1.3	10359
Mexico	-5.99	-1.27	-0.03	1.18	5.01	-0.07	1.86	36894
Montenegro	-6.61	-1.29	-0.01	1.13	4.52	-0.05	1.85	5690
Morocco	-5.18	-1.29	-0.02	1.49	5.16	0.03	1.9	19369
Namibia	-5.99	-1.17	-0.0	0.92	3.99	-0.34	1.7	1371
Netherlands	-7.29	-1.62	0.03	1.61	6.56	0.05	2.34	51891
New Zealand	-4.22	-1.43	0.02	1.29	5.18	-0.05	1.93	33972
Nigeria	-5.99	-1.11	-0.03	1.79	6.47	0.31	2.13	35060
Norway	-7.29	-1.15	-0.01	1.23	6.75	0.1	1.79	76358
Oman	-5.5	-0.93	0.01	1.13	5.07	0.06	1.54	21889
Pakistan	-5.99	-1.55	-0.03	1.68	6.47	0.08	2.25	97107
Peru	-5.99	-1.32	-0.02	1.56	5.01	0.05	1.92	20832
Philippines	-5.99	-1.21	0.01	1.51	5.68	0.22	1.87	71848
Poland	-6.85	-1.3	-0.07	1.44	7.5	0.18	2.06	157464
Portugal	-7.29	-1.54	0.03	1.85	5.33	0.02	2.48	22108
Qatar	-5.99	-1.48	0.03	1.04	4.01	-0.17	1.65	9952
Romania	-7.29	-1.15	-0.03	1.2	7.5	0.14	2.02	35777
Russian Federation	-7.29	-1.64	-0.01	1.73	7.5	0.08	2.45	47665
Rwanda	-3.71	-1.72	-0.02	0.36	1.95	-0.51	1.33	406
Saudi Arabia	-4.58	-0.85	-0.01	1.32	6.47	0.32	1.6	38732
Serbia	-6.51	-1.25	-0.06	1.26	6.31	0.07	1.86	23092
Singapore	-4.22	-0.97	-0.01	1.24	6.93	0.27	1.74	196752
Slovakia	-7.29	-1.34	0.0	2.21	6.28	0.45	2.5	4924
Slovenia	-7.29	-1.19	-0.01	1.56	7.5	0.31	2.35	13898
South Africa	-5.99	-1.61	-0.01	1.67	6.47	0.03	2.26	120363
South Korea	-4.22	-0.71	0.01	0.96	7.18	0.24	1.49	599084
Spain	-7.29	-1.46	-0.02	1.56	6.05	0.05	2.18	62199
Sri Lanka	-5.99	-0.98	-0.05	1.03	4.86	0.09	1.54	50425
Sweden	-7.29	-1.5	-0.07	1.7	7.5	0.21	2.32	177984
Switzerland	-7.29	-1.31	0.02	1.31	7.5	0.05	2.05	86549
Taiwan	-4.22	-0.8	0.0	0.91	7.18	0.15	1.42	260688
Tanzania	-4.87	-1.8	-0.09	1.01	4.38	-0.22	1.92	1944
Thailand	-5.25	-0.93	-0.0	1.16	6.47	0.24	1.61	189994
Tunisia	-4.74	-0.97	-0.04	1.16	4.16	0.08	1.42	16238
Turkey	-6.43	-1.16	0.01	1.34	6.16	0.16	1.86	113049
UK	-7.29	-1.45	-0.04	1.62	7.5	0.19	2.27	599335
US	-6.18	-1.31	0.01	1.46	6.74	0.13	2.02	2180544
Uganda	-3.88	-1.73	0.02	0.64	3.06	-0.41	1.66	1261
Ukraine	-7.29	-1.02	-0.01	0.82	3.87	-0.11	1.52	8997
United Arab Emirates	-4.26	-1.06	-0.01	1.23	6.02	0.17	1.69	17352
Venezuela	-5.99	-1.79	-0.0	3.73	6.47	0.64	3.41	6946
Vietnam	-5.06	-0.95	0.04	1.26	6.47	0.25	1.78	119456

SIZE Trend

Country	Min	25%	Median	75%	Max	Mean	StdDev	Observations
Argentina	-1.79	-0.18	-0.0	0.18	1.97	0.01	0.38	23021
Australia	-1.58	-0.22	-0.01	0.2	1.84	0.01	0.42	516522
Austria	-2.09	-0.13	-0.01	0.11	2.22	-0.01	0.29	33313
Bahrain	-1.24	-0.09	-0.0	0.08	1.97	-0.01	0.18	6254
Bangladesh	-1.79	-0.15	-0.03	0.09	1.97	-0.02	0.25	46917
Belgium	-2.09	-0.12	-0.02	0.09	2.22	-0.02	0.28	56624
Bosnia and Herzegovina	-2.09	-0.13	-0.0	0.11	2.22	0.01	0.29	17114
Botswana	-1.79	-0.11	-0.01	0.09	1.97	-0.01	0.25	5219
Brazil	-1.79	-0.2	-0.02	0.17	1.97	-0.01	0.37	96084
Bulgaria	-2.09	-0.14	-0.02	0.12	2.22	-0.01	0.36	31525
Canada	-1.92	-0.18	0.01	0.21	2.02	0.02	0.42	389632
Chile	-1.79	-0.12	-0.0	0.12	1.97	0.01	0.25	48490
China	-0.91	-0.13	-0.01	0.12	1.19	0.0	0.23	677845
Colombia	-1.79	-0.14	-0.01	0.11	1.97	-0.01	0.25	11022
Croatia	-2.09	-0.14	-0.0	0.14	2.22	0.0	0.32	24802
Cyprus	-2.09	-0.17	0.0	0.16	2.22	-0.01	0.33	24526
Czech Republic	-2.09	-0.11	0.04	0.21	2.22	0.05	0.3	10100
Denmark	-2.09	-0.11	0.0	0.12	2.22	0.01	0.28	66962
Egypt	-1.79	-0.15	0.0	0.17	1.97	0.02	0.31	42388
Estonia	-1.99	-0.14	0.0	0.14	2.22	0.01	0.31	4933
Finland	-2.09	-0.12	0.01	0.16	2.22	0.03	0.28	48636
France	-2.09	-0.12	0.01	0.14	2.22	0.01	0.31	281108
Germany	-2.09	-0.15	-0.0	0.15	2.22	-0.01	0.37	326355
Ghana	-1.51	-0.22	-0.01	0.17	1.97	-0.03	0.31	3288
Greece	-2.09	-0.19	-0.01	0.17	2.22	-0.01	0.34	78977
Hong Kong	-1.58	-0.18	-0.01	0.16	1.84	-0.0	0.36	471713
Hungary	-2.09	-0.17	-0.01	0.15	2.22	-0.0	0.35	12819
Iceland	-2.09	-0.16	-0.02	0.11	2.22	-0.02	0.3	7679
India	-1.68	-0.22	-0.02	0.19	2.03	-0.0	0.39	948720
Indonesia	-1.79	-0.19	-0.02	0.16	1.97	-0.0	0.38	135517
Ireland	-2.09	-0.15	0.0	0.16	2.22	-0.0	0.33	13378
Israel	-2.09	-0.16	-0.01	0.16	2.22	0.01	0.35	142021
Italy	-2.09	-0.11	0.0	0.13	2.22	0.02	0.25	106475
Jamaica	-1.79	-0.15	0.0	0.18	1.97	0.03	0.33	13452
Japan	-1.58	-0.1	0.0	0.12	1.84	0.02	0.22	1284009
Jordan	-1.79	-0.11	-0.01	0.1	1.97	-0.0	0.23	48720
Kazakhstan	-1.79	-0.25	0.0	0.22	1.97	-0.02	0.49	2877
Kenya	-1.79	-0.14	0.0	0.14	1.97	0.01	0.26	14836
Kuwait	-1.79	-0.12	0.0	0.12	1.97	0.01	0.25	42438
Latvia	-2.09	-0.19	0.0	0.21	2.22	0.02	0.36	6288
Lithuania	-2.09	-0.15	-0.01	0.14	2.22	0.0	0.32	9016
Luxembourg	-2.09	-0.11	0.0	0.12	2.22	-0.01	0.32	5218
Macedonia	-1.47	-0.14	-0.01	0.11	2.14	0.02	0.3	8195
Malawi	-1.79	-0.14	0.02	0.21	1.97	0.01	0.48	2009
Malaysia	-1.79	-0.14	-0.01	0.14	1.97	0.0	0.3	309444
Malta	-1.49	-0.07	0.01	0.11	1.99	0.04	0.24	4404
Mauritius	-1.79	-0.11	-0.01	0.08	1.97	-0.01	0.2	10359
Mexico	-1.79	-0.12	0.0	0.13	1.97	0.0	0.27	36894
Montenegro	-2.09	-0.12	0.0	0.15	2.22	0.01	0.37	5690
Morocco	-1.79	-0.11	-0.0	0.11	1.76	0.01	0.21	19369
Namibia	-1.79	-0.07	0.02	0.13	1.97	0.05	0.36	1371
Netherlands	-2.09	-0.13	-0.01	0.11	2.22	-0.01	0.28	51891
New Zealand	-1.58	-0.14	-0.01	0.12	1.84	-0.0	0.28	33972
Nigeria	-1.79	-0.16	-0.02	0.15	1.97	0.0	0.34	35060
Norway	-2.09	-0.16	-0.0	0.16	2.22	0.01	0.37	76358
Oman	-1.79	-0.11	-0.0	0.11	1.97	0.0	0.26	21889
Pakistan	-1.79	-0.2	-0.03	0.18	1.97	0.02	0.38	97107
Peru	-1.79	-0.15	-0.0	0.14	1.97	0.01	0.31	20832
Philippines	-1.79	-0.16	-0.02	0.13	1.97	0.0	0.32	71848
Poland	-2.09	-0.18	-0.0	0.19	2.22	0.01	0.38	157464
Portugal	-2.09	-0.16	-0.02	0.11	2.22	-0.02	0.27	22108
Qatar	-1.79	-0.12	-0.01	0.11	1.97	-0.01	0.23	9952
Romania	-2.09	-0.14	0.0	0.18	2.22	0.03	0.37	35777
Russian Federation	-2.09	-0.19	-0.01	0.15	2.22	-0.01	0.37	47665
Rwanda	-1.79	-0.16	-0.03	0.09	1.91	0.01	0.49	406
Saudi Arabia	-1.79	-0.11	0.01	0.14	1.97	0.01	0.24	38732
Serbia	-2.09	-0.11	0.01	0.15	2.22	0.03	0.31	23092
Singapore	-1.58	-0.15	-0.01	0.13	1.84	-0.0	0.3	196752
Slovakia	-2.09	-0.17	0.02	0.25	2.22	0.04	0.44	4924
Slovenia	-2.09	-0.12	0.02	0.16	2.22	0.0	0.33	13898
South Africa	-1.79	-0.18	-0.02	0.15	1.97	-0.02	0.36	120363
South Korea	-1.58	-0.18	-0.03	0.14	1.84	-0.01	0.34	599084
Spain	-2.09	-0.11	0.01	0.14	2.22	0.02	0.28	62199
Sri Lanka	-1.79	-0.13	0.0	0.16	1.97	0.02	0.29	50425
Sweden	-2.09	-0.14	0.02	0.19	2.22	0.03	0.37	177984
Switzerland	-2.09	-0.11	-0.0	0.11	2.22	-0.0	0.26	86549
Taiwan	-1.58	-0.12	-0.01	0.12	1.84	0.0	0.24	260688
Tanzania	-0.98	-0.09	0.03	0.23	1.6	0.09	0.35	1944
Thailand	-1.79	-0.15	-0.01	0.13	1.97	0.0	0.29	189994
Tunisia	-1.79	-0.1	-0.01	0.1	1.82	0.0	0.2	16238
Turkey	-2.09	-0.2	-0.01	0.19	2.22	0.0	0.36	113049
UK	-2.09	-0.16	0.0	0.17	2.22	0.0	0.37	599335
US	-1.92	-0.16	0.0	0.15	2.02	-0.01	0.34	2180544
Uganda	-1.08	-0.15	-0.03	0.08	1.46	-0.02	0.29	1261
Ukraine	-2.09	-0.25	0.0	0.27	2.22	-0.0	0.53	8997
United Arab Emirates	-1.79	-0.11	0.0	0.12	1.97	0.01	0.25	17352
Venezuela	-1.79	-0.37	-0.05	0.24	1.97	-0.06	0.75	6946
Vietnam	-1.79	-0.18	-0.04	0.11	1.97	-0.03	0.28	119456

M/B

Country	Min	25%	Median	75%	Max	Mean	StdDev	Observations
Argentina	0.11	0.83	1.0	1.26	15.95	1.4	1.9	21805
Australia	0.15	0.67	1.0	1.78	15.01	1.8	2.42	481342
Austria	0.11	0.88	1.0	1.26	20.42	1.23	1.07	29859
Bahrain	0.24	0.88	1.0	1.14	5.52	1.08	0.4	5940
Bangladesh	0.12	0.82	1.0	1.48	15.95	1.5	1.63	42004
Belgium	0.11	0.85	1.0	1.33	20.42	1.36	1.52	46602
Bosnia and Herzegovina	0.13	0.66	1.0	1.48	20.42	1.16	1.02	9302
Botswana	0.29	0.83	1.0	1.35	15.95	1.32	1.3	4876
Brazil	0.11	0.79	1.0	1.39	15.95	1.61	2.41	87991
Bulgaria	0.11	0.72	1.0	1.36	20.42	1.29	1.46	19347
Canada	0.15	0.73	1.0	1.65	95.06	2.43	7.68	345592
Chile	0.11	0.78	1.0	1.35	15.95	1.27	1.42	45430
China	0.28	0.73	1.0	1.47	23.53	1.32	1.35	632407
Colombia	0.11	0.83	1.0	1.2	6.0	1.08	0.53	9998
Croatia	0.15	0.78	1.0	1.23	20.42	1.12	0.9	22620
Cyprus	0.11	0.78	1.0	1.28	20.42	1.23	1.46	20426
Czech Republic	0.2	0.77	1.0	1.27	20.42	1.18	1.14	8116
Denmark	0.11	0.88	1.0	1.42	20.42	1.6	2.13	62797
Egypt	0.18	0.82	1.0	1.37	15.95	1.31	1.22	39446
Estonia	0.23	0.85	1.0	1.29	20.42	1.25	1.22	4572
Finland	0.14	0.8	1.0	1.39	20.42	1.35	1.43	46370
France	0.11	0.82	1.0	1.38	20.42	1.4	1.62	236210
Germany	0.11	0.81	1.0	1.43	20.42	1.46	1.81	268367
Ghana	0.39	0.88	1.0	1.31	7.73	1.28	0.93	3043
Greece	0.11	0.82	1.0	1.29	20.42	1.21	0.96	75092
Hong Kong	0.15	0.74	1.0	1.54	15.01	1.53	1.88	431918
Hungary	0.11	0.75	1.0	1.38	20.42	1.74	3.15	11624
Iceland	0.11	0.87	1.0	1.21	4.69	1.09	0.41	6740
India	0.17	0.75	1.0	1.51	15.31	1.58	2.05	873039
Indonesia	0.11	0.8	1.0	1.44	15.95	1.46	1.68	129072
Ireland	0.16	0.81	1.0	1.39	20.42	1.32	1.32	12082
Israel	0.11	0.86	1.0	1.33	20.42	1.6	2.46	120573
Italy	0.11	0.86	1.0	1.28	20.42	1.23	1.01	98785
Jamaica	0.11	0.77	1.0	1.45	15.95	1.43	1.66	12148
Japan	0.16	0.84	1.0	1.25	15.01	1.29	1.24	1232151
Jordan	0.11	0.77	1.0	1.23	15.95	1.14	0.78	45361
Kazakhstan	0.24	0.88	1.0	1.2	15.95	1.43	1.75	2462
Kenya	0.19	0.78	1.0	1.23	15.95	1.24	1.07	13357
Kuwait	0.11	0.82	1.0	1.25	15.95	1.12	0.61	40566
Latvia	0.15	0.74	1.0	1.25	12.91	1.13	0.83	5388
Lithuania	0.29	0.83	1.0	1.22	7.38	1.1	0.49	7578
Luxembourg	0.27	0.81	1.0	1.23	20.42	1.77	3.64	4310
Macedonia	0.11	0.74	1.0	1.18	20.42	1.19	1.76	5175
Malawi	0.11	0.85	1.0	1.28	15.95	1.29	1.37	1771
Malaysia	0.11	0.79	1.0	1.33	15.95	1.29	1.24	292357
Malta	0.33	0.9	1.0	1.49	14.98	1.48	1.42	3855
Mauritius	0.11	0.77	1.0	1.23	15.95	1.19	0.98	9579
Mexico	0.11	0.81	1.0	1.32	14.74	1.15	0.58	34931
Montenegro	0.11	0.66	1.0	1.53	20.42	1.4	1.85	3731
Morocco	0.22	0.85	1.0	1.46	11.69	1.26	0.69	18424
Namibia	0.46	0.89	1.0	1.13	4.08	1.24	0.7	1254
Netherlands	0.11	0.81	1.0	1.38	20.42	1.45	1.97	48131
New Zealand	0.15	0.77	1.0	1.57	15.01	1.61	2.08	31843
Nigeria	0.12	0.82	1.0	1.36	15.95	1.39	1.45	31509
Norway	0.11	0.83	1.0	1.48	20.42	1.57	1.95	71302
Oman	0.15	0.87	1.0	1.23	5.53	1.12	0.47	20469
Pakistan	0.15	0.82	1.0	1.29	15.95	1.32	1.29	53723
Peru	0.11	0.74	1.0	1.39	15.95	1.26	0.98	18902
Philippines	0.11	0.74	1.0	1.6	15.95	1.92	2.99	68434
Poland	0.11	0.78	1.0	1.41	20.42	1.54	2.21	112461
Portugal	0.11	0.86	1.0	1.22	20.42	1.1	0.6	20101
Qatar	0.11	0.84	1.0	1.31	11.22	1.16	0.55	9461
Romania	0.11	0.75	1.0	1.35	20.42	1.26	1.49	22676
Russian Federation	0.11	0.72	1.0	1.35	20.42	1.36	1.92	43996
Rwanda	0.35	0.8	1.0	1.59	2.11	1.12	0.44	349
Saudi Arabia	0.14	0.77	1.0	1.48	15.95	1.32	1.07	36423
Serbia	0.11	0.76	1.0	1.25	20.42	1.09	0.79	15267
Singapore	0.15	0.8	1.0	1.35	15.01	1.33	1.36	187091
Slovakia	0.15	0.79	1.0	1.15	9.7	1.03	0.5	3274
Slovenia	0.11	0.77	1.0	1.2	20.42	1.09	0.97	10013
South Africa	0.11	0.77	1.0	1.44	15.95	1.36	1.53	110619
South Korea	0.15	0.81	1.0	1.4	15.01	1.38	1.41	534892
Spain	0.11	0.84	1.0	1.29	20.42	1.24	0.99	57689
Sri Lanka	0.16	0.81	1.0	1.24	15.95	1.25	1.21	46998
Sweden	0.11	0.71	1.0	1.68	20.42	1.62	2.0	166699
Switzerland	0.11	0.83	1.0	1.45	20.42	1.4	1.39	81485
Taiwan	0.21	0.83	1.0	1.34	15.01	1.24	0.83	245725
Tanzania	0.44	0.75	1.0	1.59	15.95	1.73	2.25	1678
Thailand	0.14	0.8	1.0	1.36	15.95	1.26	1.0	179388
Tunisia	0.2	0.88	1.0	1.3	6.4	1.21	0.61	14844
Turkey	0.11	0.79	1.0	1.4	20.42	1.7	3.04	107226
UK	0.11	0.72	1.0	1.59	20.42	1.63	2.29	547646
US	0.15	0.78	1.0	1.59	95.06	1.64	3.32	2081993
Uganda	0.43	0.82	1.0	1.13	15.95	1.11	0.94	1170
Ukraine	0.11	0.76	1.0	1.37	20.42	1.41	1.95	7523
United Arab Emirates	0.21	0.84	1.0	1.16	15.95	1.15	0.9	16794
Venezuela	0.11	0.11	1.0	6.61	15.95	4.51	6.2	4632
Vietnam	0.11	0.86	1.0	1.2	15.95	1.13	0.62	114639

SIGMA

Country	Min	25%	Median	75%	Max	Mean	StdDev	Observations
Argentina	0.02	0.09	0.11	0.15	0.72	0.13	0.05	19786
Australia	0.03	0.13	0.23	0.33	1.05	0.25	0.16	436380
Austria	0.02	0.06	0.09	0.13	1.33	0.12	0.1	28364
Bahrain	0.02	0.06	0.08	0.12	0.4	0.09	0.05	2701
Bangladesh	0.01	0.08	0.11	0.14	0.67	0.11	0.05	46053
Belgium	0.02	0.06	0.08	0.12	1.4	0.1	0.08	45744
Bosnia and Herzegovina	0.02	0.1	0.15	0.21	0.77	0.17	0.1	4546
Botswana	0.01	0.03	0.04	0.06	0.42	0.05	0.04	2140
Brazil	0.02	0.09	0.13	0.2	1.06	0.17	0.12	73821
Bulgaria	0.02	0.1	0.15	0.23	1.11	0.19	0.13	13276
Canada	0.01	0.1	0.18	0.3	1.12	0.23	0.18	350006
Chile	0.01	0.06	0.08	0.11	0.83	0.1	0.06	32384
China	0.03	0.09	0.11	0.14	0.41	0.12	0.04	672413
Colombia	0.02	0.06	0.08	0.11	0.61	0.1	0.06	7381
Croatia	0.02	0.09	0.13	0.19	1.19	0.15	0.1	16518
Cyprus	0.02	0.14	0.2	0.28	1.4	0.24	0.18	17068
Czech Republic	0.02	0.07	0.11	0.16	0.66	0.12	0.06	7367
Denmark	0.02	0.07	0.1	0.16	1.23	0.13	0.1	54315
Egypt	0.01	0.09	0.11	0.15	0.64	0.13	0.07	39213
Estonia	0.02	0.06	0.1	0.16	0.68	0.12	0.09	4506
Finland	0.02	0.08	0.1	0.14	1.4	0.12	0.09	44086
France	0.02	0.08	0.11	0.16	1.4	0.13	0.09	237805
Germany	0.02	0.09	0.14	0.25	1.4	0.23	0.25	299288
Ghana	0.01	0.06	0.08	0.12	1.06	0.1	0.09	1576
Greece	0.02	0.1	0.14	0.19	0.9	0.16	0.09	75160
Hong Kong	0.03	0.1	0.15	0.23	1.05	0.18	0.1	459527
Hungary	0.02	0.08	0.12	0.2	0.83	0.15	0.1	10850
Iceland	0.03	0.06	0.08	0.12	0.61	0.1	0.07	5108
India	0.04	0.14	0.17	0.21	1.02	0.2	0.11	844987
Indonesia	0.01	0.11	0.16	0.24	1.06	0.19	0.12	116114
Ireland	0.03	0.08	0.11	0.17	1.4	0.16	0.14	10496
Israel	0.02	0.08	0.12	0.18	1.1	0.15	0.09	124764
Italy	0.02	0.07	0.09	0.13	0.77	0.11	0.05	101864
Jamaica	0.03	0.14	0.19	0.27	0.84	0.22	0.11	10331
Japan	0.03	0.07	0.1	0.15	1.05	0.12	0.07	1228817
Jordan	0.01	0.09	0.12	0.15	0.88	0.12	0.05	38668
Kazakhstan	0.01	0.06	0.1	0.16	0.95	0.15	0.14	1557
Kenya	0.03	0.09	0.12	0.16	0.52	0.13	0.05	12831
Kuwait	0.02	0.09	0.12	0.16	1.06	0.13	0.07	35037
Latvia	0.03	0.09	0.12	0.2	0.94	0.16	0.11	3177
Lithuania	0.02	0.07	0.1	0.15	1.02	0.12	0.08	7531
Luxembourg	0.02	0.08	0.1	0.14	0.52	0.11	0.05	3243
Macedonia	0.02	0.07	0.1	0.15	0.66	0.12	0.07	3224
Malawi	0.01	0.06	0.09	0.13	0.58	0.11	0.08	437
Malaysia	0.01	0.09	0.14	0.2	1.06	0.16	0.11	294978
Malta	0.02	0.05	0.07	0.1	0.59	0.09	0.06	1766
Mauritius	0.02	0.04	0.06	0.09	0.43	0.08	0.05	7340
Mexico	0.01	0.07	0.09	0.12	1.03	0.11	0.07	28264
Montenegro	0.05	0.13	0.19	0.34	1.4	0.3	0.28	2081
Morocco	0.02	0.07	0.1	0.12	0.47	0.1	0.04	15956
Namibia	0.02	0.04	0.06	0.09	0.34	0.07	0.05	464
Netherlands	0.02	0.06	0.09	0.13	1.4	0.11	0.09	48886
New Zealand	0.03	0.06	0.08	0.14	1.05	0.12	0.11	28483
Nigeria	0.01	0.1	0.13	0.16	0.6	0.13	0.06	27555
Norway	0.02	0.09	0.14	0.2	1.26	0.17	0.11	64186
Oman	0.01	0.06	0.08	0.11	0.98	0.09	0.06	13978
Pakistan	0.03	0.1	0.14	0.22	1.06	0.19	0.15	82454
Peru	0.02	0.08	0.11	0.16	0.53	0.13	0.07	11221
Philippines	0.02	0.1	0.14	0.22	0.97	0.18	0.11	60268
Poland	0.02	0.11	0.16	0.27	1.4	0.21	0.15	147399
Portugal	0.02	0.07	0.1	0.16	1.21	0.13	0.1	16765
Qatar	0.02	0.06	0.08	0.11	0.49	0.09	0.05	9592
Romania	0.03	0.11	0.16	0.24	1.4	0.19	0.13	21073
Russian Federation	0.02	0.09	0.13	0.2	1.25	0.16	0.11	36000
Rwanda	0.01	0.03	0.05	0.07	0.13	0.05	0.03	197
Saudi Arabia	0.02	0.06	0.08	0.11	0.64	0.09	0.05	37656
Serbia	0.02	0.11	0.19	0.26	1.4	0.2	0.11	8038
Singapore	0.03	0.09	0.14	0.23	1.05	0.19	0.17	171062
Slovakia	0.02	0.08	0.11	0.17	0.55	0.13	0.09	1436
Slovenia	0.02	0.06	0.09	0.16	1.27	0.14	0.13	8505
South Africa	0.01	0.09	0.13	0.22	1.06	0.19	0.17	105662
South Korea	0.03	0.1	0.14	0.2	1.05	0.16	0.08	587953
Spain	0.02	0.06	0.09	0.13	0.95	0.11	0.06	52227
Sri Lanka	0.01	0.1	0.14	0.19	1.06	0.16	0.09	47692
Sweden	0.02	0.1	0.15	0.25	1.4	0.2	0.14	167460
Switzerland	0.02	0.06	0.09	0.12	1.4	0.11	0.09	75907
Taiwan	0.03	0.07	0.09	0.12	0.62	0.1	0.04	256813
Tanzania	0.01	0.05	0.08	0.11	0.39	0.09	0.06	1275
Thailand	0.01	0.08	0.12	0.16	1.06	0.14	0.09	177469
Tunisia	0.02	0.06	0.08	0.1	0.58	0.08	0.04	14127
Turkey	0.03	0.1	0.14	0.18	1.09	0.15	0.07	111484
UK	0.02	0.08	0.12	0.19	1.4	0.15	0.1	528636
US	0.01	0.09	0.14	0.22	1.12	0.17	0.12	2092393
Uganda	0.01	0.08	0.12	0.16	0.47	0.14	0.09	670
Ukraine	0.02	0.11	0.17	0.26	1.17	0.22	0.16	3944
United Arab Emirates	0.01	0.08	0.1	0.15	0.49	0.12	0.06	11828
Venezuela	0.01	0.15	0.23	0.33	1.06	0.26	0.15	4642
Vietnam	0.01	0.11	0.14	0.19	0.72	0.15	0.07	107698

CASH/TA Level

Country	Min	25%	Median	75%	Max	Mean	StdDev	Observations
Argentina	-9.4	-3.35	-2.09	-1.64	-0.3	-2.52	1.3	3764
Australia	-9.53	-4.01	-2.76	-1.62	-0.01	-2.9	1.66	56843
Austria	-10.93	-4.22	-2.85	-1.92	-0.41	-3.29	1.87	8932
Bahrain	-7.12	-2.34	-1.91	-1.49	-0.09	-2.06	0.96	4532
Bangladesh	-9.24	-2.54	-1.89	-1.0	-0.0	-2.08	1.4	15228
Belgium	-12.68	-5.59	-4.28	-2.66	-0.04	-4.25	2.12	15768
Bosnia and Herzegovina	-8.33	-2.92	-1.57	-1.08	-0.39	-2.21	1.74	1537
Botswana	-7.93	-3.67	-2.43	-1.83	-0.02	-2.86	1.5	2668
Brazil	-11.84	-4.15	-2.46	-1.51	-0.0	-3.04	2.04	16764
Bulgaria	-11.11	-4.06	-2.84	-1.91	-0.0	-3.19	1.79	6921
Canada	-9.78	-4.39	-3.14	-1.85	-0.0	-3.19	1.81	38724
Chile	-11.84	-4.89	-3.29	-2.39	-0.0	-3.88	2.2	13711
China	-7.17	-2.56	-2.07	-1.56	-0.06	-2.12	0.92	49111
Colombia	-11.84	-3.02	-2.46	-2.13	-0.0	-2.83	1.57	4284
Croatia	-11.74	-3.63	-1.58	-1.39	-0.89	-2.5	1.72	3525
Cyprus	-11.53	-4.2	-2.74	-1.62	-0.09	-3.16	1.92	8364
Czech Republic	-11.68	-4.42	-2.06	-1.36	-0.66	-3.05	2.38	1080
Denmark	-12.68	-3.53	-2.53	-1.92	0.0	-2.86	1.42	23293
Egypt	-10.53	-3.52	-2.37	-1.59	-0.03	-2.73	1.52	12449
Estonia	-7.61	-3.87	-2.99	-1.68	-0.56	-2.99	1.51	947
Finland	-11.73	-4.09	-2.91	-2.04	-0.1	-3.33	1.97	5038
France	-12.68	-5.26	-3.55	-2.47	-0.03	-4.2	2.49	42477
Germany	-12.68	-4.57	-3.15	-1.91	0.0	-3.51	2.15	62659
Ghana	-7.86	-2.0	-1.46	-1.18	-0.59	-1.66	0.83	1307
Greece	-10.97	-3.79	-2.64	-1.69	-0.19	-2.96	1.74	9292
Hong Kong	-9.53	-3.25	-2.34	-1.63	-0.01	-2.53	1.35	108787
Hungary	-11.86	-4.08	-2.99	-2.02	0.0	-3.23	1.71	3079
Iceland	-7.87	-3.86	-3.18	-2.41	-0.99	-3.22	1.06	1623
India	-9.81	-4.74	-3.58	-2.43	-0.01	-3.64	1.7	169004
Indonesia	-10.67	-3.75	-2.52	-1.83	-0.04	-2.89	1.43	35989
Ireland	-8.12	-3.41	-2.36	-1.74	-0.24	-2.75	1.42	2659
Israel	-12.65	-3.75	-2.81	-2.0	0.0	-3.02	1.53	39805
Italy	-12.68	-4.32	-2.97	-1.94	-0.0	-3.69	2.63	25038
Jamaica	-11.32	-3.35	-2.25	-1.21	-0.0	-2.43	1.63	4453
Japan	-9.53	-3.21	-2.59	-1.88	-0.01	-2.58	1.02	114527
Jordan	-10.03	-4.49	-3.03	-1.6	-0.01	-3.26	1.97	23567
Kazakhstan	-4.45	-2.26	-1.93	-1.61	-0.44	-2.0	0.61	1548
Kenya	-7.93	-3.06	-2.27	-1.9	-0.89	-2.65	1.11	4441
Kuwait	-10.82	-4.18	-3.19	-2.33	-0.02	-3.35	1.48	25541
Latvia	-5.85	-3.63	-2.81	-1.53	-0.16	-2.78	1.35	377
Lithuania	-9.12	-4.44	-2.78	-1.74	-0.29	-3.17	1.86	1182
Luxembourg	-9.97	-3.61	-2.57	-1.95	-0.69	-3.12	1.85	2796
Macedonia	-9.02	-1.6	-1.41	-1.1	-0.26	-1.9	1.65	1471
Malawi	-6.8	-3.36	-1.63	-1.21	-0.35	-2.28	1.47	1249
Malaysia	-11.84	-4.34	-3.19	-2.18	-0.0	-3.36	1.6	58262
Malta	-7.89	-3.61	-2.53	-1.53	-0.69	-2.77	1.57	2441
Mauritius	-11.55	-4.86	-3.55	-2.66	-0.78	-4.2	2.29	2805
Mexico	-11.84	-4.12	-2.92	-2.18	-0.39	-3.36	1.87	7752
Montenegro	-6.78	-3.03	-1.81	-1.55	-0.81	-2.28	1.25	558
Morocco	-11.84	-5.69	-3.84	-2.53	-0.02	-4.5	2.74	6517
Namibia	-9.4	-5.31	-2.89	-2.17	-0.52	-3.54	1.99	1021
Netherlands	-12.68	-4.89	-3.31	-2.31	0.0	-3.73	1.96	8175
New Zealand	-9.53	-5.84	-3.79	-2.26	-0.01	-4.02	2.11	5291
Nigeria	-11.84	-2.28	-1.55	-1.12	-0.0	-1.93	1.29	11055
Norway	-7.54	-3.82	-3.25	-2.61	-0.01	-3.19	1.05	15225
Oman	-10.19	-3.96	-2.77	-1.94	-0.02	-3.02	1.44	8259
Pakistan	-8.8	-2.7	-2.21	-1.68	-0.11	-2.39	1.24	12043
Peru	-6.56	-2.28	-1.69	-1.46	-0.0	-1.99	0.96	2945
Philippines	-11.84	-4.07	-2.48	-1.66	-0.0	-3.05	1.96	27534
Poland	-11.15	-3.86	-2.73	-1.88	0.0	-3.0	1.63	20121
Portugal	-12.68	-4.44	-2.83	-2.01	-0.08	-3.56	2.46	4185
Qatar	-6.68	-2.64	-1.97	-1.4	-0.0	-2.07	1.08	4858
Romania	-8.63	-4.26	-2.55	-1.47	-0.39	-3.05	1.94	2680
Russian Federation	-12.68	-2.24	-1.74	-1.26	-0.01	-1.99	1.61	4580
Rwanda	-6.22	-4.41	-1.95	-1.59	-1.14	-2.6	1.53	240
Saudi Arabia	-10.8	-2.7	-1.95	-1.04	-0.0	-2.12	1.49	11596
Serbia	-7.13	-1.58	-1.25	-0.81	-0.03	-1.5	1.22	2222
Singapore	-8.7	-3.64	-2.57	-1.73	-0.01	-2.77	1.39	39841
Slovakia	-8.39	-3.21	-2.44	-1.72	-1.1	-2.64	1.21	1384
Slovenia	-11.79	-5.4	-4.1	-3.01	-0.08	-4.31	1.92	2570
South Africa	-11.84	-4.2	-2.75	-1.91	-0.0	-3.13	1.71	26455
South Korea	-9.53	-4.28	-3.26	-2.51	-0.01	-3.56	1.51	38396
Spain	-10.42	-4.34	-3.08	-2.15	0.0	-3.38	1.75	17975
Sri Lanka	-9.45	-3.79	-2.85	-2.24	-0.0	-3.02	1.28	14997
Sweden	-11.42	-4.2	-3.13	-2.09	0.0	-3.22	1.63	25629
Switzerland	-9.12	-3.66	-2.55	-1.57	0.0	-2.72	1.48	22141
Taiwan	-9.38	-3.68	-2.78	-2.11	-0.01	-2.97	1.24	25040
Tanzania	-4.93	-1.91	-1.62	-1.07	-0.27	-1.65	0.94	719
Thailand	-10.56	-4.12	-3.08	-2.22	-0.0	-3.22	1.43	40297
Tunisia	-11.42	-3.98	-3.14	-2.34	-0.86	-3.26	1.24	6164
Turkey	-12.68	-4.06	-2.46	-1.63	-0.0	-3.07	2.04	25800
UK	-12.6	-3.58	-2.44	-1.48	0.0	-2.7	1.74	105387
US	-9.78	-3.94	-3.19	-2.48	-0.0	-3.29	1.36	450102
Uganda	-4.36	-1.97	-1.44	-1.24	-0.59	-1.93	1.13	628
Ukraine	-9.44	-2.23	-1.86	-1.47	-0.45	-2.31	1.74	1076
United Arab Emirates	-5.77	-2.6	-1.96	-1.49	-0.0	-2.12	0.91	11021
Venezuela	-5.24	-3.03	-1.62	-1.32	-0.18	-2.1	1.15	2437
Vietnam	-7.87	-3.7	-2.43	-1.35	-0.0	-2.61	1.54	16675

CASH/TA Trend

Country	Min	25%	Median	75%	Max	Mean	StdDev	Observations
Argentina	-4.02	-0.13	0.0	0.16	4.09	0.02	0.5	3764
Australia	-3.5	-0.21	0.0	0.16	3.58	-0.02	0.64	56843
Austria	-4.43	-0.13	0.0	0.1	4.71	-0.01	0.64	8932
Bahrain	-2.17	-0.14	-0.0	0.12	2.93	0.0	0.37	4532
Bangladesh	-4.02	-0.06	-0.0	0.05	4.09	0.01	0.4	15228
Belgium	-4.43	-0.18	0.0	0.17	4.71	-0.0	0.65	15768
Bosnia and Herzegovina	-3.65	-0.06	0.0	0.06	3.22	0.01	0.44	1537
Botswana	-4.02	-0.15	0.0	0.14	4.09	0.01	0.52	2668
Brazil	-4.02	-0.2	0.0	0.17	4.09	-0.01	0.72	16764
Bulgaria	-4.43	-0.13	0.0	0.09	4.71	-0.01	0.65	6921
Canada	-3.42	-0.22	0.0	0.18	3.35	-0.02	0.68	38724
Chile	-4.02	-0.22	0.0	0.22	4.09	0.03	0.93	13711
China	-2.25	-0.15	-0.0	0.12	2.36	-0.01	0.38	49111
Colombia	-4.02	-0.15	-0.0	0.13	4.09	0.01	0.65	4284
Croatia	-3.41	-0.08	0.0	0.09	3.06	0.01	0.38	3525
Cyprus	-4.43	-0.18	0.0	0.07	4.71	-0.05	0.77	8364
Czech Republic	-4.43	-0.08	0.0	0.09	4.71	-0.01	0.59	1080
Denmark	-4.43	-0.17	0.0	0.17	4.71	0.0	0.6	23293
Egypt	-4.02	-0.2	-0.0	0.17	4.09	-0.01	0.58	12449
Estonia	-2.29	-0.24	0.0	0.18	3.87	0.01	0.63	947
Finland	-4.43	-0.22	0.0	0.16	4.71	-0.01	0.61	5038
France	-4.43	-0.14	0.0	0.15	4.71	0.01	0.68	42477
Germany	-4.43	-0.18	0.0	0.14	4.71	-0.01	0.75	62659
Ghana	-1.46	-0.12	0.0	0.14	1.56	0.01	0.28	1307
Greece	-4.43	-0.18	0.0	0.14	4.71	0.01	0.76	9292
Hong Kong	-3.5	-0.17	-0.0	0.14	3.58	-0.01	0.54	108787
Hungary	-3.93	-0.18	0.0	0.22	4.71	0.02	0.72	3079
Iceland	-3.47	-0.18	0.0	0.14	4.07	-0.0	0.55	1623
India	-4.57	-0.18	0.0	0.17	4.78	0.0	0.79	169004
Indonesia	-4.02	-0.17	0.0	0.15	4.09	0.0	0.5	35989
Ireland	-4.34	-0.1	0.0	0.11	3.35	0.01	0.49	2659
Israel	-4.43	-0.23	0.0	0.21	4.71	-0.0	0.7	39805
Italy	-4.43	-0.16	0.0	0.13	4.71	0.01	0.67	25038
Jamaica	-4.02	-0.15	0.0	0.15	4.09	-0.01	0.59	4453
Japan	-3.5	-0.12	0.0	0.13	3.58	0.0	0.32	114527
Jordan	-4.02	-0.19	0.0	0.14	4.09	-0.03	0.71	23567
Kazakhstan	-3.23	-0.12	0.0	0.12	1.34	-0.0	0.3	1548
Kenya	-2.88	-0.13	0.0	0.1	3.86	-0.01	0.4	4441
Kuwait	-4.02	-0.22	0.0	0.22	4.09	0.0	0.66	25541
Latvia	-1.9	-0.17	-0.0	0.15	1.36	-0.03	0.41	377
Lithuania	-2.66	-0.17	0.0	0.16	4.71	0.03	0.64	1182
Luxembourg	-4.43	-0.15	0.0	0.14	4.71	0.01	0.64	2796
Macedonia	-2.32	-0.07	0.0	0.04	3.76	-0.02	0.33	1471
Malawi	-4.02	-0.08	0.0	0.09	2.92	0.01	0.44	1249
Malaysia	-4.02	-0.18	0.0	0.2	4.09	0.02	0.62	58262
Malta	-3.43	-0.11	0.0	0.1	2.84	0.01	0.4	2441
Mauritius	-4.02	-0.14	0.0	0.13	4.09	-0.01	0.64	2805
Mexico	-4.02	-0.2	0.0	0.18	4.09	0.01	0.59	7752
Montenegro	-3.1	-0.01	0.0	0.07	1.2	-0.01	0.33	558
Morocco	-4.02	-0.16	0.0	0.17	4.09	-0.01	0.69	6517
Namibia	-3.8	-0.14	0.0	0.15	4.09	0.01	0.76	1021
Netherlands	-4.43	-0.15	0.0	0.16	4.71	0.01	0.76	8175
New Zealand	-3.5	-0.24	0.0	0.21	3.58	-0.01	0.67	5291
Nigeria	-3.72	-0.12	0.0	0.11	4.09	0.0	0.45	11055
Norway	-4.2	-0.22	0.0	0.19	4.71	-0.01	0.49	15225
Oman	-4.02	-0.24	0.0	0.2	4.09	-0.02	0.71	8259
Pakistan	-4.02	-0.12	0.0	0.09	4.09	-0.01	0.46	12043
Peru	-4.02	-0.1	0.0	0.09	3.19	-0.0	0.35	2945
Philippines	-4.02	-0.17	-0.0	0.13	4.09	-0.01	0.63	27534
Poland	-4.43	-0.25	0.0	0.19	4.71	-0.02	0.72	20121
Portugal	-4.43	-0.12	-0.0	0.07	4.71	-0.01	0.48	4185
Qatar	-2.48	-0.16	-0.01	0.12	3.33	-0.01	0.38	4858
Romania	-4.43	-0.15	-0.0	0.17	4.47	0.02	0.65	2680
Russian Federation	-4.43	-0.14	0.0	0.15	4.71	-0.01	0.67	4580
Rwanda	-0.78	-0.15	0.0	0.15	1.66	0.01	0.33	240
Saudi Arabia	-4.02	-0.16	-0.01	0.12	4.09	-0.03	0.6	11596
Serbia	-4.35	-0.08	0.0	0.04	2.45	-0.03	0.38	2222
Singapore	-3.5	-0.16	0.0	0.15	3.58	-0.0	0.49	39841
Slovakia	-4.43	-0.14	-0.0	0.07	2.78	-0.02	0.43	1384
Slovenia	-4.43	-0.16	0.0	0.18	4.71	0.01	0.84	2570
South Africa	-4.02	-0.15	0.0	0.13	4.09	-0.0	0.62	26455
South Korea	-3.5	-0.24	-0.0	0.24	3.58	-0.01	0.72	38396
Spain	-4.43	-0.18	0.0	0.15	4.71	-0.0	0.61	17975
Sri Lanka	-4.02	-0.18	0.0	0.19	4.09	-0.0	0.58	14997
Sweden	-4.43	-0.26	-0.0	0.2	4.71	-0.03	0.69	25629
Switzerland	-4.43	-0.1	0.0	0.09	4.71	-0.0	0.48	22141
Taiwan	-3.5	-0.16	0.0	0.14	3.58	-0.0	0.52	25040
Tanzania	-1.03	-0.1	-0.0	0.04	1.4	-0.01	0.22	719
Thailand	-4.02	-0.22	0.0	0.19	4.09	-0.0	0.58	40297
Tunisia	-4.02	-0.13	0.0	0.14	4.09	0.0	0.51	6164
Turkey	-4.43	-0.24	0.0	0.21	4.71	0.0	0.92	25800
UK	-4.43	-0.18	0.0	0.13	4.71	-0.02	0.64	105387
US	-3.42	-0.22	-0.01	0.17	3.35	-0.02	0.53	450102
Uganda	-1.04	-0.08	0.0	0.1	0.79	-0.0	0.24	628
Ukraine	-2.51	-0.12	0.0	0.08	1.8	-0.02	0.28	1076
United Arab Emirates	-3.28	-0.13	0.0	0.1	3.4	-0.01	0.35	11021
Venezuela	-2.21	-0.05	0.0	0.06	2.8	0.01	0.36	2437
Vietnam	-4.02	-0.25	-0.01	0.17	4.09	-0.05	0.64	16675

Table A.9: Exits classified as ”Defaults”.

Default	
Action Type	**Subcategory**
Bankruptcy filing	Administration, Arrangement, Canadian Companies' Creditors Arrangement Act (CCAA), Chapter 7,11,15 (United States bankruptcy code), Conservatorship, Insolvency, Japanese Corporate Reogranization Law (CRL), Judicial management, Liquidation, Pre-negotiation Chapter 11, Protection, Receivership, Rehabilitation, Rehabilitation (Thailand 1997), Reorganization, Restructuring, Section 304, Supreme Court declaration, Winding up, Work out, Sued by creditor, Petition withdrawn
Delisting	Followed by bankruptcy
Default corporate action	Bankruptcy, Coupon & principal payment, Coupon payment only, Debt restructuring, Interest payment, Loan payment, Principal payment, Alternative Dispute Resolution (ADR, Japan only), Declared sick (India only), Regulatory action (Taiwan only), Financial difficulty and shutdown (Taiwan only), Buyback option, Substantial Subsidiary defaults (those which make up more than 75% holdings of the listed parent)

Table A.10: Exits classified as ”Other Exits”.

Other Exits	
Action Type	**Subcategory**
Delisting	Acquired/merged, Assimilated with underlying shares, Bid price below minimum, Cancellation of listing, Failure to meet listing requirements, Failure to pay listing fees, Inactive security, Insufficient assets, Insufficient capital and surplus, Insufficient number of market makers, Issue postponed, Lack of market maker interest, Lack of public interest, Liquidated, Not current in required filings, NP/FP finished, Privatized, Reorganization, Security called for redemptions, the company's request, Scheme of arrangement, Selective capital reduction of the company, From exchange to Over-the-Counter (OTC), Privatised

Table A.11: Number of defaults and other exits of 88 economics from 1990 to 2022.

Economy: Argentina

		Defaults		**Others**	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	1	0	0.0	0	0.0
1993	1	0	0.0	0	0.0
1994	25	0	0.0	1	4.0
1995	97	0	0.0	4	4.12
1996	100	0	0.0	5	5.0
1997	97	0	0.0	12	12.37
1998	89	1	1.12	8	8.99
1999	85	1	1.18	12	14.12
2000	79	1	1.27	5	6.33
2001	75	2	2.67	12	16.0
2002	79	7	8.86	3	3.8
2003	77	3	3.9	3	3.9
2004	74	2	2.7	1	1.35
2005	73	0	0.0	1	1.37
2006	75	0	0.0	0	0.0
2007	80	0	0.0	1	1.25
2008	80	0	0.0	5	6.25
2009	75	1	1.33	6	8.0
2010	73	1	1.37	0	0.0
2011	73	0	0.0	0	0.0
2012	74	0	0.0	1	1.35
2013	73	0	0.0	4	5.48
2014	70	0	0.0	4	5.71
2015	68	0	0.0	1	1.47
2016	73	1	1.37	0	0.0
2017	80	0	0.0	2	2.5
2018	78	0	0.0	3	3.85
2019	76	0	0.0	6	7.89
2020	76	3	3.95	3	3.95
2021	72	1	1.39	1	1.39
2022	72	0	0.0	3	4.17

Economy: Australia

		Defaults		**Others**	
Year	Active	#	%	#	%
1990	761	0	0.0	39	5.12
1991	742	4	0.54	26	3.5
1992	766	0	0.0	20	2.61
1993	849	0	0.0	11	1.3
1994	951	0	0.0	12	1.26
1995	986	0	0.0	24	2.43
1996	1036	2	0.19	29	2.8
1997	1087	2	0.18	56	5.15
1998	1087	3	0.28	66	6.07
1999	1138	3	0.26	50	4.39
2000	1265	9	0.71	58	4.58
2001	1272	27	2.12	63	4.95
2002	1267	9	0.71	59	4.66
2003	1294	8	0.62	53	4.1
2004	1394	4	0.29	47	3.37
2005	1527	5	0.33	55	3.6
2006	1671	3	0.18	76	4.55
2007	1857	4	0.22	78	4.2
2008	1850	24	1.3	73	3.95
2009	1798	27	1.5	64	3.56
2010	1825	5	0.27	76	4.16
2011	1865	1	0.05	97	5.2
2012	1820	2	0.11	94	5.16
2013	1788	5	0.28	69	3.86
2014	1800	7	0.39	95	5.28
2015	1814	3	0.17	94	5.18
2016	1853	2	0.11	113	6.1
2017	1866	12	0.64	92	4.93
2018	1885	9	0.48	107	5.68
2019	1845	19	1.03	132	7.15
2020	1788	9	0.5	82	4.59
2021	1925	9	0.47	75	3.9
2022	1959	6	0.31	59	3.01

Economy: Austria

		Defaults		Others	
Year	Active	#	%	#	%
1990	1	0	0.0	1	100.0
1991	78	0	0.0	0	0.0
1992	89	0	0.0	0	0.0
1993	100	0	0.0	0	0.0
1994	111	0	0.0	0	0.0
1995	118	0	0.0	1	0.85
1996	120	0	0.0	3	2.5
1997	123	0	0.0	4	3.25
1998	122	0	0.0	8	6.56
1999	119	0	0.0	10	8.4
2000	126	0	0.0	8	6.35
2001	127	2	1.57	6	4.72
2002	124	0	0.0	9	7.26
2003	123	0	0.0	13	10.57
2004	113	0	0.0	10	8.85
2005	111	0	0.0	8	7.21
2006	111	0	0.0	4	3.6
2007	115	0	0.0	5	4.35
2008	114	2	1.75	3	2.63
2009	111	1	0.9	3	2.7
2010	111	1	0.9	9	8.11
2011	103	0	0.0	9	8.74
2012	96	1	1.04	6	6.25
2013	92	0	0.0	4	4.35
2014	90	0	0.0	0	0.0
2015	93	1	1.08	10	10.75
2016	84	0	0.0	8	9.52
2017	81	0	0.0	8	9.88
2018	75	0	0.0	3	4.0
2019	78	0	0.0	4	5.13
2020	79	0	0.0	5	6.33
2021	80	0	0.0	2	2.5
2022	81	0	0.0	2	2.47

Economy: Bahrain

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	0	0	NaN	0	NaN
2001	0	0	NaN	0	NaN
2002	0	0	NaN	0	NaN
2003	0	0	NaN	0	NaN
2004	32	0	0.0	0	0.0
2005	36	0	0.0	0	0.0
2006	39	0	0.0	0	0.0
2007	40	0	0.0	1	2.5
2008	41	1	2.44	2	4.88
2009	38	0	0.0	1	2.63
2010	39	0	0.0	1	2.56
2011	38	1	2.63	2	5.26
2012	35	0	0.0	3	8.57
2013	32	0	0.0	0	0.0
2014	34	0	0.0	0	0.0
2015	34	0	0.0	2	5.88
2016	34	0	0.0	3	8.82
2017	34	0	0.0	3	8.82
2018	32	0	0.0	1	3.12
2019	33	0	0.0	1	3.03
2020	33	0	0.0	0	0.0
2021	36	0	0.0	1	2.78
2022	37	0	0.0	0	0.0

Economy: Bangladesh

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	161	0	0.0	0	0.0
2000	171	0	0.0	37	21.64
2001	144	0	0.0	35	24.31
2002	121	0	0.0	7	5.79
2003	125	0	0.0	22	17.6
2004	111	0	0.0	4	3.6
2005	208	0	0.0	1	0.48
2006	216	0	0.0	2	0.93
2007	226	0	0.0	2	0.88
2008	235	0	0.0	6	2.55
2009	237	0	0.0	42	17.72
2010	233	0	0.0	9	3.86
2011	232	1	0.43	3	1.29
2012	241	0	0.0	0	0.0
2013	256	0	0.0	1	0.39
2014	274	1	0.36	0	0.0
2015	285	0	0.0	0	0.0
2016	294	0	0.0	1	0.34
2017	301	0	0.0	0	0.0
2018	312	0	0.0	2	0.64
2019	318	0	0.0	1	0.31
2020	325	0	0.0	2	0.62
2021	335	0	0.0	3	0.9
2022	342	0	0.0	0	0.0

Economy: Belgium

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	115	0	0.0	1	0.87
1991	139	0	0.0	2	1.44
1992	140	0	0.0	0	0.0
1993	145	0	0.0	0	0.0
1994	151	0	0.0	1	0.66
1995	160	0	0.0	0	0.0
1996	173	0	0.0	5	2.89
1997	183	0	0.0	15	8.2
1998	193	0	0.0	16	8.29
1999	204	1	0.49	5	2.45
2000	206	1	0.49	6	2.91
2001	201	2	1.0	9	4.48
2002	191	3	1.57	11	5.76
2003	186	1	0.54	9	4.84
2004	181	0	0.0	10	5.52
2005	183	2	1.09	10	5.46
2006	192	2	1.04	6	3.12
2007	224	1	0.45	10	4.46
2008	226	0	0.0	9	3.98
2009	220	1	0.45	6	2.73
2010	218	0	0.0	11	5.05
2011	209	0	0.0	11	5.26
2012	200	1	0.5	3	1.5
2013	201	2	1.0	11	5.47
2014	192	1	0.52	16	8.33
2015	184	0	0.0	8	4.35
2016	182	1	0.55	10	5.49
2017	175	0	0.0	6	3.43
2018	174	0	0.0	10	5.75
2019	171	1	0.58	8	4.68
2020	168	1	0.6	5	2.98
2021	169	0	0.0	5	2.96
2022	203	0	0.0	6	2.96

Economy: Bosnia and Herzegovina					
		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	0	0.0	NaN	0	NaN
1997	0	0.0	NaN	0	NaN
1998	0	0.0	NaN	0	NaN
1999	0	0.0	NaN	0	NaN
2000	0	0.0	NaN	0	NaN
2001	0	0.0	NaN	0	NaN
2002	0	0.0	NaN	0	NaN
2003	0	0.0	NaN	0	NaN
2004	0	0.0	NaN	0	NaN
2005	0	0.0	NaN	0	NaN
2006	286	0.0	0.0	0	0.0
2007	325	0.0	0.0	1	0.31
2008	338	0.0	0.0	27	7.99
2009	316	0.0	0.0	114	36.08
2010	211	0.0	0.0	39	18.48
2011	185	0.0	0.0	50	27.03
2012	148	0.0	0.0	20	13.51
2013	140	0.0	0.0	18	12.86
2014	129	0.0	0.0	16	12.4
2015	128	0.0	0.0	11	8.59
2016	121	0.0	0.0	15	12.4
2017	116	0.0	0.0	8	6.9
2018	111	0.0	0.0	19	17.12
2019	106	0.0	0.0	9	8.49
2020	114	0.0	0.0	11	9.65
2021	132	0.0	0.0	16	12.12
2022	156	0.0	0.0	3	1.92

Economy: Botswana					
		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	8	0.0	0.0	0	0.0
1997	11	0.0	0.0	0	0.0
1998	12	0.0	0.0	0	0.0
1999	15	0.0	0.0	0	0.0
2000	16	0.0	0.0	0	0.0
2001	16	0.0	0.0	0	0.0
2002	18	0.0	0.0	0	0.0
2003	19	0.0	0.0	0	0.0
2004	19	0.0	0.0	2	10.53
2005	17	0.0	0.0	0	0.0
2006	17	0.0	0.0	0	0.0
2007	18	0.0	0.0	0	0.0
2008	21	0.0	0.0	1	4.76
2009	20	0.0	0.0	0	0.0
2010	22	0.0	0.0	1	4.55
2011	22	0.0	0.0	0	0.0
2012	23	0.0	0.0	0	0.0
2013	24	0.0	0.0	1	4.17
2014	23	0.0	0.0	1	4.35
2015	23	0.0	0.0	2	8.7
2016	23	0.0	0.0	0	0.0
2017	25	0.0	0.0	1	4.0
2018	26	0.0	0.0	2	7.69
2019	25	0.0	0.0	3	12.0
2020	24	0.0	0.0	0	0.0
2021	24	0.0	0.0	0	0.0
2022	25	0.0	0.0	0	0.0

Economy: Brazil

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	266	0	0.0	0	0.0
1995	298	0	0.0	5	1.68
1996	310	0	0.0	6	1.94
1997	326	1	0.31	22	6.75
1998	362	1	0.28	33	9.12
1999	351	1	0.28	26	7.41
2000	338	2	0.59	29	8.58
2001	316	0	0.0	34	10.76
2002	298	2	0.67	23	7.72
2003	288	2	0.69	14	4.86
2004	287	0	0.0	14	4.88
2005	288	1	0.35	17	5.9
2006	302	0	0.0	14	4.64
2007	360	0	0.0	14	3.89
2008	360	1	0.28	21	5.83
2009	347	0	0.0	14	4.03
2010	347	0	0.0	19	5.48
2011	341	0	0.0	14	4.11
2012	339	7	2.06	22	6.49
2013	325	7	2.15	8	2.46
2014	318	7	2.2	11	3.46
2015	320	4	1.25	14	4.38
2016	324	10	3.09	18	5.56
2017	321	5	1.56	13	4.05
2018	310	0	0.0	6	1.94
2019	313	0	0.0	15	4.79
2020	331	1	0.3	14	4.23
2021	372	0	0.0	13	3.49
2022	367	1	0.27	12	3.27

Economy: Bulgaria

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	14	0	0.0	0	0.0
2001	25	0	0.0	0	0.0
2002	32	0	0.0	0	0.0
2003	36	0	0.0	1	2.78
2004	39	0	0.0	0	0.0
2005	141	1	0.71	1	0.71
2006	218	0	0.0	0	0.0
2007	242	0	0.0	8	3.31
2008	256	0	0.0	14	5.47
2009	246	0	0.0	21	8.54
2010	230	1	0.43	25	10.87
2011	210	0	0.0	19	9.05
2012	200	0	0.0	18	9.0
2013	189	0	0.0	13	6.88
2014	181	2	1.1	15	8.29
2015	168	0	0.0	10	5.95
2016	165	0	0.0	9	5.45
2017	160	0	0.0	15	9.38
2018	153	0	0.0	4	2.61
2019	159	0	0.0	7	4.4
2020	159	0	0.0	4	2.52
2021	170	2	1.18	5	2.94
2022	185	0	0.0	5	2.7

Economy: Canada

		Defaults		Others	
Year	Active	#	%	#	%
1990	987	0	0.0	68	6.89
1991	990	0	0.0	55	5.56
1992	1056	1	0.09	23	2.18
1993	1256	0	0.0	8	0.64
1994	1443	0	0.0	11	0.76
1995	1615	0	0.0	18	1.11
1996	1839	0	0.0	36	1.96
1997	2146	6	0.28	106	4.94
1998	2305	9	0.39	207	8.98
1999	2242	13	0.58	1045	46.61
2000	1371	8	0.58	181	13.2
2001	1268	20	1.58	239	18.85
2002	1077	6	0.56	98	9.1
2003	1068	12	1.12	85	7.96
2004	1104	7	0.63	78	7.07
2005	1141	2	0.18	83	7.27
2006	1209	3	0.25	92	7.61
2007	1260	3	0.24	109	8.65
2008	1249	10	0.8	97	7.77
2009	1202	14	1.16	111	9.23
2010	1194	2	0.17	83	6.95
2011	1207	5	0.41	87	7.21
2012	1188	6	0.51	91	7.66
2013	1168	3	0.26	83	7.11
2014	1177	7	0.59	85	7.22
2015	1199	9	0.75	98	8.17
2016	1168	12	1.03	87	7.45
2017	1169	5	0.43	85	7.27
2018	1237	1	0.08	72	5.82
2019	1305	3	0.23	82	6.28
2020	1362	13	0.95	86	6.31
2021	1504	6	0.4	78	5.19
2022	1581	8	0.51	64	4.05

Economy: Chile

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	145	0	0.0	0	0.0
1995	167	0	0.0	1	0.6
1996	177	0	0.0	0	0.0
1997	190	0	0.0	0	0.0
1998	193	0	0.0	4	2.07
1999	192	0	0.0	9	4.69
2000	184	0	0.0	6	3.26
2001	182	1	0.55	6	3.3
2002	180	1	0.56	5	2.78
2003	176	0	0.0	7	3.98
2004	181	1	0.55	2	1.1
2005	186	0	0.0	5	2.69
2006	187	0	0.0	7	3.74
2007	181	0	0.0	3	1.66
2008	181	0	0.0	5	2.76
2009	181	0	0.0	5	2.76
2010	182	0	0.0	8	4.4
2011	178	0	0.0	6	3.37
2012	182	0	0.0	7	3.85
2013	182	0	0.0	5	2.75
2014	179	1	0.56	2	1.12
2015	181	0	0.0	9	4.97
2016	180	0	0.0	12	6.67
2017	173	0	0.0	5	2.89
2018	173	0	0.0	10	5.78
2019	167	0	0.0	11	6.59
2020	160	2	1.25	7	4.38
2021	159	0	0.0	3	1.89
2022	170	0	0.0	1	0.59

Economy: China					
		Defaults		Others	
Year	Active	#	%	#	%
1990	8	0	0.0	0	0.0
1991	10	0	0.0	0	0.0
1992	45	0	0.0	0	0.0
1993	159	0	0.0	0	0.0
1994	271	1	0.37	0	0.0
1995	308	6	1.95	0	0.0
1996	518	10	1.93	0	0.0
1997	729	15	2.06	1	0.14
1998	869	34	3.91	0	0.0
1999	948	23	2.43	0	0.0
2000	1093	27	2.47	0	0.0
2001	1191	49	4.11	2	0.17
2002	1252	51	4.07	5	0.4
2003	1305	44	3.37	4	0.31
2004	1458	105	7.2	9	0.62
2005	1447	93	6.43	13	0.9
2006	1465	62	4.23	28	1.91
2007	1539	51	3.31	20	1.3
2008	1585	39	2.46	7	0.44
2009	1688	38	2.25	11	0.65
2010	2013	40	1.99	15	0.75
2011	2264	14	0.62	12	0.53
2012	2416	16	0.66	9	0.37
2013	2430	14	0.58	7	0.29
2014	2542	6	0.24	11	0.43
2015	2760	4	0.14	10	0.36
2016	2986	7	0.23	12	0.4
2017	3423	21	0.61	13	0.38
2018	3541	44	1.24	9	0.25
2019	3750	66	1.76	13	0.35
2020	4112	47	1.14	21	0.51
2021	4623	90	1.95	17	0.37
2022	4928	61	1.24	38	0.77

Economy: Colombia					
		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	1	0	0.0	0	0.0
1995	48	0	0.0	0	0.0
1996	51	0	0.0	4	7.84
1997	52	0	0.0	6	11.54
1998	62	0	0.0	12	19.35
1999	53	0	0.0	4	7.55
2000	51	0	0.0	5	9.8
2001	54	0	0.0	6	11.11
2002	50	0	0.0	1	2.0
2003	53	0	0.0	2	3.77
2004	53	0	0.0	2	3.77
2005	60	0	0.0	7	11.67
2006	53	0	0.0	8	15.09
2007	53	0	0.0	4	7.55
2008	48	0	0.0	4	8.33
2009	49	0	0.0	3	6.12
2010	49	0	0.0	1	2.04
2011	49	0	0.0	1	2.04
2012	50	1	2.0	2	4.0
2013	48	0	0.0	1	2.08
2014	48	0	0.0	3	6.25
2015	45	0	0.0	1	2.22
2016	44	0	0.0	3	6.82
2017	42	0	0.0	2	4.76
2018	40	0	0.0	3	7.5
2019	39	1	2.56	0	0.0
2020	39	1	2.56	1	2.56
2021	38	0	0.0	4	10.53
2022	38	0	0.0	0	0.0

Economy: Croatia

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	0	0	NaN	0	NaN
2001	0	0	NaN	0	NaN
2002	30	0	0.0	0	0.0
2003	47	0	0.0	2	4.26
2004	56	0	0.0	2	3.57
2005	61	0	0.0	2	3.28
2006	202	0	0.0	3	1.49
2007	224	0	0.0	4	1.79
2008	221	0	0.0	30	13.57
2009	192	0	0.0	23	11.98
2010	173	1	0.58	13	7.51
2011	164	0	0.0	10	6.1
2012	157	1	0.64	14	8.92
2013	147	0	0.0	14	9.52
2014	146	1	0.68	14	9.59
2015	137	0	0.0	11	8.03
2016	135	0	0.0	13	9.63
2017	123	0	0.0	9	7.32
2018	116	0	0.0	25	21.55
2019	97	1	1.03	9	9.28
2020	89	0	0.0	6	6.74
2021	89	0	0.0	8	8.99
2022	91	0	0.0	2	2.2

Economy: Cyprus

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	37	0	0.0	1	2.7
1997	43	0	0.0	0	0.0
1998	50	0	0.0	2	4.0
1999	59	0	0.0	1	1.69
2000	120	0	0.0	3	2.5
2001	145	0	0.0	5	3.45
2002	150	0	0.0	0	0.0
2003	150	0	0.0	3	2.0
2004	149	0	0.0	5	3.36
2005	146	0	0.0	6	4.11
2006	143	0	0.0	3	2.1
2007	145	0	0.0	7	4.83
2008	140	0	0.0	11	7.86
2009	130	0	0.0	9	6.92
2010	124	0	0.0	10	8.06
2011	114	0	0.0	11	9.65
2012	105	0	0.0	22	20.95
2013	86	2	2.33	21	24.42
2014	66	0	0.0	9	13.64
2015	64	0	0.0	4	6.25
2016	66	0	0.0	4	6.06
2017	63	0	0.0	4	6.35
2018	60	0	0.0	5	8.33
2019	57	0	0.0	11	19.3
2020	48	0	0.0	6	12.5
2021	51	0	0.0	4	7.84
2022	58	0	0.0	3	5.17

Economy: Czech Republic

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	1	0	0.0	0	0.0
1995	53	0	0.0	1	1.89
1996	150	0	0.0	0	0.0
1997	588	0	0.0	319	54.25
1998	270	1	0.37	30	11.11
1999	241	4	1.66	85	35.27
2000	154	7	4.55	25	16.23
2001	123	2	1.63	39	31.71
2002	83	1	1.2	22	26.51
2003	60	0	0.0	15	25.0
2004	48	0	0.0	11	22.92
2005	37	0	0.0	15	40.54
2006	24	0	0.0	8	33.33
2007	17	0	0.0	2	11.76
2008	16	0	0.0	0	0.0
2009	17	0	0.0	4	23.53
2010	16	0	0.0	0	0.0
2011	19	1	5.26	1	5.26
2012	17	0	0.0	1	5.88
2013	17	0	0.0	3	17.65
2014	15	0	0.0	1	6.67
2015	15	0	0.0	0	0.0
2016	17	0	0.0	2	11.76
2017	15	0	0.0	0	0.0
2018	15	0	0.0	4	26.67
2019	15	0	0.0	0	0.0
2020	18	0	0.0	0	0.0
2021	21	0	0.0	1	4.76
2022	26	0	0.0	2	7.69

Economy: Denmark

		Defaults		Others	
Year	Active	#	%	#	%
1990	105	0	0.0	1	0.95
1991	145	0	0.0	1	0.69
1992	167	0	0.0	0	0.0
1993	173	0	0.0	0	0.0
1994	181	0	0.0	0	0.0
1995	207	0	0.0	0	0.0
1996	220	0	0.0	0	0.0
1997	225	0	0.0	5	2.22
1998	232	0	0.0	11	4.74
1999	227	0	0.0	12	5.29
2000	227	0	0.0	10	4.41
2001	220	4	1.82	15	6.82
2002	201	3	1.49	10	4.98
2003	193	1	0.52	9	4.66
2004	186	1	0.54	10	5.38
2005	182	1	0.55	9	4.95
2006	196	0	0.0	6	3.06
2007	222	1	0.45	3	1.35
2008	227	0	0.0	9	3.96
2009	218	5	2.29	6	2.75
2010	211	0	0.0	13	6.16
2011	200	2	1.0	10	5.0
2012	189	2	1.06	11	5.82
2013	179	4	2.23	10	5.59
2014	168	2	1.19	11	6.55
2015	159	0	0.0	7	4.4
2016	157	0	0.0	15	9.55
2017	147	0	0.0	5	3.4
2018	155	1	0.65	3	1.94
2019	157	0	0.0	5	3.18
2020	164	0	0.0	7	4.27
2021	182	0	0.0	6	3.3
2022	176	0	0.0	3	1.7

Economy: Egypt

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	0	0	NaN	0	NaN
2001	0	0	NaN	0	NaN
2002	0	0	NaN	0	NaN
2003	0	0	NaN	0	NaN
2004	0	0	NaN	0	NaN
2005	0	0	NaN	0	NaN
2006	174	0	0.0	4	2.3
2007	195	0	0.0	4	2.05
2008	207	0	0.0	3	1.45
2009	209	0	0.0	7	3.35
2010	235	0	0.0	20	8.51
2011	229	0	0.0	3	1.31
2012	232	0	0.0	4	1.72
2013	239	0	0.0	2	0.84
2014	246	0	0.0	4	1.63
2015	249	1	0.4	3	1.2
2016	252	0	0.0	2	0.79
2017	256	0	0.0	2	0.78
2018	263	0	0.0	6	2.28
2019	263	0	0.0	7	2.66
2020	260	0	0.0	6	2.31
2021	264	0	0.0	14	5.3
2022	256	0	0.0	3	1.17

Economy: Estonia

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	0	0.0	NaN	0	NaN
1997	17	0.0	0.0	0	0.0
1998	19	0.0	0.0	0	0.0
1999	20	0.0	0.0	0	0.0
2000	21	0.0	0.0	3	14.29
2001	18	0.0	0.0	3	16.67
2002	15	0.0	0.0	3	20.0
2003	12	0.0	0.0	0	0.0
2004	12	0.0	0.0	0	0.0
2005	15	0.0	0.0	1	6.67
2006	16	0.0	0.0	2	12.5
2007	17	0.0	0.0	0	0.0
2008	18	0.0	0.0	0	0.0
2009	18	0.0	0.0	2	11.11
2010	17	0.0	0.0	1	5.88
2011	16	0.0	0.0	0	0.0
2012	17	0.0	0.0	0	0.0
2013	17	0.0	0.0	0	0.0
2014	17	0.0	0.0	1	5.88
2015	17	0.0	0.0	0	0.0
2016	18	0.0	0.0	0	0.0
2017	19	0.0	0.0	0	0.0
2018	20	0.0	0.0	1	5.0
2019	20	0.0	0.0	0	0.0
2020	21	0.0	0.0	0	0.0
2021	28	0.0	0.0	0	0.0
2022	34	0.0	0.0	0	0.0

Economy: Finland

		Defaults		Others	
Year	Active	#	%	#	%
1990	17	0	0.0	1	5.88
1991	27	0	0.0	0	0.0
1992	92	0	0.0	0	0.0
1993	95	0	0.0	0	0.0
1994	99	0	0.0	1	1.01
1995	106	0	0.0	0	0.0
1996	111	0	0.0	0	0.0
1997	124	0	0.0	0	0.0
1998	135	1	0.74	5	3.7
1999	159	0	0.0	9	5.66
2000	169	0	0.0	11	6.51
2001	166	1	0.6	9	5.42
2002	154	1	0.65	5	3.25
2003	149	1	0.67	5	3.36
2004	144	0	0.0	9	6.25
2005	141	0	0.0	5	3.55
2006	141	0	0.0	7	4.96
2007	139	0	0.0	5	3.6
2008	134	1	0.75	3	2.24
2009	131	1	0.76	2	1.53
2010	129	0	0.0	3	2.33
2011	126	1	0.79	1	0.79
2012	126	0	0.0	5	3.97
2013	127	2	1.57	1	0.79
2014	131	0	0.0	4	3.05
2015	142	3	2.11	3	2.11
2016	146	0	0.0	6	4.11
2017	150	1	0.67	5	3.33
2018	156	0	0.0	2	1.28
2019	159	1	0.63	5	3.14
2020	158	1	0.63	4	2.53
2021	183	0	0.0	5	2.73
2022	188	0	0.0	4	2.13

Economy: France

		Defaults		Others	
Year	Active	#	%	#	%
1990	260	0	0.0	4	1.54
1991	413	0	0.0	14	3.39
1992	651	0	0.0	6	0.92
1993	674	0	0.0	9	1.34
1994	733	0	0.0	9	1.23
1995	764	0	0.0	6	0.79
1996	823	0	0.0	15	1.82
1997	888	1	0.11	61	6.87
1998	953	0	0.0	112	11.75
1999	931	0	0.0	55	5.91
2000	1002	2	0.2	54	5.39
2001	1021	9	0.88	52	5.09
2002	992	6	0.6	58	5.85
2003	944	5	0.53	37	3.92
2004	932	2	0.21	55	5.9
2005	938	1	0.11	44	4.69
2006	987	5	0.51	37	3.75
2007	1045	5	0.48	44	4.21
2008	1030	5	0.49	59	5.73
2009	999	9	0.9	50	5.01
2010	978	2	0.2	76	7.77
2011	933	1	0.11	59	6.32
2012	901	2	0.22	66	7.33
2013	868	3	0.35	58	6.68
2014	856	3	0.35	46	5.37
2015	873	2	0.23	36	4.12
2016	882	3	0.34	41	4.65
2017	869	5	0.58	43	4.95
2018	852	2	0.23	49	5.75
2019	821	2	0.24	34	4.14
2020	809	4	0.49	35	4.33
2021	832	1	0.12	36	4.33
2022	857	0	0.0	26	3.03

Economy: Germany

		Defaults		Others	
Year	Active	#	%	#	%
1990	196	0	0.0	2	1.02
1991	386	0	0.0	0	0.0
1992	414	0	0.0	3	0.72
1993	440	0	0.0	5	1.14
1994	611	0	0.0	2	0.33
1995	633	0	0.0	1	0.16
1996	664	4	0.6	9	1.36
1997	699	3	0.43	19	2.72
1998	774	2	0.26	15	1.94
1999	961	2	0.21	19	1.98
2000	1110	2	0.18	24	2.16
2001	1154	27	2.34	26	2.25
2002	1159	39	3.36	75	6.47
2003	1070	18	1.68	52	4.86
2004	1034	8	0.77	30	2.9
2005	1069	4	0.37	39	3.65
2006	1224	7	0.57	34	2.78
2007	1385	5	0.36	45	3.25
2008	1494	17	1.14	60	4.02
2009	1484	11	0.74	76	5.12
2010	1528	1	0.07	80	5.24
2011	1696	4	0.24	243	14.33
2012	1489	9	0.6	412	27.67
2013	1101	16	1.45	66	5.99
2014	1048	7	0.67	74	7.06
2015	1014	6	0.59	81	7.99
2016	954	3	0.31	65	6.81
2017	925	6	0.65	44	4.76
2018	910	4	0.44	38	4.18
2019	889	2	0.22	27	3.04
2020	894	3	0.34	45	5.03
2021	896	3	0.33	48	5.36
2022	868	1	0.12	22	2.53

Economy: Ghana

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	0	0.0	NaN	0	NaN
1997	0	0.0	NaN	0	NaN
1998	0	0.0	NaN	0	NaN
1999	0	0.0	NaN	0	NaN
2000	0	0.0	NaN	0	NaN
2001	0	0.0	NaN	0	NaN
2002	0	0.0	NaN	0	NaN
2003	0	0.0	NaN	0	NaN
2004	0	0.0	NaN	0	NaN
2005	0	0.0	NaN	0	NaN
2006	0	0.0	NaN	0	NaN
2007	0	0.0	NaN	0	NaN
2008	0	0.0	NaN	0	NaN
2009	0	0.0	NaN	0	NaN
2010	12	0.0	0.0	0	0.0
2011	24	0.0	0.0	0	0.0
2012	24	0.0	0.0	0	0.0
2013	25	0.0	0.0	0	0.0
2014	25	0.0	0.0	0	0.0
2015	26	0.0	0.0	0	0.0
2016	28	0.0	0.0	0	0.0
2017	28	0.0	0.0	2	7.14
2018	27	0.0	0.0	0	0.0
2019	28	0.0	0.0	5	17.86
2020	24	0.0	0.0	1	4.17
2021	27	0.0	0.0	1	3.7
2022	28	0.0	0.0	0	0.0

Economy: Greece

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	90	0	0.0	0	0.0
1993	97	0	0.0	0	0.0
1994	162	0	0.0	0	0.0
1995	183	0	0.0	1	0.55
1996	202	0	0.0	6	2.97
1997	211	0	0.0	3	1.42
1998	234	0	0.0	4	1.71
1999	278	0	0.0	6	2.16
2000	318	0	0.0	7	2.2
2001	329	0	0.0	13	3.95
2002	337	0	0.0	18	5.34
2003	329	0	0.0	9	2.74
2004	330	0	0.0	10	3.03
2005	328	0	0.0	20	6.1
2006	310	0	0.0	15	4.84
2007	301	0	0.0	13	4.32
2008	297	0	0.0	15	5.05
2009	284	0	0.0	12	4.23
2010	273	0	0.0	12	4.4
2011	261	0	0.0	14	5.36
2012	247	0	0.0	23	9.31
2013	225	0	0.0	16	7.11
2014	209	0	0.0	12	5.74
2015	203	6	2.96	11	5.42
2016	190	0	0.0	8	4.21
2017	190	1	0.53	12	6.32
2018	180	1	0.56	7	3.89
2019	173	0	0.0	13	7.51
2020	161	0	0.0	9	5.59
2021	155	0	0.0	5	3.23
2022	154	0	0.0	5	3.25

Economy: Hong Kong

		Defaults		Others	
Year	Active	#	%	#	%
1990	239	0	0.0	4	1.67
1991	319	0	0.0	4	1.25
1992	365	0	0.0	2	0.55
1993	433	0	0.0	2	0.46
1994	483	0	0.0	7	1.45
1995	510	0	0.0	5	0.98
1996	554	0	0.0	10	1.81
1997	634	0	0.0	8	1.26
1998	660	2	0.3	9	1.36
1999	705	7	0.99	7	0.99
2000	790	5	0.63	9	1.14
2001	879	10	1.14	16	1.82
2002	976	4	0.41	17	1.74
2003	1028	5	0.49	28	2.72
2004	1066	0	0.0	30	2.81
2005	1108	2	0.18	31	2.8
2006	1150	3	0.26	22	1.91
2007	1233	2	0.16	13	1.05
2008	1261	5	0.4	16	1.27
2009	1310	3	0.23	12	0.92
2010	1391	1	0.07	19	1.37
2011	1453	0	0.0	19	1.31
2012	1504	2	0.13	22	1.46
2013	1600	4	0.25	19	1.19
2014	1698	1	0.06	19	1.12
2015	1819	8	0.44	20	1.1
2016	1924	8	0.42	21	1.09
2017	2068	10	0.48	49	2.37
2018	2238	4	0.18	33	1.47
2019	2373	3	0.13	35	1.47
2020	2483	7	0.28	63	2.54
2021	2540	31	1.22	95	3.74
2022	2546	47	1.85	41	1.61

Economy: Hungary

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	32	0	0.0	0	0.0
1996	37	0	0.0	1	2.7
1997	43	0	0.0	4	9.3
1998	46	0	0.0	1	2.17
1999	55	0	0.0	0	0.0
2000	59	1	1.69	4	6.78
2001	53	0	0.0	4	7.55
2002	49	0	0.0	8	16.33
2003	43	0	0.0	2	4.65
2004	43	0	0.0	3	6.98
2005	41	0	0.0	3	7.32
2006	41	0	0.0	5	12.2
2007	37	0	0.0	3	8.11
2008	36	0	0.0	0	0.0
2009	39	0	0.0	0	0.0
2010	44	0	0.0	0	0.0
2011	48	0	0.0	3	6.25
2012	51	1	1.96	3	5.88
2013	48	0	0.0	2	4.17
2014	48	0	0.0	2	4.17
2015	47	0	0.0	5	10.64
2016	43	1	2.33	5	11.63
2017	40	0	0.0	2	5.0
2018	39	0	0.0	0	0.0
2019	42	0	0.0	1	2.38
2020	44	0	0.0	6	13.64
2021	42	0	0.0	1	2.38
2022	48	0	0.0	0	0.0

Economy: Iceland

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	24	0	0.0	0	0.0
1997	34	0	0.0	0	0.0
1998	51	0	0.0	0	0.0
1999	58	0	0.0	1	1.72
2000	69	0	0.0	5	7.25
2001	68	0	0.0	7	10.29
2002	66	0	0.0	11	16.67
2003	56	0	0.0	16	28.57
2004	40	0	0.0	10	25.0
2005	31	0	0.0	7	22.58
2006	28	0	0.0	3	10.71
2007	28	0	0.0	3	10.71
2008	25	2	8.0	9	36.0
2009	15	1	6.67	2	13.33
2010	12	0	0.0	3	25.0
2011	10	0	0.0	0	0.0
2012	13	0	0.0	0	0.0
2013	16	0	0.0	0	0.0
2014	17	0	0.0	1	5.88
2015	19	0	0.0	0	0.0
2016	21	0	0.0	0	0.0
2017	22	0	0.0	0	0.0
2018	25	0	0.0	0	0.0
2019	27	0	0.0	0	0.0
2020	27	0	0.0	1	3.7
2021	30	0	0.0	1	3.33
2022	31	0	0.0	0	0.0

Economy: India					
		Defaults		Others	
Year	Active	#	%	#	%
1990	250	0	0.0	1	0.4
1991	1284	0	0.0	0	0.0
1992	1527	1	0.07	6	0.39
1993	1961	0	0.0	38	1.94
1994	2949	0	0.0	33	1.12
1995	4219	2	0.05	45	1.07
1996	4680	5	0.11	244	5.21
1997	4499	11	0.24	772	17.16
1998	3806	8	0.21	523	13.74
1999	3571	12	0.34	479	13.41
2000	3352	0	0.0	197	5.88
2001	3316	2	0.06	137	4.13
2002	3383	52	1.54	815	24.09
2003	2669	37	1.39	162	6.07
2004	2683	21	0.78	134	4.99
2005	2786	27	0.97	243	8.72
2006	2767	17	0.61	52	1.88
2007	3030	35	1.16	28	0.92
2008	3184	21	0.66	57	1.79
2009	3267	35	1.07	41	1.25
2010	3453	32	0.93	64	1.85
2011	3587	31	0.86	47	1.31
2012	3797	73	1.92	80	2.11
2013	3852	87	2.26	98	2.54
2014	3921	82	2.09	34	0.87
2015	4119	97	2.35	230	5.58
2016	4053	67	1.65	112	2.76
2017	4220	103	2.44	168	3.98
2018	4479	335	7.48	92	2.05
2019	4372	167	3.82	172	3.93
2020	4318	142	3.29	128	2.96
2021	4366	80	1.83	89	2.04
2022	4498	60	1.33	34	0.76

Economy: Indonesia					
		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	110	0	0.0	0	0.0
1992	140	0	0.0	0	0.0
1993	163	0	0.0	2	1.23
1994	208	0	0.0	5	2.4
1995	231	0	0.0	1	0.43
1996	250	1	0.4	0	0.0
1997	283	2	0.71	4	1.41
1998	301	19	6.31	2	0.66
1999	297	24	8.08	5	1.68
2000	299	12	4.01	12	4.01
2001	317	14	4.42	8	2.52
2002	327	7	2.14	14	4.28
2003	319	3	0.94	7	2.19
2004	324	3	0.93	13	4.01
2005	323	2	0.62	13	4.02
2006	327	0	0.0	6	1.83
2007	351	2	0.57	7	1.99
2008	366	0	0.0	16	4.37
2009	378	4	1.06	14	3.7
2010	392	2	0.51	10	2.55
2011	414	0	0.0	10	2.42
2012	441	1	0.23	5	1.13
2013	475	1	0.21	12	2.53
2014	491	3	0.61	4	0.81
2015	508	1	0.2	10	1.97
2016	518	2	0.39	3	0.58
2017	556	3	0.54	8	1.44
2018	606	0	0.0	8	1.32
2019	661	3	0.45	17	2.57
2020	697	2	0.29	24	3.44
2021	734	4	0.54	13	1.77
2022	781	1	0.13	2	0.26

Economy: Ireland					
		Defaults		Others	
Year	Active	#	%	#	%
1990	30	0	0.0	0	0.0
1991	31	0	0.0	0	0.0
1992	31	0	0.0	0	0.0
1993	34	0	0.0	0	0.0
1994	37	0	0.0	3	8.11
1995	35	0	0.0	0	0.0
1996	39	0	0.0	0	0.0
1997	49	0	0.0	2	4.08
1998	50	0	0.0	2	4.0
1999	52	0	0.0	3	5.77
2000	56	0	0.0	1	1.79
2001	54	0	0.0	6	11.11
2002	48	0	0.0	6	12.5
2003	42	0	0.0	5	11.9
2004	38	0	0.0	3	7.89
2005	37	0	0.0	2	5.41
2006	42	0	0.0	2	4.76
2007	47	0	0.0	1	2.13
2008	46	0	0.0	3	6.52
2009	44	1	2.27	5	11.36
2010	38	0	0.0	4	10.53
2011	34	0	0.0	2	5.88
2012	34	1	2.94	3	8.82
2013	34	1	2.94	1	2.94
2014	35	0	0.0	1	2.86
2015	36	0	0.0	3	8.33
2016	33	0	0.0	2	6.06
2017	36	0	0.0	3	8.33
2018	33	0	0.0	1	3.03
2019	33	0	0.0	4	12.12
2020	30	0	0.0	1	3.33
2021	31	0	0.0	5	16.13
2022	26	0	0.0	1	3.85

Economy: Israel					
		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	9	0	0.0	0	0.0
1995	83	0	0.0	0	0.0
1996	627	0	0.0	6	0.96
1997	646	0	0.0	19	2.94
1998	646	0	0.0	22	3.41
1999	642	0	0.0	17	2.65
2000	667	0	0.0	37	5.55
2001	639	0	0.0	60	9.39
2002	593	1	0.17	67	11.3
2003	540	0	0.0	39	7.22
2004	538	0	0.0	17	3.16
2005	552	0	0.0	23	4.17
2006	572	0	0.0	17	2.97
2007	618	0	0.0	17	2.75
2008	606	0	0.0	25	4.13
2009	583	0	0.0	18	3.09
2010	585	2	0.34	23	3.93
2011	574	1	0.17	36	6.27
2012	541	0	0.0	50	9.24
2013	498	2	0.4	32	6.43
2014	472	2	0.42	32	6.78
2015	446	2	0.45	21	4.71
2016	433	1	0.23	18	4.16
2017	433	0	0.0	15	3.46
2018	430	0	0.0	20	4.65
2019	427	0	0.0	16	3.75
2020	439	0	0.0	16	3.64
2021	521	0	0.0	14	2.69
2022	528	0	0.0	3	0.57

Economy: Italy					
		Defaults		Others	
Year	Active	#	%	#	%
1990	170	0	0.0	2	1.18
1991	183	0	0.0	2	1.09
1992	187	0	0.0	2	1.07
1993	186	0	0.0	2	1.08
1994	198	0	0.0	2	1.01
1995	216	0	0.0	6	2.78
1996	222	0	0.0	6	2.7
1997	228	0	0.0	13	5.7
1998	240	0	0.0	11	4.58
1999	259	0	0.0	7	2.7
2000	297	0	0.0	16	5.39
2001	303	0	0.0	18	5.94
2002	298	1	0.34	12	4.03
2003	298	4	1.34	24	8.05
2004	272	4	1.47	10	3.68
2005	278	0	0.0	11	3.96
2006	294	0	0.0	15	5.1
2007	311	0	0.0	13	4.18
2008	304	1	0.33	15	4.93
2009	299	3	1.0	16	5.35
2010	291	0	0.0	11	3.78
2011	295	1	0.34	11	3.73
2012	293	2	0.68	15	5.12
2013	300	4	1.33	16	5.33
2014	308	1	0.32	13	4.22
2015	327	1	0.31	18	5.5
2016	330	2	0.61	16	4.85
2017	360	2	0.56	16	4.44
2018	386	3	0.78	14	3.63
2019	408	0	0.0	27	6.62
2020	406	0	0.0	18	4.43
2021	436	0	0.0	23	5.28
2022	443	0	0.0	17	3.84

Economy: Jamaica					
		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	32	0.0	0.0	0	0.0
1994	35	0.0	0.0	0	0.0
1995	36	0.0	0.0	0	0.0
1996	36	0.0	0.0	1	2.78
1997	35	0.0	0.0	5	14.29
1998	30	0.0	0.0	0	0.0
1999	31	0.0	0.0	0	0.0
2000	33	0.0	0.0	0	0.0
2001	33	0.0	0.0	1	3.03
2002	32	0.0	0.0	0	0.0
2003	33	0.0	0.0	0	0.0
2004	33	0.0	0.0	0	0.0
2005	35	0.0	0.0	0	0.0
2006	36	0.0	0.0	1	2.78
2007	36	0.0	0.0	2	5.56
2008	38	0.0	0.0	2	5.26
2009	37	0.0	0.0	0	0.0
2010	45	0.0	0.0	0	0.0
2011	49	0.0	0.0	4	8.16
2012	46	0.0	0.0	4	8.7
2013	49	0.0	0.0	2	4.08
2014	50	0.0	0.0	1	2.0
2015	54	0.0	0.0	1	1.85
2016	63	0.0	0.0	2	3.17
2017	69	0.0	0.0	3	4.35
2018	75	0.0	0.0	1	1.33
2019	84	0.0	0.0	1	1.19
2020	87	0.0	0.0	1	1.15
2021	89	0.0	0.0	0	0.0
2022	94	0.0	0.0	1	1.06

Economy: Japan

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	2405	0	0.0	5	0.21
1991	2529	0	0.0	2	0.08
1992	2557	3	0.12	3	0.12
1993	2646	4	0.15	6	0.23
1994	2787	0	0.0	5	0.18
1995	2971	2	0.07	5	0.17
1996	3133	5	0.16	7	0.22
1997	3268	7	0.21	16	0.49
1998	3340	16	0.48	21	0.63
1999	3417	7	0.2	40	1.17
2000	3603	13	0.36	54	1.5
2001	3724	16	0.43	59	1.58
2002	3814	30	0.79	96	2.52
2003	3857	19	0.49	96	2.49
2004	3953	13	0.33	86	2.18
2005	4052	9	0.22	88	2.17
2006	4166	2	0.05	81	1.94
2007	4227	6	0.14	99	2.34
2008	4215	36	0.85	108	2.56
2009	4130	28	0.68	135	3.27
2010	4035	9	0.22	129	3.2
2011	3943	4	0.1	100	2.54
2012	3904	6	0.15	98	2.51
2013	3876	3	0.08	74	1.91
2014	3885	0	0.0	44	1.13
2015	3958	4	0.1	68	1.72
2016	3989	0	0.0	70	1.75
2017	4018	1	0.02	41	1.02
2018	4082	0	0.0	66	1.62
2019	4112	0	0.0	44	1.07
2020	4170	2	0.05	59	1.41
2021	4258	0	0.0	92	2.16
2022	4287	0	0.0	79	1.84

Economy: Jordan

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	71	0.0	0.0	1	1.41
1997	105	0.0	0.0	0	0.0
1998	119	0.0	0.0	1	0.84
1999	122	0.0	0.0	0	0.0
2000	128	0.0	0.0	2	1.56
2001	133	0.0	0.0	7	5.26
2002	130	0.0	0.0	4	3.08
2003	139	0.0	0.0	3	2.16
2004	148	0.0	0.0	2	1.35
2005	164	0.0	0.0	2	1.22
2006	195	0.0	0.0	4	2.05
2007	210	0.0	0.0	3	1.43
2008	228	0.0	0.0	3	1.32
2009	233	0.0	0.0	8	3.43
2010	231	0.0	0.0	6	2.6
2011	230	0.0	0.0	4	1.74
2012	228	0.0	0.0	7	3.07
2013	221	0.0	0.0	2	0.9
2014	223	0.0	0.0	11	4.93
2015	214	0.0	0.0	6	2.8
2016	209	0.0	0.0	2	0.96
2017	207	0.0	0.0	20	9.66
2018	188	0.0	0.0	5	2.66
2019	185	0.0	0.0	6	3.24
2020	183	0.0	0.0	16	8.74
2021	168	0.0	0.0	8	4.76
2022	163	0.0	0.0	6	3.68

Economy: Kazakhstan

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	0	0	NaN	0	NaN
2001	1	0	0.0	0	0.0
2002	7	0	0.0	0	0.0
2003	7	0	0.0	0	0.0
2004	8	0	0.0	2	25.0
2005	6	0	0.0	0	0.0
2006	6	0	0.0	4	66.67
2007	24	0	0.0	0	0.0
2008	27	0	0.0	0	0.0
2009	28	3	10.71	5	17.86
2010	23	2	8.7	4	17.39
2011	18	0	0.0	1	5.56
2012	22	2	9.09	0	0.0
2013	20	0	0.0	3	15.0
2014	18	0	0.0	5	27.78
2015	15	0	0.0	1	6.67
2016	17	0	0.0	0	0.0
2017	19	0	0.0	0	0.0
2018	21	1	4.76	3	14.29
2019	19	1	5.26	1	5.26
2020	17	0	0.0	0	0.0
2021	18	0	0.0	2	11.11
2022	23	0	0.0	0	0.0

Economy: Kenya

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	44	0	0.0	0	0.0
1998	44	0	0.0	0	0.0
1999	44	0	0.0	0	0.0
2000	44	0	0.0	2	4.55
2001	46	0	0.0	1	2.17
2002	45	0	0.0	0	0.0
2003	47	0	0.0	1	2.13
2004	46	0	0.0	1	2.17
2005	46	0	0.0	2	4.35
2006	48	0	0.0	0	0.0
2007	51	0	0.0	0	0.0
2008	53	0	0.0	0	0.0
2009	54	0	0.0	3	5.56
2010	51	0	0.0	0	0.0
2011	55	0	0.0	1	1.82
2012	56	0	0.0	0	0.0
2013	58	0	0.0	3	5.17
2014	59	1	1.69	0	0.0
2015	59	0	0.0	0	0.0
2016	63	2	3.17	0	0.0
2017	63	2	3.17	1	1.59
2018	60	2	3.33	0	0.0
2019	58	0	0.0	3	5.17
2020	56	1	1.79	1	1.79
2021	54	0	0.0	0	0.0
2022	55	0	0.0	0	0.0

Economy: Kuwait

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	51	0	0.0	0	0.0
1997	65	0	0.0	0	0.0
1998	67	0	0.0	0	0.0
1999	75	0	0.0	3	4.0
2000	73	0	0.0	2	2.74
2001	72	0	0.0	0	0.0
2002	80	0	0.0	2	2.5
2003	92	0	0.0	0	0.0
2004	103	0	0.0	0	0.0
2005	140	0	0.0	1	0.71
2006	162	0	0.0	0	0.0
2007	181	0	0.0	2	1.1
2008	187	0	0.0	4	2.14
2009	198	1	0.51	6	3.03
2010	201	0	0.0	9	4.48
2011	196	0	0.0	8	4.08
2012	199	0	0.0	3	1.51
2013	197	0	0.0	5	2.54
2014	195	0	0.0	5	2.56
2015	193	0	0.0	7	3.63
2016	193	0	0.0	16	8.29
2017	178	0	0.0	16	8.99
2018	164	0	0.0	2	1.22
2019	167	0	0.0	7	4.19
2020	166	0	0.0	9	5.42
2021	162	0	0.0	6	3.7
2022	157	0	0.0	6	3.82

Economy: Latvia

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	18	0	0.0	0	0.0
2001	34	0	0.0	3	8.82
2002	33	0	0.0	1	3.03
2003	32	0	0.0	7	21.88
2004	30	0	0.0	0	0.0
2005	33	0	0.0	0	0.0
2006	34	0	0.0	2	5.88
2007	36	0	0.0	0	0.0
2008	36	0	0.0	1	2.78
2009	35	0	0.0	2	5.71
2010	33	0	0.0	0	0.0
2011	33	0	0.0	1	3.03
2012	33	0	0.0	1	3.03
2013	33	1	3.03	1	3.03
2014	31	0	0.0	1	3.23
2015	32	1	3.12	3	9.38
2016	29	0	0.0	1	3.45
2017	29	0	0.0	2	6.9
2018	27	1	3.7	3	11.11
2019	23	0	0.0	3	13.04
2020	20	0	0.0	1	5.0
2021	21	0	0.0	6	28.57
2022	16	0	0.0	2	12.5

Economy: Lithuania

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	35	0	0.0	1	2.86
2001	36	0	0.0	0	0.0
2002	42	0	0.0	1	2.38
2003	44	0	0.0	4	9.09
2004	42	0	0.0	0	0.0
2005	42	0	0.0	0	0.0
2006	44	0	0.0	2	4.55
2007	42	0	0.0	3	7.14
2008	40	0	0.0	0	0.0
2009	40	0	0.0	2	5.0
2010	41	0	0.0	2	4.88
2011	40	1	2.5	5	12.5
2012	34	0	0.0	0	0.0
2013	35	1	2.86	1	2.86
2014	37	1	2.7	2	5.41
2015	36	0	0.0	5	13.89
2016	32	0	0.0	2	6.25
2017	31	0	0.0	0	0.0
2018	32	0	0.0	0	0.0
2019	33	0	0.0	2	6.06
2020	32	0	0.0	2	6.25
2021	30	0	0.0	0	0.0
2022	30	0	0.0	0	0.0

Economy: Luxembourg

		Defaults		Others	
Year	Active	#	%	#	%
1990	1	0	0.0	0	0.0
1991	2	0	0.0	1	50.0
1992	1	0	0.0	0	0.0
1993	1	0	0.0	0	0.0
1994	1	0	0.0	0	0.0
1995	22	0	0.0	0	0.0
1996	23	0	0.0	0	0.0
1997	28	0	0.0	2	7.14
1998	28	0	0.0	1	3.57
1999	30	0	0.0	4	13.33
2000	31	0	0.0	3	9.68
2001	28	0	0.0	1	3.57
2002	27	0	0.0	2	7.41
2003	26	0	0.0	0	0.0
2004	26	0	0.0	0	0.0
2005	27	0	0.0	1	3.7
2006	27	0	0.0	3	11.11
2007	25	0	0.0	3	12.0
2008	23	0	0.0	2	8.7
2009	22	1	4.55	3	13.64
2010	19	0	0.0	1	5.26
2011	19	0	0.0	2	10.53
2012	18	0	0.0	2	11.11
2013	16	0	0.0	1	6.25
2014	18	0	0.0	2	11.11
2015	18	0	0.0	2	11.11
2016	17	0	0.0	2	11.76
2017	15	0	0.0	1	6.67
2018	15	0	0.0	2	13.33
2019	13	0	0.0	0	0.0
2020	13	0	0.0	3	23.08
2021	10	0	0.0	0	0.0
2022	10	0	0.0	1	10.0

Economy: Macedonia

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	0	0	NaN	0	NaN
2001	0	0	NaN	0	NaN
2002	0	0	NaN	0	NaN
2003	0	0	NaN	0	NaN
2004	11	0	0.0	0	0.0
2005	68	0	0.0	0	0.0
2006	88	0	0.0	0	0.0
2007	101	0	0.0	7	6.93
2008	98	0	0.0	7	7.14
2009	91	1	1.1	6	6.59
2010	84	0	0.0	14	16.67
2011	70	0	0.0	4	5.71
2012	70	0	0.0	10	14.29
2013	63	0	0.0	6	9.52
2014	62	0	0.0	4	6.45
2015	59	0	0.0	3	5.08
2016	58	2	3.45	3	5.17
2017	53	0	0.0	3	5.66
2018	51	0	0.0	4	7.84
2019	48	0	0.0	3	6.25
2020	49	0	0.0	2	4.08
2021	57	0	0.0	7	12.28
2022	78	0	0.0	2	2.56

Economy: Malawi

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	0	0.0	NaN	0	NaN
1997	0	0.0	NaN	0	NaN
1998	2	0.0	0.0	0	0.0
1999	2	0.0	0.0	0	0.0
2000	3	0.0	0.0	0	0.0
2001	4	0.0	0.0	0	0.0
2002	4	0.0	0.0	0	0.0
2003	5	0.0	0.0	0	0.0
2004	5	0.0	0.0	0	0.0
2005	5	0.0	0.0	0	0.0
2006	5	0.0	0.0	5	100.0
2007	0	0.0	NaN	0	NaN
2008	0	0.0	NaN	0	NaN
2009	11	0.0	0.0	0	0.0
2010	11	0.0	0.0	0	0.0
2011	11	0.0	0.0	0	0.0
2012	13	0.0	0.0	0	0.0
2013	13	0.0	0.0	0	0.0
2014	13	0.0	0.0	0	0.0
2015	13	0.0	0.0	0	0.0
2016	13	0.0	0.0	1	7.69
2017	12	0.0	0.0	1	8.33
2018	12	0.0	0.0	0	0.0
2019	13	0.0	0.0	0	0.0
2020	14	0.0	0.0	0	0.0
2021	15	0.0	0.0	0	0.0
2022	15	0.0	0.0	0	0.0

Economy: Malaysia

		Defaults		Others	
Year	Active	#	%	#	%
1990	271	0	0.0	0	0.0
1991	314	0	0.0	0	0.0
1992	361	0	0.0	1	0.28
1993	405	0	0.0	0	0.0
1994	472	0	0.0	0	0.0
1995	524	0	0.0	0	0.0
1996	615	0	0.0	0	0.0
1997	703	0	0.0	1	0.14
1998	738	14	1.9	19	2.57
1999	741	8	1.08	11	1.48
2000	779	13	1.67	8	1.03
2001	791	15	1.9	15	1.9
2002	828	13	1.57	24	2.9
2003	885	7	0.79	15	1.69
2004	952	6	0.63	8	0.84
2005	1028	5	0.49	26	2.53
2006	1054	13	1.23	26	2.47
2007	1061	14	1.32	60	5.66
2008	1029	23	2.24	40	3.89
2009	996	19	1.91	30	3.01
2010	1000	22	2.2	28	2.8
2011	991	11	1.11	33	3.33
2012	976	9	0.92	35	3.59
2013	953	5	0.52	27	2.83
2014	939	2	0.21	16	1.7
2015	935	1	0.11	14	1.5
2016	938	2	0.21	23	2.45
2017	938	3	0.32	19	2.03
2018	944	4	0.42	16	1.69
2019	952	7	0.74	14	1.47
2020	952	5	0.53	13	1.37
2021	975	12	1.23	21	2.15
2022	992	7	0.71	10	1.01

Economy: Malta

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	5	0.0	0.0	0	0.0
1997	6	0.0	0.0	0	0.0
1998	7	0.0	0.0	0	0.0
1999	7	0.0	0.0	0	0.0
2000	9	0.0	0.0	0	0.0
2001	11	0.0	0.0	0	0.0
2002	12	0.0	0.0	1	8.33
2003	11	0.0	0.0	0	0.0
2004	11	0.0	0.0	0	0.0
2005	11	0.0	0.0	0	0.0
2006	12	0.0	0.0	0	0.0
2007	13	0.0	0.0	0	0.0
2008	16	0.0	0.0	2	12.5
2009	14	0.0	0.0	2	14.29
2010	12	0.0	0.0	0	0.0
2011	15	0.0	0.0	0	0.0
2012	20	0.0	0.0	0	0.0
2013	21	0.0	0.0	0	0.0
2014	21	0.0	0.0	0	0.0
2015	22	0.0	0.0	2	9.09
2016	22	0.0	0.0	1	4.55
2017	22	0.0	0.0	0	0.0
2018	24	0.0	0.0	0	0.0
2019	25	0.0	0.0	0	0.0
2020	25	0.0	0.0	0	0.0
2021	29	0.0	0.0	0	0.0
2022	32	0.0	0.0	0	0.0

Economy: Mauritius

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	26	0	0.0	0	0.0
1996	29	0	0.0	0	0.0
1997	29	0	0.0	0	0.0
1998	29	0	0.0	0	0.0
1999	29	0	0.0	0	0.0
2000	29	0	0.0	0	0.0
2001	29	0	0.0	0	0.0
2002	30	0	0.0	0	0.0
2003	30	0	0.0	0	0.0
2004	30	0	0.0	0	0.0
2005	31	0	0.0	0	0.0
2006	32	0	0.0	0	0.0
2007	32	0	0.0	0	0.0
2008	33	0	0.0	0	0.0
2009	33	0	0.0	0	0.0
2010	33	0	0.0	0	0.0
2011	34	0	0.0	0	0.0
2012	38	0	0.0	0	0.0
2013	39	0	0.0	0	0.0
2014	42	0	0.0	0	0.0
2015	42	0	0.0	1	2.38
2016	42	0	0.0	0	0.0
2017	43	0	0.0	2	4.65
2018	45	0	0.0	4	8.89
2019	45	0	0.0	0	0.0
2020	45	1	2.22	1	2.22
2021	50	0	0.0	0	0.0
2022	53	0	0.0	1	1.89

Economy: Mexico

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	96	0	0.0	3	3.12
1995	100	0	0.0	1	1.0
1996	115	0	0.0	3	2.61
1997	132	1	0.76	8	6.06
1998	126	0	0.0	15	11.9
1999	119	1	0.84	10	8.4
2000	116	1	0.86	6	5.17
2001	111	1	0.9	4	3.6
2002	111	1	0.9	8	7.21
2003	112	2	1.79	3	2.68
2004	111	0	0.0	4	3.6
2005	116	0	0.0	5	4.31
2006	116	0	0.0	2	1.72
2007	121	1	0.83	9	7.44
2008	119	2	1.68	6	5.04
2009	116	5	4.31	2	1.72
2010	122	3	2.46	2	1.64
2011	122	0	0.0	7	5.74
2012	123	3	2.44	3	2.44
2013	133	6	4.51	2	1.5
2014	131	4	3.05	1	0.76
2015	139	1	0.72	3	2.16
2016	146	0	0.0	4	2.74
2017	151	3	1.99	2	1.32
2018	152	0	0.0	3	1.97
2019	151	1	0.66	13	8.61
2020	148	4	2.7	2	1.35
2021	148	2	1.35	3	2.03
2022	150	2	1.33	4	2.67

Economy: Montenegro

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	0	0.0	NaN	0	NaN
1997	0	0.0	NaN	0	NaN
1998	0	0.0	NaN	0	NaN
1999	0	0.0	NaN	0	NaN
2000	0	0.0	NaN	0	NaN
2001	0	0.0	NaN	0	NaN
2002	0	0.0	NaN	0	NaN
2003	40	0.0	0.0	1	2.5
2004	69	0.0	0.0	3	4.35
2005	101	0.0	0.0	2	1.98
2006	132	0.0	0.0	3	2.27
2007	150	0.0	0.0	5	3.33
2008	147	0.0	0.0	29	19.73
2009	126	0.0	0.0	27	21.43
2010	101	0.0	0.0	3	2.97
2011	99	0.0	0.0	26	26.26
2012	74	0.0	0.0	18	24.32
2013	58	0.0	0.0	13	22.41
2014	47	0.0	0.0	7	14.89
2015	42	0.0	0.0	0	0.0
2016	45	0.0	0.0	6	13.33
2017	41	0.0	0.0	4	9.76
2018	41	0.0	0.0	4	9.76
2019	42	0.0	0.0	4	9.52
2020	40	0.0	0.0	6	15.0
2021	42	0.0	0.0	7	16.67
2022	53	0.0	0.0	0	0.0

Economy: Morocco

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	16	0	0.0	0	0.0
1997	43	0	0.0	0	0.0
1998	49	0	0.0	0	0.0
1999	52	0	0.0	1	1.92
2000	53	0	0.0	0	0.0
2001	55	0	0.0	1	1.82
2002	54	0	0.0	0	0.0
2003	54	0	0.0	2	3.7
2004	54	0	0.0	1	1.85
2005	55	0	0.0	2	3.64
2006	63	0	0.0	1	1.59
2007	72	0	0.0	0	0.0
2008	78	0	0.0	1	1.28
2009	77	0	0.0	1	1.3
2010	79	0	0.0	4	5.06
2011	77	0	0.0	1	1.3
2012	77	0	0.0	0	0.0
2013	78	0	0.0	3	3.85
2014	76	0	0.0	2	2.63
2015	77	1	1.3	3	3.9
2016	75	0	0.0	2	2.67
2017	72	0	0.0	2	2.78
2018	72	0	0.0	0	0.0
2019	72	0	0.0	1	1.39
2020	74	0	0.0	0	0.0
2021	75	0	0.0	1	1.33
2022	76	0	0.0	2	2.63

Economy: Namibia

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	0	0.0	NaN	0	NaN
1997	0	0.0	NaN	0	NaN
1998	0	0.0	NaN	0	NaN
1999	0	0.0	NaN	0	NaN
2000	0	0.0	NaN	0	NaN
2001	0	0.0	NaN	0	NaN
2002	0	0.0	NaN	0	NaN
2003	5	0.0	0.0	0	0.0
2004	5	0.0	0.0	0	0.0
2005	5	0.0	0.0	0	0.0
2006	6	0.0	0.0	1	16.67
2007	5	0.0	0.0	0	0.0
2008	5	0.0	0.0	1	20.0
2009	4	0.0	0.0	0	0.0
2010	5	0.0	0.0	0	0.0
2011	6	0.0	0.0	1	16.67
2012	5	0.0	0.0	0	0.0
2013	8	0.0	0.0	0	0.0
2014	8	0.0	0.0	0	0.0
2015	8	0.0	0.0	0	0.0
2016	8	0.0	0.0	0	0.0
2017	10	0.0	0.0	0	0.0
2018	10	0.0	0.0	0	0.0
2019	11	0.0	0.0	1	9.09
2020	11	0.0	0.0	0	0.0
2021	12	0.0	0.0	0	0.0
2022	13	0.0	0.0	0	0.0

Economy: Netherlands

		Defaults		Others	
Year	Active	#	%	#	%
1990	136	0	0.0	3	2.21
1991	153	0	0.0	1	0.65
1992	156	0	0.0	0	0.0
1993	163	0	0.0	0	0.0
1994	167	0	0.0	1	0.6
1995	177	0	0.0	0	0.0
1996	186	1	0.54	0	0.0
1997	200	0	0.0	11	5.5
1998	212	1	0.47	8	3.77
1999	226	0	0.0	16	7.08
2000	213	0	0.0	18	8.45
2001	207	8	3.86	20	9.66
2002	186	8	4.3	9	4.84
2003	169	5	2.96	12	7.1
2004	155	0	0.0	6	3.87
2005	156	0	0.0	8	5.13
2006	152	1	0.66	7	4.61
2007	149	0	0.0	9	6.04
2008	143	1	0.7	9	6.29
2009	137	4	2.92	2	1.46
2010	133	0	0.0	5	3.76
2011	130	0	0.0	6	4.62
2012	125	0	0.0	5	4.0
2013	122	1	0.82	8	6.56
2014	118	1	0.85	6	5.08
2015	124	2	1.61	7	5.65
2016	124	0	0.0	5	4.03
2017	120	2	1.67	2	1.67
2018	124	0	0.0	6	4.84
2019	122	0	0.0	6	4.92
2020	120	1	0.83	3	2.5
2021	139	0	0.0	5	3.6
2022	141	0	0.0	11	7.8

Economy: New Zealand

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	30	0	0.0	0	0.0
1993	33	0	0.0	0	0.0
1994	41	0	0.0	0	0.0
1995	43	0	0.0	1	2.33
1996	47	0	0.0	1	2.13
1997	49	0	0.0	0	0.0
1998	51	0	0.0	0	0.0
1999	57	0	0.0	0	0.0
2000	64	0	0.0	0	0.0
2001	72	0	0.0	0	0.0
2002	77	0	0.0	0	0.0
2003	89	0	0.0	0	0.0
2004	104	0	0.0	0	0.0
2005	109	0	0.0	0	0.0
2006	114	0	0.0	0	0.0
2007	121	0	0.0	0	0.0
2008	122	0	0.0	1	0.82
2009	122	0	0.0	0	0.0
2010	127	0	0.0	3	2.36
2011	129	0	0.0	2	1.55
2012	130	0	0.0	5	3.85
2013	134	2	1.49	7	5.22
2014	142	0	0.0	6	4.23
2015	140	0	0.0	5	3.57
2016	146	1	0.68	7	4.79
2017	141	1	0.71	8	5.67
2018	135	1	0.74	10	7.41
2019	126	0	0.0	5	3.97
2020	127	0	0.0	6	4.72
2021	127	0	0.0	2	1.57
2022	127	0	0.0	4	3.15

Economy: Nigeria

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	0	0	NaN	0	NaN
2001	0	0	NaN	0	NaN
2002	103	0	0.0	0	0.0
2003	107	0	0.0	5	4.67
2004	130	0	0.0	4	3.08
2005	141	0	0.0	2	1.42
2006	157	0	0.0	3	1.91
2007	170	0	0.0	1	0.59
2008	197	0	0.0	12	6.09
2009	198	0	0.0	9	4.55
2010	193	0	0.0	7	3.63
2011	189	0	0.0	12	6.35
2012	180	0	0.0	2	1.11
2013	186	0	0.0	6	3.23
2014	183	0	0.0	4	2.19
2015	180	0	0.0	1	0.56
2016	182	1	0.55	13	7.14
2017	171	1	0.58	18	10.53
2018	158	0	0.0	12	7.59
2019	154	0	0.0	10	6.49
2020	146	0	0.0	4	2.74
2021	145	0	0.0	7	4.83
2022	143	0	0.0	1	0.7

Economy: Norway					
		Defaults		Others	
Year	Active	#	%	#	%
1990	38	0	0.0	3	7.89
1991	61	0	0.0	0	0.0
1992	82	0	0.0	0	0.0
1993	98	0	0.0	0	0.0
1994	112	0	0.0	0	0.0
1995	134	0	0.0	0	0.0
1996	157	0	0.0	0	0.0
1997	209	0	0.0	8	3.83
1998	229	0	0.0	11	4.8
1999	229	0	0.0	22	9.61
2000	230	1	0.43	29	12.61
2001	241	3	1.24	18	7.47
2002	224	4	1.79	9	4.02
2003	220	4	1.82	26	11.82
2004	211	0	0.0	13	6.16
2005	251	0	0.0	17	6.77
2006	291	0	0.0	30	10.31
2007	296	0	0.0	33	11.15
2008	280	2	0.71	27	9.64
2009	249	5	2.01	21	8.43
2010	239	1	0.42	18	7.53
2011	237	2	0.84	11	4.64
2012	227	1	0.44	12	5.29
2013	227	4	1.76	22	9.69
2014	219	1	0.46	14	6.39
2015	220	5	2.27	14	6.36
2016	223	6	2.69	5	2.24
2017	235	6	2.55	12	5.11
2018	232	0	0.0	8	3.45
2019	239	1	0.42	9	3.77
2020	286	2	0.7	7	2.45
2021	347	1	0.29	14	4.03
2022	349	0	0.0	15	4.3

Economy: Oman					
		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	52	0.0	0.0	0	0.0
1997	74	0.0	0.0	0	0.0
1998	88	0.0	0.0	6	6.82
1999	83	0.0	0.0	6	7.23
2000	81	0.0	0.0	2	2.47
2001	80	0.0	0.0	13	16.25
2002	89	0.0	0.0	0	0.0
2003	98	0.0	0.0	2	2.04
2004	102	0.0	0.0	2	1.96
2005	106	0.0	0.0	5	4.72
2006	109	0.0	0.0	3	2.75
2007	108	0.0	0.0	4	3.7
2008	106	0.0	0.0	9	8.49
2009	98	0.0	0.0	1	1.02
2010	99	0.0	0.0	9	9.09
2011	91	0.0	0.0	4	4.4
2012	90	0.0	0.0	4	4.44
2013	91	0.0	0.0	0	0.0
2014	95	0.0	0.0	5	5.26
2015	91	0.0	0.0	6	6.59
2016	89	0.0	0.0	2	2.25
2017	91	0.0	0.0	5	5.49
2018	90	0.0	0.0	2	2.22
2019	90	0.0	0.0	3	3.33
2020	91	0.0	0.0	4	4.4
2021	92	0.0	0.0	1	1.09
2022	96	0.0	0.0	1	1.04

Economy: Pakistan

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	347	0	0.0	0	0.0
1999	420	0	0.0	2	0.48
2000	446	0	0.0	0	0.0
2001	462	1	0.22	7	1.52
2002	492	1	0.2	3	0.61
2003	508	0	0.0	0	0.0
2004	523	0	0.0	2	0.38
2005	538	0	0.0	7	1.3
2006	543	0	0.0	10	1.84
2007	557	0	0.0	6	1.08
2008	564	0	0.0	9	1.6
2009	573	1	0.17	30	5.24
2010	554	2	0.36	26	4.69
2011	532	1	0.19	47	8.83
2012	494	2	0.4	21	4.25
2013	480	0	0.0	8	1.67
2014	485	3	0.62	8	1.65
2015	485	3	0.62	6	1.24
2016	485	0	0.0	11	2.27
2017	483	1	0.21	6	1.24
2018	481	0	0.0	10	2.08
2019	477	0	0.0	3	0.63
2020	480	0	0.0	6	1.25
2021	488	0	0.0	45	9.22
2022	450	0	0.0	6	1.33

Economy: Peru

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	1	0	0.0	0	0.0
1992	1	0	0.0	0	0.0
1993	1	0	0.0	0	0.0
1994	59	0	0.0	0	0.0
1995	90	0	0.0	0	0.0
1996	102	0	0.0	2	1.96
1997	126	0	0.0	8	6.35
1998	127	0	0.0	17	13.39
1999	117	0	0.0	19	16.24
2000	107	2	1.87	18	16.82
2001	92	0	0.0	10	10.87
2002	91	2	2.2	8	8.79
2003	88	2	2.27	9	10.23
2004	88	1	1.14	5	5.68
2005	89	0	0.0	3	3.37
2006	94	0	0.0	4	4.26
2007	99	1	1.01	1	1.01
2008	98	0	0.0	4	4.08
2009	98	0	0.0	3	3.06
2010	96	0	0.0	4	4.17
2011	93	0	0.0	5	5.38
2012	91	0	0.0	7	7.69
2013	87	1	1.15	6	6.9
2014	82	0	0.0	3	3.66
2015	81	0	0.0	5	6.17
2016	78	0	0.0	3	3.85
2017	80	1	1.25	6	7.5
2018	74	0	0.0	1	1.35
2019	73	0	0.0	4	5.48
2020	70	0	0.0	6	8.57
2021	69	0	0.0	6	8.7
2022	72	0	0.0	1	1.39

Economy: Philippines

		Defaults		Others	
Year	Active	#	%	#	%
1990	66	0	0.0	0	0.0
1991	71	0	0.0	0	0.0
1992	94	0	0.0	1	1.06
1993	115	1	0.87	0	0.0
1994	139	0	0.0	4	2.88
1995	161	0	0.0	1	0.62
1996	183	0	0.0	0	0.0
1997	194	0	0.0	2	1.03
1998	197	1	0.51	5	2.54
1999	202	4	1.98	3	1.49
2000	202	2	0.99	6	2.97
2001	199	3	1.51	5	2.51
2002	204	6	2.94	9	4.41
2003	203	5	2.46	2	0.99
2004	206	6	2.91	5	2.43
2005	204	3	1.47	3	1.47
2006	208	2	0.96	4	1.92
2007	224	1	0.45	8	3.57
2008	220	3	1.36	0	0.0
2009	225	3	1.33	1	0.44
2010	229	0	0.0	1	0.44
2011	240	0	0.0	1	0.42
2012	247	1	0.4	9	3.64
2013	247	0	0.0	3	1.21
2014	253	0	0.0	2	0.79
2015	256	0	0.0	13	5.08
2016	247	0	0.0	2	0.81
2017	251	1	0.4	2	0.8
2018	251	0	0.0	5	1.99
2019	250	0	0.0	1	0.4
2020	253	0	0.0	3	1.19
2021	258	1	0.39	4	1.55
2022	265	0	0.0	0	0.0

Economy: Poland

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	31	0	0.0	0	0.0
1995	58	0	0.0	0	0.0
1996	76	0	0.0	0	0.0
1997	138	0	0.0	1	0.72
1998	194	0	0.0	3	1.55
1999	214	0	0.0	3	1.4
2000	225	1	0.44	6	2.67
2001	227	1	0.44	5	2.2
2002	227	1	0.44	20	8.81
2003	210	3	1.43	14	6.67
2004	222	0	0.0	8	3.6
2005	246	1	0.41	9	3.66
2006	264	0	0.0	9	3.41
2007	340	0	0.0	9	2.65
2008	433	0	0.0	2	0.46
2009	469	1	0.21	9	1.92
2010	559	0	0.0	9	1.61
2011	750	0	0.0	13	1.73
2012	855	9	1.05	18	2.11
2013	884	6	0.68	32	3.62
2014	888	7	0.79	28	3.15
2015	903	13	1.44	38	4.21
2016	890	7	0.79	43	4.83
2017	877	6	0.68	54	6.16
2018	844	11	1.3	59	6.99
2019	794	0	0.0	57	7.18
2020	764	3	0.39	35	4.58
2021	772	1	0.13	27	3.5
2022	764	1	0.13	23	3.01

Economy: Portugal

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	1	0	0.0	0	0.0
1992	1	0	0.0	0	0.0
1993	78	0	0.0	1	1.28
1994	89	0	0.0	3	3.37
1995	98	0	0.0	1	1.02
1996	98	0	0.0	1	1.02
1997	105	0	0.0	7	6.67
1998	105	0	0.0	11	10.48
1999	106	0	0.0	14	13.21
2000	101	0	0.0	13	12.87
2001	88	0	0.0	11	12.5
2002	75	0	0.0	7	9.33
2003	70	0	0.0	3	4.29
2004	72	0	0.0	2	2.78
2005	72	0	0.0	3	4.17
2006	71	0	0.0	4	5.63
2007	70	0	0.0	6	8.57
2008	67	0	0.0	2	2.99
2009	65	0	0.0	3	4.62
2010	63	0	0.0	2	3.17
2011	61	0	0.0	3	4.92
2012	60	0	0.0	3	5.0
2013	60	1	1.67	1	1.67
2014	59	1	1.69	1	1.69
2015	58	2	3.45	1	1.72
2016	57	0	0.0	0	0.0
2017	59	0	0.0	3	5.08
2018	58	0	0.0	5	8.62
2019	54	0	0.0	3	5.56
2020	52	0	0.0	2	3.85
2021	52	0	0.0	1	1.92
2022	56	0	0.0	0	0.0

Economy: Qatar

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	0	0.0	NaN	0	NaN
1997	0	0.0	NaN	0	NaN
1998	0	0.0	NaN	0	NaN
1999	0	0.0	NaN	0	NaN
2000	1	0.0	0.0	0	0.0
2001	1	0.0	0.0	0	0.0
2002	1	0.0	0.0	0	0.0
2003	27	0.0	0.0	0	0.0
2004	29	0.0	0.0	0	0.0
2005	31	0.0	0.0	0	0.0
2006	36	0.0	0.0	0	0.0
2007	40	0.0	0.0	0	0.0
2008	43	0.0	0.0	0	0.0
2009	45	0.0	0.0	1	2.22
2010	46	0.0	0.0	3	6.52
2011	42	0.0	0.0	0	0.0
2012	42	0.0	0.0	0	0.0
2013	42	0.0	0.0	0	0.0
2014	43	0.0	0.0	0	0.0
2015	43	0.0	0.0	0	0.0
2016	45	0.0	0.0	1	2.22
2017	45	0.0	0.0	0	0.0
2018	46	0.0	0.0	0	0.0
2019	48	0.0	0.0	0	0.0
2020	48	0.0	0.0	0	0.0
2021	52	0.0	0.0	1	1.92
2022	50	0.0	0.0	0	0.0

Economy: Romania					
		Defaults		**Others**	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	50	0	0.0	0	0.0
1998	75	0	0.0	0	0.0
1999	140	0	0.0	1	0.71
2000	153	0	0.0	15	9.8
2001	148	0	0.0	26	17.57
2002	124	0	0.0	4	3.23
2003	121	0	0.0	12	9.92
2004	120	0	0.0	7	5.83
2005	151	1	0.66	12	7.95
2006	165	0	0.0	21	12.73
2007	159	0	0.0	9	5.66
2008	157	0	0.0	17	10.83
2009	141	0	0.0	21	14.89
2010	122	0	0.0	5	4.1
2011	123	0	0.0	6	4.88
2012	125	0	0.0	6	4.8
2013	123	2	1.63	7	5.69
2014	119	0	0.0	4	3.36
2015	265	3	1.13	28	10.57
2016	250	0	0.0	3	1.2
2017	268	1	0.37	16	5.97
2018	270	0	0.0	9	3.33
2019	279	1	0.36	8	2.87
2020	282	0	0.0	9	3.19
2021	307	0	0.0	20	6.51
2022	312	0	0.0	5	1.6

Economy: Russian Federation					
		Defaults		**Others**	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	58	0	0.0	0	0.0
1998	62	2	3.23	4	6.45
1999	64	0	0.0	10	15.62
2000	68	0	0.0	5	7.35
2001	76	0	0.0	4	5.26
2002	92	0	0.0	26	28.26
2003	95	0	0.0	2	2.11
2004	131	2	1.53	3	2.29
2005	175	0	0.0	6	3.43
2006	249	2	0.8	20	8.03
2007	287	0	0.0	14	4.88
2008	327	1	0.31	26	7.95
2009	327	7	2.14	15	4.59
2010	329	1	0.3	13	3.95
2011	333	0	0.0	41	12.31
2012	298	2	0.67	60	20.13
2013	254	0	0.0	52	20.47
2014	205	2	0.98	33	16.1
2015	237	2	0.84	21	8.86
2016	224	2	0.89	13	5.8
2017	222	6	2.7	13	5.86
2018	205	1	0.49	14	6.83
2019	193	0	0.0	8	4.15
2020	189	0	0.0	6	3.17
2021	194	0	0.0	8	4.12
2022	189	0	0.0	5	2.65

Economy: Rwanda

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	0	0.0	NaN	0	NaN
1997	0	0.0	NaN	0	NaN
1998	0	0.0	NaN	0	NaN
1999	0	0.0	NaN	0	NaN
2000	0	0.0	NaN	0	NaN
2001	0	0.0	NaN	0	NaN
2002	0	0.0	NaN	0	NaN
2003	0	0.0	NaN	0	NaN
2004	0	0.0	NaN	0	NaN
2005	0	0.0	NaN	0	NaN
2006	0	0.0	NaN	0	NaN
2007	0	0.0	NaN	0	NaN
2008	0	0.0	NaN	0	NaN
2009	0	0.0	NaN	0	NaN
2010	0	0.0	NaN	0	NaN
2011	0	0.0	NaN	0	NaN
2012	0	0.0	NaN	0	NaN
2013	2	0.0	0.0	0	0.0
2014	2	0.0	0.0	0	0.0
2015	3	0.0	0.0	0	0.0
2016	3	0.0	0.0	0	0.0
2017	3	0.0	0.0	0	0.0
2018	4	0.0	0.0	0	0.0
2019	4	0.0	0.0	0	0.0
2020	5	0.0	0.0	0	0.0
2021	6	0.0	0.0	1	16.67
2022	5	0.0	0.0	0	0.0

Economy: Saudi Arabia

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	62	0	0.0	0	0.0
2001	65	0	0.0	0	0.0
2002	68	0	0.0	1	1.47
2003	69	0	0.0	0	0.0
2004	72	0	0.0	0	0.0
2005	76	0	0.0	0	0.0
2006	86	0	0.0	0	0.0
2007	111	0	0.0	2	1.8
2008	126	0	0.0	0	0.0
2009	135	0	0.0	1	0.74
2010	145	0	0.0	0	0.0
2011	149	0	0.0	0	0.0
2012	157	0	0.0	0	0.0
2013	163	1	0.61	0	0.0
2014	168	0	0.0	5	2.98
2015	167	1	0.6	0	0.0
2016	172	1	0.58	0	0.0
2017	189	1	0.53	0	0.0
2018	200	0	0.0	1	0.5
2019	207	0	0.0	4	1.93
2020	208	0	0.0	2	0.96
2021	225	0	0.0	2	0.89
2022	271	0	0.0	3	1.11

Economy: Serbia

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	0	0	NaN	0	NaN
2001	0	0	NaN	0	NaN
2002	0	0	NaN	0	NaN
2003	0	0	NaN	0	NaN
2004	1	0	0.0	0	0.0
2005	183	0	0.0	0	0.0
2006	317	0	0.0	11	3.47
2007	449	0	0.0	29	6.46
2008	467	0	0.0	104	22.27
2009	386	0	0.0	101	26.17
2010	305	0	0.0	62	20.33
2011	273	0	0.0	68	24.91
2012	226	0	0.0	46	20.35
2013	200	0	0.0	36	18.0
2014	173	1	0.58	35	20.23
2015	147	0	0.0	29	19.73
2016	129	0	0.0	29	22.48
2017	109	0	0.0	17	15.6
2018	103	0	0.0	22	21.36
2019	90	0	0.0	20	22.22
2020	79	0	0.0	13	16.46
2021	80	0	0.0	11	13.75
2022	94	0	0.0	10	10.64

Economy: Singapore

		Defaults		Others	
Year	Active	#	%	#	%
1990	161	0	0.0	8	4.97
1991	167	0	0.0	3	1.8
1992	180	0	0.0	4	2.22
1993	200	0	0.0	0	0.0
1994	230	0	0.0	0	0.0
1995	251	1	0.4	0	0.0
1996	275	2	0.73	1	0.36
1997	309	1	0.32	6	1.94
1998	330	3	0.91	3	0.91
1999	375	4	1.07	11	2.93
2000	446	0	0.0	10	2.24
2001	475	2	0.42	22	4.63
2002	479	2	0.42	21	4.38
2003	517	1	0.19	11	2.13
2004	587	2	0.34	7	1.19
2005	643	3	0.47	8	1.24
2006	694	2	0.29	19	2.74
2007	727	0	0.0	15	2.06
2008	741	4	0.54	23	3.1
2009	749	13	1.74	16	2.14
2010	758	2	0.26	31	4.09
2011	745	1	0.13	34	4.56
2012	732	0	0.0	28	3.83
2013	731	1	0.14	24	3.28
2014	734	0	0.0	27	3.68
2015	728	4	0.55	26	3.57
2016	720	10	1.39	36	5.0
2017	701	10	1.43	34	4.85
2018	681	6	0.88	25	3.67
2019	664	1	0.15	52	7.83
2020	625	1	0.16	36	5.76
2021	602	1	0.17	31	5.15
2022	594	2	0.34	22	3.7

Economy: Slovakia					
		Defaults		**Others**	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	0	0.0	NaN	0	NaN
1997	0	0.0	NaN	0	NaN
1998	10	0.0	0.0	0	0.0
1999	12	0.0	0.0	0	0.0
2000	13	0.0	0.0	0	0.0
2001	18	0.0	0.0	1	5.56
2002	27	0.0	0.0	0	0.0
2003	41	0.0	0.0	0	0.0
2004	42	0.0	0.0	0	0.0
2005	44	0.0	0.0	6	13.64
2006	39	0.0	0.0	2	5.13
2007	39	0.0	0.0	6	15.38
2008	38	0.0	0.0	2	5.26
2009	49	0.0	0.0	7	14.29
2010	47	0.0	0.0	1	2.13
2011	51	0.0	0.0	2	3.92
2012	50	0.0	0.0	5	10.0
2013	46	0.0	0.0	3	6.52
2014	43	0.0	0.0	6	13.95
2015	37	0.0	0.0	9	24.32
2016	28	0.0	0.0	4	14.29
2017	24	0.0	0.0	4	16.67
2018	20	0.0	0.0	1	5.0
2019	20	0.0	0.0	2	10.0
2020	19	0.0	0.0	1	5.26
2021	22	0.0	0.0	4	18.18
2022	20	0.0	0.0	0	0.0

Economy: Slovenia					
		Defaults		**Others**	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	74	0	0.0	1	1.35
1999	98	0	0.0	3	3.06
2000	118	0	0.0	4	3.39
2001	131	0	0.0	17	12.98
2002	124	0	0.0	19	15.32
2003	116	0	0.0	8	6.9
2004	126	0	0.0	12	9.52
2005	119	0	0.0	26	21.85
2006	95	0	0.0	16	16.84
2007	82	0	0.0	9	10.98
2008	80	0	0.0	2	2.5
2009	79	3	3.8	8	10.13
2010	69	0	0.0	4	5.8
2011	65	0	0.0	6	9.23
2012	60	2	3.33	3	5.0
2013	57	2	3.51	7	12.28
2014	52	2	3.85	4	7.69
2015	46	0	0.0	5	10.87
2016	41	0	0.0	7	17.07
2017	34	0	0.0	2	5.88
2018	47	0	0.0	6	12.77
2019	42	0	0.0	3	7.14
2020	44	0	0.0	0	0.0
2021	46	0	0.0	6	13.04
2022	53	0	0.0	4	7.55

Economy: South Africa

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	389	0	0.0	0	0.0
1993	401	0	0.0	0	0.0
1994	430	0	0.0	2	0.47
1995	476	0	0.0	3	0.63
1996	503	0	0.0	7	1.39
1997	550	0	0.0	12	2.18
1998	640	2	0.31	58	9.06
1999	640	3	0.47	53	8.28
2000	603	5	0.83	86	14.26
2001	515	9	1.75	79	15.34
2002	432	7	1.62	65	15.05
2003	366	1	0.27	41	11.2
2004	332	3	0.9	36	10.84
2005	311	2	0.64	21	6.75
2006	322	0	0.0	17	5.28
2007	362	0	0.0	15	4.14
2008	360	0	0.0	18	5.0
2009	346	1	0.29	16	4.62
2010	341	2	0.59	18	5.28
2011	328	1	0.3	17	5.18
2012	320	5	1.56	17	5.31
2013	327	3	0.92	21	6.42
2014	325	0	0.0	20	6.15
2015	325	2	0.62	24	7.38
2016	309	0	0.0	15	4.85
2017	314	0	0.0	15	4.78
2018	309	0	0.0	13	4.21
2019	301	1	0.33	19	6.31
2020	284	0	0.0	21	7.39
2021	269	1	0.37	16	5.95
2022	259	0	0.0	14	5.41

Economy: South Korea

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	617	0	0.0	0	0.0
1991	634	0	0.0	0	0.0
1992	638	1	0.16	0	0.0
1993	645	0	0.0	0	0.0
1994	675	0	0.0	0	0.0
1995	704	1	0.14	0	0.0
1996	760	6	0.79	1	0.13
1997	1112	52	4.68	2	0.18
1998	1125	81	7.2	12	1.07
1999	1162	32	2.75	39	3.36
2000	1296	14	1.08	44	3.4
2001	1433	20	1.4	27	1.88
2002	1576	14	0.89	37	2.35
2003	1617	11	0.68	30	1.86
2004	1649	8	0.49	53	3.21
2005	1696	8	0.47	53	3.12
2006	1731	2	0.12	14	0.81
2007	1802	1	0.06	15	0.83
2008	1856	10	0.54	27	1.45
2009	1907	7	0.37	81	4.25
2010	1941	10	0.52	91	4.69
2011	1922	4	0.21	69	3.59
2012	1886	5	0.27	74	3.92
2013	1906	11	0.58	46	2.41
2014	1961	5	0.25	38	1.94
2015	2090	2	0.1	42	2.01
2016	2188	4	0.18	37	1.69
2017	2276	3	0.13	54	2.37
2018	2351	1	0.04	69	2.93
2019	2406	5	0.21	71	2.95
2020	2446	0	0.0	72	2.94
2021	2510	1	0.04	50	1.99
2022	2618	0	0.0	28	1.07

Economy: Spain

		Defaults		Others	
Year	Active	#	%	#	%
1990	104	0	0.0	0	0.0
1991	156	0	0.0	0	0.0
1992	164	0	0.0	1	0.61
1993	191	0	0.0	5	2.62
1994	257	0	0.0	1	0.39
1995	273	0	0.0	4	1.47
1996	283	0	0.0	5	1.77
1997	291	0	0.0	7	2.41
1998	301	0	0.0	47	15.61
1999	269	0	0.0	33	12.27
2000	248	0	0.0	14	5.65
2001	246	0	0.0	20	8.13
2002	241	2	0.83	18	7.47
2003	227	0	0.0	40	17.62
2004	195	0	0.0	15	7.69
2005	186	0	0.0	8	4.3
2006	197	0	0.0	26	13.2
2007	187	1	0.53	13	6.95
2008	178	2	1.12	8	4.49
2009	175	0	0.0	12	6.86
2010	174	1	0.57	11	6.32
2011	171	0	0.0	12	7.02
2012	165	2	1.21	5	3.03
2013	171	6	3.51	7	4.09
2014	174	1	0.57	9	5.17
2015	191	1	0.52	9	4.71
2016	205	1	0.49	2	0.98
2017	224	3	1.34	6	2.68
2018	241	3	1.24	10	4.15
2019	245	1	0.41	17	6.94
2020	239	4	1.67	14	5.86
2021	247	1	0.4	14	5.67
2022	264	0	0.0	3	1.14

Economy: Sri Lanka

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	1	0	0.0	0	0.0
1994	1	0	0.0	0	0.0
1995	132	0	0.0	0	0.0
1996	145	0	0.0	0	0.0
1997	152	0	0.0	0	0.0
1998	164	0	0.0	1	0.61
1999	167	0	0.0	1	0.6
2000	174	0	0.0	1	0.57
2001	178	0	0.0	1	0.56
2002	186	0	0.0	1	0.54
2003	193	0	0.0	3	1.55
2004	197	0	0.0	0	0.0
2005	211	0	0.0	0	0.0
2006	219	0	0.0	0	0.0
2007	220	0	0.0	1	0.45
2008	222	0	0.0	3	1.35
2009	223	0	0.0	0	0.0
2010	234	0	0.0	0	0.0
2011	261	0	0.0	2	0.77
2012	277	0	0.0	1	0.36
2013	277	0	0.0	1	0.36
2014	283	0	0.0	5	1.77
2015	280	1	0.36	3	1.07
2016	281	1	0.36	6	2.14
2017	280	1	0.36	4	1.43
2018	280	0	0.0	10	3.57
2019	272	0	0.0	8	2.94
2020	268	1	0.37	1	0.37
2021	279	0	0.0	5	1.79
2022	284	0	0.0	5	1.76

Economy: Sweden

		Defaults		Others	
Year	Active	#	%	#	%
1990	41	0	0.0	0	0.0
1991	62	0	0.0	0	0.0
1992	121	0	0.0	0	0.0
1993	145	0	0.0	1	0.69
1994	173	0	0.0	2	1.16
1995	184	0	0.0	0	0.0
1996	238	0	0.0	0	0.0
1997	308	0	0.0	36	11.69
1998	322	1	0.31	20	6.21
1999	367	1	0.27	26	7.08
2000	407	1	0.25	34	8.35
2001	396	4	1.01	26	6.57
2002	388	6	1.55	21	5.41
2003	368	2	0.54	21	5.71
2004	382	1	0.26	21	5.5
2005	407	2	0.49	13	3.19
2006	458	0	0.0	21	4.59
2007	522	1	0.19	13	2.49
2008	543	2	0.37	29	5.34
2009	531	4	0.75	24	4.52
2010	536	2	0.37	28	5.22
2011	537	3	0.56	32	5.96
2012	524	0	0.0	41	7.82
2013	515	3	0.58	21	4.08
2014	572	3	0.52	26	4.55
2015	640	2	0.31	21	3.28
2016	717	1	0.14	21	2.93
2017	824	3	0.36	19	2.31
2018	877	4	0.46	27	3.08
2019	893	2	0.22	24	2.69
2020	930	7	0.75	37	3.98
2021	1046	1	0.1	29	2.77
2022	1072	2	0.19	38	3.54

Economy: Switzerland

		Defaults		Others	
Year	Active	#	%	#	%
1990	140	0	0.0	0	0.0
1991	159	0	0.0	6	3.77
1992	158	0	0.0	1	0.63
1993	175	0	0.0	0	0.0
1994	185	0	0.0	1	0.54
1995	195	0	0.0	2	1.03
1996	212	0	0.0	1	0.47
1997	223	2	0.9	3	1.35
1998	233	0	0.0	5	2.15
1999	250	0	0.0	8	3.2
2000	268	0	0.0	7	2.61
2001	269	2	0.74	9	3.35
2002	266	1	0.38	10	3.76
2003	253	2	0.79	10	3.95
2004	246	1	0.41	7	2.85
2005	250	1	0.4	6	2.4
2006	260	0	0.0	13	5.0
2007	261	0	0.0	6	2.3
2008	265	0	0.0	8	3.02
2009	264	0	0.0	6	2.27
2010	265	0	0.0	8	3.02
2011	263	2	0.76	10	3.8
2012	277	1	0.36	8	2.89
2013	276	0	0.0	5	1.81
2014	279	1	0.36	7	2.51
2015	276	1	0.36	13	4.71
2016	270	0	0.0	10	3.7
2017	265	0	0.0	14	5.28
2018	266	0	0.0	8	3.01
2019	270	0	0.0	11	4.07
2020	268	0	0.0	19	7.09
2021	253	0	0.0	9	3.56
2022	248	0	0.0	9	3.63

Economy: Taiwan					
		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	191	0	0.0	0	0.0
1992	232	0	0.0	2	0.86
1993	253	0	0.0	0	0.0
1994	285	0	0.0	0	0.0
1995	332	0	0.0	0	0.0
1996	367	0	0.0	0	0.0
1997	396	0	0.0	2	0.51
1998	428	3	0.7	3	0.7
1999	465	7	1.51	6	1.29
2000	540	7	1.3	9	1.67
2001	602	8	1.33	12	1.99
2002	674	7	1.04	28	4.15
2003	686	1	0.15	10	1.46
2004	756	5	0.66	7	0.93
2005	769	3	0.39	22	2.86
2006	765	2	0.26	15	1.96
2007	794	2	0.25	18	2.27
2008	803	3	0.37	10	1.25
2009	816	1	0.12	4	0.49
2010	849	1	0.12	9	1.06
2011	864	0	0.0	6	0.69
2012	885	0	0.0	4	0.45
2013	898	0	0.0	4	0.45
2014	919	2	0.22	7	0.76
2015	928	0	0.0	3	0.32
2016	951	1	0.11	7	0.74
2017	946	0	0.0	6	0.63
2018	961	0	0.0	10	1.04
2019	962	0	0.0	6	0.62
2020	970	0	0.0	9	0.93
2021	979	1	0.1	7	0.72
2022	987	0	0.0	8	0.81

Economy: Tanzania					
		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	0	0.0	NaN	0	NaN
1997	0	0.0	NaN	0	NaN
1998	0	0.0	NaN	0	NaN
1999	0	0.0	NaN	0	NaN
2000	0	0.0	NaN	0	NaN
2001	0	0.0	NaN	0	NaN
2002	0	0.0	NaN	0	NaN
2003	0	0.0	NaN	0	NaN
2004	0	0.0	NaN	0	NaN
2005	0	0.0	NaN	0	NaN
2006	0	0.0	NaN	0	NaN
2007	0	0.0	NaN	0	NaN
2008	0	0.0	NaN	0	NaN
2009	9	0.0	0.0	0	0.0
2010	9	0.0	0.0	0	0.0
2011	9	0.0	0.0	0	0.0
2012	10	0.0	0.0	0	0.0
2013	10	0.0	0.0	0	0.0
2014	12	0.0	0.0	0	0.0
2015	12	0.0	0.0	0	0.0
2016	13	0.0	0.0	1	7.69
2017	13	0.0	0.0	0	0.0
2018	16	0.0	0.0	0	0.0
2019	17	0.0	0.0	0	0.0
2020	20	0.0	0.0	0	0.0
2021	20	0.0	0.0	0	0.0
2022	20	0.0	0.0	0	0.0

Economy: Thailand

		Defaults		Others	
Year	Active	#	%	#	%
1990	147	0	0.0	0	0.0
1991	190	0	0.0	1	0.53
1992	279	0	0.0	0	0.0
1993	330	0	0.0	0	0.0
1994	377	0	0.0	0	0.0
1995	408	1	0.25	4	0.98
1996	445	5	1.12	1	0.22
1997	450	21	4.67	29	6.44
1998	409	13	3.18	31	7.58
1999	379	15	3.96	19	5.01
2000	371	20	5.39	9	2.43
2001	362	7	1.93	8	2.21
2002	381	5	1.31	9	2.36
2003	405	4	0.99	6	1.48
2004	449	0	0.0	10	2.23
2005	495	3	0.61	16	3.23
2006	500	0	0.0	5	1.0
2007	510	1	0.2	11	2.16
2008	516	3	0.58	11	2.13
2009	527	10	1.9	8	1.52
2010	526	4	0.76	10	1.9
2011	529	2	0.38	11	2.08
2012	536	1	0.19	6	1.12
2013	561	1	0.18	4	0.71
2014	594	0	0.0	5	0.84
2015	633	1	0.16	10	1.58
2016	652	2	0.31	8	1.23
2017	741	5	0.67	11	1.48
2018	747	0	0.0	3	0.4
2019	784	2	0.26	11	1.4
2020	804	5	0.62	7	0.87
2021	835	0	0.0	15	1.8
2022	870	0	0.0	5	0.57

Economy: Tunisia

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0.0	NaN	0	NaN
1991	0	0.0	NaN	0	NaN
1992	0	0.0	NaN	0	NaN
1993	0	0.0	NaN	0	NaN
1994	0	0.0	NaN	0	NaN
1995	0	0.0	NaN	0	NaN
1996	0	0.0	NaN	0	NaN
1997	0	0.0	NaN	0	NaN
1998	0	0.0	NaN	0	NaN
1999	33	0.0	0.0	0	0.0
2000	37	0.0	0.0	0	0.0
2001	41	0.0	0.0	0	0.0
2002	43	0.0	0.0	0	0.0
2003	43	0.0	0.0	0	0.0
2004	43	0.0	0.0	1	2.33
2005	45	0.0	0.0	0	0.0
2006	48	0.0	0.0	0	0.0
2007	51	0.0	0.0	0	0.0
2008	53	0.0	0.0	4	7.55
2009	51	0.0	0.0	0	0.0
2010	55	0.0	0.0	1	1.82
2011	55	0.0	0.0	0	0.0
2012	56	0.0	0.0	0	0.0
2013	65	0.0	0.0	0	0.0
2014	75	0.0	0.0	1	1.33
2015	77	0.0	0.0	0	0.0
2016	78	0.0	0.0	0	0.0
2017	80	0.0	0.0	0	0.0
2018	81	0.0	0.0	0	0.0
2019	81	0.0	0.0	1	1.23
2020	81	0.0	0.0	3	3.7
2021	79	0.0	0.0	0	0.0
2022	81	0.0	0.0	0	0.0

Economy: Turkey

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	9	0	0.0	0	0.0
1993	15	0	0.0	0	0.0
1994	34	0	0.0	0	0.0
1995	201	0	0.0	0	0.0
1996	223	1	0.45	2	0.9
1997	257	0	0.0	1	0.39
1998	277	0	0.0	2	0.72
1999	284	0	0.0	9	3.17
2000	313	0	0.0	17	5.43
2001	298	0	0.0	13	4.36
2002	293	0	0.0	7	2.39
2003	291	0	0.0	6	2.06
2004	296	0	0.0	0	0.0
2005	305	0	0.0	2	0.66
2006	320	0	0.0	6	1.88
2007	324	0	0.0	5	1.54
2008	320	0	0.0	4	1.25
2009	321	0	0.0	4	1.25
2010	337	0	0.0	0	0.0
2011	364	0	0.0	2	0.55
2012	401	0	0.0	5	1.25
2013	422	0	0.0	6	1.42
2014	431	0	0.0	13	3.02
2015	426	0	0.0	12	2.82
2016	418	0	0.0	14	3.35
2017	412	1	0.24	10	2.43
2018	408	1	0.25	8	1.96
2019	405	0	0.0	5	1.23
2020	411	3	0.73	15	3.65
2021	445	0	0.0	2	0.45
2022	484	0	0.0	2	0.41

Economy: Uganda

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	0	0	NaN	0	NaN
2001	0	0	NaN	0	NaN
2002	0	0	NaN	0	NaN
2003	0	0	NaN	0	NaN
2004	0	0	NaN	0	NaN
2005	0	0	NaN	0	NaN
2006	0	0	NaN	0	NaN
2007	0	0	NaN	0	NaN
2008	0	0	NaN	0	NaN
2009	6	0	0.0	0	0.0
2010	7	0	0.0	0	0.0
2011	7	0	0.0	0	0.0
2012	8	0	0.0	0	0.0
2013	8	0	0.0	0	0.0
2014	9	1	11.11	0	0.0
2015	8	0	0.0	0	0.0
2016	8	0	0.0	0	0.0
2017	8	0	0.0	1	12.5
2018	8	0	0.0	0	0.0
2019	8	0	0.0	0	0.0
2020	8	0	0.0	0	0.0
2021	9	0	0.0	0	0.0
2022	9	0	0.0	0	0.0

Economy: Ukraine

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	30	0	0.0	1	3.33
1999	38	0	0.0	0	0.0
2000	39	0	0.0	5	12.82
2001	34	0	0.0	12	35.29
2002	27	0	0.0	5	18.52
2003	29	0	0.0	7	24.14
2004	44	0	0.0	0	0.0
2005	75	0	0.0	1	1.33
2006	118	0	0.0	2	1.69
2007	133	0	0.0	2	1.5
2008	138	0	0.0	9	6.52
2009	135	1	0.74	39	28.89
2010	98	0	0.0	44	44.9
2011	67	0	0.0	13	19.4
2012	65	0	0.0	8	12.31
2013	77	0	0.0	11	14.29
2014	69	0	0.0	14	20.29
2015	57	0	0.0	27	47.37
2016	31	0	0.0	18	58.06
2017	14	0	0.0	6	42.86
2018	11	0	0.0	1	9.09
2019	10	0	0.0	1	10.0
2020	10	0	0.0	3	30.0
2021	7	0	0.0	5	71.43
2022	4	0	0.0	1	25.0

Economy: United Arab Emirates

		Defaults		Others	
Year	Active	#	%	#	%
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	0	0	NaN	0	NaN
2001	0	0	NaN	0	NaN
2002	0	0	NaN	0	NaN
2003	0	0	NaN	0	NaN
2004	0	0	NaN	0	NaN
2005	0	0	NaN	0	NaN
2006	76	0	0.0	0	0.0
2007	87	0	0.0	2	2.3
2008	92	0	0.0	5	5.43
2009	89	0	0.0	1	1.12
2010	93	0	0.0	2	2.15
2011	95	0	0.0	2	2.11
2012	96	1	1.04	1	1.04
2013	96	0	0.0	3	3.12
2014	103	0	0.0	1	0.97
2015	105	0	0.0	5	4.76
2016	103	0	0.0	1	0.97
2017	113	2	1.77	4	3.54
2018	110	0	0.0	5	4.55
2019	108	0	0.0	3	2.78
2020	112	0	0.0	5	4.46
2021	119	0	0.0	3	2.52
2022	134	0	0.0	3	2.24

Economy: UK					
		Defaults		Others	
Year	Active	#	%	#	%
1990	261	0	0.0	2	0.77
1991	1057	1	0.09	5	0.47
1992	1113	0	0.0	6	0.54
1993	1202	0	0.0	5	0.42
1994	1311	0	0.0	2	0.15
1995	1461	0	0.0	2	0.14
1996	1658	0	0.0	10	0.6
1997	1801	0	0.0	36	2.0
1998	1878	0	0.0	147	7.83
1999	1829	2	0.11	199	10.88
2000	1916	3	0.16	171	8.92
2001	1854	10	0.54	114	6.15
2002	1816	16	0.88	109	6.0
2003	1771	5	0.28	126	7.11
2004	1930	1	0.05	97	5.03
2005	2197	2	0.09	120	5.46
2006	2370	0	0.0	175	7.38
2007	2444	3	0.12	169	6.91
2008	2347	17	0.72	231	9.84
2009	2132	39	1.83	216	10.13
2010	1957	4	0.2	172	8.79
2011	1844	9	0.49	131	7.1
2012	1763	19	1.08	127	7.2
2013	1710	10	0.58	107	6.26
2014	1718	5	0.29	97	5.65
2015	1750	9	0.51	125	7.14
2016	1716	3	0.17	131	7.63
2017	1695	4	0.24	95	5.6
2018	1699	7	0.41	103	6.06
2019	1636	4	0.24	120	7.33
2020	1570	6	0.38	104	6.62
2021	1621	1	0.06	82	5.06
2022	1618	2	0.12	95	5.87

Economy: US					
		Defaults		Others	
Year	Active	#	%	#	%
1990	3839	5	0.13	85	2.21
1991	4145	18	0.43	102	2.46
1992	5423	16	0.3	88	1.62
1993	6191	27	0.44	143	2.31
1994	6954	17	0.24	223	3.21
1995	7449	16	0.21	362	4.86
1996	8011	17	0.21	401	5.01
1997	8390	48	0.57	568	6.77
1998	8440	75	0.89	891	10.56
1999	8170	84	1.03	921	11.27
2000	7808	106	1.36	784	10.04
2001	7111	174	2.45	758	10.66
2002	6360	118	1.86	534	8.4
2003	5934	80	1.35	472	7.95
2004	5773	37	0.64	371	6.43
2005	5741	35	0.61	384	6.69
2006	5682	21	0.37	382	6.72
2007	5714	23	0.4	463	8.1
2008	5378	58	1.08	382	7.1
2009	5096	104	2.04	323	6.34
2010	4939	29	0.59	313	6.34
2011	4803	35	0.73	305	6.35
2012	4678	44	0.94	263	5.62
2013	4714	28	0.59	241	5.11
2014	4851	26	0.54	215	4.43
2015	5002	45	0.9	278	5.56
2016	4978	83	1.67	368	7.39
2017	4856	47	0.97	314	6.47
2018	4869	29	0.6	265	5.44
2019	4905	43	0.88	293	5.97
2020	5111	92	1.8	242	4.73
2021	5970	21	0.35	277	4.64
2022	6030	26	0.43	442	7.33

Economy: Venezuela

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	7	0	0.0	0	0.0
1994	12	0	0.0	0	0.0
1995	15	0	0.0	1	6.67
1996	14	0	0.0	0	0.0
1997	47	0	0.0	2	4.26
1998	45	0	0.0	4	8.89
1999	45	0	0.0	9	20.0
2000	36	0	0.0	3	8.33
2001	35	1	2.86	4	11.43
2002	32	0	0.0	5	15.62
2003	30	0	0.0	3	10.0
2004	30	0	0.0	2	6.67
2005	29	0	0.0	0	0.0
2006	30	0	0.0	3	10.0
2007	27	0	0.0	0	0.0
2008	31	0	0.0	1	3.23
2009	30	0	0.0	1	3.33
2010	29	0	0.0	2	6.9
2011	27	0	0.0	7	25.93
2012	21	0	0.0	3	14.29
2013	18	0	0.0	1	5.56
2014	20	0	0.0	0	0.0
2015	21	0	0.0	0	0.0
2016	21	0	0.0	0	0.0
2017	25	0	0.0	0	0.0
2018	26	0	0.0	0	0.0
2019	26	0	0.0	3	11.54
2020	24	0	0.0	0	0.0
2021	27	0	0.0	16	59.26
2022	14	0	0.0	0	0.0

Economy: Vietnam

Year	Active	Defaults #	Defaults %	Others #	Others %
1990	0	0	NaN	0	NaN
1991	0	0	NaN	0	NaN
1992	0	0	NaN	0	NaN
1993	0	0	NaN	0	NaN
1994	0	0	NaN	0	NaN
1995	0	0	NaN	0	NaN
1996	0	0	NaN	0	NaN
1997	0	0	NaN	0	NaN
1998	0	0	NaN	0	NaN
1999	0	0	NaN	0	NaN
2000	5	0	0.0	0	0.0
2001	10	0	0.0	0	0.0
2002	20	0	0.0	0	0.0
2003	22	0	0.0	0	0.0
2004	25	0	0.0	0	0.0
2005	31	0	0.0	0	0.0
2006	89	0	0.0	0	0.0
2007	216	0	0.0	3	1.39
2008	280	0	0.0	2	0.71
2009	412	0	0.0	28	6.8
2010	614	0	0.0	10	1.63
2011	666	1	0.15	13	1.95
2012	678	0	0.0	11	1.62
2013	683	0	0.0	24	3.51
2014	689	0	0.0	19	2.76
2015	732	0	0.0	21	2.87
2016	755	1	0.13	8	1.06
2017	805	0	0.0	17	2.11
2018	833	0	0.0	48	5.76
2019	815	0	0.0	44	5.4
2020	811	0	0.0	41	5.06
2021	817	0	0.0	51	6.24
2022	784	0	0.0	36	4.59

B APPENDIX: PERFORMANCE ANALYSIS

Table B.1: Accuracy ratios (AR) and Area Under Receiver Operating Characteristic (AUROC) for four calibration groups and different economies.

	AR				AUROC			
Economy	1mth	1yr	2yr	5yr	1mth	1yr	2yr	5yr
Argentina	0.823	0.734	0.612	0.39	0.912	0.868	0.808	0.706
Australia	0.849	0.68	0.559	0.367	0.925	0.841	0.781	0.687
Belgium	0.939	0.848	0.733	0.564	0.97	0.924	0.867	0.783
Brazil	0.833	0.789	0.712	0.586	0.916	0.895	0.857	0.797
Canada	0.936	0.829	0.715	0.576	0.968	0.915	0.859	0.791
China	0.727	0.694	0.651	0.557	0.864	0.848	0.828	0.785
Denmark	0.906	0.823	0.674	0.549	0.953	0.912	0.838	0.778
France	0.827	0.751	0.681	0.585	0.913	0.876	0.841	0.794
Germany	0.88	0.74	0.643	0.518	0.94	0.87	0.823	0.764
Hong Kong	0.789	0.647	0.547	0.342	0.895	0.824	0.774	0.673
India	0.734	0.706	0.686	0.623	0.867	0.854	0.846	0.819
Indonesia	0.706	0.678	0.641	0.541	0.853	0.84	0.822	0.776
Italy	0.859	0.809	0.687	0.55	0.93	0.905	0.844	0.777
Japan	0.911	0.863	0.817	0.705	0.955	0.932	0.909	0.853
Malaysia	0.8	0.75	0.687	0.535	0.9	0.875	0.845	0.772
Mexico	0.794	0.756	0.736	0.631	0.897	0.879	0.87	0.821
Netherlands	0.89	0.859	0.749	0.559	0.945	0.93	0.875	0.782
Norway	0.928	0.848	0.727	0.53	0.964	0.924	0.865	0.77
Philippines	0.662	0.656	0.646	0.649	0.831	0.829	0.824	0.828
Poland	0.87	0.746	0.645	0.436	0.935	0.873	0.824	0.723
Russian Federation	0.608	0.438	0.233	0.124	0.804	0.72	0.619	0.567
Singapore	0.791	0.723	0.606	0.349	0.896	0.862	0.804	0.679
South Africa	0.918	0.839	0.719	0.47	0.959	0.92	0.86	0.738
South Korea	0.896	0.776	0.727	0.659	0.948	0.888	0.864	0.831
Spain	0.784	0.635	0.515	0.365	0.892	0.818	0.759	0.687
Sweden	0.902	0.841	0.776	0.57	0.951	0.921	0.888	0.787
Taiwan	0.927	0.827	0.739	0.637	0.964	0.914	0.87	0.819
Thailand	0.858	0.821	0.779	0.681	0.929	0.911	0.89	0.844
UK	0.9	0.761	0.629	0.433	0.95	0.881	0.815	0.719
US	0.945	0.858	0.773	0.618	0.972	0.929	0.888	0.813
Developed Asia-Pacific	0.873	0.768	0.694	0.562	0.936	0.884	0.847	0.783
Emerging MKT	0.805	0.755	0.699	0.586	0.903	0.878	0.851	0.796
Europe	0.873	0.763	0.659	0.502	0.936	0.882	0.83	0.754
North America	0.944	0.854	0.767	0.613	0.972	0.928	0.884	0.81

Note: This table only shows the economies with more than 20 defaults in the testing period.

Figure B.1: Plots of US default parameters across all horizons for the Stock index one-year return, Short-term interest rate, Aggregate DTDs (financial and non–financial), CA/CL Level and Trend (non–financial firms), and CASH/TA Level and Trend (financial firms). Solid lines are the parameter estimates and dashed lines are the 90% confidence level. Horizontal axis is the horizon in months.

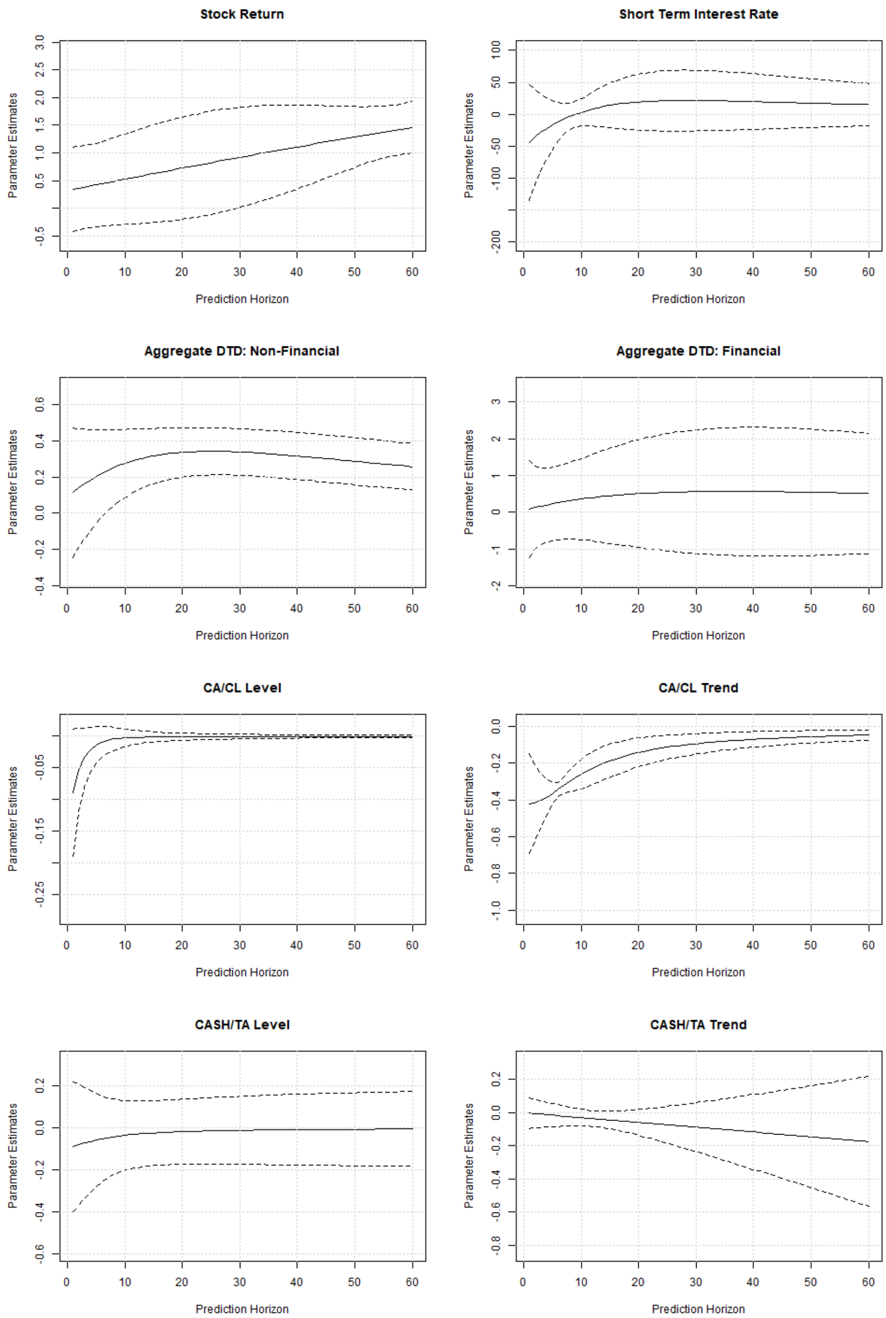


Figure B.2: Plots of US default parameters across all horizons for DTD Level, DTD Trend, the NI/TA Level, NI/TA Trend, SIZE Level, SIZE Trend, M/B, and SIGMA. Solid lines are the parameter estimates and dashed lines are the 90% confidence level. Horizontal axis is the horizon in months.

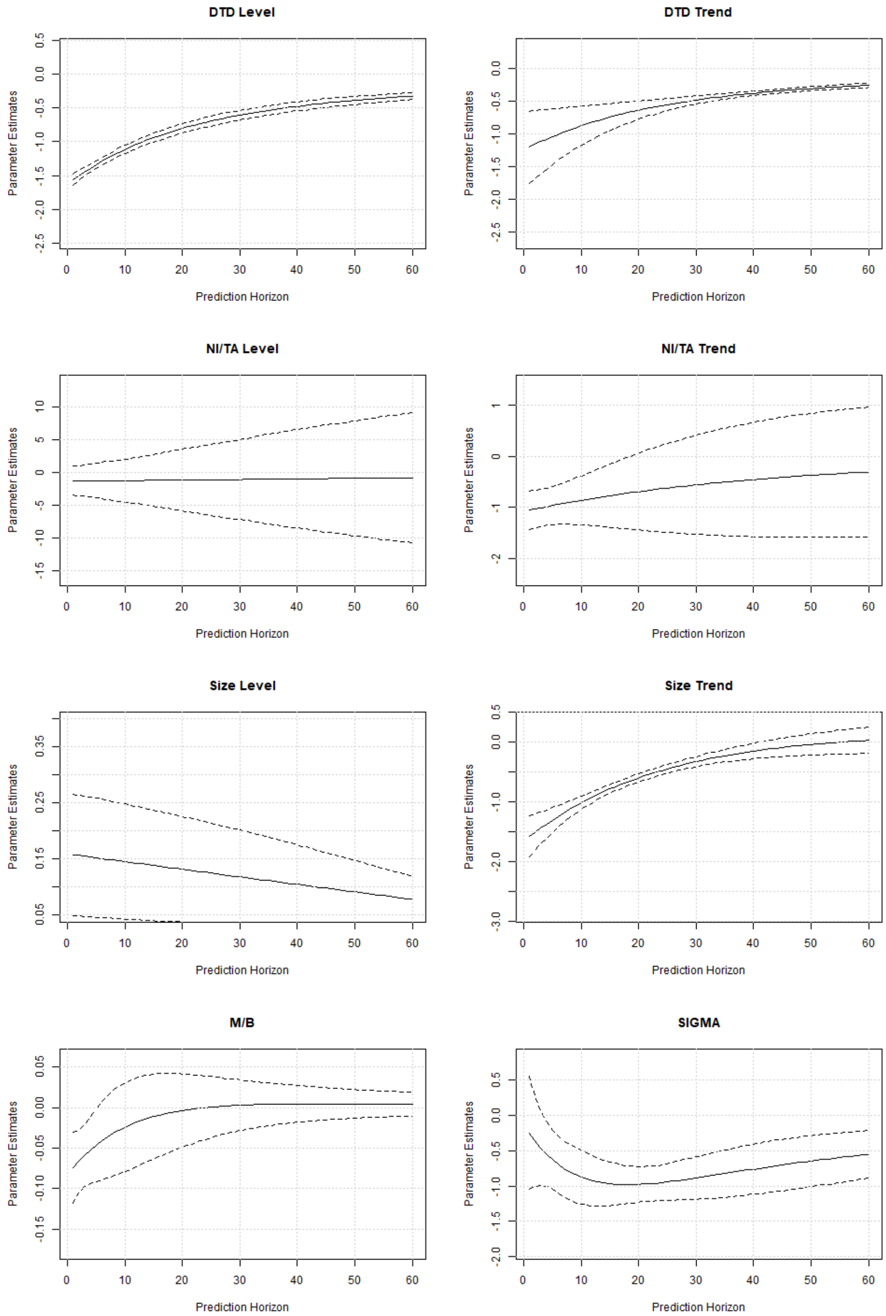
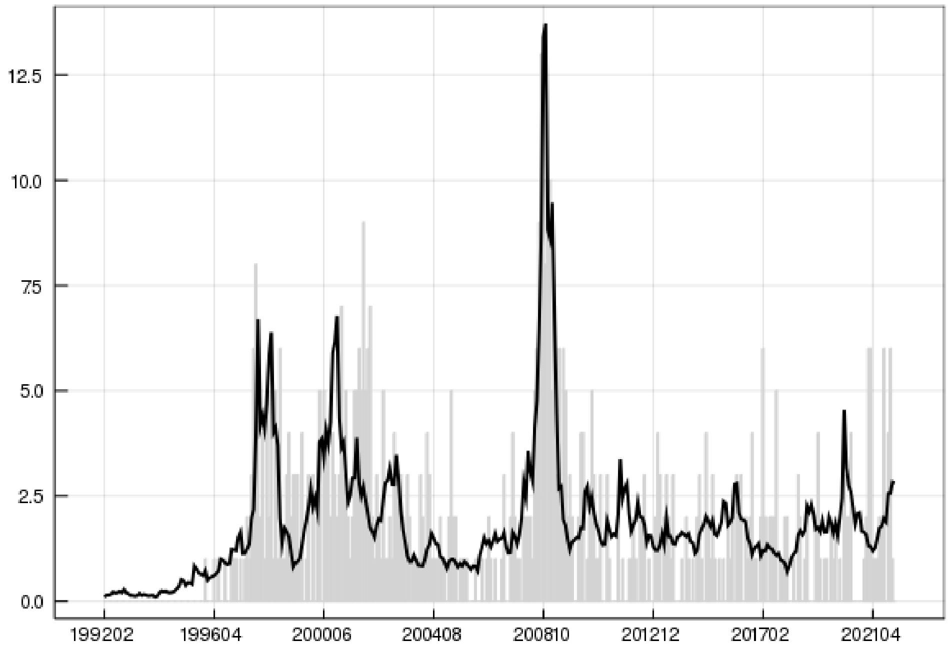
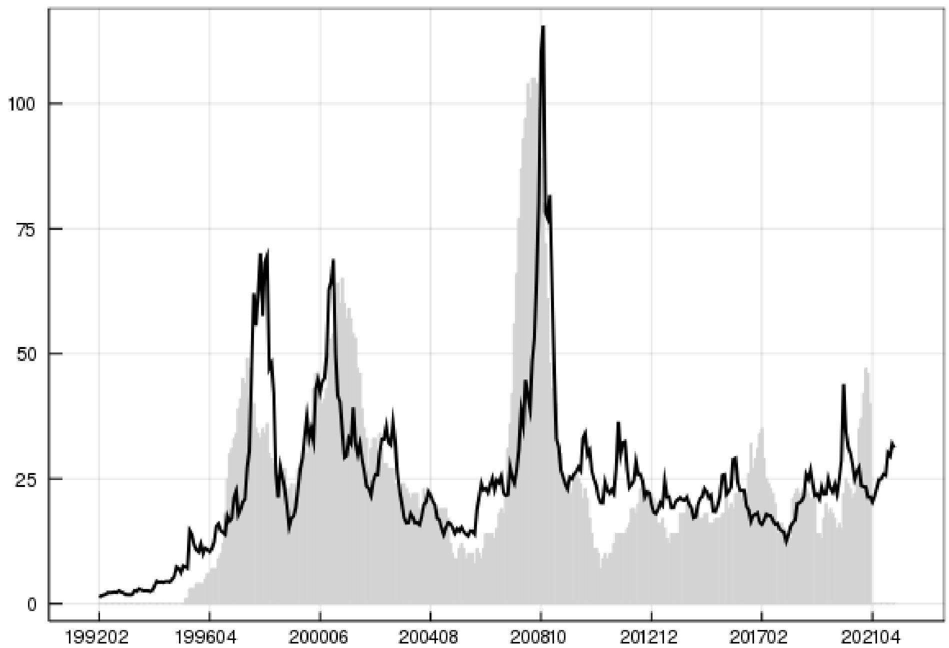


Figure B.3: Performance test with different prediction horizons for Asia Pacific (Developed), in sample. The solid lines represent the predicted default number, whereas the grey bars represent the actual default number. x-axis is the time period, and y-axis is the number of default.

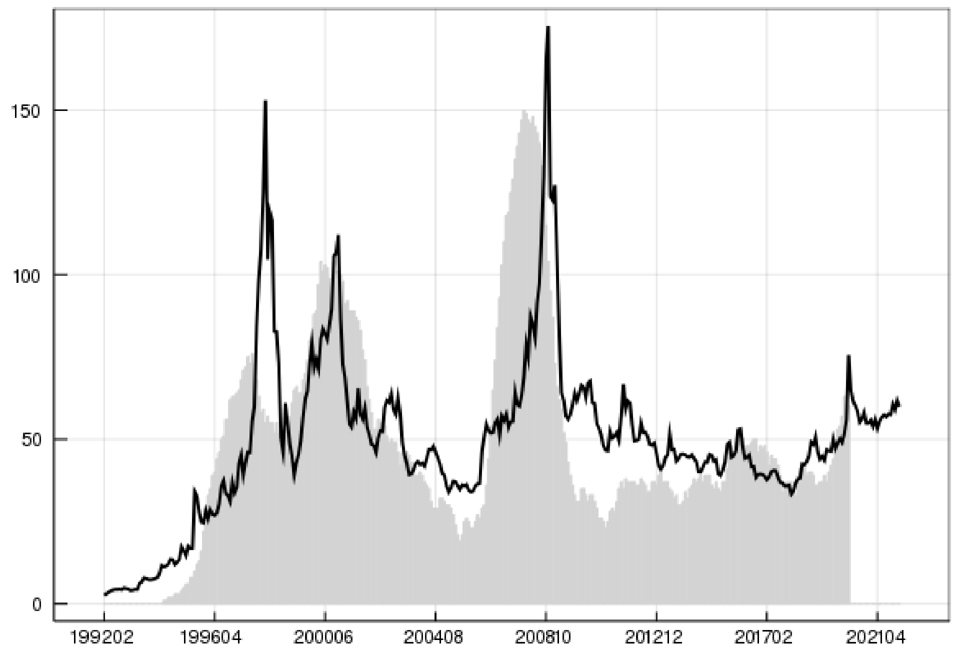
B.4(a) Horizon = 1 month



B.4(b) Horizon = 12 months



B.4(c) Horizon = 2 years



B.4(d) Horizon = 5 years

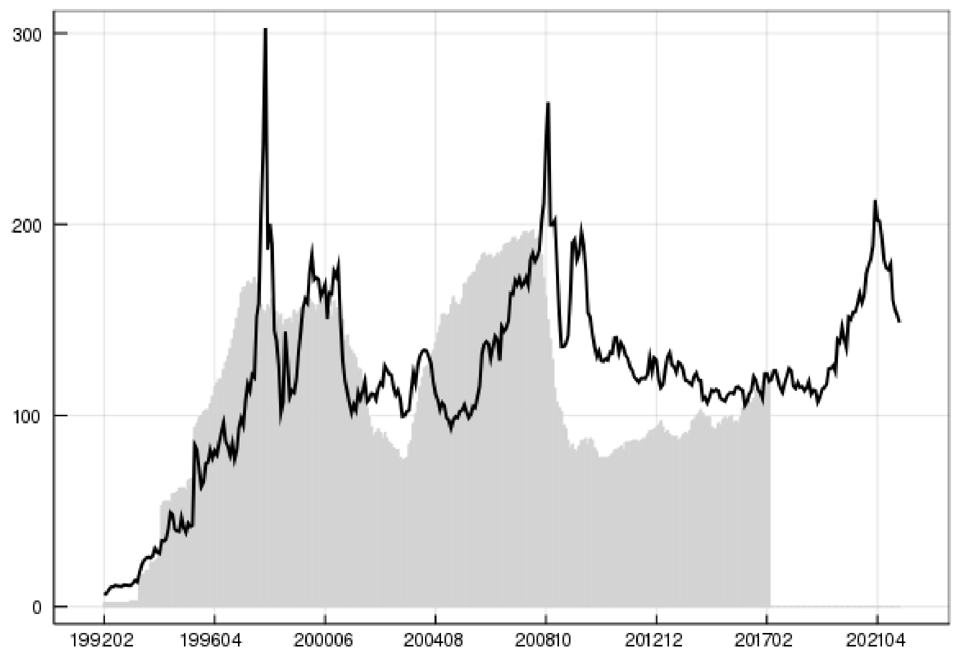
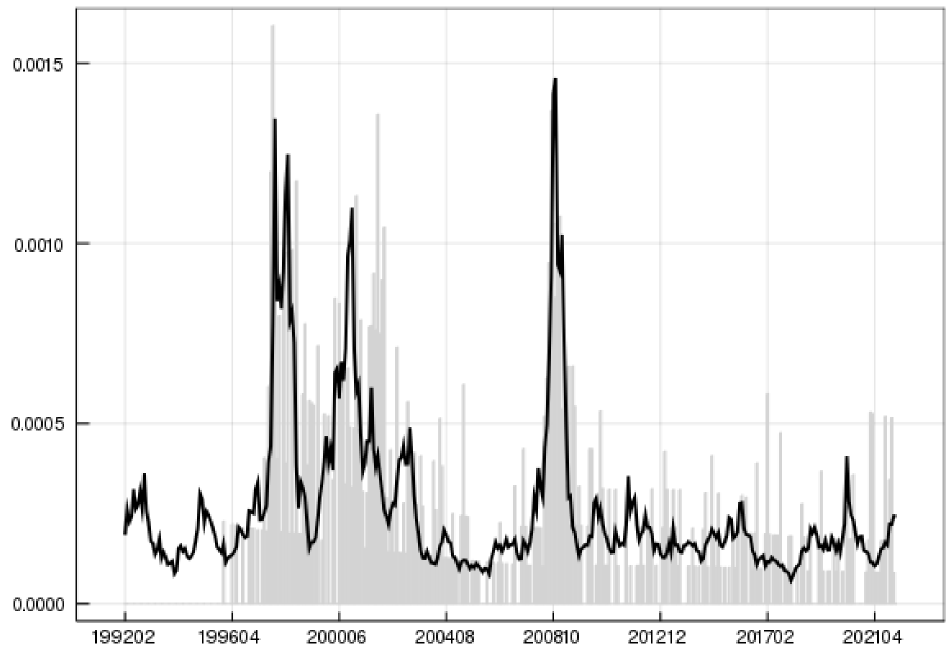
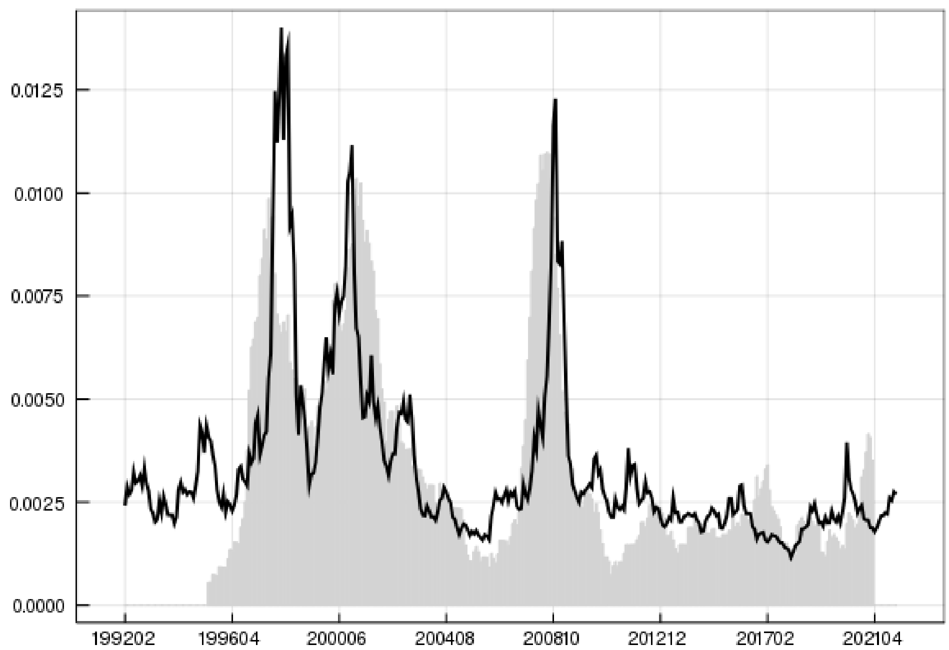


Figure B.4: Performance test with different prediction horizons for Asia Pacific (Developed), in sample. The solid lines represent the predicted default rate, whereas the grey bars represent the actual default rate. x-axis is the time period, and y-axis is the default rate.

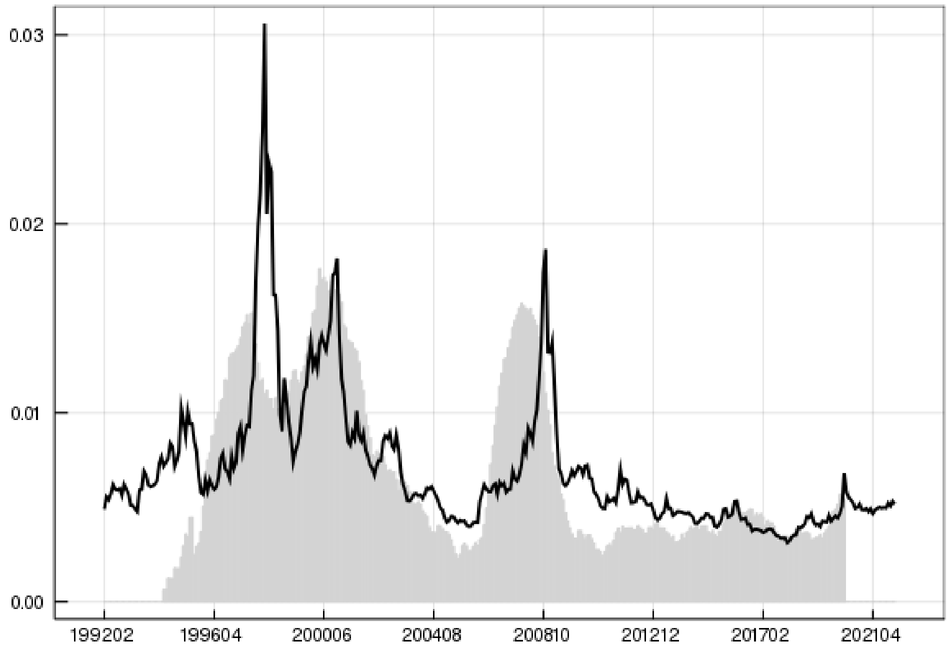
B.4(a) Horizon = 1 month



B.4(b) Horizon = 12 months



B.4(c) Horizon = 2 years



B.4(d) Horizon = 5 years

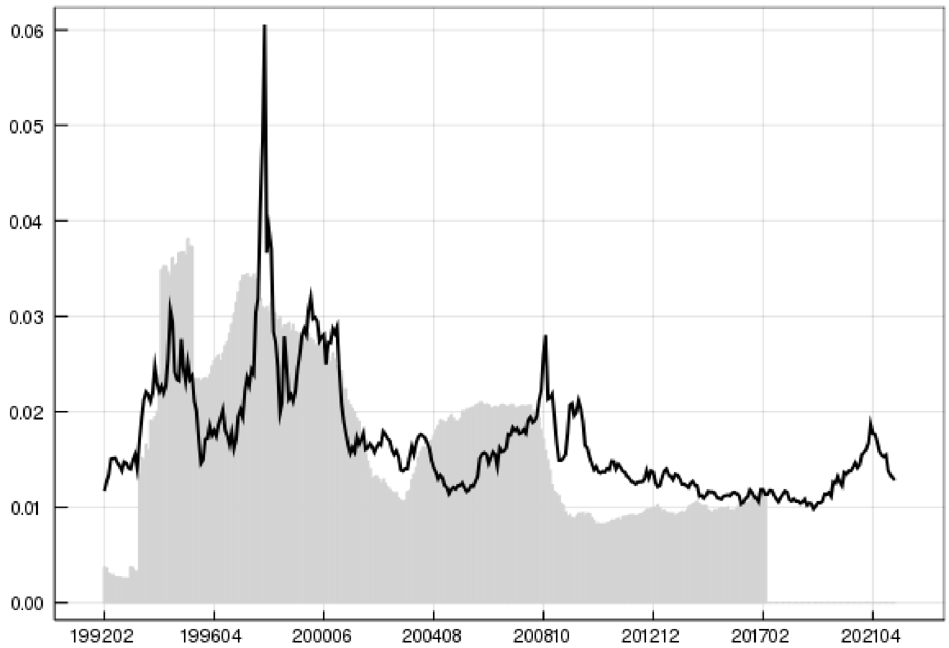
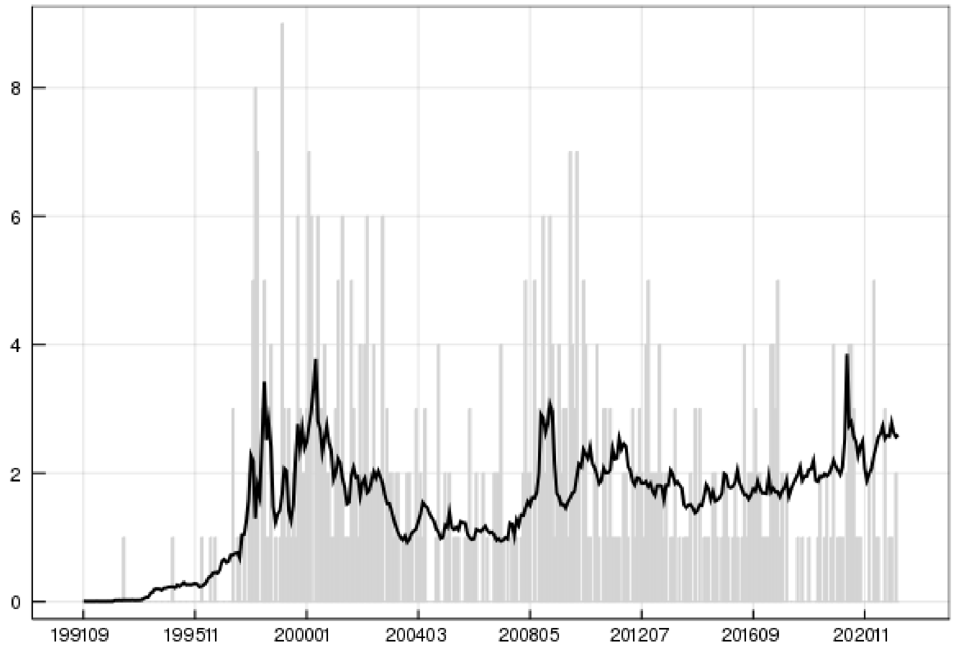
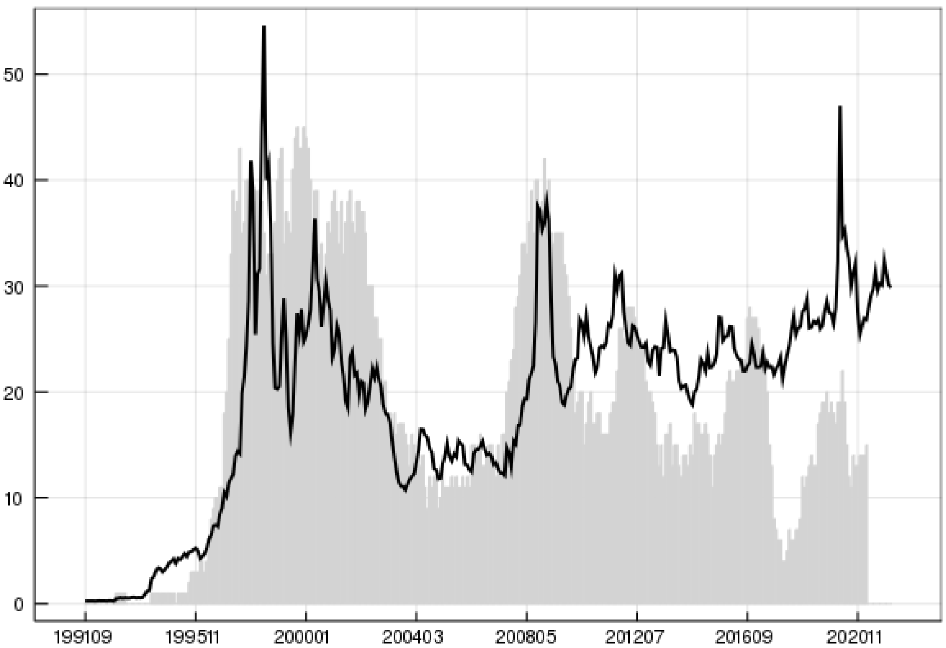


Figure B.5: Performance test with different prediction horizons for the Emerging Market, in sample.The solid lines represent the predicted default number, whereas the grey bars represent the actual default number. x-axis is the time period, and y-axis is the number of default.

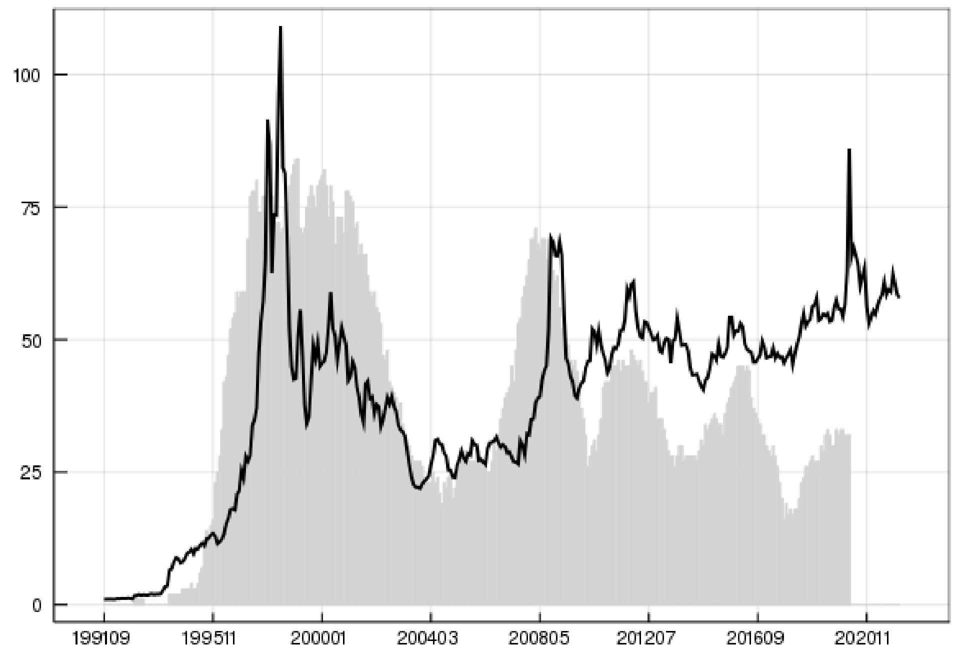
B.6(a) Horizon = 1 month



B.6(b) Horizon = 12 months



B.6(c) Horizon = 2 years



B.6(d) Horizon = 5 years

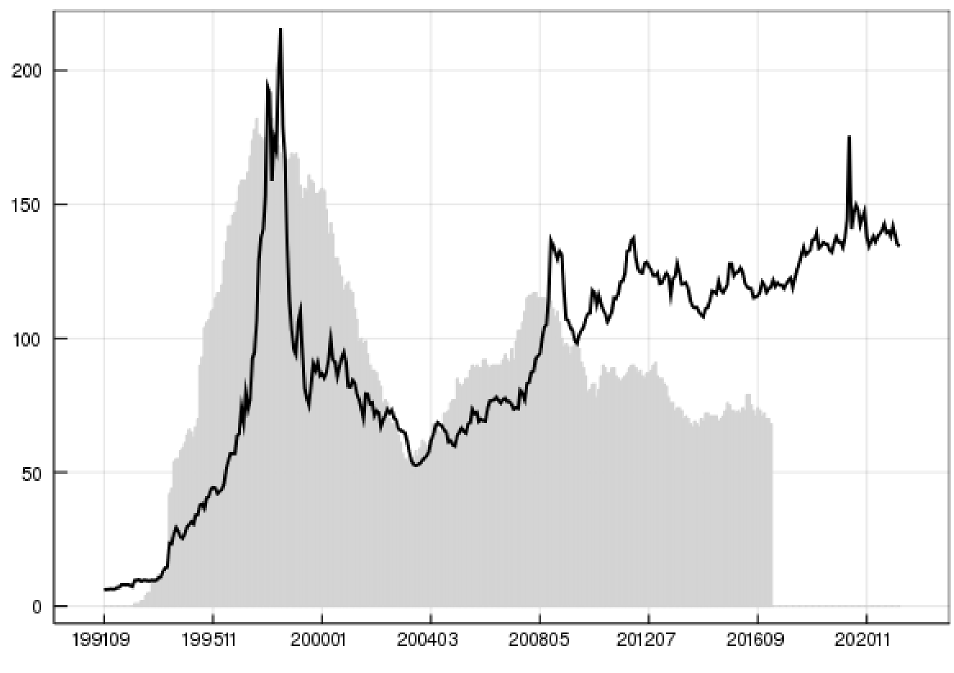
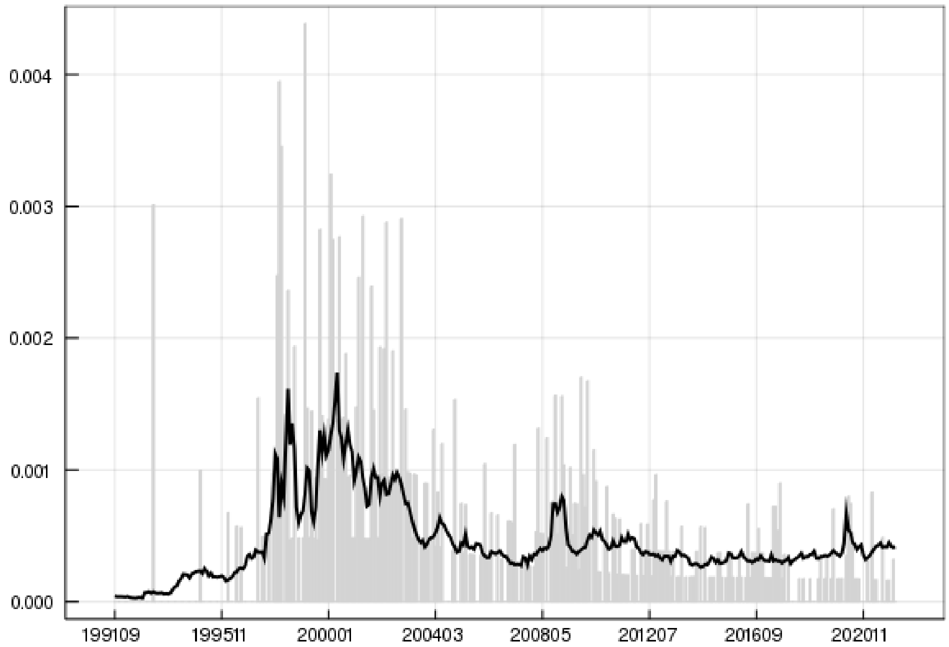
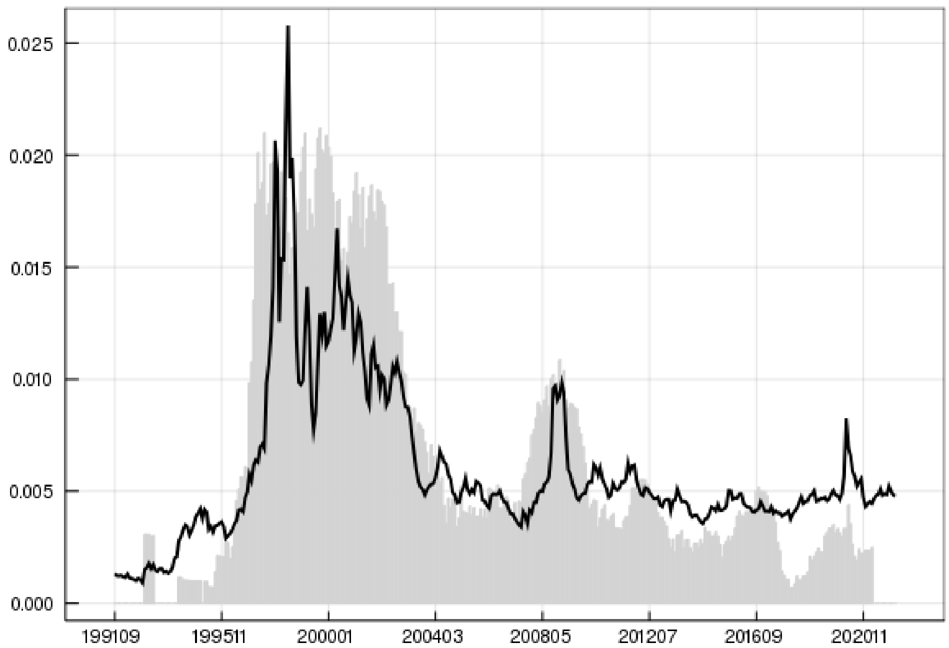


Figure B.6: Performance test with different prediction horizons for the Emerging Market, in sample.The solid lines represent the predicted default rate, whereas the grey bars represent the actual default rate. x-axis is the time period, and y-axis is the default rate.

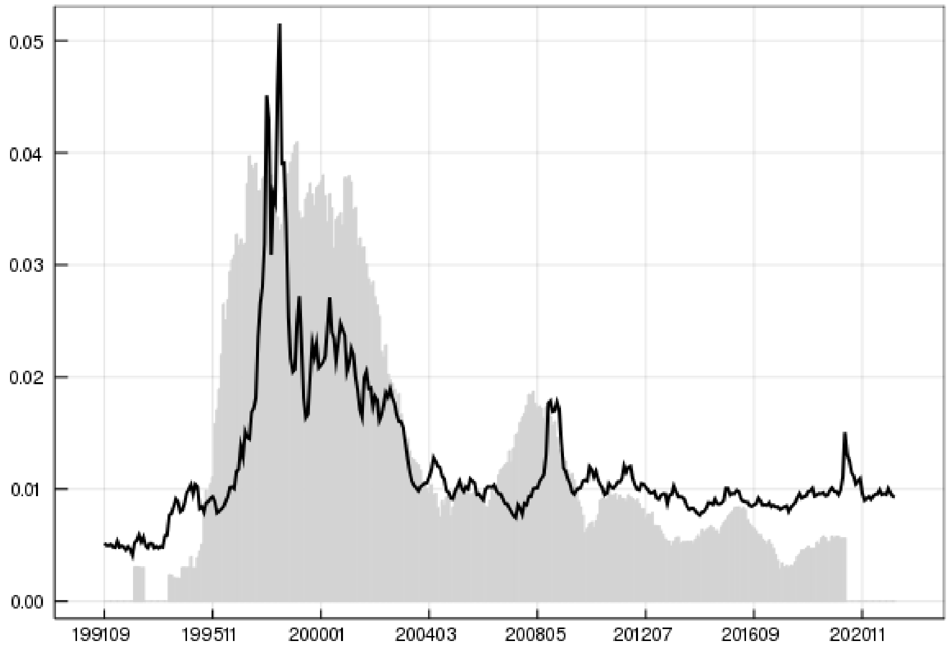
B.6(a) Horizon = 1 month



B.6(b) Horizon = 12 months



B.6(c) Horizon = 2 years



B.6(d) Horizon = 5 years

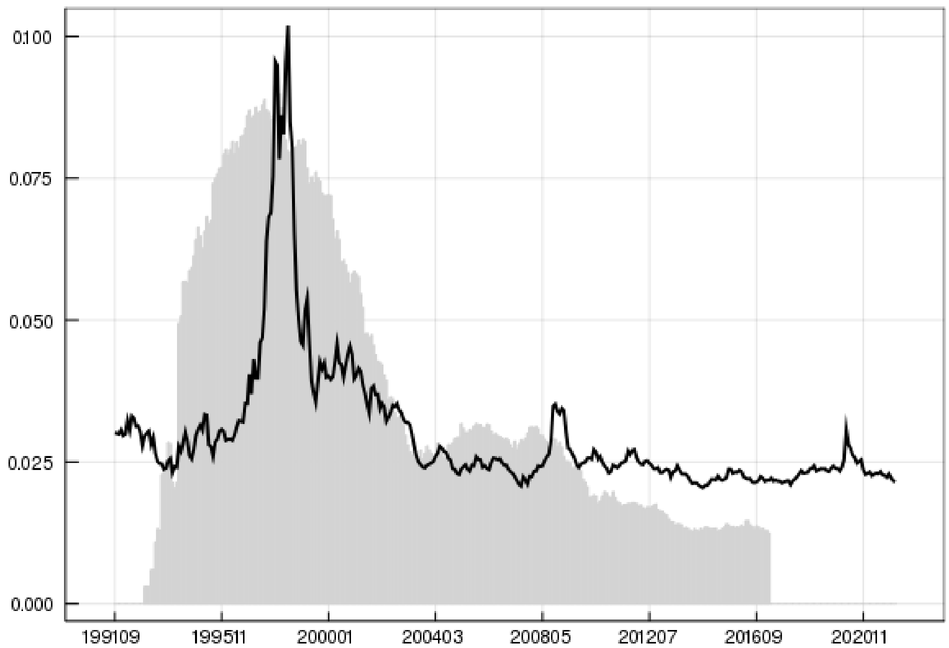
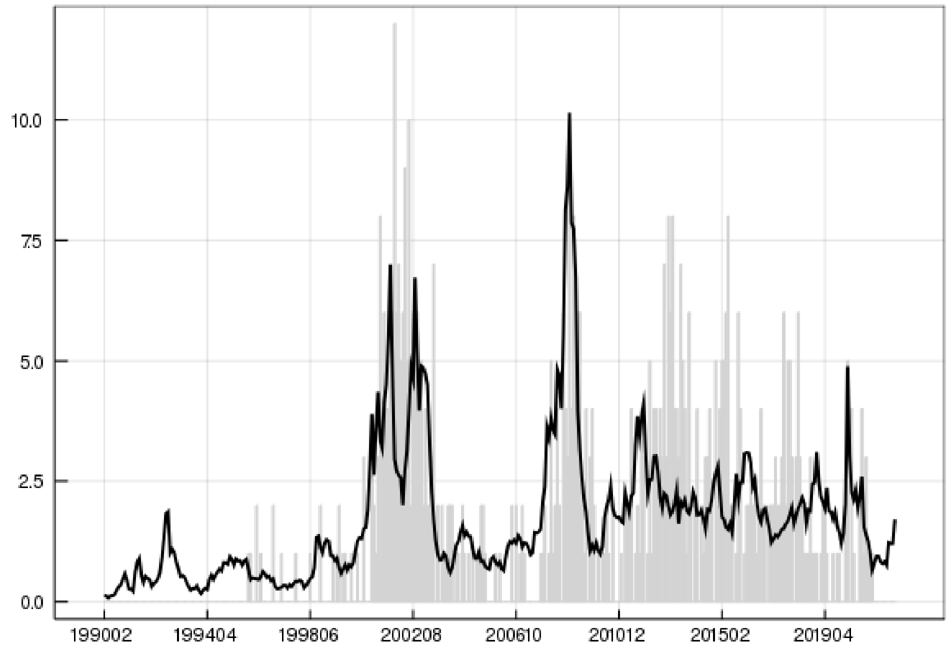
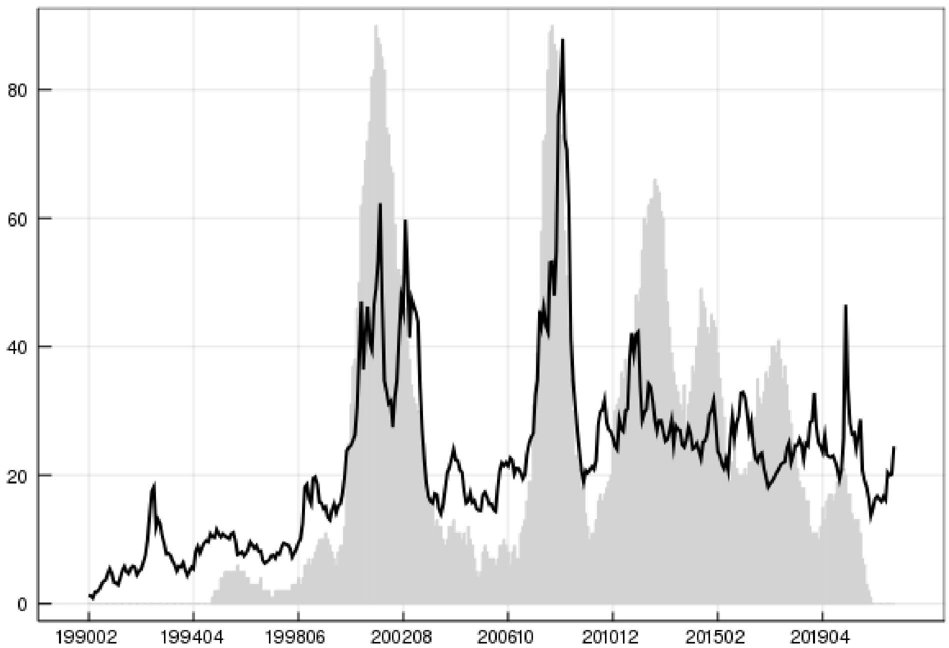


Figure B.7: Performance test with different prediction horizons for the Europe group, in sample. The solid lines represent the predicted default number, whereas the grey bars represent the actual default number. x-axis is the time period, and y-axis is the number of default.

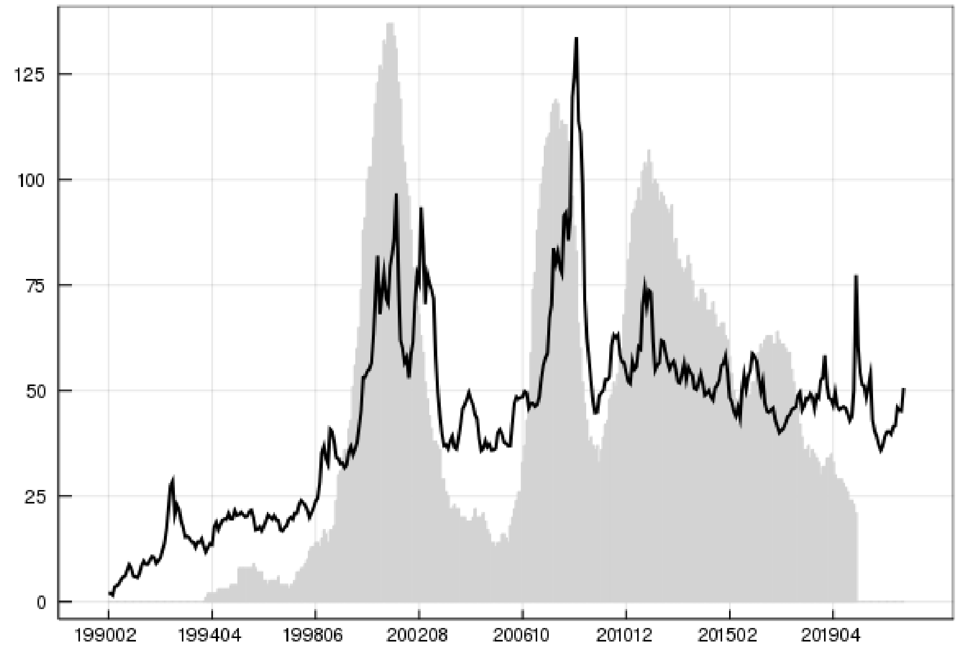
B.8(a) Horizon = 1 month



B.8(b) Horizon = 12 months



B.8(c) Horizon = 2 years



B.8(d) Horizon = 5 years

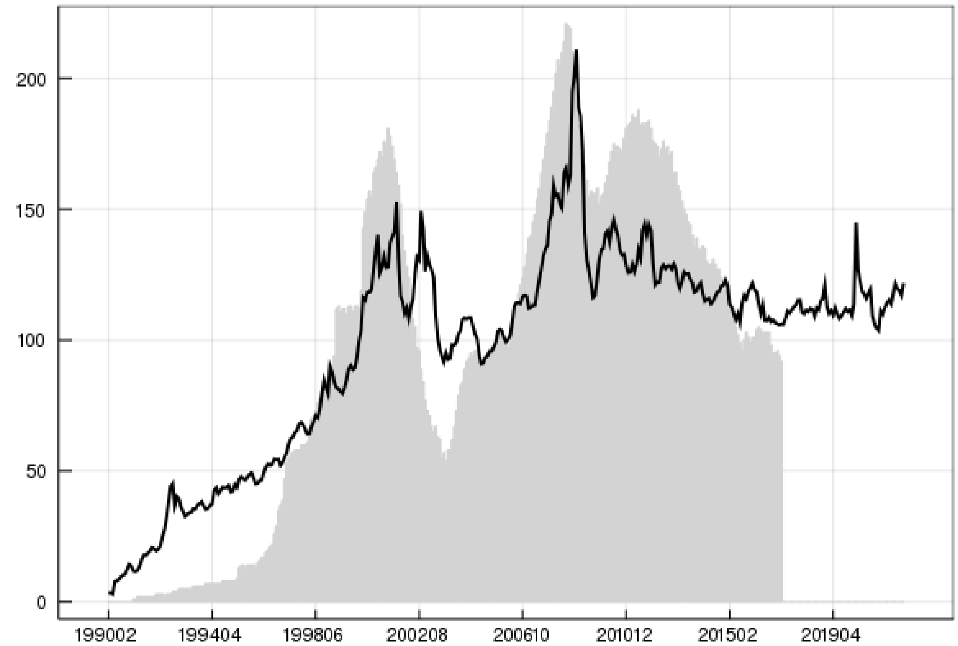
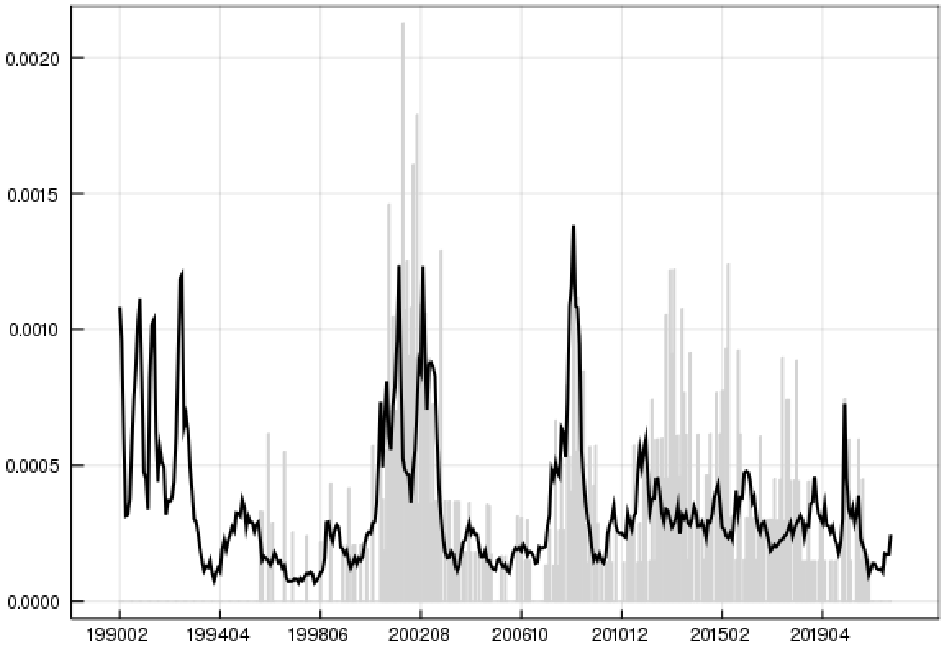
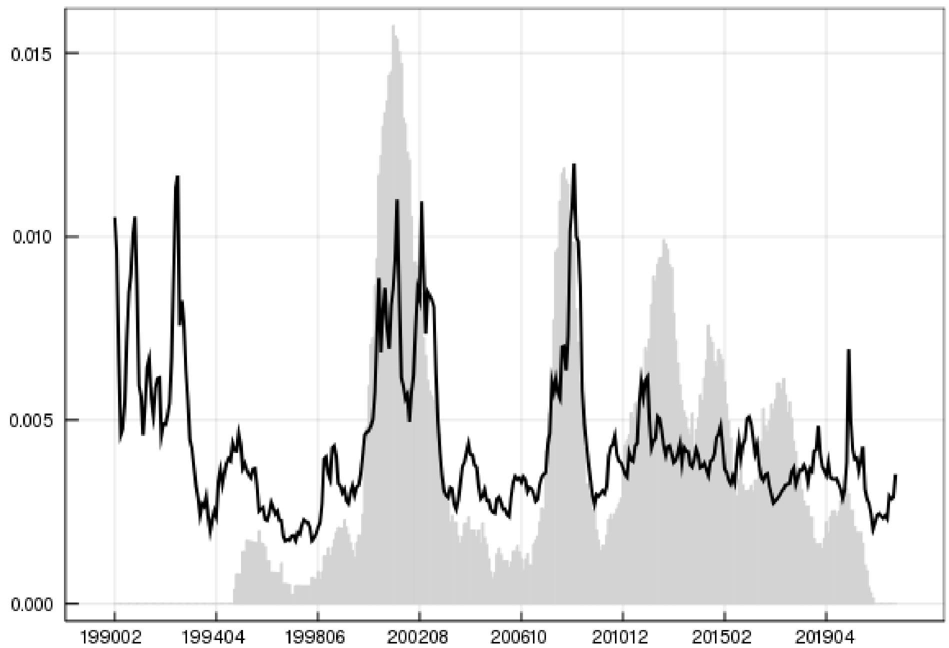


Figure B.8: Performance test with different prediction horizons for the Europe group, in sample. The solid lines represent the predicted default rate, whereas the grey bars represent the actual default rate. x-axis is the time period, and y-axis is the default rate.

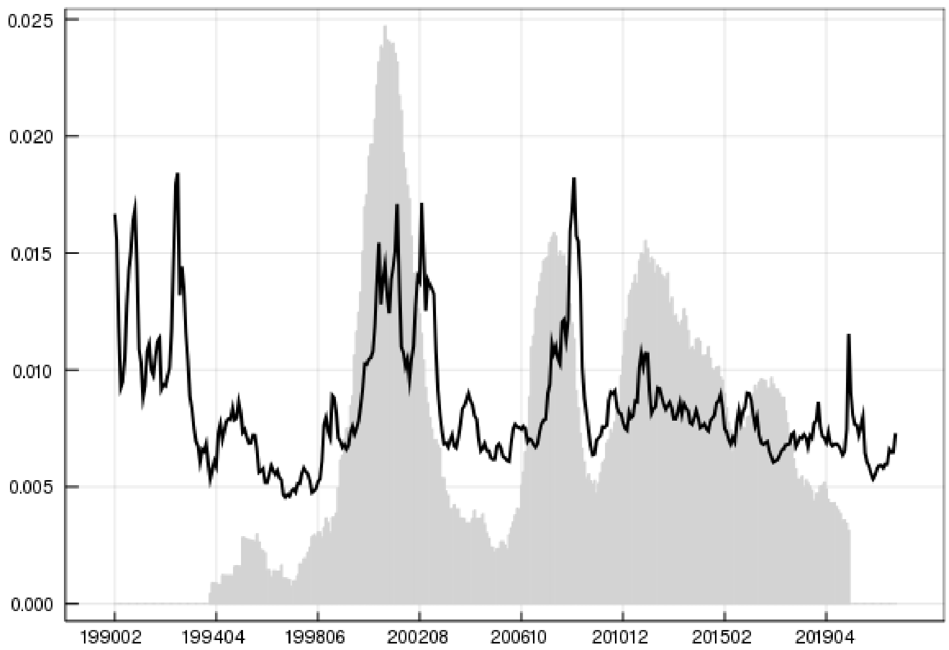
B.8(a) Horizon = 1 month



B.8(b) Horizon = 12 months



B.8(c) Horizon = 2 years



B.8(d) Horizon = 5 years

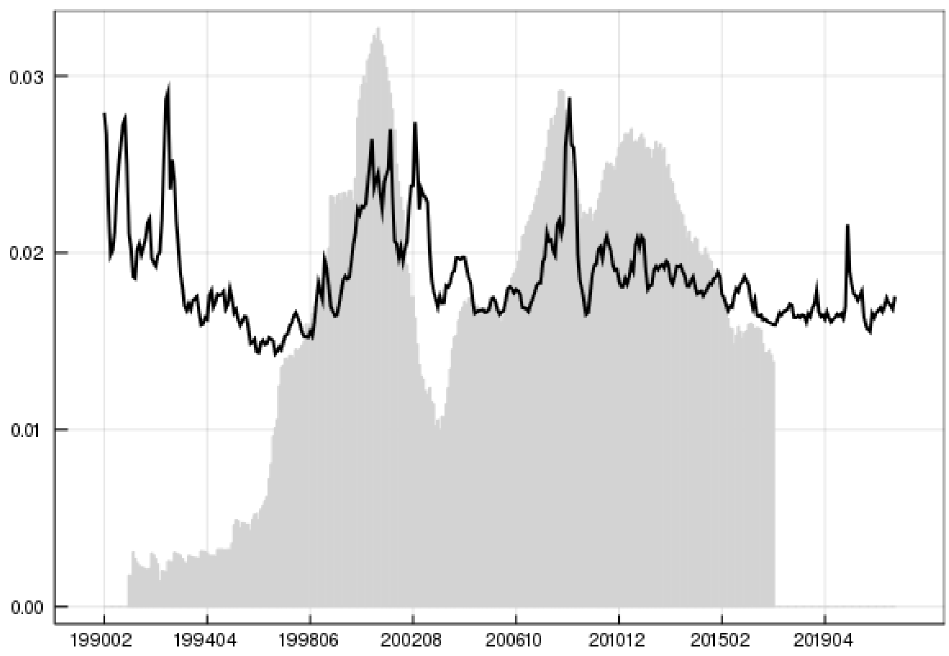
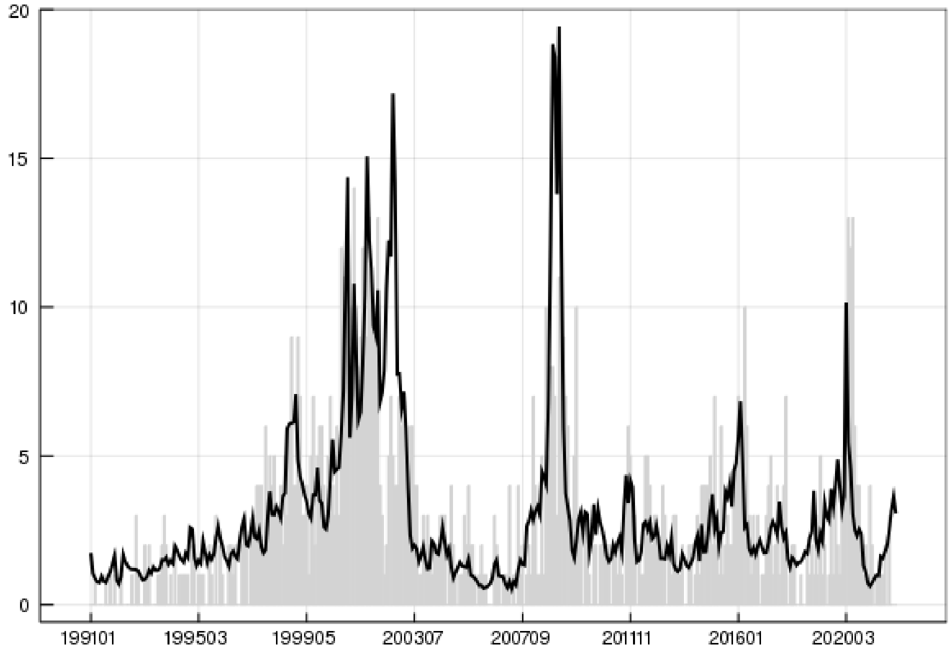
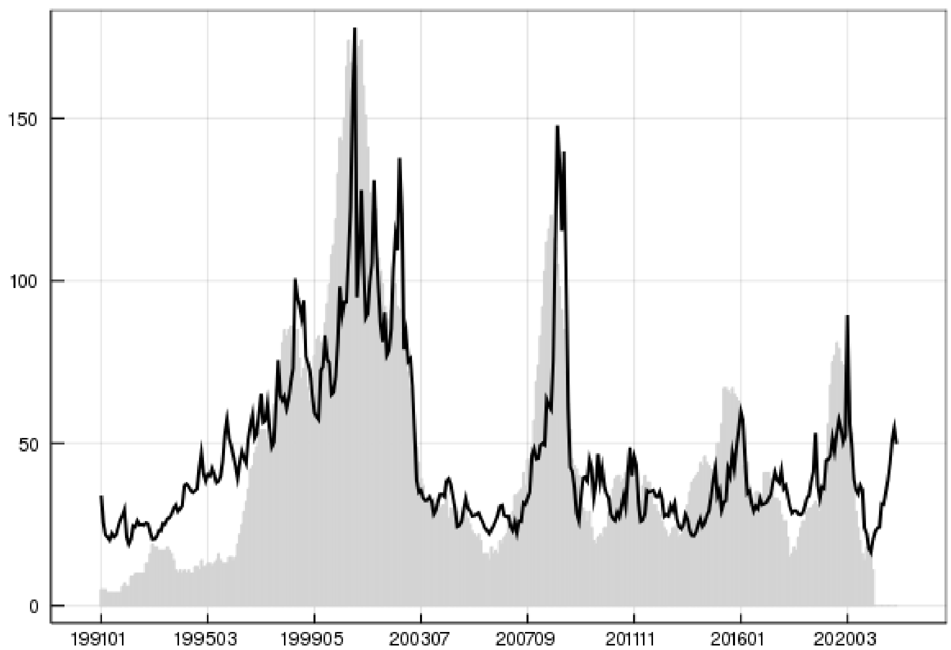


Figure B.9: Performance test with different horizons for North America group, in sample. The solid lines represent the predicted default number, whereas the grey bars represent the actual default number. x-axis is the time period, and y-axis is the number of default.

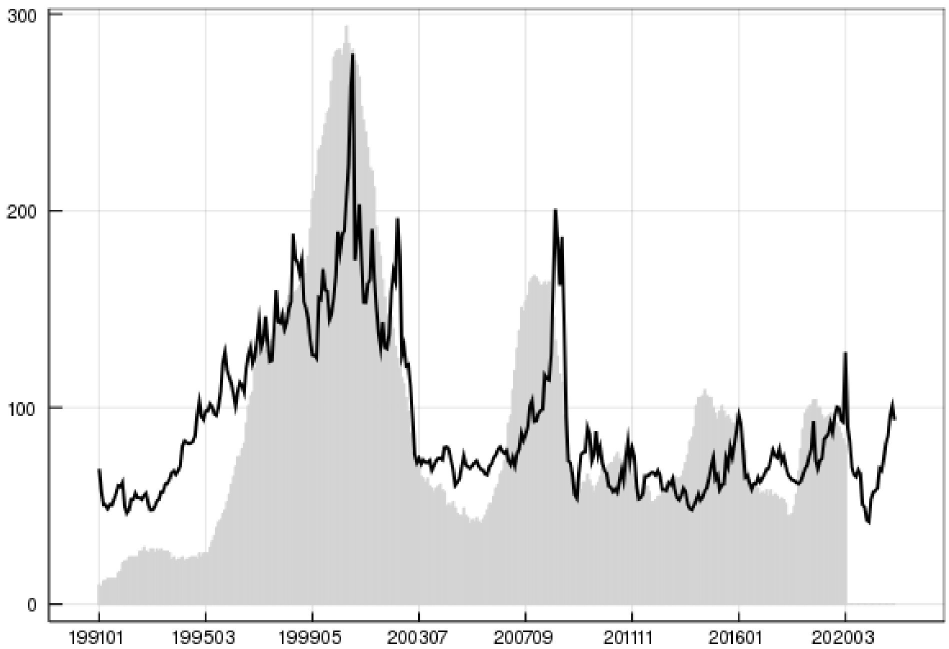
B.10(a) Horizon = 1 month



B.10(b) Horizon = 12 months



B.10(c) Horizon = 2 years



B.10(d) Horizon = 5 years

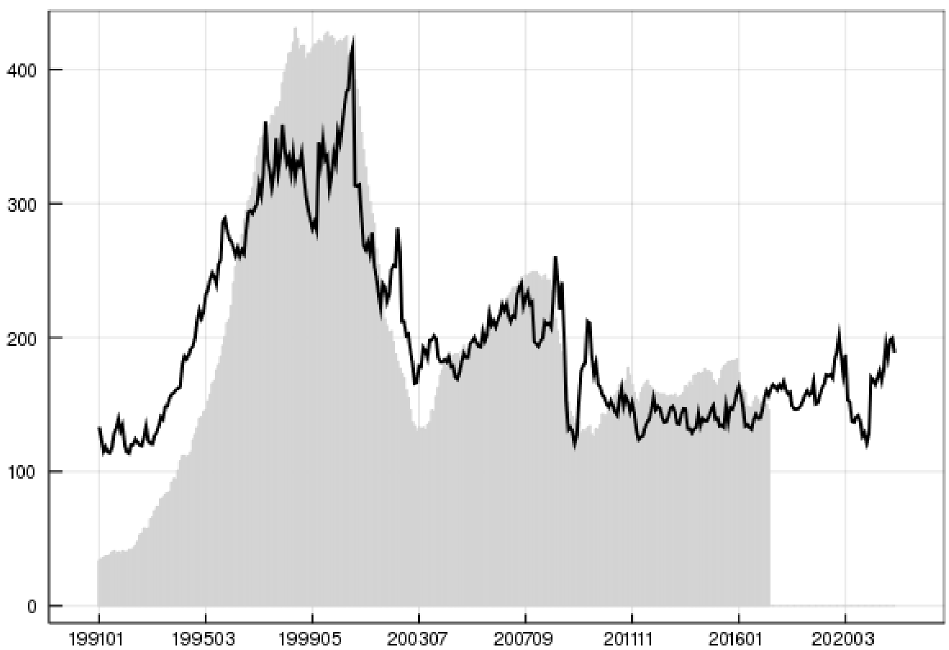
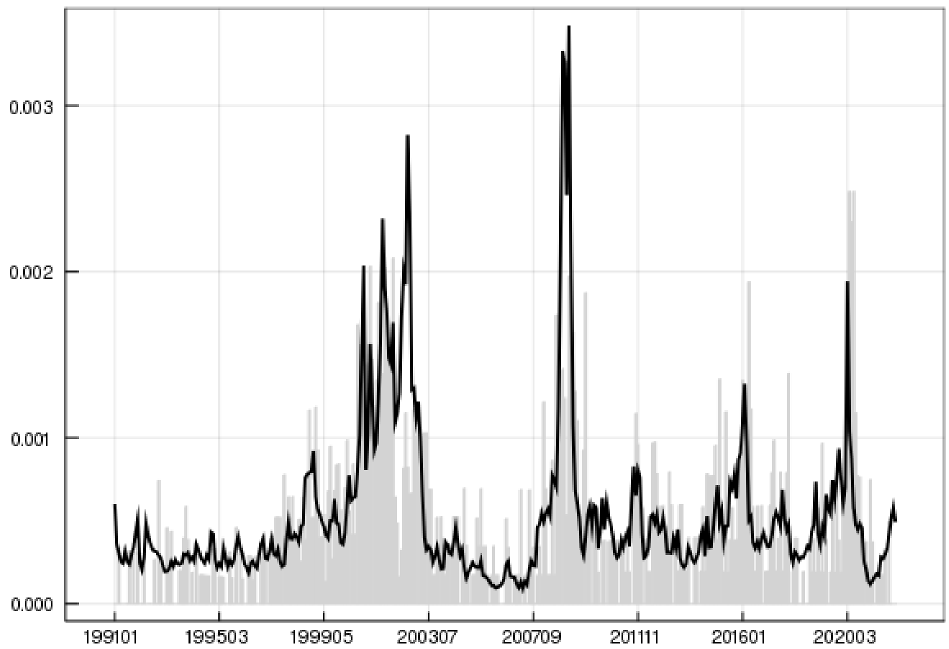
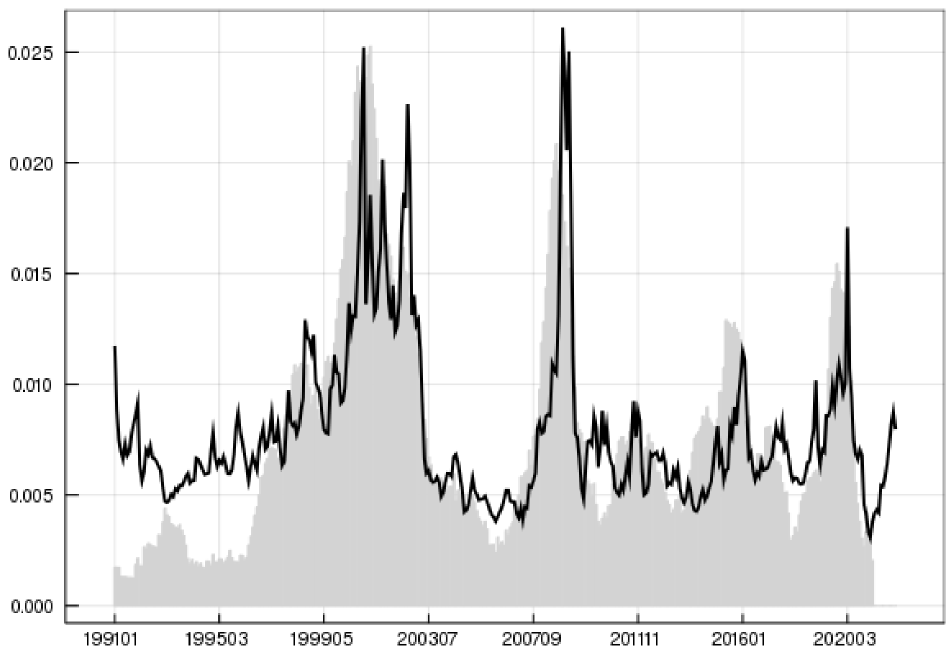


Figure B.10: Performance test with different horizons for North America group, in sample. The solid lines represent the predicted default rate, whereas the grey bars represent the actual default rate. x-axis is the time period, and y-axis is the default rate.

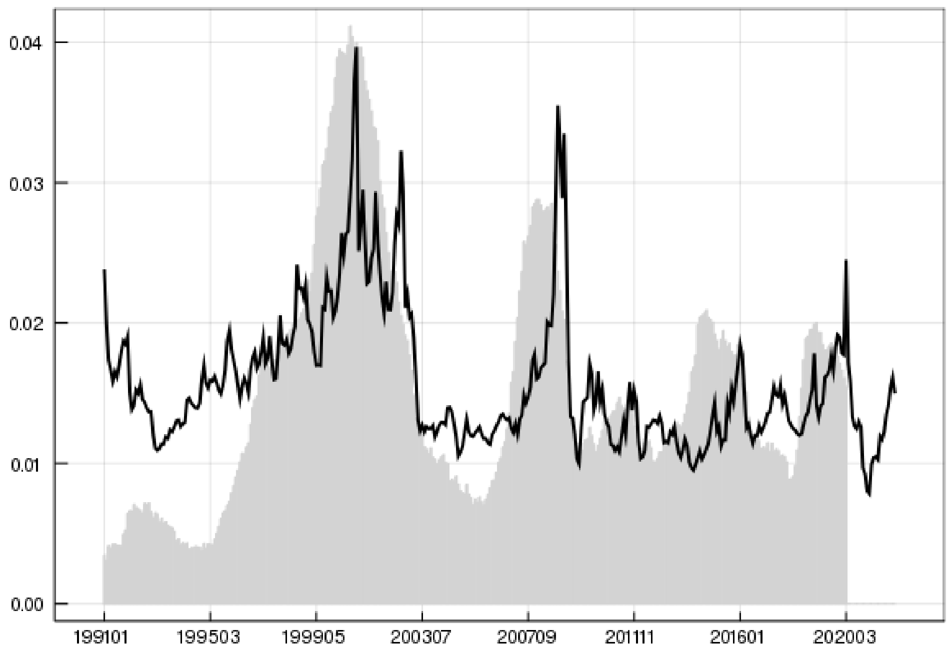
B.10(a) Horizon = 1 month



B.10(b) Horizon = 12 months



B.10(c) Horizon = 2 years



B.10(d) Horizon = 5 years

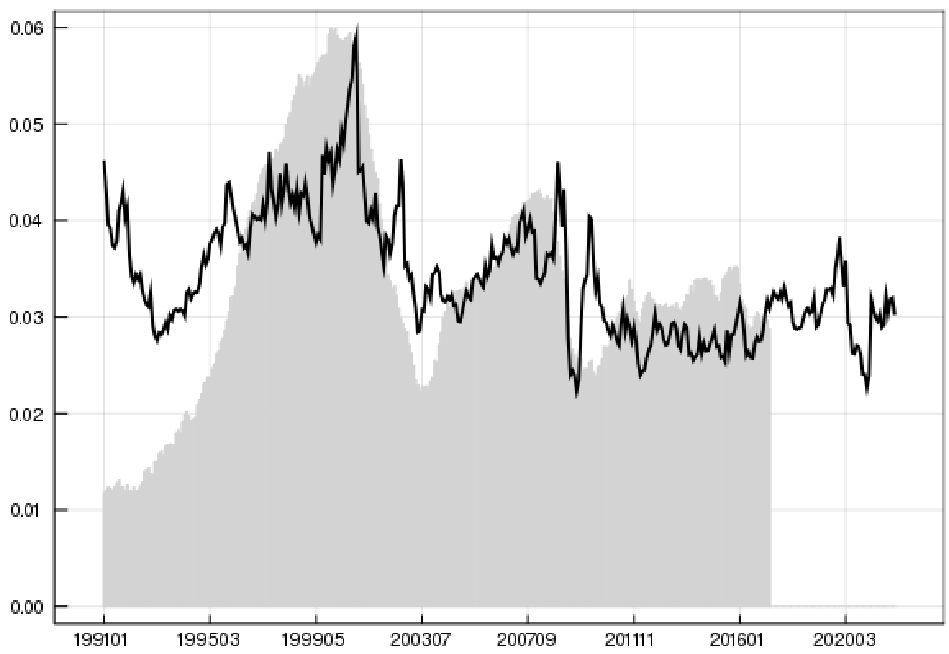
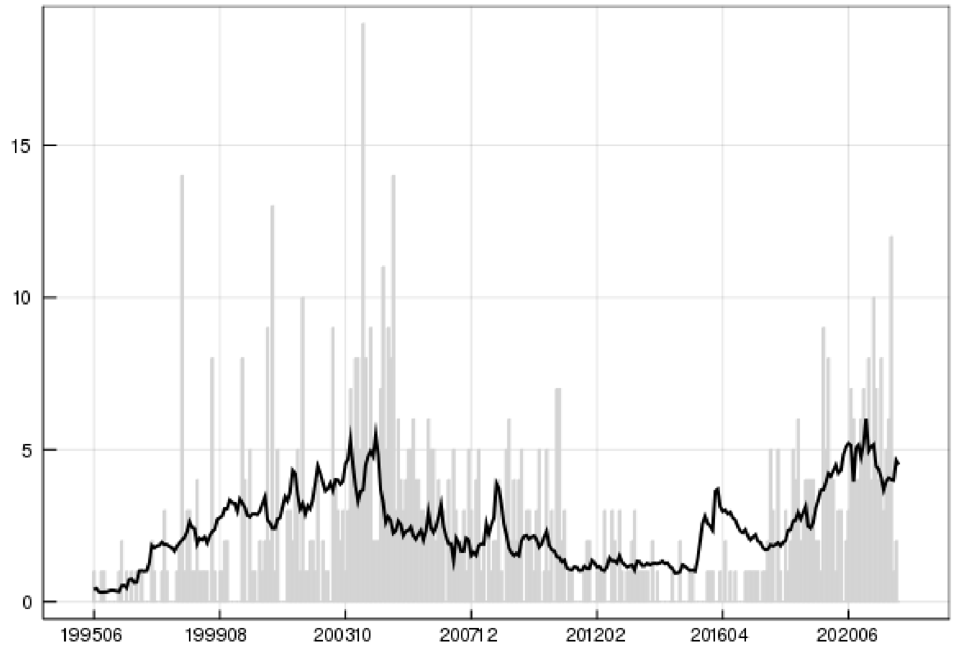
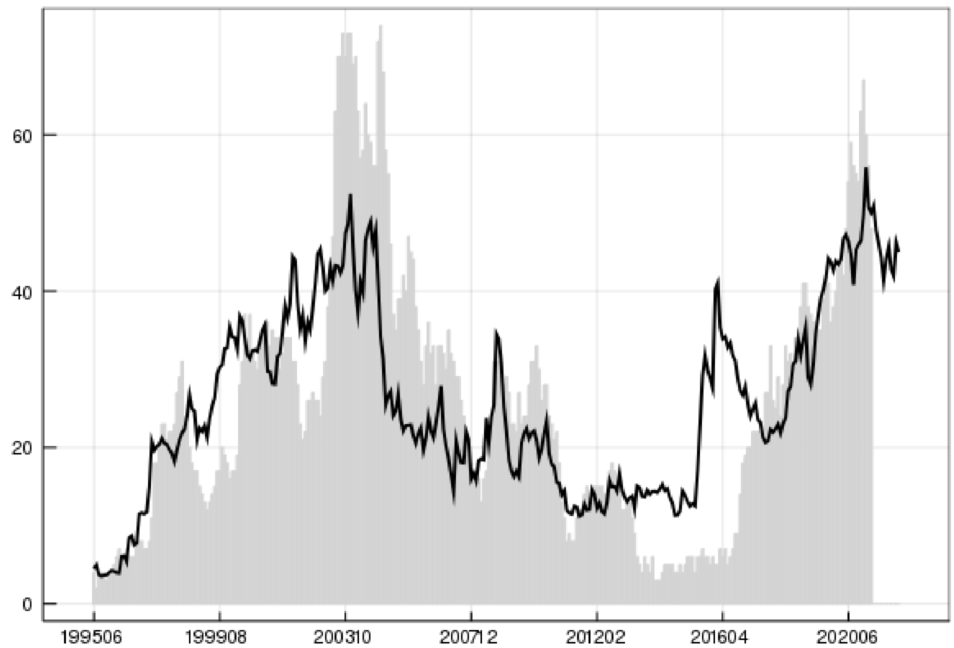


Figure B.11: Performance test with different prediction horizons for China, in sample. The solid lines represent the predicted default number, whereas the grey bars represent the actual default number. x-axis is the time period, and y-axis is the number of default.

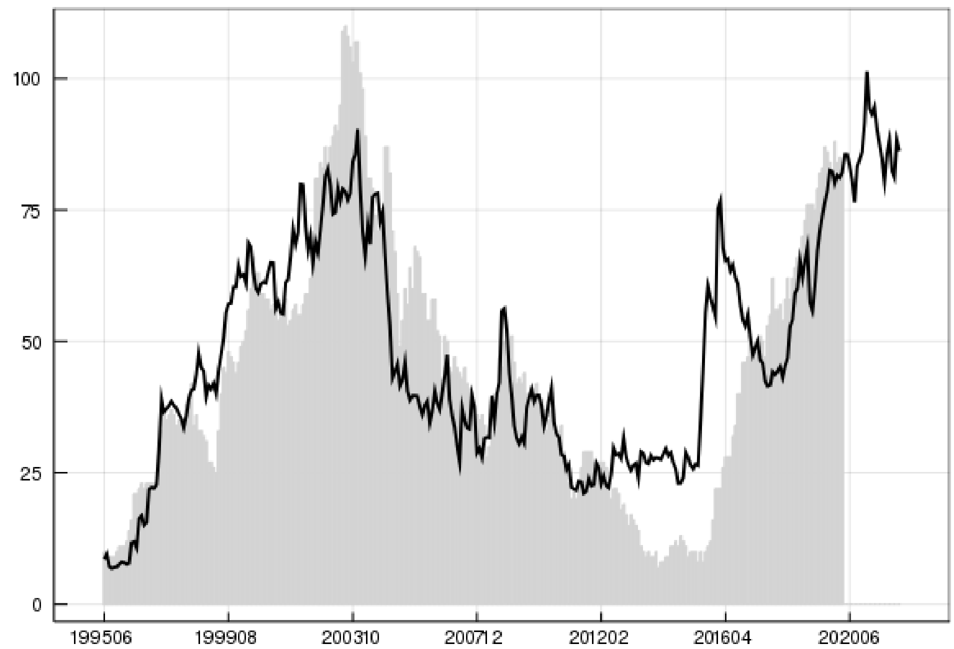
B.12(a) Horizon = 1 month



B.12(b) Horizon = 12 months



B.12(c) Horizon = 2 years



B.12(d) Horizon = 5 years

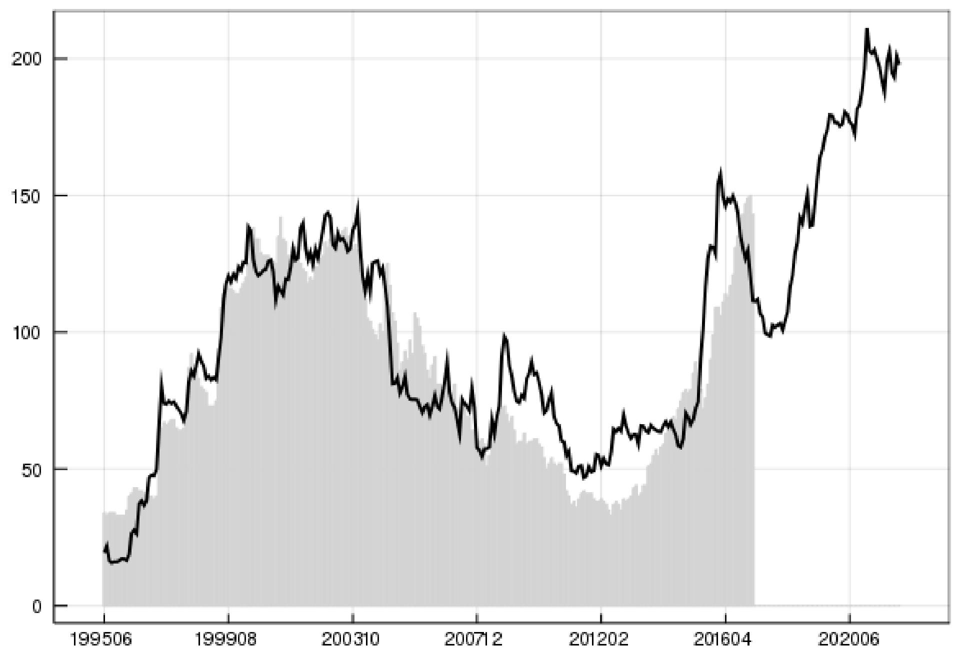
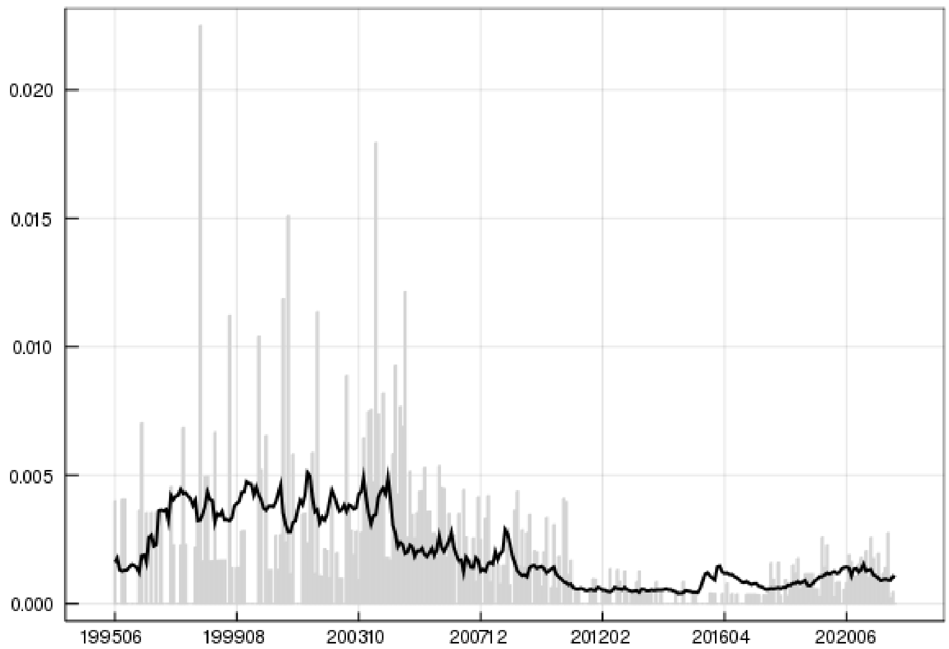
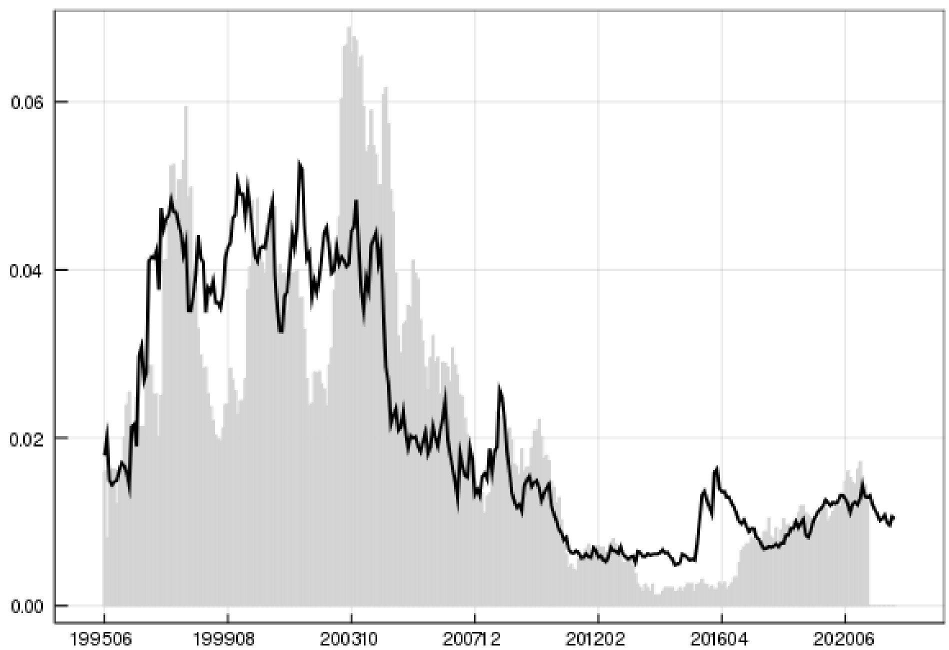


Figure B.12: Performance test with different prediction horizons for China, in sample. The solid lines represent the predicted default rate, whereas the grey bars represent the actual default rate. x-axis is the time period, and y-axis is the default rate.

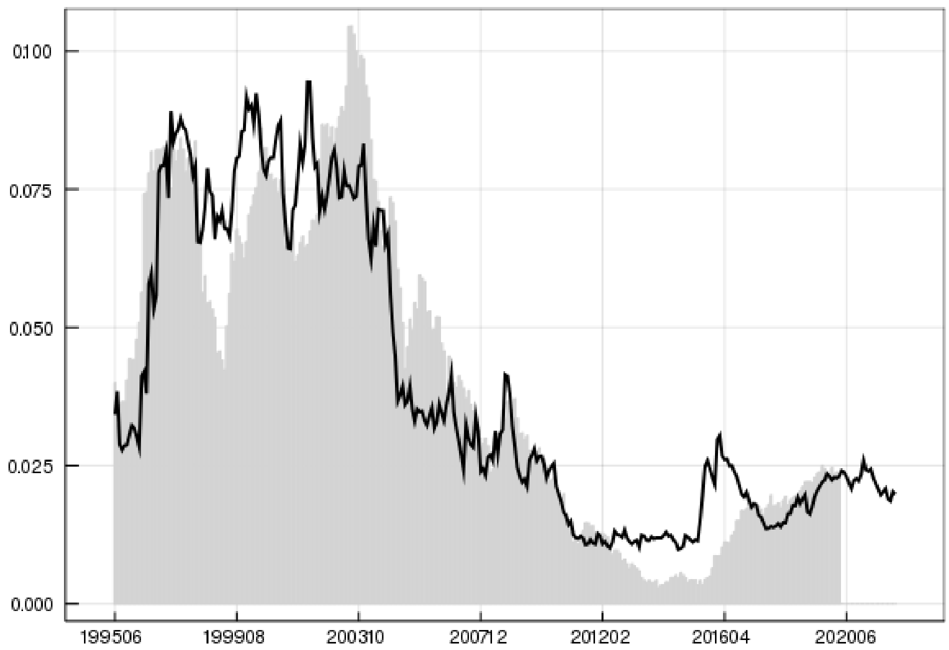
B.12(a) Horizon = 1 month



B.12(b) Horizon = 12 months



B.12(c) Horizon = 2 years



B.12(d) Horizon = 5 years

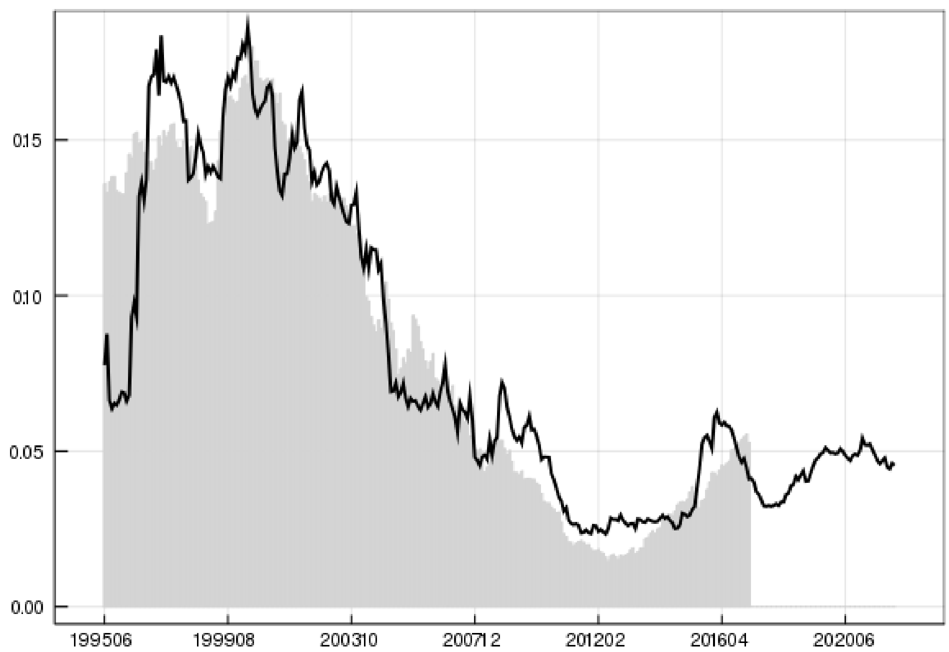
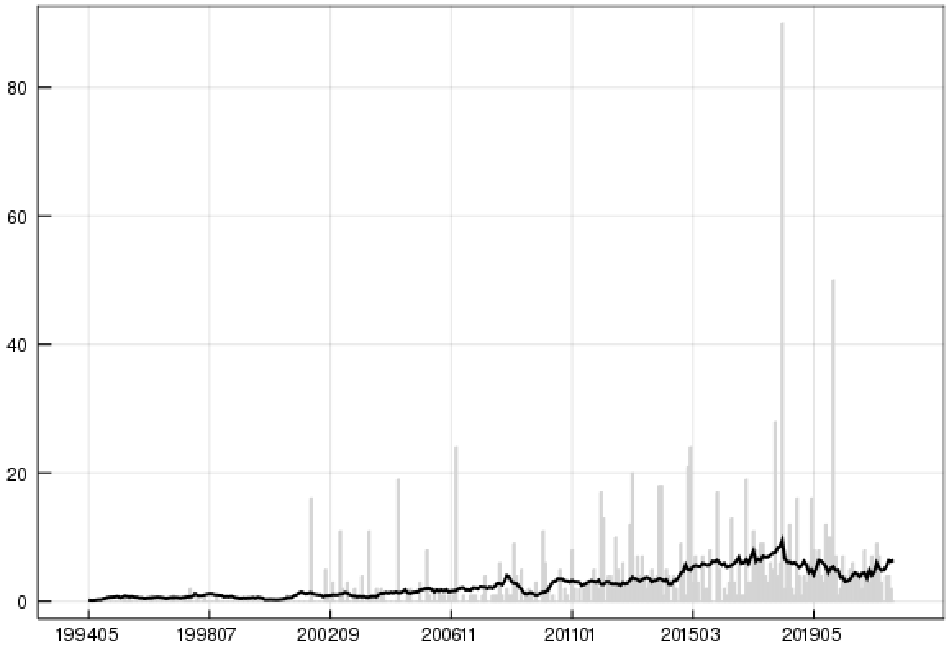
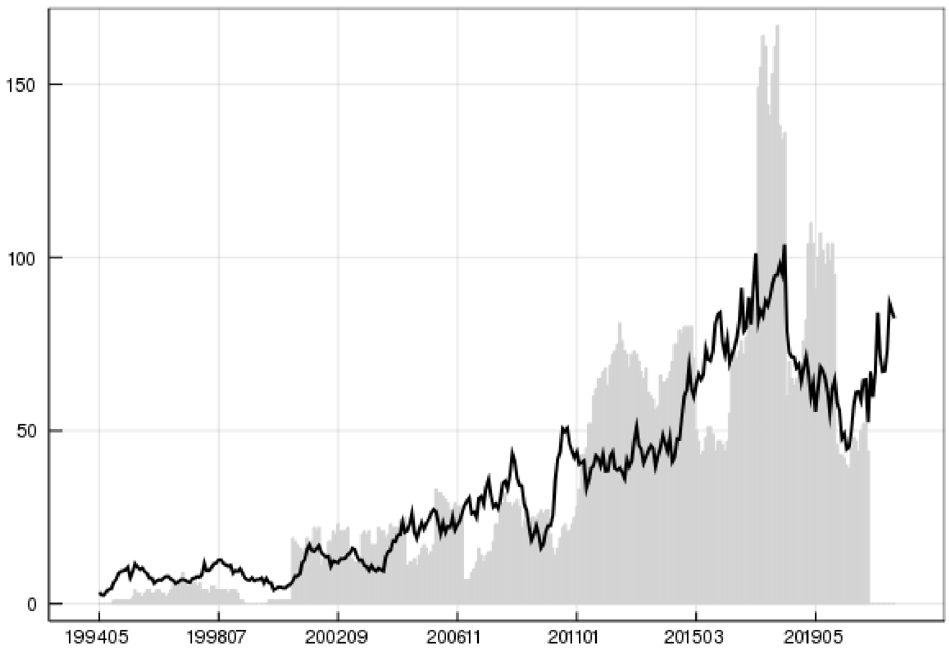


Figure B.13: Performance test with different prediction horizons for India, in sample. The solid lines represent the predicted default number, whereas the grey bars represent the actual default number. x-axis is the time period, and y-axis is the number of default.

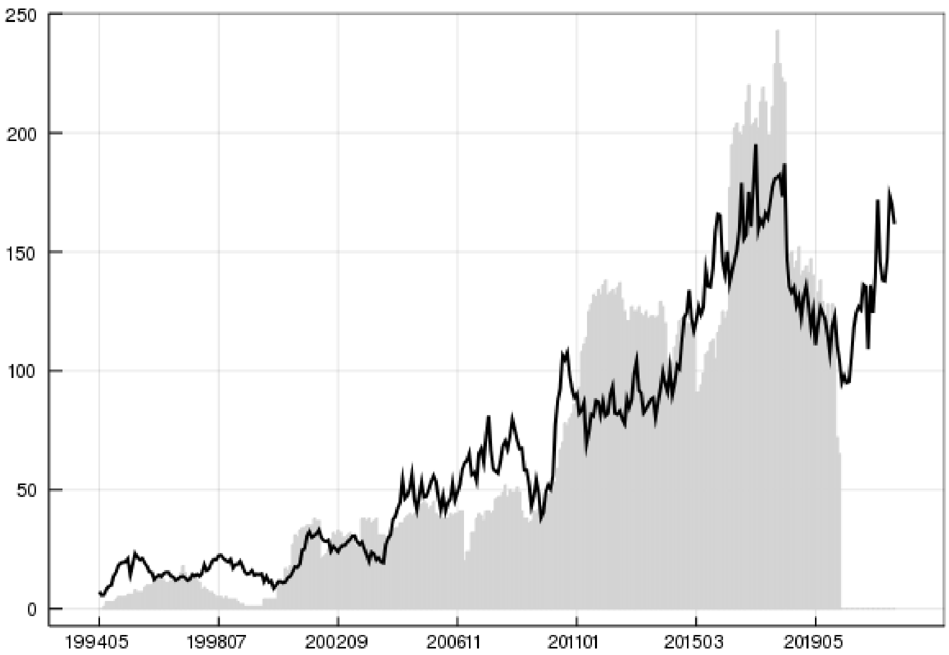
B.14(a) Horizon = 1 month



B.14(b) Horizon = 12 months



B.14(c) Horizon = 2 years



B.14(d) Horizon = 5 years

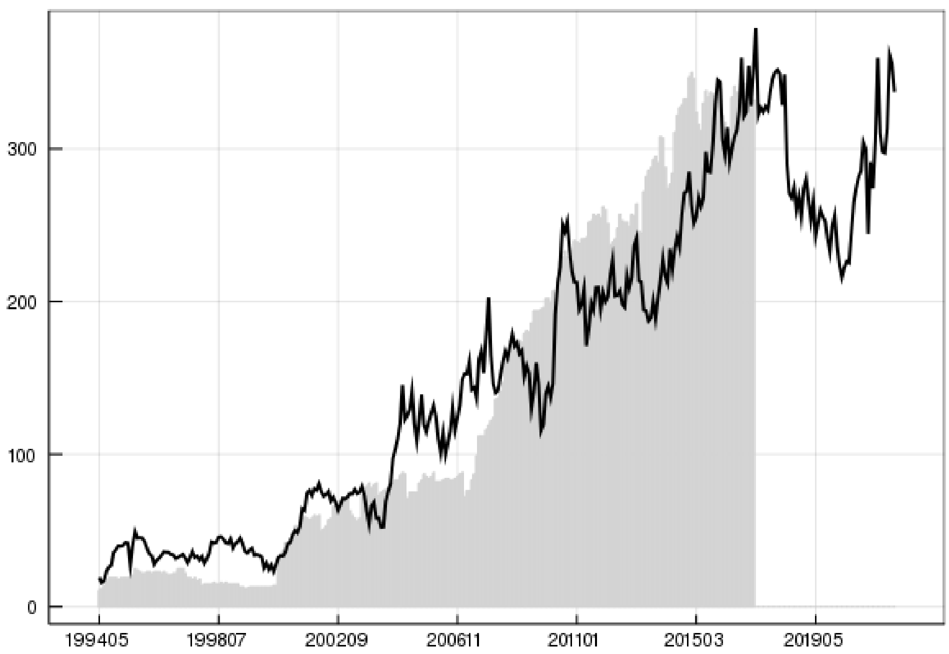
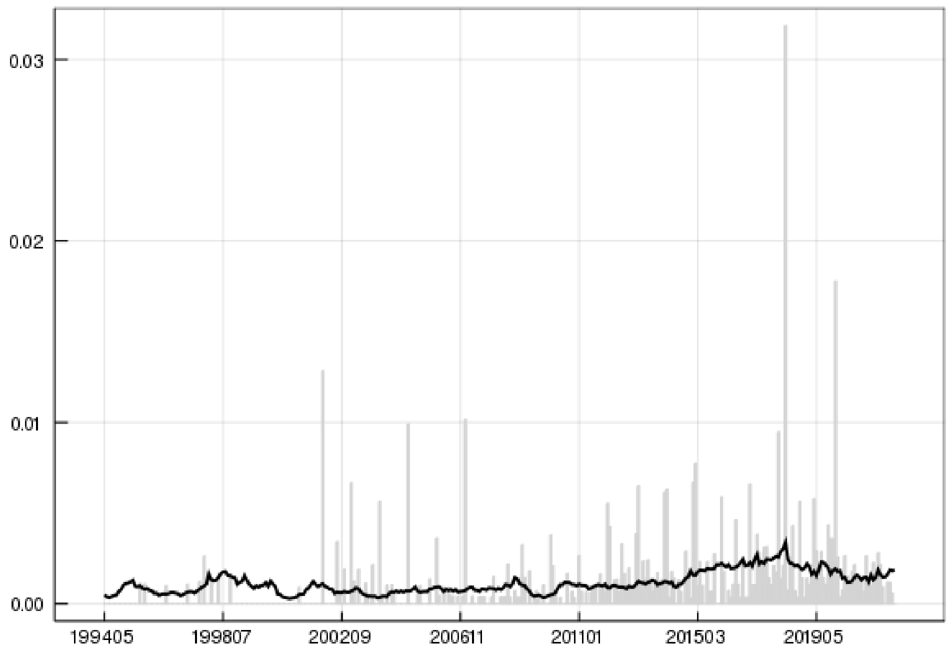
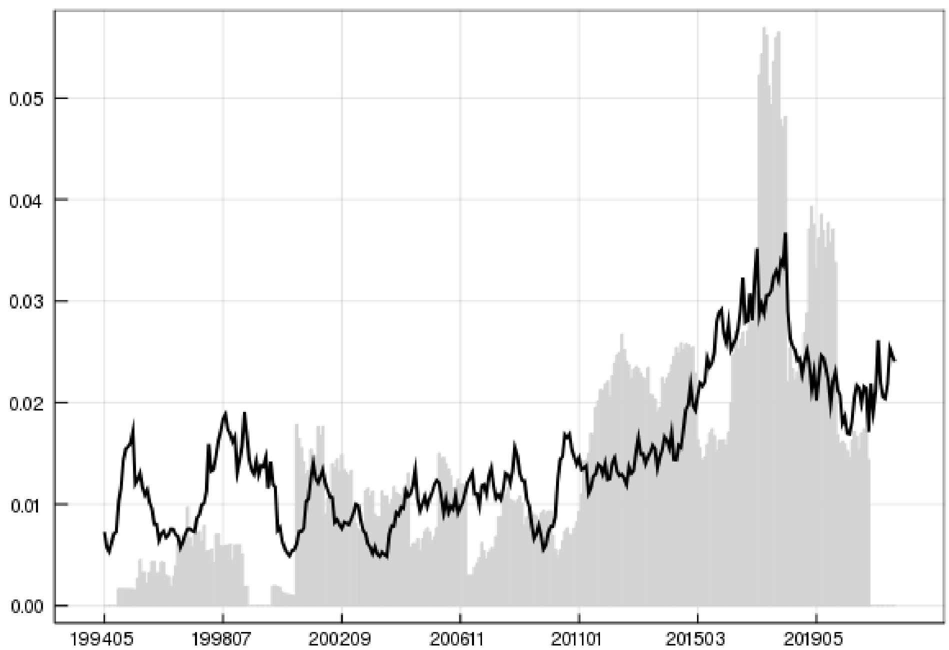


Figure B.14: Performance test with different prediction horizons for India, in sample. The solid lines represent the predicted default rate, whereas the grey bars represent the actual default rate. x-axis is the time period, and y-axis is the default rate.

B.14(a) Horizon = 1 month



B.14(b) Horizon = 12 months



B.14(c) Horizon = 2 years

B.14(d) Horizon = 5 years

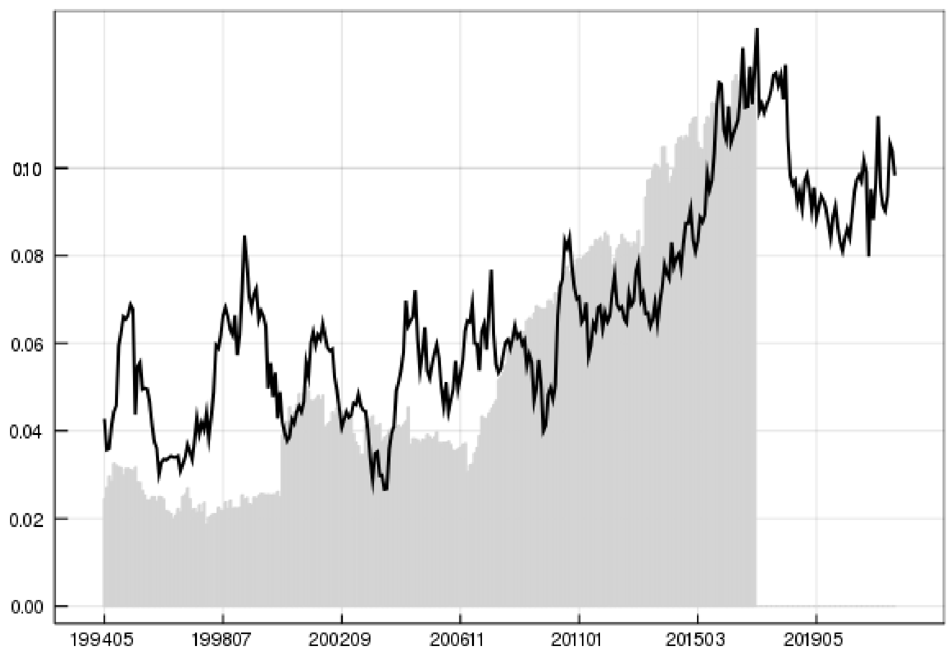


Table B.2: Regression results of forward looking prediction accuracy for different calibration groups at $\tau = 0$

	Point Estimate				P-Value	
Economy	α	$std(\alpha)$	β	$std(\beta)$	$H0: \alpha = 0$	$H0: \beta = 1$
China	0.0002	0.0021	1.0144	0.1604	0.93	0.93
India	-0.0009	0.0014	1.2083	0.1982	0.52	0.29
Asia-Pacific Developed	0.0006	0.0004	0.8292	0.1408	0.15	0.23
Emerging Market	-0.0006	0.0006	1.2283	0.1686	0.35	0.18
Europe	-0.0011	0.0006	1.4406	0.2397	0.06	0.07
North America	-0.0002	0.0012	0.9984	0.1741	0.87	0.99

Table B.3: Regression results of forward looking prediction accuracy for different calibration groups at $\tau = 1$

	Point Estimate				P-Value	
Economy	α	$std(\alpha)$	β	$std(\beta)$	$H0: \alpha = 0$	$H0: \beta = 1$
China	-0.0002	0.0021	1.0327	0.1582	0.93	0.84
India	-0.0009	0.0013	1.1359	0.1717	0.48	0.43
Asia-Pacific Developed	0.0007	0.0005	0.6909	0.1603	0.17	0.05
Emerging Market	-0.0005	0.0007	1.0257	0.1505	0.45	0.86
Europe	-0.0013	0.0007	1.2813	0.2571	0.07	0.27
North America	-0.0006	0.0013	0.9222	0.1497	0.61	0.60

Table B.4: Regression results of forward looking prediction accuracy for different calibration groups at $\tau = 3$

	Point Estimate				P-Value	
Economy	α	$std(\alpha)$	β	$std(\beta)$	$H0: \alpha = 0$	$H0: \beta = 1$
China	-0.0002	0.0021	1.0961	0.1679	0.94	0.57
India	-0.0010	0.0012	1.1401	0.1632	0.44	0.39
Asia-Pacific Developed	0.0007	0.0006	0.6812	0.1918	0.22	0.10
Emerging Market	-0.0003	0.0008	0.9704	0.1617	0.74	0.85
Europe	-0.0017	0.0009	1.3802	0.3251	0.07	0.24
North America	-0.0014	0.0014	1.0111	0.1663	0.31	0.95

Table B.5: Regression results of forward looking prediction accuracy for different calibration groups at $\tau = 6$

	Point Estimate				P-Value	
Economy	α	$std(\alpha)$	β	$std(\beta)$	$H0: \alpha = 0$	$H0: \beta = 1$
China	0.0001	0.0022	1.1688	0.1769	0.95	0.34
India	-0.0011	0.0011	1.1685	0.1528	0.33	0.27
Asia-Pacific Developed	0.0008	0.0008	0.6574	0.2407	0.27	0.16
Emerging Market	0.0000	0.0008	0.9206	0.1587	0.96	0.62
Europe	-0.0021	0.0012	1.5216	0.4262	0.09	0.22
North America	-0.0020	0.0016	1.1174	0.1993	0.21	0.56

Table B.6: Regression results of forward looking prediction accuracy for different calibration groups at $\tau = 12$

	Point Estimate				**P-Value**	
Economy	α	$std(\alpha)$	β	$std(\beta)$	$H0 : \alpha = 0$	$H0 : \beta = 1$
China	0.0009	0.0027	1.2947	0.2061	0.72	0.15
India	-0.0015	0.0011	1.2693	0.1501	0.17	0.07
Asia-Pacific Developed	0.0010	0.0009	0.6387	0.3065	0.30	0.24
Emerging Market	0.0006	0.0008	0.8474	0.1412	0.45	0.28
Europe	-0.0022	0.0014	1.6743	0.5270	0.11	0.20
North America	-0.0024	0.0019	1.2822	0.2607	0.22	0.28

C APPENDIX: PDiR MAPPING TABLE OF 1-YEAR CRI-PD

Table C.1: Mapping 10-day moving average 1-year CRI PD to the S&P experience

Rating Category	Initial Assignment		Upgrade To		Downgrade To	
	lb (bps)	ub (bps)	lb (bps)	ub (bps)	lb (bps)	ub (bps)
AAA	0	0.0035	0	0.0027	-	-
AA+	0.0035	0.1044	0.0027	0.0035	0.1044	0.3060
AA	0.1044	0.3060	0.0035	0.1044	0.3060	0.4069
AA-	0.3060	0.4069	0.1044	0.3060	0.4069	1.2928
A+	0.4069	1.2928	0.3060	0.4069	1.2928	3.0646
A	1.2928	3.0646	0.4069	1.2928	3.0646	3.9506
A-	3.0646	3.9506	1.2928	3.0646	3.9506	9.9936
BBB+	3.9506	9.9936	3.0646	3.9506	9.9936	22.0796
BBB	9.9936	22.0796	3.9506	9.9936	22.0796	28.1227
BBB-	22.0796	28.1227	9.9936	22.0796	28.1227	46.2056
BB+	28.1227	46.2056	22.0796	28.1227	46.2056	82.3715
BB	46.2056	82.3715	28.1227	46.2056	82.3715	100.4544
BB-	82.3715	100.4544	46.2056	82.3715	100.4544	357.0556
B+	100.4544	357.0556	82.3715	100.4544	357.0556	870.2578
B	357.0556	870.2578	100.4544	357.0556	870.2578	1126.8589
B-	870.2578	1126.8589	357.0556	870.2578	1126.8589	1630.8764
CCC+	1126.8589	1630.8764	870.2578	1126.8589	1630.8764	2638.9113
CCC	1630.8764	2638.9113	1126.8589	1630.8764	2638.9113	3142.9287
CCC-	2638.9113	3142.9287	1630.8764	2638.9113	3142.9287	4449.8571
CC	3142.9287	8370.6423	2638.9113	7063.7139	4449.8571	8777.9817
C	8370.6423	10000	-	-	8777.9817	10000

Table C.2: Mapping 10-day moving average 1-year CRI PDs to Moody's experience

Rating Category	initial assignment		Upgrade to		Downgrade to	
	lb (bps)	ub (bps)	lb (bps)	ub (bps)	lb (bps)	ub (bps)
Aaa	0	0.0065	0	0.0049	-	-
Aa1	0.0065	0.0662	0.0049	0.0065	0.0662	0.1860
Aa2	0.0662	0.1860	0.0065	0.0662	0.1860	0.2450
Aa3	0.1860	0.2450	0.0662	0.1860	0.2450	0.8970
A1	0.2450	0.8970	0.1860	0.2450	0.8970	2.2008
A2	0.8970	2.2008	0.2450	0.8970	2.2008	2.8526
A3	2.2008	2.8526	0.8970	2.2008	2.8526	9.2961
Baa1	2.8526	9.2961	2.2008	2.8526	9.2961	22.1830
Baa2	9.2961	22.1830	2.8526	9.2961	22.1830	28.6265
Baa3	22.1830	28.6265	9.2961	22.1830	28.6265	43.3585
Ba1	28.6265	43.3585	22.1830	28.6265	43.3585	72.8224
Ba2	43.3585	72.8224	28.6265	43.3585	72.8224	87.5544
Ba3	72.8224	87.5544	43.3585	72.8224	87.5544	122.7975
B1	87.5544	122.7975	72.8224	87.5544	122.7975	193.2836
B2	122.7975	193.2836	87.5544	122.7975	193.2836	228.5267
B3	193.2836	228.5267	122.7975	193.2836	228.5267	356.9571
Caa1	228.5267	356.9571	193.2836	228.5267	356.9571	613.8180
Caa2	356.9571	613.8180	228.5267	356.9571	613.8180	742.2484
Caa3	613.8180	742.2484	356.9571	613.8180	742.2484	857.5755
Ca	742.2484	1203.5566	613.8180	1088.2295	857.5755	3402.6674
C	1203.5566	10000	-	-	3402.6674	10000

D APPENDIX: Constructing the forward-looking PD partial correlation matrix (Old Methodology)

This appendix details how the NUS-CRI system, prior to June 2023, used to calculate the forward-looking PD partial correlation matrix in the computation for CriSIFI. The new methodology can be found in Chapter 7.

It is important to note that the old methodology follows that of Chan-Lau et al. [2016], which is largely based on Duan and Miao [2016] except for deploying a logit transformation instead of a double–log transformation.

(a) Define one pair of predetermined global factors, ten pairs of predetermined industry factors, and one pair of predetermined economy factors for each economy of domicile (one–month, logit–transformed, median PD and POE). The logit transformation, denoted by a hat, has the following form:

$$\widehat{PD} = \log \frac{PD}{1 - PD} \text{ and } \widehat{POE} = \log \frac{POE}{1 - POE}.$$

The logit transformation is valid because PDs and POEs all fall in (0,1). A dynamic model is then constructed on these 24 $\widehat{PD}$ and $\widehat{POE}$ factors. Later, the inverse transformation will be applied to recover simulated model PD and/or POE factors:

$$PD = \frac{\exp(\widehat{PD})}{1 + \exp(\widehat{PD})} \text{ and } POE = \frac{\exp(\widehat{POE})}{1 + \exp(\widehat{POE})}.$$

(b) In particular, the predetermined economy pair should have at least 30 observations available in the domicile economy. Otherwise, we use the median PD/POE pair of aggregation groups as a substitution: Asia Pacific (Developed), Asia Pacific (Emerging), Europe, Latin America & Caribbean, Sub–Saharan Africa, or Middle East, North Africa & Central Asia. In case an economy has sufficient observations (equal or more than 30) in the history but not later on, we continue to use the economy median. If the economy has fewer observations earlier but sufficiently large later on, we allow the switch from the group median to the economy median to happen but for only once.

(c) The global pair of $\widehat{PD}$ and $\widehat{POE}$ are normalized to have mean 0 and variance 1. For each industry factor, regress $\widehat{PD}$ (or $\widehat{POE}$ factor) on the pair of the global factors to remove any shared information arising from the global factors (i.e., orthogonalization). Henceforth, the industry factors refer to the "orthogonalized regression residuals" uncorrelated with the global factors. We then normalize the 10 industry pairs of $\widehat{PD}$ and $\widehat{POE}$ residuals and the 1 predetermined pair of $\widehat{PD}$ and $\widehat{POE}$ to have a standard deviation of 1 (i.e., normalization).

(d) Model the factors with a bivariate vector autoregressive process of order one without intercept terms, i.e., VAR(1), for each of the 12 pairs of $\widehat{PD}$ and $\widehat{POE}$ factors by deploying entire historical data series up to the point of analysis. Doing so ensures that the factor dynamics are estimated with data covering different phases of a credit cycle and over several credit cycles. Note that the intercept terms are set to zero because normalization has removed the mean.

(e) Estimate the "best" factor model by regressing individual firm $\widehat{PD}$ on 12 global, industry, and economy $\widehat{PD}$ factors based on NUS-CRI 2020 industry classificaiton using a 60–month moving data window. Likewise, regress individual firm $\widehat{POE}$ on the same 12 global, industrial, economy $\widehat{POE}$ factors. Deploy the adaptive lasso technique of Zou [2006] with cross–validation in these regressions to avoid overfitting.

(f) Individual firm's factor model residuals (60 data points at most) are treated as an AR(1) process, and the AR residuals are then used to compute cross–firm correlations. Note that some individual firm's $\widehat{PD}$ and $\widehat{POE}$ are missing due to bankruptcies and/or mergers/acquisitions. We thus construct the AR residual correlation matrix by first computing pairwise correlations, and then apply thresholding coupled with cross–validation to identify a legitimate "sparse" AR residual total correlation matrix.

(g) Use the estimated factor model along with sparse residual correlations to simulate future PDs and POEs for all financial institutions under consideration, and with which we can apply the survival/default formula on the simulated PDs and POEs to obtain PD over any prediction horizon of interest via Monte Carlo averaging of the stochastic PD term structure for each financial institution. This theoretical PD term structure under a particular parameter value serves as the basis to recalibrate factor loadings for every financial institution via a single firm–specific scaling factor and the parameters of its residual AR(1) model. Our recalibration is implemented to fit the 5–year PD term structure provided by the CRI system. This recalibration step ensures that default correlations are obtained not at the expense of poorly matching the available PD term structure individually.

(h) Use the recalibrated model to simulate PDs and POEs for a specific horizon of interest (e.g., one year) at any future time point (e.g., one month later), and estimate the forward–looking total default correlation matrix using the simulated sample.

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